TESIS DOCTORAL

COMPENDIO DE PUBLICACIONES

PROPUESTA DE HERRAMIENTAS BASADAS EN FIABILIDAD PARA EL MODELADO DE SISTEMAS PRODUCTIVOS COMPLEJOS

DOCTORADO EN INGENIERÍA MECÁNICA Y DE ORGANIZACIÓN INDUSTRIAL

Presenta:
Fredy Ariel Kristjanpoller Rodríguez

Director:
Adolfo Crespo Márquez

Sevilla, enero de 2017

ÍNDICE GENERAL

A. DOCUMENTO: TESIS DOCTORAL COMPENDIO DE PUBLICACIONES

B. DOCUMENTO: DOCUMENTACIÓN TESIS POR COMPENDIO

ÍNDICE DE FIGURAS

ÍNDICE DE TABLAS

NOMENCLATURA

Notación	
IEF:	Metodología de Impacto Esperado de Fallos
RBD:	Reliability Blocks Diagram – Diagrama de Bloques de Fiabilidad
FPD:	Factor de Propagación del Tiempo de Detención
ICO:	Impacto Esperado de Criticidad Operacional
KPI:	Key Process Indicator – Indicador Clave del Proceso
MTTF:	Mean time to failure – Tiempo medio hasta el fallo
MTTR:	Mean time to repair – Tiempo medio para reparar
MTBM:	Mean time between maintenance – Tiempo medio entre mantenimientos
AHP:	Proceso de Análisis Jerárquico
CAPEX:	Capital Expenditures – Gastos de Capital
OPEX:	Operational Expenditures – Gastos Operacionales
JCR:	Journal Citation Report ®
A:	Disponibilidad
RAM:	Reliability, availability, maintainability methodology – Metodología de evaluación de fiabilidad, disponibilidad, mantenibilidad
LCC:	Life Cycle Cost – Coste de Ciclo de Vida
CMMS	Computerized Maintenance Management System – Gestión del mantenimiento asistido por ordenador (GMAO)

Tabla 1 Nomenclatura

1. INTRODUCCIÓN

La importancia de los costes de mantenimiento en procesos intensivos en el uso de activos, puede alcanzar hasta el 40% de los costes de producción, como, por ejemplo, en los procesos de la gran minería del Cobre (Consejo Minero, 2015). Dada su relevancia, resulta indispensable un estudio acabado de cada uno de los procesos, bajo un enfoque de mantenimiento y de coste de ciclo de vida. El estudio y modelado de fiabilidad, es la piedra angular para un análisis de mantenimiento, ya que se relaciona directamente con el comportamiento de fallos de cada uno de los componentes hasta establecer la relación de dependencia dinámica de cada uno de los equipos en estudio, aspectos que son fundamentales para evaluar criticidad y proyectar costes en fases de inversión y operación (CAPEX y OPEX) (Parra et al., 2012).

El modelado de fiabilidad, basa su análisis en la ocurrencia de los fallos de un equipo, a través de distribuciones probabilísticas que permiten ajustar los tiempos de buen funcionamiento, las que dan origen a la función de fiabilidad. Dentro de las distribuciones más utilizadas, están la Exponencial y la Weibull, que permiten modelar el comportamiento de un componente durante todo su ciclo de vida; con fases de rodaje, vida útil y degaste, a través de la curva de la bañera (Dhillon, 2006).

El modelado de fiabilidad por componentes se hace extensivo a procesos productivos, lo que permite conocer la fiabilidad por componente y sistemas en su conjunto. Sobre este punto, existen diversas metodologías como Reliability Block Diagram (RBD) (Rausand and Hoyland, 2003; Guo and Yang, 2007), Cadenas de Markov (Welte, 2009), Árboles de Fallo (Rauzy et al., 2007), Gráficos de Fiabilidad (Distefano and Puliafito, 2009), Redes de Petri (PNs) (Volovoi, 2014), entre otros. No obstante a lo anterior, existen relaciones de equipos que, dada su configuración, no es posible modelarlas con las técnicas tradicionales.

La realidad de los procesos industriales evidencia que una mayor flexibilidad en dichos procesos mejora la productividad, la eficiencia del propio proceso y, en definitiva, los resultados generales de la empresa. En ese contexto, los sistemas dinámicos alcanzan una gran importancia en el modelado de los procesos productivos. Los sistemas dinámicos son aquellos que cambian con el tiempo, es decir, pueden variar sus relaciones de dependencia con el entorno o bien, su habilidad de funcionar en diversos escenarios.

El tema de investigación principal de la presente Tesis Doctoral, presentado en el formato por Compendio de Publicaciones, se desarrolla en la revisión y proposición de las técnicas de modelado de fiabilidad, para la evaluación de impacto de fiabilidad y fallos de elementos individuales que se encuentren inmersos en procesos productivos complejos, permitiendo evaluar la criticidad operacional de cada uno de ellos.

La determinación del indicador de criticidad operacional es de vital importancia para la identificación de riesgos operacionales en el interior de los procesos productivos de las empresas, permitiendo facilitar el proceso de toma de decisión de manera efectiva. Actualmente , en la literatura existen diversas investigaciones desarrolladas para identificar los factores que afectan directamente la maximización de beneficios. Estos factores se fundamentan en la consideración empírica de los indicadores de fiabilidad, mantenibilidad y disponibilidad (RAM) (Viveros et al., 2012).

Como resultado principal del trabajo de doctorado, se obtienen 3 artículos ISI – JCR y la presentación de 4 artículos en congresos internacionales con proceedings. En cada una de estas publicaciones, el candidato a doctor es el primer autor y su tutor, el segundo.

El proyecto de Tesis Doctoral que se presenta, se enmarca dentro de la línea de investigación del grupo Sistemas Inteligentes de Mantenimiento - SIM, perteneciente al Departamento de Organización Industrial y Gestión de Empresas de la Universidad de Sevilla.

2. OBJETIVOS

El objetivo principal de esta Tesis Doctoral, presentado en el formato por Compendio de Publicaciones, es el desarrollo de una metodología que permita evaluar el impacto de fiabilidad para elementos individuales, que se encuentren ubicados en sistemas productivos cuya configuración sea compleja.

Para cumplir con el objetivo antes señalado, la metodología del trabajo de investigación considera las siguientes cinco fases:

1. Revisión y caracterización de las técnicas para el modelado de fiabilidad

2. Evaluación y comparación de las técnicas para el modelado de fiabilidad

3. Propuesta de nuevos algoritmos para desarrollar el modelado de fiabilidad y la medición de su impacto en configuraciones complejas.

4. Diseño de una metodología para desarrollar modelados de impacto de fiabilidad

3. RESUMEN GLOBAL DE LOS RESULTADOS

3.1. INTRODUCCIÓN

La aplicación de técnicas de fiabilidad con el propósito de apoyar la toma de decisiones, es una tarea fundamental para la gestión eficiente y precisa de los activos y recursos en cualquier organización industrial. Es conocido que la capacidad productiva real de una planta depende fuertemente de la disponibilidad sistémica, la cual, a su vez, está determinada por la configuración lógica en la que se encuentran los equipos. Equipos dispuestos en serie o con alguna clase de redundancia, tendrán per se distintos impactos en la disponibilidad del sistema, independientemente de su propia fiabilidad y disponibilidad individual. Es decir, el tiempo de indisponibilidad del sistema, no tiene por qué corresponder con el tiempo de indisponibilidad de los equipos en fallo, pues cada equipo tiene un distinto "factor de propagación" de su tiempo de detención en la indisponibilidad del sistema. Sin embargo, a pesar de la utilidad y relevancia de conocer esta información, durante la ejecución de la mayoría de los planes de gestión de activos, el análisis del mencionado "factor de propagación" y el impacto de cada equipo en la disponibilidad sistémica no es común. Esta carencia no es menor, ya que conocer el impacto real de cada activo en la configuración del sistema total, proporciona ventajas en la planificación de la producción y mantenimiento.

En general, se reconoce que la teoría de la fiabilidad, junto con el análisis de ciclo de vida de los activos, constituyen un apoyo trascendente para el análisis y mejora en plantas industriales (Daylan et al., 2016). La evaluación de la fiabilidad y disponibilidad, involucrando parámetros técnicos y de costes, es crucial en la evaluación del desempeño de un proceso industrial, específicamente, en procesos productivos intensivos en capital (Gang et al., 2015). Por otro lado, es sabido que el análisis de los KPI (Key Performance Indicators), son efectivos para medir cuantitativamente los resultados y el desempeño de un proceso (Koontz et al., 2014). De aquí se infiere que, el contar con KPI que arrojen información relacionada con la cuantificación de la disponibilidad y del peso relativo de cada equipo en el sistema, resulta indispensable para estudiar la criticidad de los activos y así poder priorizar y focalizar las actividades de control del riesgo operacional (Crespo et al., 2016).

A pesar de las ventajas de conocer el impacto esperado de fallo de cada elemento en la disponibilidad del sistema, no se ha encontrado una metodología directa para su determinación. Por lo anterior, es fundamental el desarrollo de una metodología para la evaluación continua de la criticidad operacional que complemente las tradicionales metodologías de medio y largo plazo. De esta manera, con el desarrollo de esta nueva metodología, es posible contar con los indicadores e información necesaria para planificar y programar recursos, de acuerdo a los requerimientos propios de cada proceso productivo, tomando decisiones de corto de plazo y de alto impacto sobre el negocio. En la práctica industrial, frecuentemente, se recurre a enfoques semi-cuantitativos como matrices de criticidad basadas en factores ponderados y flujogramas de análisis de riesgo, o bien, se utilizan herramientas más bien genéricas desde el punto de vista de la toma de decisiones, como es el caso del Proceso de Análisis Jerárquico (AHP), las cuales necesariamente deben ser contextualizadas y adaptadas a cada caso. Estas últimas, por la misma razón, no entregan necesariamente resultados homogéneos y comparables entre procesos o instalaciones físicas.

3.2. METODOLOGÍA PROPUESTA

La metodología del impacto esperado de fallos (IEF) (Kristjanpoller et al., 2016; Kristjanpoller et al., 2017a; Kristjanpoller et al., 2017b), es aplicable sobre cualquier configuración lógico-funcional, cuantitativa e integral para el análisis de la disponibilidad. Esta propuesta diseña un nuevo algoritmo para calcular dos índices de impacto, a saber, el Índice de Criticidad Operacional esperado (ICO) y el Factor de Propagación del tiempo de Detención esperado (FPD). Ambos, basados en la fiabilidad y capacidad de mantenimiento de los elementos y el impacto esperado de cada uno, de acuerdo a diferentes escenarios y configuraciones. Estos índices de impacto, sustentados en un enfoque probabilístico, definirán las condiciones previstas en el sistema, desde el punto de vista de la evaluación de sus posibles estados (comportamiento intrínseco), y en relación con la configuración lógica y funcional en el sistema. De esta manera, estos permitirán la comparación global de los elementos, su priorización y evaluación parcial de su efectividad.

Para plantear más claramente la diferencia entre el ICO y el FPD, resulta pertinente efectuar una analogía con el impacto de distintas acciones sobre el rendimiento de una bolsa de valores. Cada acción puede representar un elemento del sistema y el rendimiento final de la bolsa, puede asemejarse al rendimiento en disponibilidad del sistema. Si una acción disminuye un determinado porcentaje, no quiere decir que la bolsa disminuirá en la misma medida. El valor que pondera la propagación de ese decremento hacia el rendimiento de la bolsa sería el factor FPD, el cual tomará en consideración también el comportamiento de las demás acciones. Por otro lado, analizando el desempeño total de la bolsa de valores, puede determinarse que una caída está conformada en diversas proporciones por la caída de distintas acciones individuales. Así, ese valor que relaciona el desempeño total con cada elemento del sistema será el ICO. En resumen, tanto el FPD como el ICO detallan el impacto de la detención de un elemento sobre el sistema, para hacer el análisis en disponibilidad y costes que se estime conveniente.

La metodología se estructura en cuatro etapas que se resumen en la Figura 1. La primera etapa gestiona y prepara los datos e información del proceso sujetos a análisis. La segunda etapa, se encarga del cálculo de la fiabilidad y disponibilidad de cada elemento individual hasta obtener datos sistémicos de disponibilidad. La tercera etapa, toma los datos de disponibilidad del sistema y con ellos encuentra la influencia real de cada elemento en el sistema, es decir, su ICO y su FPD. La cuarta y última etapa, corresponden al análisis de los indicadores para la toma de decisiones.

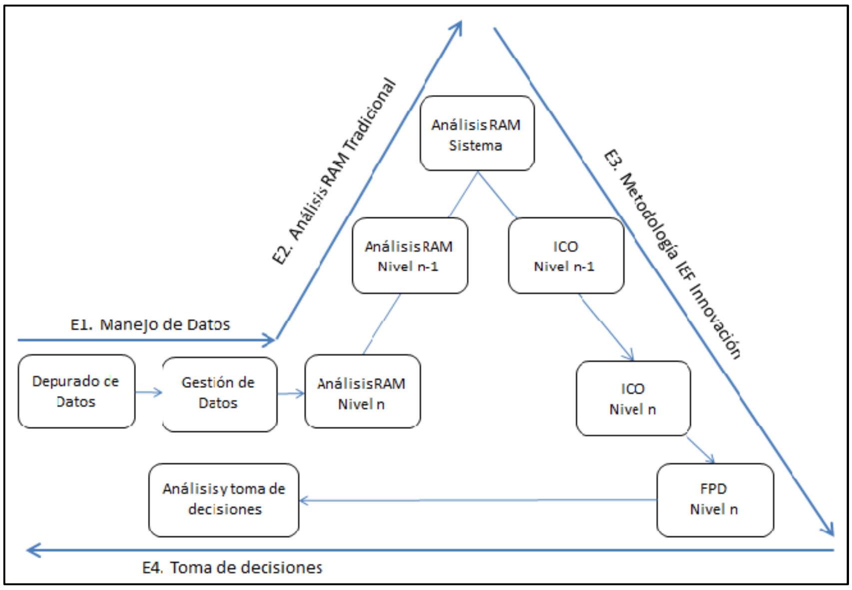


Figura 1 Etapas de la Metodología IEF

Etapa 1: Depurado y Gestión de Datos

Sin un suministro de información adecuado, el análisis de datos es tiempo perdido. Por tanto, el primer paso de esta metodología implica la depuración y filtrado de los datos industriales con el fin de mejorar sus atributos, detectando la ausencia de valores y datos erróneos, discriminando asimismo datos correspondientes a distintos elementos y condiciones operacionales y evaluando, en general, la calidad de los registros (Chapman, 2005).

En vista de lo anterior, es necesario diseñar un procedimiento para recabar los datos útiles del proceso, con el objeto de tener datos fiables y representativos de cada elemento a analizar. Posteriormente, el uso de técnicas estadísticas como el análisis de dominancia y percentiles significativos, puede ser útil para filtrar los datos y lograr una base de datos depurada (Carnero, 2004).

Etapa 2: Análisis ascendente. Análisis clásico RAM desde el elemento más pequeño hacia el sistema.

Para llevar a cabo esta etapa, se desarrolla un análisis clásico de Diagrama de Bloques de Fiabilidad (RBD) (Rausand and Hoyland, 2003; Guo and Yang, 2007) en el que se realiza un análisis de fiabilidad y disponibilidad del proceso por niveles. Comenzando con el cálculo de la fiabilidad y disponibilidad de cada elemento y, dada su configuración lógico-funcional, se asciende para el cálculo de la disponibilidad sistémica. Este proceso puede ser entendido como ir de “abajo – arriba”, ya que parte del cálculo de los indicadores RAM del elemento de nivel más bajo y, posteriormente, estos indicadores se utilizan para construir los índices de todo el sistema complejo bajo el uso de las relaciones lógicas de RBD (Dhillon, 2006).

La disponibilidad corresponde a una proporción de tiempo que podría ser expresada como la probabilidad de que el equipo está disponible cuando se requiere. De esta manera, y suponiendo que el equipo requerido siempre debe ser utilizado y, que las órdenes de producción se inician inmediatamente después de un fallo, es posible definir la disponibilidad prevista de un elemento específico, como por ejemplo (Dhillon, 2006):

$$= \frac{\quad}{\quad + \quad} \qquad (1)$$

Para la generación del análisis sistémico RBD y para la obtención de la disponibilidad del sistema, se utilizan los modelos desarrollados por Dhillon (2016) para las configuraciones de serie, redundancia total, stand by, redundancia parcial y fraccionamiento.

Etapa 3: Análisis desde el sistema hasta el elemento. Determinación del desempeño sistémico y del impacto de los elementos.

Esta fase corresponde a un análisis de "arriba - abajo", proceso para el cálculo de los indicadores de impacto a partir de la disponibilidad del sistema hasta el elemento de nivel inferior. Así, es posible calcular el ICO (impacto esperado de criticidad operacional) que permite conocer la contribución del fallo de cada elemento a la pérdida de producción del sistema debido a su indisponibilidad, siendo la sumatoria de los ICO de todos los elementos el 100%.

Dado un sistema complejo compuesto por I niveles, desde i=0 hasta i= r, donde el i=0 corresponde al nivel del sistema en general, i=1 al nivel de los elementos “padres” en que inicialmente se divide el sistema (subsistemas), i=2 al nivel de los elementos “hijos” o sub-elementos del nivel anterior y así hasta el nivel r. Sea J el conjunto de elementos mantenibles del sistema; habrá desde j=1 hasta j=n elementos en cada nivel i del sistema. El factor ICO de cada elemento en el sistema se determina a través de la descomposición del índice global y de cada uno de los subsistemas. El desglose del ICO de cada nivel se expresa con las ecuaciones 2, 3 y 4:

$$(\quad)\qquad {}_{=0} = 1 \qquad (2)$$

$$\sum_{=1} {}_{;} = {}_{-1} \quad \forall \ : 0, \ldots, \ ; \ \forall \ : 1, \ldots, \qquad (3)$$

$$\frac{{}_{;}}{{}_{;\ +1}} = \frac{(1 - \ {}_{;})}{(1 - \ {}_{;\ +1})} \quad \forall \ : 0, \ldots, \ ; \ \forall \ : 1, \ldots, \qquad (4)$$

Donde:

ICO $_{i;\,j}$: Es el ICO para el elemento j (de 1 a n) que se encuentra en el nivel de descomposición i (de 1 a r).

$A_{i;j}$: Es la disponibilidad esperada para el elemento j (de 1 a n) que se encuentra en el nivel de descomposición i (de 1 a r).

En términos simples, el ICO muestra el resultado final de la contribución de cada elemento sobre el sistema, exponiendo el posible impacto de un fallo en la pérdida de capacidad de producción. Al considerar el nivel de detalle más bajo, esto es el sistema en su totalidad o nivel i=0, la suma de todos los ICO es 100% del sistema (ecuación 5).

$$\quad_{=1} \quad {}_{;} = 1 \qquad \forall\ : 0, \ldots ,\ ; \qquad (5)$$

Por último, una vez conocido el $ICO_{i;\,j}$ de cada elemento, su nivel de impacto se puede descomponer en dos aspectos principales: la frecuencia (por la falta de disponibilidad del elemento) y la consecuencia (a través del impacto del elemento según su configuración lógico funcional). Este último índice se llamará Factor de Propagación esperado de Detención $FPD_{i;\,j}$ el cual representa el efecto que causa una parada del elemento $i; j$ en el sistema (ecuación 6). El efecto de detener un elemento j puede tener diferentes resultados, dependiendo del estado de los demás elementos que se encuentran en el mismo nivel i.

$${}_{;} = \frac{{}_{;} * (1 - \qquad)}{(1 - \quad {}_{;})} \qquad (6)$$

Considerando una estructura sistema-subsistema-equipo, el algoritmo de cálculos para esta etapa sería el siguiente:

1. Calcular la suma de la indisponibilidad total de todos los subsistemas de cada nivel i: $\sum \quad (1 - \qquad) \ \forall\ : 1, \ldots ,\ $ -1
2. El ICO del sistema será ICO_{sis}= 100% (i=0)
3. El ICO del subsistema ICO_{sub} será la proporción de impacto del subsistema con respecto al total de indisponibilidades, multiplicado por el ICO_{sis} lo que quedaría: $(1 - \qquad)/ \sum \quad (1 - \qquad) \ \forall\ : 1, \ldots ,\ $ -1

4. Calcular la suma de la indisponibilidad de los equipos pertenecientes a un subsistema: $\sum \quad (1 - \quad) \ \forall$. En caso de fraccionamiento, dicha indisponibilidad deberá multiplicarse por la capacidad de cada elemento.
5. El ICO del equipo ICO_{equ} será la proporción de impacto del equipo con respecto al total de indisponibilidades para el subsistema en análisis, multiplicado por el ICO_{sub} lo que quedaría: $(1 - \quad)/ \sum \quad (1 - \quad) * \quad \forall$. En caso de fraccionamiento, es necesario multiplicar la indisponibilidad del equipo por la capacidad,
6. El FPD del equipo FPD_{equ} se calcula con la ecuación 6.

La figura 2 muestra un diagrama explicativo, para caracterizar la medición de cada uno de los indicadores.

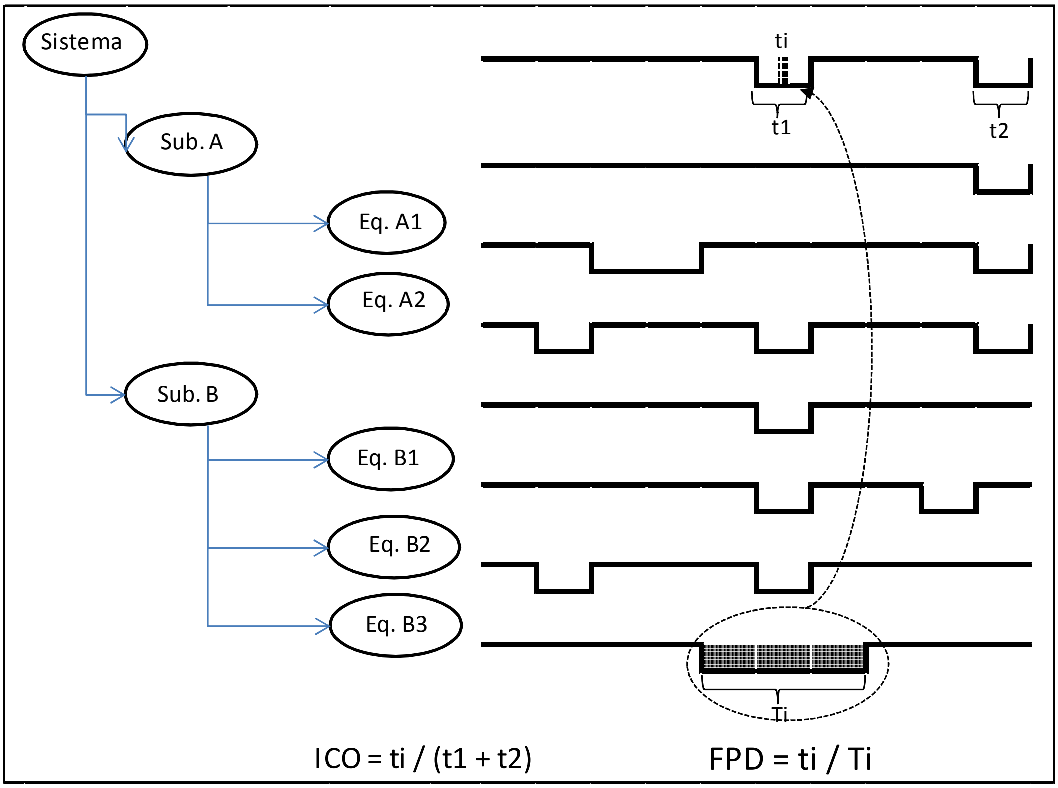


Figura 2 Esquema de impactos esperados FPD e ICO

Etapa 4: Análisis de indicadores y resultados

Esta fase recoge los resultados numéricos obtenidos en las etapas anteriores y los analiza para la toma de decisiones estratégicas. Los primeros análisis, pueden ir enfocados en la cuantificación de la indisponibilidad del sistema. Dicha indisponibilidad será el elemento de estudio para determinar el aporte de cada equipo y subsistema, en términos de consecuencia de posibles fallos. Posteriormente, el análisis de los subsistemas y equipos con mayor ICO indican cuáles son los elementos más críticos y sobre los que debería enfocarse la gestión de activos con mayor énfasis. En esta etapa, se propone la elaboración de un Gráfico de Dispersión IEF, el cual relaciona en su eje X la indisponibilidad de los equipos y en el eje Y su FPD. De acuerdo a la localización de los equipos dentro del gráfico, es posible hacer una clasificación de los equipos para enfocar diversas acciones de mejora.

3.3. RESULTADOS ESPECÍFICOS

Kristjanpoller, F., Crespo, A., Barberá, L., Viveros, P. (2017). Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C pp. 301-310.

Este artículo desarrolla el análisis de fiabilidad y de impacto esperado de fallos (IEF), sobre una planta de biometanización localizada en España. Este tipo de proceso es de vital importancia bajo el enfoque de la Industria 4.0 (Lee et al., 2015) y la constante búsqueda de soluciones eco-amigables con el medio ambiente. Bajo esta perspectiva, una evaluación de su fiabilidad, mantenibilidad y disponibilidad, para la detección de oportunidades de mejora y su correspondiente priorización, resulta de alto impacto para el cumplimiento de sus objetivos operacionales.

Para desarrollar la metodología IEF, el proceso fue descompuesto en 6 subprocesos: proceso de mezclado, sistema de calentamiento, sistema digestivo, proceso de biogas, proceso digerido y proceso de tratamiento.

Al aplicar la metodología IEF, fue posible determinar que los elementos de mayor impacto sobre el proceso son la Bomba DU1-PD1 con un Impacto de Criticidad Operacional (ICO) del 10,49%; la bomba de purines 1 con un 10,10%; la bomba DP1 – PU1 con un 9,14%; el agitador IT1 – SI1 con un 7,83%; y el compresor 1-CO1 con un 6,60%. Al considerar la frecuencia de sus fallos y su consecuencia, es posible establecer que en conjunto estos 5 equipos explican cerca del 50% de pérdidas productivas del sistema. Lo anterior puede ser visualizado directamente en la Figura 3.

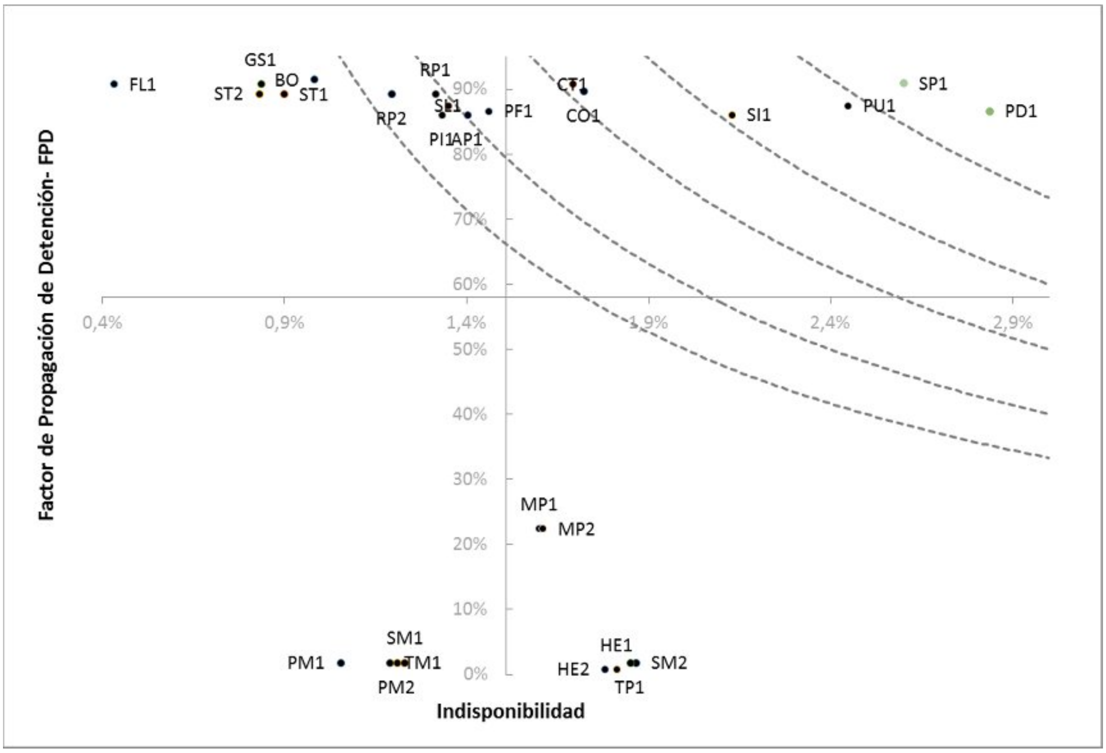


Figura 3 Evaluación IEF Planta de Bioetanol

Kristjanpoller, F., Crespo, A., Viveros, P., Barberá, L. (2016). Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13.

El artículo desarrolla el análisis de impacto de criticidad operacional basado en fiabilidad, a través de la implementación de la metodología IEF sobre una planta de fundición de un proceso de cobre localizado Chile. La fundición es uno de los puntos más críticos en el proceso de producción del cobre, principal industria productiva chilena, que a su vez es el mayor productor mundial del mineral. En este sentido, un adecuado estudio del rendimiento, impactos, fiabilidad, mantenibilidad y disponibilidad de cada uno de los elementos que componen la planta, puede generar importantes beneficios, tanto económicos como operacionales. No obstante, pese a la madurez que tiene en Chile este tipo de procesos productivos, existe una carencia en metodologías que permitan identificar y aislar el impacto de cada elemento sobre el proceso.

Las fortalezas de la aplicación de la metodología se centran en su habilidad para medir de manera sistemática y cuantitativa, y basado en los indicadores RAM, los efectos de las detenciones de los equipos, valorando la frecuencia y la consecuencia, como pilares fundamentales para esta medición.

La determinación del impacto de eficiencia operacional para cada elemento, permite la priorización inequívoca de los elementos bajo una perspectiva de pérdida de producción.

Para poder realizar el análisis de fiabilidad de manera estricta y rigurosa, es necesario contar con una base de datos histórica, representativa y certera. Para lo anterior, se desarrolla una metodología para la limpieza y validación de los datos a utilizar, conformándose en el requisito fundamental para desarrollar un análisis robusto.

Dada la estructura de la metodología IEF, es posible concluir que es factible y recomendable su programación en un sistema computacional CMMS, permitiendo su actualización y adaptación instantánea a diversos procesos productivos.

El proceso productivo se divide en cuatro subprocesos (secado, concentrado, conversión y refinación) en configuración en serie. El subsistema de refinación está compuesto por dos líneas de proceso en configuración de fraccionamiento, por este motivo, su FPD es menor a la de los otros sistemas.

La figura 4 muestra el gráfico de dispersión de indisponibilidad versus FPD, señalando que los equipos ordenados por su ICO en orden decreciente son: CA1, D1, D2, RAF1, RAF2, AF1, CA2,AF2, CB1,CB3 y CB2.

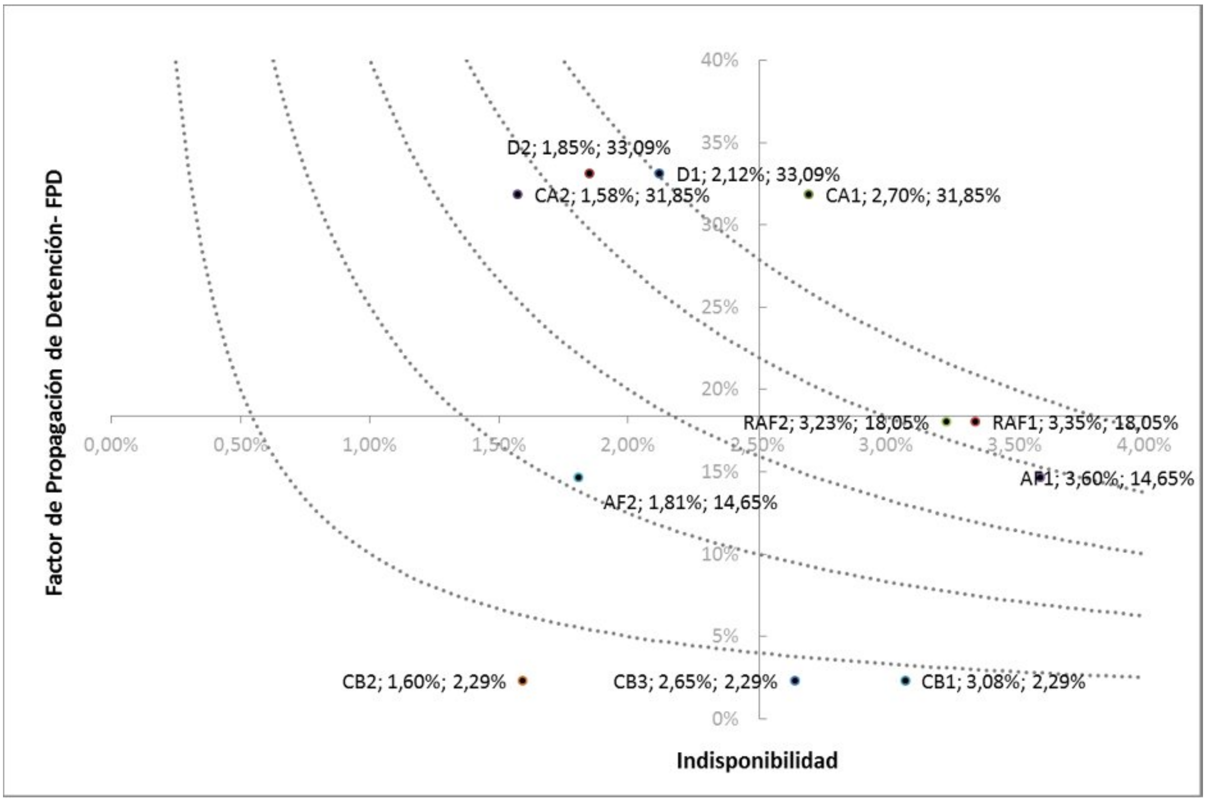


Figura 4 Evaluación IEF Planta de Fundición de Cobre

Kristjanpoller, F., Crespo, A., Campos-López, M., Viveros, P. (2017b). Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna.

Este artículo analiza en profundidad una planta de triturado de un proceso de cobre en Chile, para determinar la priorización de sus equipos bajo el enfoque de la metodología IEF y poder evaluar el impacto de criticidad operacional de cada uno de ellos. Una planta de triturado es una instalación compleja, que consta de una variedad de elementos. La elección del tipo y el diseño de una planta de triturado se determina principalmente por su importancia en el proceso de producción del cobre.

El proceso de obtención del cobre, comienza con la extracción del material desde la mina, el cual se transporta a través de camiones al proceso de trituración primario, posteriormente a través de correas transportadoras es derivado al triturador secundario, para culminar el proceso de conminución en el triturador terciario. Una vez finalizado el proceso de trituración, el material es tratado con el curado ácido en correas transportadoras, para culminar el proceso en las pilas de lixiviación. El presente estudio, se focalizará en el proceso de trituración, en particular para la fase más crítica del proceso que es el de trituración secundaria.

- Trituración Primaria: este proceso tiene como objetivo el reducir el tamaño del material a un diámetro inferior a 8 pulgadas, de manera homogénea. En la fase previa al triturador primario, se encuentra un equipo Picador de Rocas, que facilita la entrada de las rocas de mayor tamaño. Este proceso tiene una capacidad de 15.000 ton/h. El material triturado es trasladado por una Correa Transportadora de 1 km hacia el proceso de trituración secundaria.
- Trituración Secundaria: este proceso es alimentado por la producción del triturador primario y se compone por cuatros líneas independientes, cuyo objetivo es obtener un 100% de la granulometría bajo 1 pulgada, la cual es seleccionado por un harnero; todo el material que no cumple es procesado en el triturador secundario, con un proceso de retroalimentación repetitivo, hasta lograr el cumplimiento del objetivo.

Cada una de las líneas de trituración secundaria se compone por cuatro equipos: Alimentador, Correa, Harnero y Triturador.

La Figura 5 a través del Gráfico de Dispersión IEF, facilita la interpretación de los conceptos y del índice ICO, teniendo en cuenta en el eje X la falta de disponibilidad de equipos (indisponibilidad) y en el eje Y el FPD. El motivo de esta disposición es la evaluación estándar que se realiza de un riesgo operacional, que considera el producto de dos factores: frecuencia y consecuencia. Quedando los equipos más críticos para el funcionamiento sistémico por su factor de propagación e indisponibilidad, en el área más noreste posible del diagrama. Es fácil de confirmar, a través de las curvas de Iso ICO, que los trituradores ocupan los primeros lugares de mayor impacto en el sistema (en el orden por número de triturador 3, 1, 2 y 4), el quinto lugar es para el alimentador de la línea 2 y el sexto para la correa de la línea 4.

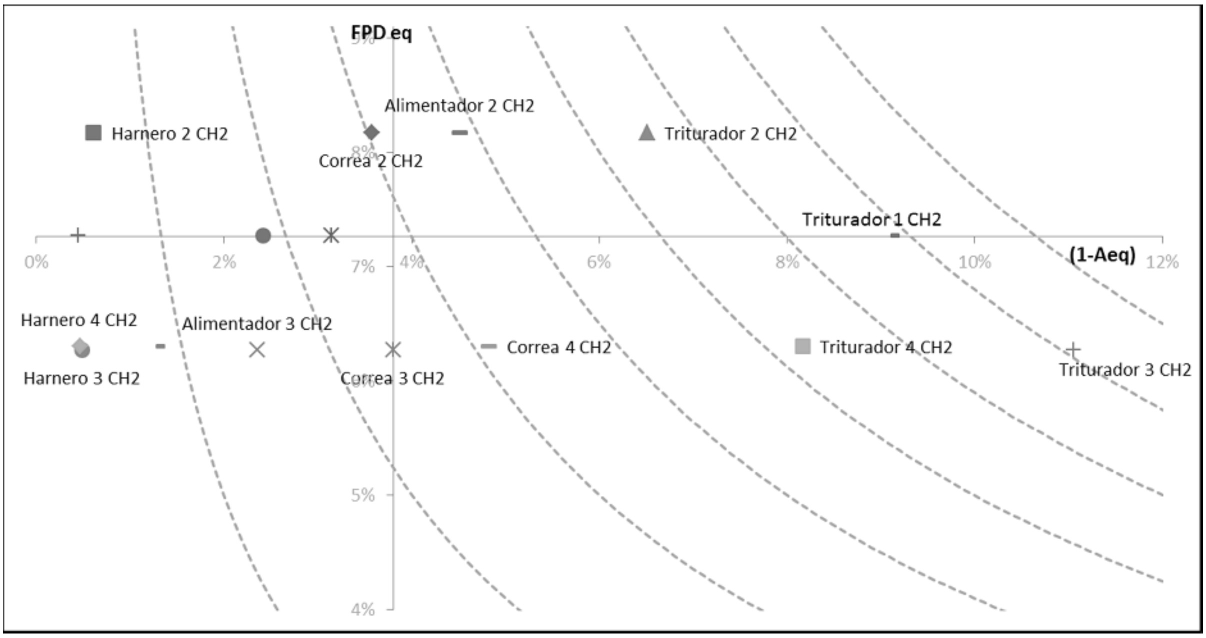


Figura 5 Evaluación IEF Planta de Triturado de Cobre

4. DISCUSIÓN

La metodología IEF, presenta un algoritmo cuantitativo, aplicable a elementos que se encuentren en configuraciones complejas, bajo una perspectiva sistémica y flexible, basado en un análisis probabilístico de impactos de fallo. Lo anterior, lo transforma en una poderosa herramienta para la evaluación y toma de decisiones en un corto y medio plazo. La Tabla 2 resume las características de métodos / metodologías asociadas a la criticidad operacionales y sus principales características.

Metodología	Tipología	Foco	Estimación del Efecto de Fallos	Flexibilidad
Árbol de Fallo[1]	Cualitativa	Individual	Análisis de Fallo	Alta
US Department[2]	Cualitativa	Individual	Análisis de Fallo	Alta
Análisis de Criticidad[3]	Cuantitativa	Sistémico	Criterio de Expertos (1 to 5)	Media
IEF[4]	Cuantitativa	Sistémico	Análisis Probabilístico de Impactos	Alta

Tabla 1 Comparación de metodologías de evaluación de impacto operativo

En relación a la aplicación, existen diversos ámibitos y modelos que pueden ser influenciados positivamente por la implementación de la metodología IEF. A continuación se presentan algunos de ellos con un alto potencial de aplicación e innovación.

Mantenimiento Preventivo (MP).

Existen variados modelos al respecto, uno de los más utilizados es el propuesto por Jardine & Tsang (2013). En este modelo los autores recomiendan una frecuencia óptima para la implementación de una política de mantenimiento preventivo a edad constante, basada en la probabilidad de supervivencia hasta el tiempo t (fiabilidad) y la consecuencia de sobrevivir hasta ese instante o no, cuantificado a través de los costes de una intervención preventiva o una intervención correctiva, según corresponda. Respecto del coste de intervención correctiva, es posible descomponerlo en diversos ítems, como los costes directos del mantenimiento, como así también, costes indirectos producto de la intervención emergencia, como los costes de la falta o también conocidos como costes de ineficiencia.

[1] Rauzy et al., 2007
[2] US Department, 1977
[3] Crespo et al., 2016
[4] Kristjanpoller et al., 2016; Kristjanpoller et al., 2017a; Kristjanpoller et al., 2017b

Generalmente, los costes de la falta para un proceso son conocidos y, por ende, cuando es necesario estimar estos costes a nivel de equipos, se realiza una asignación directa. Pero, ¿qué sucede cuando el elemento se encuentra en un subsistema con una configuración lógica compuesta (stand by, redundancia total o parcial), ¿es posible estimar el coste de una hora de detención producto de una intervención de emergencia? La respuesta es no, dado que un equipo con redundancia al fallar puede no provocar ningún impacto, o bien, un impacto parcial sobre el proceso, dependiendo del estado de los equipos que componen el mismo subsistema.

Bajo la perspectiva antes señalada, la metodología IEF realiza un aporte importante a estos modelos, ya que a través del indicador FPD se puede estimar el coste esperado por cada hora de detención por fallo de un equipo, independientemente de la configuración lógica en la cual se encuentre inmerso. En este sentido, el producto en el coste de la falta de un sistema y el FPD de un equipo, permiten conocer el coste esperado de la falta para el equipo y, de esta manera, poder realizar una estimación más fidedigna de los costes de mantenimiento correctivo.

Análisis de Reemplazo de Activos

La evaluación y definición del momento adecuado para el reemplazo de un activo, es una decisión compleja, ya que combina indicadores técnicos y de rendimiento, con indicadores financieros y económicos, todos bajo una variable temporal, riesgos e incertidumbre. Al respecto Campbell & Jardine (2001), proponen un modelo muy completo, identificando cada una de las variables, como también, la definición temporal que deben tener asociada. Uno de los aspectos que tradicionalmente permiten justificar el reemplazo y los altos costes de reposición de los activos, es el desgaste de los equipos y sus crecientes costes de mantenimiento correctivo. A través de la metodología IEF y sus indicadores, se facilita el proceso de cuantificación del impacto de los fallos, incluso permitiendo evaluar alternativas al reemplazo de equipos, como la incorporación de redundancia y cambios en el diseño de los procesos. Dada la flexibilidad de la metodología IEF, puede adapatarse a cada uno de estos escenarios, incluso como un referente para modelos basado en opciones reales.

Evaluación de Coste de Ciclo de Vida

Uno de los modelos más completos es el desarrollado por Parra et al. (2012). El artículo presenta una metodología para la evaluación del coste de ciclo de vida para diversas realidades industriales. Los aspectos más relevantes e innovadores de la propuesta, radican en la evaluación de los costes provocados por los fallos de los equipos, a través del modelo no homogéneo de Poisson, diferenciándola de los modelos tradicionales, cuya orientación mayoritaria es hacia la cuantificación de los mantenimientos planificados.

La evaluación de los impactos del fallo y la criticidad operacional, a través de la metodología IEF, permite pulir los efectos del mantenimiento correctivo, sus impactos y costes, que es el parámetro de entrada utilizado por el modelo propuesto por Parra et al. (2012), bajo una lógica sistémica / probabilística, posibilitando una evaluación del LCC de manera más precisa y ajustada al contexto operacional del elemento en estudio.

El factor FPD, en conjunto con el indicador ICO, permitirían incorporar el efecto asociado a la configuración lógica del proceso y sus subprocesos, ponderando de manera adecuado los riesgos asociados a los fallos y emergencias.

Análisis de Repuestos Críticos

Existen variados modelos y artículos que analizan el dimensionamiento de inventarios para repuestos críticos, basado en fiabilidad. Las características de estos repuestos, como su elevado valor, baja tasa de rotación y alto impacto sobre el proceso, hacen que las metodologías tradicionales de inventarios no tengan campo de acción sobre ellos. Por lo anterior, los modelos basados en fiabilidad y riesgo, cobran cada vez mayor relevancia. Una propuesta muy interesante es la presentada por van Jaarsveld & Dekker (2011), quienes profundizan la aplicación para elementos redundantes.

Sobre esta base se evalúan dos escenarios, los costes probables por mantener el repuesto en almacén versus los costes asociados a no tener el repuesto en almacén. Ciertamente respecto de estos últimos, hay dos alternativas: el componente en operación no falla, por lo tanto el no tener el repuesto en almacén no implica ningún coste adicional; o bien el por el contrario, el componente en operación falla y al no haber repuesto en almacén, se debe asumir la pérdida de producción durante todo el período de reposición. En específico, sobre este último escenario la metodología IEF puede implicar un gran aporte, para la valoración del impacto del fallo del componente sobre el proceso productivo, cuantificando a través del FPD las pérdidas económicas que genera esta carencia, considerando la configuración lógica del equipo cuyo componente ha fallado y del cual no se posee repuesto.

Potencialidad de aplicación en sectores productivos

Las características específicas de cada industria y proceso productivo son únicas, y por tanto, su análisis y estudio exigen generar procedimientos acordes a sus condiciones. Por lo anterior, las metodologías deben ser flexibles y adaptables a cada una de estas realidades. La propuesta de la metodología IEF, cumple con estos requerimientos, tal como es posible apreciarlo en el desarrollo de los casos prácticos mostrados en la sección de Resultados Específicos.

Bajo esta perspectiva, se puede concluir que la metodología IEF puede tener un alto impacto y su aplicación presenta un gran potencial en sectores donde los sistemas productivos son complejos, contando con configuraciones lógicas redundantes como: siderurgia, minería, alimentación, petróleo, celulosa, entre otras.

5. CONCLUSIONES

De acuerdo al objetivo del trabajo de tesis, orientado a proponer una metodología que permita el modelado de impactos de fiabilidad para configuraciones complejas con una aplicación práctica y científica, se puede concluir que la metodología propuesta (IEF) es capaz de generar indicadores útiles para el análisis y posterior mejora en el desempeño de los sistemas productivos. Lo anterior, en términos de disponibilidad de sus equipos, así como para la priorización, focalización de las actividades y toma de decisiones relacionadas con la gestión de activos, todo independientemente del tipo de industria del que se trate y de la disposición lógico-funcional de los componentes del sistema. Por lo anteriormente expuesto, se concluye un cumplimiento racional de los objetivos propuestos, aportando una metodología con un alto potencial científico y de aplicación industrial en los más diversos procesos productivos.

La propuesta metodológica IEF consta de cuatro etapas: la primera, gestiona y prepara los datos a analizar. La segunda, de forma clásica, calcula la fiabilidad y disponibilidad operacional de cada elemento y del sistema general. La tercera, encuentra el impacto en la criticidad operacional (ICO) y el factor de propagación del tiempo de detención esperado (FPD) de cada uno de los equipos sobre el sistema; y, la última, obtiene mediante un gráfico de dispersión “indisponibilidad vs FPD” la interpretación de los resultados para la toma de decisiones. Cada una de las mencionadas etapas se ilustran con casos de análisis desarrollados en la sección de Resultados Específicos, cuyos resultados finales aporta información relevante para evaluar el diseño y el rendimiento de la planta, lo que, por supuesto, se traduce posteriormente en beneficios económicos.

En general, después de aplicar la metodología es posible obtener los siguientes elementos de información:

- Identificar los activos que tienen el ICO más alto, lo que resulta relevante para concentrar los esfuerzos en ellos dado su impacto potencial. Se debe recordar que el ICO descubre cuál es el subsistema o equipo con mayor impacto en la operatividad del sistema, asignando el % de la indisponibilidad total correspondiente.

- Identificar los equipos de mayor criticidad en el sistema (frecuencia por consecuencia), entendiendo que en este caso particular, la consecuencia medida es netamente operacional. Por ende, es basada en la indisponibilidad individual y sistémicamente impactada de cada equipo. Este análisis se facilita por medio de un gráfico de dispersión, que relaciona en su eje X la indisponibilidad de los equipos (interpretada como la frecuencia) y en el eje Y el FPD (entendido como la consecuencia). Este gráfico, como los desarrollados en las Figuras 3, 4 y 5, permite apreciar que para una misma configuración lógica, los elementos del mismo subsistema que tendrán un mismo FPD, siendo la indisponibilidad esperada de cada elemento el factor diferenciador para priorizar un equipo sobre otro. También es posible visualizar que, para una misma indisponibilidad entre equipos, la configuración lógico-funcional representada por el FPD muestra la diferencia en su criticidad.

Dado lo anterior, las acciones del plan de gestión de activos que emanan de esta metodología, pueden ser dirigidas a la fiabilidad y mantenibilidad de los elementos presentes en la zona de la derecha (eje X) del gráfico, es decir, los más indisponibles. Ello implicaría la redefinición de su estrategia de mantenimiento, de los procedimientos de mantenimiento y el análisis de piezas de repuesto. En tanto que, para los elementos situados en la zona más alta (eje Y) del gráfico de dispersión, es decir, para aquellos con mayor FPD, las acciones pueden estar relacionadas en reducir el impacto del elemento, por ejemplo: incluyendo mejoras en el diseño, la incorporación de redundancia y de exceso de capacidad, cuando sea posible.

La contribución de esta metodología tiene un alto componente económico, ya que el determinar adecuadamente la disponibilidad de un sistema industrial permite conocer su capacidad real de producción y, por lo tanto, los beneficios potenciales. Por otro lado, el identificar las oportunidades de mejora y asignar los recursos de mantenimiento a los equipos y sistemas más críticos (y no sólo a aquellos de mayor capacidad productiva), genera ahorros en el presupuesto de mantenimiento, pero además, en la consecuente disminución en tiempos de ineficiencia, producción defectuosa, pérdidas y mermas. Finalmente, es importante destacar que por su carácter genérico, la metodología de IEF se podría incorporar en cualquier base de datos de un sistema de gestión de mantenimiento asistido por ordenador - CMMS para tener una evaluación de impacto automatizada.

6. REFERENCIAS BIBLIOGRÁFICAS

Campbell, J., Jardine, A. (2001). Maintenance Excellence: Optimizing Equipment Life-Cycle Decisions. Marcel Dekker Inc. First Edition. New York, NY.

Carnero, M. (2004). The control of the setting up of a Predictive Maintenance Programme using a system of indicators. Omega-International Journal of Management Science 32, op. 57-75.

Consejo Minero. (2015). Reporte Anual Consejo Minero 2014-2015. Chile.

Chapman, A.D. (2005). Principles of Data Quality", version 1.0. Report for the Global Biodiversity Information Facility. Copenhagen: GBIF.

Crespo, A., Moreu, P., Sola, A., Gómez, J. (2016). Criticality Analysis for Maintenance Purposes: A Study for Complex In-service Engineering Assets. Quality and Reliability Engineering International 32, pp. 519-533.

Daylan, B., Ciliz, N. (2016). Life cycle assessment and environmental life cycle costing analysis of lignocellulosic bioethanol as an alternative transportation fuel. Renewable Energy 89, pp.578-587.

Dhillon, B. S. (2006). Maintainability, Maintenance, and Reliability for Engineers. Taylor & Francis Group, LLC. Boca Raton, FL.

Distefano, S., Puliafito, A. (2009). Reliability and availability analysis of dependent-dynamic systems with DRBDs. Reliability Engineering and System Safety 94, pp. 1381-1393.

Gang, W., Wang, S., Xiao, F., Gao, D. (2015). Robust optimal design of building cooling systems considering cooling load uncertainty and equipment reliability. Applied Energy 159, pp.265–275.

Jardine, A.K.S., Tsang, A.H.C. (2013). Maintenance, Replacement, and Reliability: Theory and Applications. Second Edition. CRC Press. Boca Raton, FL.

Guo, H., Yang, X. (2007). A simple reliability block diagram method for safety integrity verification. Reliability Engineering System Safety 92, pp. 1267–1273.

Koontz, A., Weihrich, H. (2014). Administración: una perspectiva global. México: McGraw-Hill / Interamericana de México. ISBN 978-607-15-0759-4.

Kristjanpoller, F., Crespo, A., Viveros, P., Barberá, L. (2016). Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13.

Kristjanpoller, F., Crespo, A., Barberá, L., Viveros, P. (2017a). Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C pp. 301-310.

Kristjanpoller, F., Crespo, A., Campos-López, M., Viveros, P. (2017b). Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna.

Lee, J., Bagheri, B., Kao, H. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters 3, pp. 18–23.

Parra C., Crespo A., Kristjanpoller F. and Viveros P. (2012). Stochastic model applied to evaluate the economic impact of the failure in the cycle cost analysis (LCCA). Case Study for the Rail Freight and Oil Industries. Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability Volume: 226 Issue:O4. Pages: 392-405.

Rausand, M., Hoyland, A. (2003). System reliability theory: models, statistical methods, and applications. 3rd ed. Wiley, New York, NY.

Rauzy, A.B., Gauthier, J., Leduc, X. (2007). Assessment of large automatically generated fault trees by means of binary decision diagrams. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 221, pp. 95-105.

US Department of Defense. (1977). Procedures for performing a failure mode and effects analysis, MIL-STD-1629A. Washington: Department of Defense.

Van Jaarsveld, W., Dekker, R. (2011). Spare parts stock control for redundant systems using reliability centered maintenance data. Reliability Engineering & System Safety 96 (11), pp. 1576-1586.

Viveros, P., Zio E, Arata, A., Kristjanpoller, F. (2012). Integrated system reliability and productive capacity analysis of a production line. A Case Study for a Chilean Mining Process. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 226, pp. 305-317.

Volovoi, V. (2004). Modeling of system reliability Petri nets with aging tokens. Reliability Engineering and System Safety 84, pp. 149-161.

Welte, T.M. (2009). A rule-based approach for establishing states in a Markov process applied to maintenance modeling. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability; 223: 1-12.

7. LISTADO DE PUBLICACIONES PARA TESIS DOCTORAL

7.1. PUBLICACIONES ISI

1. Kristjanpoller, F., Crespo, A., Barberá, L., Viveros, P. (2017). Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

2. Kristjanpoller, F., Crespo, A., Viveros, P., Barberá, L. (2016). Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

3. Kristjanpoller, F., Crespo, A., Campos-López, M., Viveros, P. (2017). Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088

7.2. CONGRESOS INTERNACIONALES

1. F. Kristjanpoller, A. Crespo, M. Lopez-Campos, P. Viveros, T. Grubessich. Reliability assessment methodology for multiproduct and flexible industrial process. The Annual European Safety and Reliability Conference (ESREL). Glasgow, Scotland. Sept 25-29, 2016. ISBN: 978-1-138-02997-2.

2. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Reliability assessment based on energy consumption as a failure rate factor. 6th IESM Conference, October 2015, Seville, Spain.

3. F. Kristjanpoller, A. Crespo, P. Viveros, T. Grubessich, R. Stegmaier. RAM-C: A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations. The Annual European Safety and Reliability Conference (ESREL). Zurich, Switzerland. Sept 7-10, 2015.

4. F. Kristjanpoller, A. Crespo, P. Viveros, R. Mena, R. Stegmaier. A novel methodology for availability assessment of complex load sharing systems. The Annual European Safety and Reliability Conference (ESREL). Wroclaw, Poland. Sept 14-18, 2014.

DOCUMENTACIÓN TESIS POR COMPENDIO

DOCTORADO EN INGENIERÍA MECÁNICA Y DE ORGANIZACIÓN INDUSTRIAL

Presenta:

Fredy Ariel Kristjanpoller Rodríguez

Director:

Adolfo Crespo Márquez

INDICE

1. COPIA COMPLETA DE LAS PUBLICACIONES

2. INFORME DE LA RELEVANCIA CIENTÍFICA DE LAS PUBLICACIONES

3. ACEPTACIÓN DE LOS COAUTORES DE LA PRESENTACIÓN DE LOS TRABAJOS COMO TESIS.

4. RENUNCIA DE LAS PERSONAS QUE COMPARTAN AUTORÍA QUE NO SEAN DOCTORES A PRESENTARLOS COMO PARTE DE OTRA TESIS

5. PUBLICACIONES EN CONGRESOS INTERNACIONALES

6. CURRICULUM VITAE

1. COPIA COMPLETA DE LAS PUBLICACIONES

1.1 Kristjanpoller, F., Crespo, A., Barberá, L., Viveros, P. (2017). Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

1.2 Kristjanpoller, F., Crespo, A., Viveros, P., Barberá, L. (2016). Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

1.3 Kristjanpoller, F., Crespo, A., Campos-López, M., Viveros, P. (2017). Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088

Renewable Energy 101 (2017) 301–310

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Biomethanation plant assessment based on reliability impact on operational effectiveness

Fredy Kristjanpoller [a, b, *], Adolfo Crespo [b], Luis Barberá [b], Pablo Viveros [a, b]

[a] Department of Industrial Engineering, Universidad Técnica Federico Santa María, Avenida España 1680, Valparaíso, Chile
[b] Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n, 41092, Seville, Spain

A R T I C L E I N F O

Article history:
Received 11 January 2016
Received in revised form
3 August 2016
Accepted 30 August 2016

Keywords:
Biomethanation
Operational effectiveness
Maintenance optimisation
Decision making
Reliability

A B S T R A C T

The biomethanation process is a promising eco-friendly solution for the treatment of organic biomass that can further lead to efficient bioenergy production. Thus, the analysis of operational reliability and maintainability is important when considering the availability assessment of operative plant conditions, and accordingly, an analysis of plant operational effectiveness impact (P-OEI) is necessary to identify the opportunities for improvement in asset management. A fundamental aspect of an industrial plant is to determine what the effect of each element is on the system. To clarify the importance of the primary equipment and improve the decision making related to asset management, a novel methodology proposal has been developed and applied to real data of a biomethanation plant located in Spain. This new methodology develops an analysis based on a reliability block diagram configuration that structures the process analysis by levels, i.e., ascending for availability analysis from the element to the system and descending for the P-OEI analysis from the system to the smallest element.

The expected operational impact of EOI (i.e., the expected effect of an element constraint on the overall system) is also calculated. The P-OEI analysis conducted in this study reveals important results that can be used to evaluate the design and performance of an industrial plant.

1. Introduction

The current global scenario presents a grim picture of solid waste generation, especially in developing countries where the optimisation of waste management is necessary. Treating the waste at its source of generation is the best way to reduce the pollution load of a city [1], which means that consumer habits and commitment to the environment play a critically important role. The U.S. Environmental Protection Agency considers MSW to be a renewable energy resource [2].

Anaerobic digestion (AD), also known as biomethanation, is widely used for waste management [3,4]. Anaerobic digestion is a simple and effective biological process for the treatment of various organic wastes (MSW as well as other waste biomass, such as animal manure, crop residues, slaughterhouse and dairy production waste) and for the production of energy in the form of biogas [5]. Because oxygen is not required for the decomposition of waste, the anaerobic process is inherently the most energy efficient option for the safe disposal of organic waste with simultaneous biogas generation, which can then be used as fuel [6]. This technology requires, in all cases, the pre-treatment of the waste to ensure an adequate separation of metal, plastic, glass, paper, etc., and it has been successfully implemented in the treatment of agricultural wastes, food wastes and wastewater sludge [7]. One of the main advantages of anaerobic digestion based on the global need to reduce greenhouse gas emissions is associated with fossil fuel based energy production. A wide variety of process applications for biomethanation of wastewater, slurries, and solid waste have been developed [8]. It is generally accepted that post-treatment after anaerobic digestion is necessary to obtain a high-quality, finished product [9] as the biogas generated is not suitable for direct use. Rather, it requires a cleaning treatment prior to its use to remove components that can decrease the performance of processes or cause damage to the equipment involved in these processes. The main objective behind the cleaning of generated biogas is to reduce the concentrations of H2S, CO2 and CO, as these compounds are toxic, they reduce the quality of biogas as a fuel, and they damage metal equipment and engines in which they are used to generate

* Corresponding author. Av. España 1680, Valparaíso, Chile.
E-mail addresses: fredy.kristjanpoller@usm.cl (F. Kristjanpoller), adolfo@us.es (A. Crespo), lubarmar@us.es (L. Barberá), pablo.viveros@usm.cl (P. Viveros).

http://dx.doi.org/10.1016/j.renene.2016.08.065
0960-1481/

Nomenclature and parameters

α	Scale Parameter of Weibull Distribution
A	Availability
AD	Anaerobic Digestion
β	Form Parameter of Weibull Distribution
CMMS	Computerised Maintenance Management System
EOI	Expected Operational Impact
Γ	Gamma Function
KPI	Key Performance Indicators
λ	Failure Rate
LCSA	Life Cycle Sustainability Assessment
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
MSW	Municipal Solid Waste
P-OEI	Plant Operational Effectiveness Impact
RAM	Reliability, Availability and Maintainability
RBD	Reliability Block Diagram
RES	Renewable Energy Sources

electric power. Moreover, methane production through biomethanation technology has been evaluated as one of the most energy-efficient and environmentally benign ways of producing vehicle biofuels, and as such, it can provide multiple benefits to the users. The use of biogas in vehicles, i.e., vehicles capable of running solely on biogas or on a coordinated mix of biogas/petrol is now a reality, especially in fleets of garbage trucks, buses and cars for internal use in industrial installations. The autonomy of these vehicles is generally lower compared to the autonomy of a petrol or diesel vehicle due to the lower heating value of biogas per litre of fuel. However, the estimated life of a biogas vehicle is usually between two and three years less than equivalent petrol vehicles, which also have reduced maintenance costs compared to biogas vehicles. From the perspective of the risk of inflammation, biogas vehicles are safer than gasoline vehicle because of their narrow range of flammability and because biogas is lighter than air, meaning that, in the case of leakage, biogas rises and dissipates into the atmosphere.

Recent life cycle assessment studies have demonstrated that biogas derived methane (biomethane) is one of the most energy efficient and environmentally sustainable vehicle fuels. At the same time, the nutrients contained in the remaining digestate can be used for crop production, and as well, these nutrients play a remarkable role in promoting sustainable biomass production systems [10]. Furthermore, pre-treatment, additives and reactor design according to feedstock can solve major limitations, such as low gas production from agricultural residues and large hydraulic retention time [11].

In recent times, biomethanation technology has become a more attractive source of renewable energy due to its reduced technological cost and process efficiency [10]. Moreover, household biogas digesters for rural communities have the important potential to focus on technical, economic and environmental aspects [12]. However, the application of reliable techniques to support decision making is a necessary fundamental task to achieve an accurate and efficient management of assets and resources in this type of industrial plant, even when a large number of devices with highly complex functional settings is present. A typical problem when generating and controlling action plans for improving the availability of equipment is the lack of mechanisms to support maintenance management.

The reliability theory from a life cycle perspective offers significant support for studying and generating proposals for the improvement of industrial plants [13]. Specifically, with respect to energy equipment and relevant processes, the opportunities regarding design are a relevant success factor [14], and reliability evaluation is crucial in the assessment of performance to the degree that it involves technical and cost parameters [15]. Some experiences and methodologies for power system reliability evaluation, specifically for renewable energy sources (RES), are presented in Ref. [16].

Additionally, the evaluation of assets may include the Life Cycle Sustainability Assessment (LCSA) methodology based on the ISO 14040 and 14044 environmental management principles [17].

To understand the healthiness of a productive process, it is necessary to develop an analysis of its KPI (key performance indicators). The performance measurement corresponds to the quantification process of an action, where the measurement is the process of quantification and the action leads to a performance [18].

The concepts of efficiency and effectiveness are precisely used in this context, where effectiveness refers to the extent to which the objectives or requirements defined for the process are met, and efficiency is a measure of the economy in which the resources of the company in meeting the established targets are used [19]. It is further recognised that there is a close relationship between management control through performance indicators, thus defining strategies and decision making [20,21].

Interpretation tools and methodologies to understand the performance of a single element and a total system are essential and are, as a result, continuously being requested. This deficiency is even more pronounced when the selected process for analysis must be disaggregated on many levels, where each level has been disaggregated according to several assets [22]. Therefore, a reliability, availability and maintainability analysis (RAM) must be complemented with a quantitative reliability impact analysis to interpret the real performance, to identify bottlenecks and to provide improvement opportunities. A useful and well-known indicator is the Birnaum importance measure (IM) [23], which ranks the components of the system with respect to the impact of their failure on the system's performance. Its application, however, is primarily related to epistemic uncertainties.

This article proposes an integral and quantitative innovative methodology to analyse the reliability, availability, maintainability and plant OEI [24], and it applies this methodology in a case study of a biomethanation plant. The P-OEI analysis is related specifically to production capacity and the effect of preventive and corrective maintenance intervention on system availability. This proposal designs a novel algorithm to compute an impact index based on the frequency of failures associated with the reliability and maintainability of the machinery and the expected impact according to different scenarios and configurations. This impact index, based on a probabilistic approach, defines the expected condition of the item in the system from a perspective of evaluation of its possible states (intrinsic behaviour) and related to the logical and functional configuration of the system. This approach enables an overall comparison of elements and the prioritisation of those elements, as well as a partial effectiveness evaluation.

2. Problem statement

In many industrial companies, there is no formal criteria to identify the impact of each asset and its behaviour or failure, and therefore, asset replacement decisions are made ad hoc and not as part of the business process. It is necessary to define a key performance indicator (KPI) oriented to establish a hierarchy and determine the effectiveness of the KPI's impact on the elements. For this reason, knowing the equipment impact on the system's lack of effectiveness is one of the most important tools for attaining the objectives of the KPI and addressing the efforts of high impact opportunities.

The OEI analysis identifies opportunities for the improvement of asset management. One of the most important factors is the operational effect, measured as loss of production capacity, of each element on the system in which it operates. The impact of a single element must be defined as dynamic because it depends on the element's individual reliable and sustainable performance as well as on the performance of all elements operating within the same subsystem.

When performing an OEI analysis, the following questions must be addressed. What are the bottlenecks of the system? What factors explain a system's production loss? What is the system's availability level? Where are the main improvement opportunities?

The objectives of this article are summarised as follows. First, a novel methodology is proposed to develop a tool to analyse the reliability and sustainability of the operational effectiveness of operative plant conditions and clarify the importance of the main assets while improving the decision making related to asset management. A second objective is to apply the proposed methodology to a case study by employing real data from a biomethanation plant located in Spain.

3. Proposed methodology

The proposed methodology [24] develops an analysis based on an RBD [25,26] configuration that structures the process analysis by levels, specifically, ascending for an availability analysis from the element to the system and descending for an impact analysis from the system to the smallest element. At a methodological level, the implementation and analysis should consider the joint processes necessary for the identification of opportunities to improve maintenance and to generate recommendations for maintenance and sustainability. These processes are summarised in four steps, namely, data cleaning, data management, RAM analysis, and P-OEI analysis and decision making.

The methodology considers the development of an evaluation process. A bottom – up process is applied for calculating the indicators of RAM from the lowest level element to build the indexes of the entire complex system using logical relationships of RBD [25,26]. The second phase corresponds to an up - bottom process for the calculation of impacts that begins with the system and then progresses to the lower level elements. Accordingly, by evaluating all scenarios and the likelihood of each scenario for complex configurations, it is possible to identify the P-OEI and the contribution of each element to the system's lack of effectiveness based on the production loss capacity due to unavailability and to the expected operational impact (EOI), that latter of which describes how the constraint of an element can affect the EOI of the system,.

Phase 1: Bottom – up. This constitutes an RAM analysis from the smallest element to the complete system.

This phase employs RBD methodology and considers the following functional relationships and expressions to calculate reliability and availability:

According to Dhillon [27], availability corresponds to the proportion of time expressed as the probability that the equipment is available as required. In this way, and assuming the equipment required must always be operational and that the orders are initiated immediately following a failure, it is possible to define the expected availability of specific equipment, as [24]:

$$A_i = \frac{MTTF}{MTTF + MTTR} \tag{1}$$

where.

MTTF: Mean Time to Failure of Equipment
MTTR: Mean Time to Repair of Equipment
A_i: Expected Availability of Equipment

Regarding the series configuration and based on the total dependence of the elements on the subsystem that brings them together, the subsystem analysis is performed as follows:

$$A_{serial} = \prod_{i=1}^{n} A_i \tag{2}$$

For a subsystem in a logical full redundancy configuration (parallel) that is characterised by the simultaneous operation of the elements of the subsystem and by the fact that each element can withstand 100% of the load required for the same, the following analysis is used for a redundant non-repairable system:

$$MTTF_{parellel} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} - \frac{1}{\lambda_1 + \lambda_2} \tag{3}$$

where λ_i represents the average failure rate of each of piece of equipment that participates in the system. Generalising using a Weibull model, this is represented by:

$$\lambda_i = \frac{1}{\alpha^* \Gamma\left(1 + \frac{1}{\beta}\right)} \tag{4}$$

$$MTTR_{parellel} = average\ (MTTR_i) \tag{5}$$

Finally,

$$A_{parallel} = \frac{MTTF_{parallel}}{MTTF_{parallel} + MTTR_{parallel}} \tag{6}$$

For a subsystem in a stand-by configuration, a cold standby is considered. In this configuration, at every moment, only one unit operates, and in the case of the failure of that unit, it is replaced by the following item. With regard to maintainability, both units are maintained simultaneously. In this case, the following analysis is used:

$$MTTF_{standby} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} \tag{7}$$

$$MTTR_{standby} = minimum\ (MTTR_i) \tag{8}$$

Finally,

$$A_{standby} = \frac{MTTF_{standby}}{MTBF_{standby} + MTTR_{standby}} \tag{9}$$

The partial redundancy subsystem characterised by the ability to respond to a load requirement at a fraction of the items available but with the obligation to meet 100% of the request, the model used is an extension of the reliability model:

$$A_{partial} = \sum_{j=r}^{n} \binom{n}{j} A^j (1-A)^{n-j} \quad (10)$$

where.

n: total number of elements.
r: minimum number of elements to meet the required load.

Regarding the load sharing configuration, which is characterised by the possibility to operate within the required load and to evaluate the loss, the ratio of capacities to determine the equivalent subsystem availability is used.

$$A_{loadsharing} = \sum_{i=1}^{n} \left(A_i * \frac{Q_i}{Q_T} \right) \quad (11)$$

where.

Q_i: capacity of element i
Q_T: total capacity of the subsystem.

Phase 2: Up – Bottom. This refers to the impact determination from the complete system to the smallest element.

In this phase, the P-OEI of each element in the system is determined through the decomposition of the global index and each of the subsystems simultaneously, on the following levels.

$$\textit{Plant Operational Effectiveness Impact}(POEI)_{system\ i=0} = 1 \quad (12)$$

The breakdown for each level then begins using the following equations:

$$\sum_{j=1}^{n} POEI_{i;j} = POEI_{i-1}\ \forall\ i : 1, \ldots, r; \quad \forall\ j : 1, \ldots, n \quad (13)$$

$$\frac{POEI_{i;j}}{POEI_{i;j+1}} = \frac{(1 - A_{i;j})}{(1 - A_{i;j+1})}\ \forall\ i : 1, \ldots, r; \quad \forall\ j : 1, \ldots, n \quad (14)$$

where.

$POEI_{i;j}$: the P-OEI for element j (from 1 to n) that is found in the decomposition level i (from 1 to r).
$A_{i;j}$: the expected availability for element j (from 1 to n) that is found in the decomposition level i (from 1 to r).

In simple terms, the P-OEI determines the final result of the contribution of each element on the system's lack of effectiveness based on production capacity loss. When considering the lower detail level, level r, the sum of all P-OEI is 100% of the system.

$$\sum_{i=1}^{r} \sum_{j=1}^{n} POEI_{\ i;j} = 1 \quad (15)$$

Finally, once the P-$OEI_{i;j}$ of each item is known, its level of impact can be separated into two main factors, specifically, frequency (through the unavailability of the element) and consequence (through the impact of the element). The latter index is referred to as the expected operational impact – $EOI_{i;j}$, and it represents the effect that causes a stop of element i on element j of the system. Similar to the effect of stopping an element i, j can have different results, depending on the state of the elements that are at the same level as i.

$$EOI_{i;j} = \frac{POEI_{i;j} * (1 - A_{system})}{(1 - A_{i;j})} \quad (16)$$

where.

$EOI_{i;j}$: the EOI for element j (from 1 to n) that is found in decomposition level i (from 1 to r).
$POEI_{i;j}$: the P-OEI for element j (from 1 to n) that is found in decomposition level i (from 1 to r).
$A_{i;j}$: the expected availability for element j (from 1 to n) that is found in decomposition level i (from 1 to r).

4. Background of the industrial context

A biogas plant is a complex installation that consists of a variety of elements. The type and the design of a biogas plant are mainly determined by the amount and the type of available feedstock. As there are many different feedstock types suitable for use in biogas plants, there are, correspondingly, various techniques for treating these feedstock types and different systems of operations that are dependent on feedback type.

The amount of feedstock determines the dimensions of the feedstock digester, the storage capacities and the CHP unit. Furthermore, feedstock types and their quality determine the processing technology.

With respect to the plant in this study, a predigester is used before the main digester. The predigester creates the optimal conditions for the first two steps of the AD process, namely, hydrolysis and acid formation. After the predigester, the feedstock enters the main digester, where the subsequent AD steps occur. The digested substrate (digestate) is then pumped out of the digester to be dehydrated by press filters, and subsequently deposited for aerobic composting. The produced biogas is stored, conditioned and used for energy generation and heat. The primary process steps in a biogas plant are outlined in Fig. 1, which presents a typical process diagram of a biomethanation plant and includes four separate process stages:

1. Transport, delivery, storage and pre-treatment of feedstock
2 Biogas production (AD)
3 Storage of digestate, eventual conditioning and utilisation
4 Storage of biogas, conditioning and utilisation

Once the feedstock substrates are preconditioned, the biomethanation process begins. Specifically, regarding the plant in this case study, the main processes are explained in Table 1.

5. Application and analysis of P-OEI

For the development of this article, we used the actual maintenance data regarding the main equipment of a biomethanation plant located in Spain.

The process has been decomposed into six subsystems, according to the logic of the global process (serial configuration):

- 1. Mixing Process
- 2. Heating System
- 3. Digestion System
- 4. Biogas Process
- 5. Digested Process
- 6. PTA

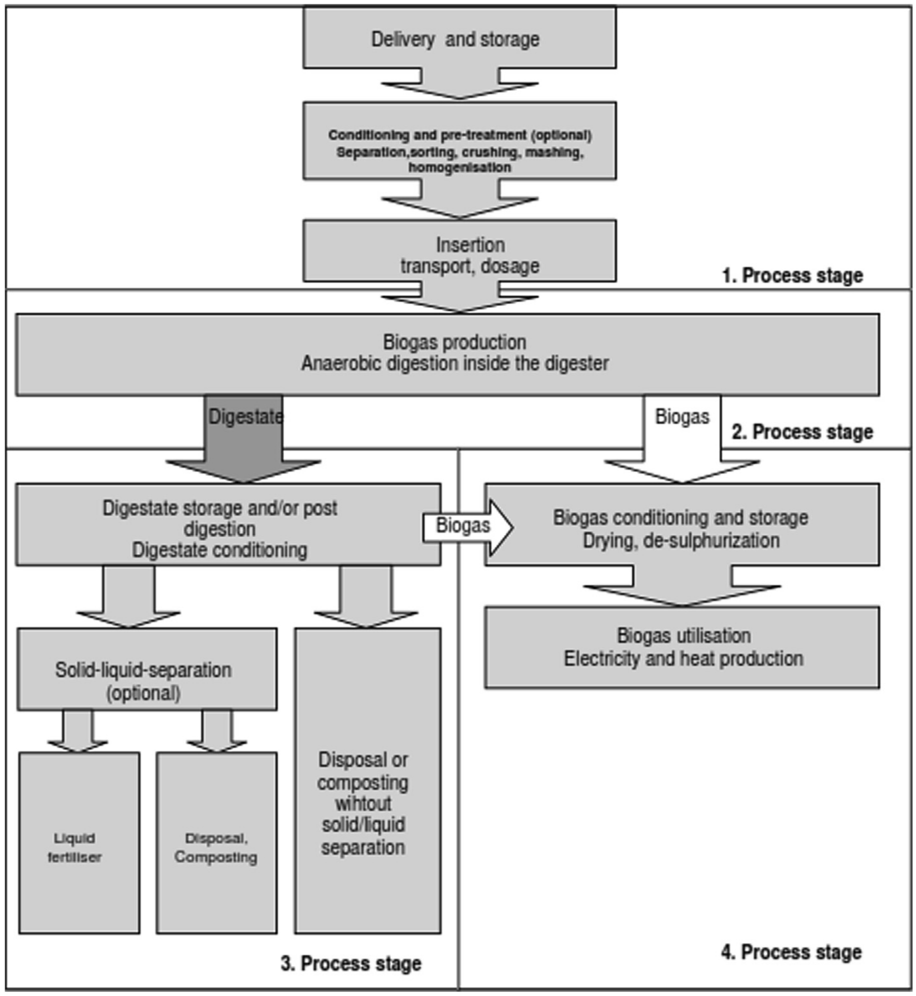


Fig. 1. Process stages of agricultural biogas plants.

Table 1
Main processes of the biomethanation plant under study.

Processes	Details
Feeding system	After storage and pre-treatment, AD feedstock is fed into the digester by pumps or conveyor screws.
Heating system/digester heating	Constant process temperature inside the digester is one of the most important operational conditions (high biogas yield). To achieve and maintain a constant process temperature, external heating sources are used. The most frequently used source is waste heat from the CHP unit of the biogas plant (through heat exchangers) and a steam boiler.
Digesters	The core of a biogas plant is the digester, where the decomposition of feedstock occurs in the absence of oxygen and where biogas is produced. A removal of sediments in the digester must be performed regularly to prevent heavy loading of the stirring systems, pumps and heat exchangers as it can cause fouling, obstructions and heavy wear. If they are not removed periodically, the sediment layers can become hard and can then only be removed with heavy equipment. The continuous removal of sediment layers from digesters is generally performed using floor rakes. •Stirring technologies A minimum stirring of biomass inside the digester is conducted through passive stirring, i.e., the insertion of fresh feedstock and the subsequent thermal convection streams, and active stirring, i.e., the up-flow of gas bubbles by a compressor as well as the use of mechanical, hydraulic or pneumatic equipment, such as submerged equipment, continuously slow rotating stirrers, submersible motor propeller stirrers or paddle stirrers).
Biogas storage	Correct selection and dimensioning of biogas storage facility brings substantial contribution to the efficiency, reliability and safety of the biogas plant while ensuring a constant supply of biogas and minimising biogas losses.
Biogas flares	In situations where there is an excess of biogas that cannot be stored or used, flaring is the ultimate solution and it is necessary to eliminate safety risks and protect the environment.
Biogas cleaning	When biogas leaves the digester, it is saturated with water vapours and contains, in addition to methane (CH4) and carbon dioxide (CO2), various amounts of hydrogen sulphide (H2S). Hydrogen sulphide is a toxic gas that forms sulphuric acid in combination with the water vapours in biogas. The sulphuric acid is corrosive and can cause damage to, for instance, the CHP engines, gas pipelines, and exhaust pipes. To prevent this, the biogas must be desulphurisated (removal of H2S). Removal of H2S from biogas (desulphurisation) can be completed in desulphurisation tanks or columns.
Digestate storage	The digested substrate is extracted and then dehydrated by press filters; subsequently, it will be deposited for aerobic composting.
Water system	The process water is used for diluting and heating the waste in the mixer-separator tanks. This water is stored in a proper tank. Much of the water entering the tank comes from the dehydration unit.

The mixing process involves two mixer separator tank lines (1 and 2) in a configuration of total redundancy. Each line is formed by a propeller mixer, a submersible mixer and a TMS pump, all of which are configured serially.

The heating system is composed of a boiler, whereas the digestion system employs two reactors (1 and 2) and a compressor in a serial configuration. Each reactor is composed of a stirrer and a reactor pump, also in a serial configuration. The biogas process is then formed by a gasholder, a flare and a compressor tower in a serial configuration. The digested process is composed of an intermediate tank, a dehydration unit, a screw loader and a pump, all in a serial configuration. The intermediate tank contains a pump, a stirrer and an automatic pump in a serial configuration, and the dehydration unit consists a pump and a press filter.

Finally, the PTA process contains a heat exchange unit, a slurry pump and a subsystem of the main pumps. The heat exchange unit is formed by two heat exchangers (1 and 2) in a total redundancy configuration, and the subsystem of the main pumps is formed by two pumps in a stand-by configuration. Fig. 2 summarises the logical configuration of the process.

Following the logical configuration of the system, the complete analysis of availability at each level is developed. The analysis is based on the individual MTBF and MTTR of each element. The plant was decomposed into five levels, from the individual equipment to the complete system. This task is the result of an RBD analysis that groups the equipment of each process, such as the digested process, into the appropriate levels. In this case, all of the equipment/elements are in the fifth level. The fourth level includes the subsystem with Intermediate Tank 1, the dehydration unit, Screw Loader 1and Pump DP 1, whereas the third and second levels of the processes, as well as the first level, consist of the main system. Fig. 3 explains the hierarchical levels of the plant.

With respect to data management of the biomethanisation system in this study, the current automatic capture systems provide rich and complete data with respect to operational parameters that are mainly focused on prognosis and health management application, data related to the state of the asset (on/off), specific process parameters and downtimes. Indeed, the data repository is complemented with information related to work notifications and work orders. Accordingly, an ERP solution permits the complete integration of information flow from all functional areas by means of a single database that is accessible through a unified interface and channel communication. As a consequence of globalisation and constant market competitiveness, most important companies and industries, e.g., waste treatment, have adopted ERP packages to fully integrate, standardise and coordinate their business processes. Hence, it is possible to apply the proposed methodology using this consolidated database (quality and quantity). Regarding indicator estimation, a period of three years of maintenance and operational data was considered.

Table 2 presents the results of the expected availability calculations for equipment, subsystems and the system in general.

Finally, for the identification of the OEI and computing the availability indicators, it is necessary to calculate the impact of each element (percentage loss of availability, production or operational capability) at the top level, this being a subsystem or main system unit. By the logic described, the PEI and the EOI of the system (maximum top level) will always be 100%. The P-OEI is the contribution of each element to the system's lack of effectiveness based on the loss of production capacity due to unavailability. The expected operational impact (EOI) is the expected effect of a constraint of each element on the system. The results are presented

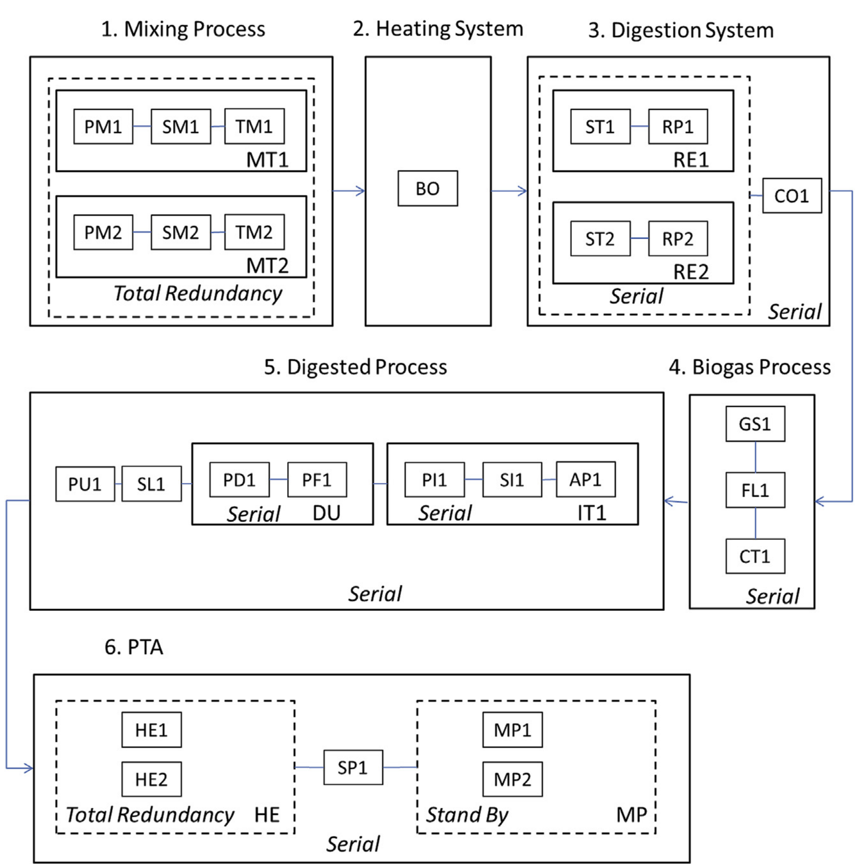


Fig. 2. Process reliability block diagram.

→ Biomethanation Plant.	Level 1
→ → 6 processes (Mixing Process, Heating System, Digestion System, Biogas Process, Digested Process, PTA).	Level 2
→ → → Subsystem inside process 1.	Level 3
→ → → → Subsystem inside process 2.	Level 4
→ → → → → Individual Equipment.	Level 5

Fig. 3. Biomethanation Plant hierarchy decomposition.

Table 2
Expected availability results.

	Nickname	5th level Avail.	4th level Avail.	3rd level Avail.	2nd level Avail.	1st level Avail.
System						76.57%
1. Mixing Process	**MP**			99.83%	99.83%	
1.1 Mixer Separator Tank 1	MT1		96.57%			
1.1.1 Propeller Mixer 1	PM1	98.95%				
1.1.2 Submersible Mixer 1	SM1	98.77%				
1.1.3 TMS Pump 1	TM1	98.81%				
1.2 Mixer Separator Tank 2	MT2		95.15%			
1.2.1 Propeller Mixer 2	PM2	98.79%				
1.2.2 Submersible Mixer 2	SM2	98.13%				
1.2.3 TMS Pump 2	TP1	98.15%				
2. Heating System	**HS**		99.02%	99.02%	99.02%	
2.1 Boiler	BO	99.02%				
3. Digestion System	**DS**			94.17%	94.17%	
3.1 Reactor 1	RE1		97.80%			
3.1.1 Stirrer 1	ST1	99.10%				
3.1.2 React. Pump 1	RP1	98.68%				
3.2 Reactor 2	RE2		97.98%			
3.2.1 Stirrer 2	ST2	99.17%				
3.2.2 React. Pump 2	RP2	98.81%				
3.3 Compressor 1	CO1	98.28%	98.28%			
4. Biogas Process	**BP**				97.07%	
4.1 Gasholder 1	GS1	99.16%	99.16%	99.16%		
4.2 Flare 1	FL1	99.57%	99.57%	99.57%		
4.3 Compressor Tower 1	CT1	98.31%	98.31%	98.31%		
5. Digested Process	**DP**				87.72%	
5.1 Intermediate Tank 1	IT1		95.21%	95.21%		
5.1.1 Pump IT 1	PI1	98.67%				
5.1.2 Stirrer IT 1	SI1	97.87%				
5.1.3 Automatic Pump 1	AP1	98.60%				
5.2 Dehydration Unit	DU		95.74%	95.74%		
5.2.1 Pump DU 1	PD1	97.16%				
5.2.2 Press Filter 1	PF1	98.54%				
5.3 Screw Loader 1	SL1	98.65%	98.65%	98.65%		
5.4 Pump DP 1	PU1	97.55%	97.55%	97.55%		
6. PTA	**PT**				96.60%	
6.1 Heat Exchange	HE		99.97%	99.97%		
6.1.1 Heat Exchanger 1	HE1	98.19%				
6.1.2 Heat Exchanger 2	HE2	98.22%				
6.2 Slurry Pump 1	SP1	97.40%	97.40%	97.40%		
6.3 Main Pumps	MP		99.21%	99.21%		
6.3.1 Main Pump 1	MP1	98.40%				
6.3.2 Main Pump 2	MP2	98.39%				

in Table 3.

The results indicate that equipment/elements with higher levels of P-OEI (fifth level of P-OEI) are Pump DU 1 – PD1 (Crt.Imp 10.49%), Slurry Pump 1 – SP1 (Crt.Imp 10.10%), Pump DP1 – PU1 (Crt.Imp 9.14%), Stirrer IT 1 – SI1 (Crt.Imp 7.83%), Compressor 1 – CO1 (Crt.Imp 6.60%) and Compressor Tower 1 – CT1 (6.56%). These six elements explain over 50% of the system's lack of effectiveness. An interpretation of the results of the P-OEI is as follows. Pump DU 1 is responsible for 10.49% of the expected production loss of the system due to its unavailability and its EOI. To understand the evaluation of the lack of effectiveness based on the P-OEI, it is necessary to analyse the concept of the expected operational impact (EOI). For example, Compressor 1 and Heat Exchanger 2 exhibit similarly expected availability results (98.28% and 98.22%, respectively), but their P-OEIs are dramatically different. In fact, the P-OEI of Compressor 1 is more than one hundred times greater than the impact of Heat Exchanger 2. This extreme variation is likely the result of the expected operational impact (EOI), given that Compressor 1 is a serial element in the digestion system, while Heat Exchanger 2 is on stand-by in the PTA process. Accordingly, the EOI of the compressor is 89.77%, whereas that of Heat Exchanger 2 is only 0.82%. This indicator suggests that constraints on Heat Exchanger 2 will rarely impact the PTA process and or the entire system because it is highly probable that Heat Exchanger 1 will be available.

Fig. 4 presents a graphical dispersion analysis to understand the concepts and the P-OEI index considering equipment unavailability (X axis) and the EOI (Y axis). From this graphic, it is confirmed that

Table 3
P-OEI and EOI calculation.

	Nickname	1st level P-OEI	2nd level P-OEI	3rd level P-OEI	4th level P-OEI	5th level P-OEI	5th level EOI
System		100.00%					
1. Mixing Process	**MP**		0.65%				
1.1 Mixer Separator Tank 1	MT1			0.27%			
1.1.1 Propeller Mixer 1	PM1				0.08%	0.08%	1.82%
1.1.2 Submersible Mixer 1	SM1				0.10%	0.10%	1.82%
1.1.3 TMS Pump 1	TM1				0.09%	0.09%	1.82%
1.2 Mixer Separator Tank 2	MT2			0.38%			
1.2.1 Propeller Mixer 2	PM2				0.09%	0.09%	1.81%
1.2.2 Submersible Mixer 2	SM2				0.14%	0.14%	1.81%
1.2.3 TMS Pump 2	TP1				0.14%	0.14%	1.81%
2. Heating System	**HS**		3.84%				
2.1 Boiler	BO			3.84%	3.84%	3.84%	91.56%
3. Digestion System	**DS**		22.76%				
3.1 Reactor 1	RE1			8.44%			
3.1.1 Stirrer 1	ST1				3.43%	3.43%	89.29%
3.1.2 React. Pump 1	RP1				5.01%	5.01%	89.29%
3.2 Reactor 2	RE2			7.72%			
3.2.1 Stirrer 2	ST2				3.17%	3.17%	89.33%
3.2.2 React. Pump 2	RP2				4.56%	4.56%	89.33%
3.3 Compressor 1	CO1			6.60%	6.60%	6.60%	89.77%
4. Biogas Process	**BP**		11.47%				
4.1 Gasholder 1	GS1			3.24%	3.24%	3.24%	90.79%
4.2 Flare 1	FL1			1.68%	1.68%	1.68%	90.79%
4.3 Compressor Tower 1	CT1			6.56%	6.56%	6.56%	90.79%
5. Digested Process	**DP**		47.98%				
5.1 Intermediate Tank 1	IT1			17.89%			
5.1.1 Pump IT 1	PI1				4.90%	4.90%	86.12%
5.1.2 Stirrer IT 1	SI1				7.83%	7.83%	86.12%
5.1.3 Automatic Pump 1	AP1				5.16%	5.16%	86.12%
5.2 Dehydration Unit	DU			15.89%			
5.2.1 Pump DU 1	PD1				10.49%	10.49%	86.65%
5.2.2 Press Filter 1	PF1				5.40%	5.40%	86.65%
5.3 Screw Loader 1	SL1			5.06%	5.06%	5.06%	87.49%
5.4 Pump DP 1	PU1			9.14%	9.14%	9.14%	87.49%
6. PTA	**PT**		13.30%				
6.1 Heat Exchange	HE			0.13%			
6.1.1 Heat Exchanger 1	HE1				0.06%	0.06%	0.82%
6.1.2 Heat Exchanger 2	HE2				0.06%	0.06%	0.82%
6.2 Slurry Pump 1	SP1			10.10%	10.10%	10.10%	90.98%
6.3 Main Pumps	MP			3.07%			
6.3.1 Main Pump 1	MP1				1.53%	1.53%	22.42%
6.3.2 Main Pump 2	MP2				1.54%	1.54%	22.42%

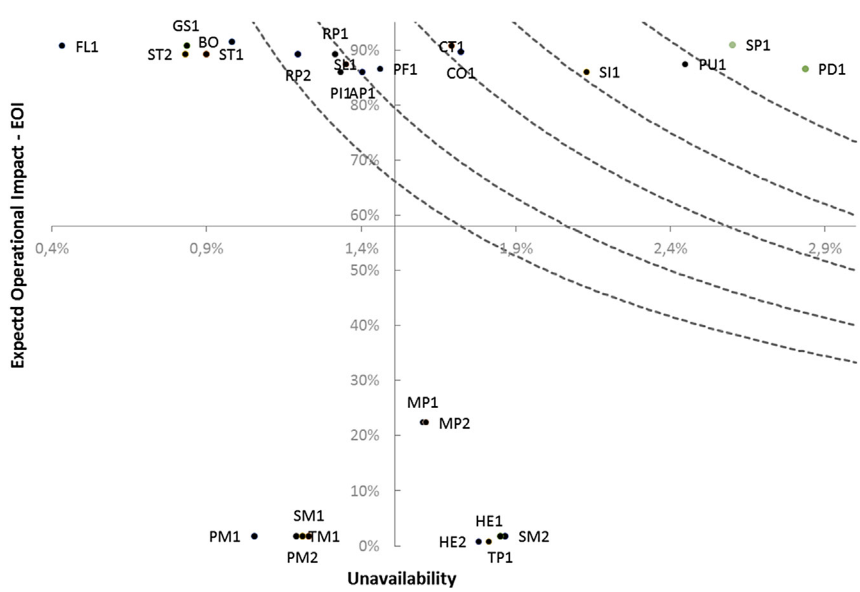


Fig. 4. P-OEI plot graph.

Pump DU 1 – PD1, Slurry Pump 1 – SP1, Pump DP1 – PU1, Stirrer IT 1 – SI1, Compressor 1 – CO1 and Compressor Tower 1 – CT1 are the elements with the highest levels of P-OEI due to their location in the high-right quadrant. With the assistance of the ISO lack of effectiveness curves, it is easy to order the elements.

6. Results and discussion

After applying the proposed methodology to the data from the biomethanation plant, the analysis reveals a lack of plant effectiveness. Furthermore, it discloses important results regarding the evaluation of the plant's design and performance. First, considering the key questions presented in the Problem Statement section, it is established that the bottlenecks of the system are caused by all of the equipment/instruments that exhibit an EOI above 86%, as they lack the capacity to respond to a failure. The 50% loss production is explained by only six elements that have a high ratio of unavailability and EOI. Thus, it is important to consider that the introduction of redundancy or overcapacity in these important elements will considerably reduce the expected loss production, as previously mentioned when comparing Compressor 1 and Heat Exchanger 2.

Because the expected availability of the system is 76.57%, it is possible to make a more fixed forecast of the system's capacity to develop a production plan.

Regarding the data analysis and the decision-making processes, it is recommended that reliable information systems be used as a base [28,29], ideally systems that capture and manage online data, i.e., real-time data and events, and that automatically record various real-time data, such as production, stoppages and process parameters. Moreover, by using advanced information analytics, networked machines will be able to perform more efficiently, collaboratively and resiliently[3]. This concept, mainly conceptualised for manufacturing systems, is known as Industry 4.0. According to cyber-physical systems (CPS), Industry 4.0 is defined as transformative technologies designed to manage interconnected systems of physical assets and computational capabilities [30] and to integrate these systems with the production, logistics and services of the current industrial practices. Industry 4.0 would transform today's factories into factories with significant economic potential [31].

The main improvement opportunities are intended to increase the availability of components with higher P-OEI by engaging in reliable and sustainable actions while considering the investment for incorporating redundancy and reducing the real impact of such actions.

7. Conclusions

In relation to the proposed objectives, it is concluded that the application of the OEI on real data of a biomethanation plant identifies several opportunities to improve decision making related to asset management of this specific type of industrial plant, thereby supporting the decision-making process and the implementation of a new maintenance plan for more relevant elements.

The operational effect (importance) of each of the tools on the biomethanation system has been determined. Moreover, the results of the calculation regarding availability expected for equipment, subsystems and systems and their EOI were also calculated. The P-OEI analysis provided relevant information to evaluate plant design and performance.

After applying the methodology, the focus can be directed toward improving plant assets and increasing P-OEI. The actions should be directed toward the reliability and maintainability of the elements in the right zone (X axis) of the P-OEI plot graph. These actions include developing a maintenance strategy definition and maintenance procedures as well as conducting a spare parts analysis. For the elements located on a higher zone (Y axis) of the P-OEI plot graph, the actions may be related to reducing the impact of the element, for example, by including design improvements and incorporating redundancy and overcapacity when possible.

Finally, it is emphasised that the P-OEI methodology can be incorporated into any computerised maintenance management system (CMMS) database to obtain an automatic impact assessment.

8. Glossary

RAM Analysis: assesses reliability, availability and maintainability.

Operational Effectiveness Impact (OEI): evaluates the fixed production capacity of a system based on analysis of reliability, availability and maintainability.

Plant Operational Effectiveness Impact (P-OEI): determines the contribution of each element with respect to the system's lack of operational effectiveness based on production capacity loss.

Expected Operational Impact – EOI: represents the effect that causes a stop of an element on the system, thus evaluating all scenarios and the likelihood of those scenarios in complex configurations.

Acknowledgements

The authors would like to acknowledge the support of Saudi BinLadin Group to this research in the area of operations and maintenance.

References

[1] S. Dahiya, J. Joseph, High rate biomethanation technology for solid waste management and rapid biogas production: an emphasis on reactor design parameters, Bioresour. Technol. 188 (2015) 73–78.
[2] U.S. Environmental Protection Agency, Solid Waste Management and Greenhouse Gases: a Life-cycle Assessment of Emissions and Sinks, third ed., U.S. Environmental Protection Agency, New York, 2006.
[3] A. González-González, F. Cuadros, Optimal and cost-effective industrial biomethanation of tobacco, Renew. Energy 63 (2014) 280–285.
[4] S. Dahiya, O. Sarkar, Y. Swamy, S. Venkata Mohan, Acidogenic fermentation of food waste for volatile fatty acid production along with co-generation of biohydrogen, Bioresour. Technol. 182 (2015) 103–113.
[5] D. Karakashev, D. Batstone, I. Angelidaki, Influence of environmental conditions on methanogenic compositions in anaerobic biogas reactors, Appl. Environ. Microbiol. 71 (1) (2005) 331–338.
[6] P. Weiland, Biogas Prod. Curr. state Perspect. Appl Microb. Biotechnol 85 (2010) 849–860.
[7] S. Jaina, S. Jainc, I. Tim Wolfa, J. Leea, Y. Wah Tong, A comprehensive review on operating parameters and different pretreatment methodologies for anaerobic digestion of municipal solid waste, Renew. Sustain. Energy Rev. 52 (2015) 142–154.
[8] I. Angelidaki, D. Karakashev, D. Batstone, C. Plugge, A. Stams, Biomethanation and its potential, Methods Enzymol. 494 (2011) 327–351.
[9] J. Mata-Alvarez, P. Llabres, F. Cecchi, P. Pavan, Anaerobic digestion of the Barcelona central food market organic wastes: experimental study Bioresour, Technol 39 (1992) 39–48.
[10] M. Krishania, V. Kumar, V. Kumar Vijay, A. Malik, Analysis of different techniques used for improvement of biomethanation process: a review, Fuel 106 (2013) 1–9.
[11] Y. Yadav, S. Santose, T. SreeKrishnan, S. Kohli, V. Rana, Enhancement of biogas production from solid substrate using different techniques – a review, Bioresour. Technol. 95 (2004) 1–10.
[12] I. Pérez, M. Garfí, E. Cadena, I. Ferrer, Technical, economic and environmental assessment of household biogas digesters for rural communities, Renew. Energy 62 (2014) 313–318.
[13] B. Daylan, N. Ciliz, Life cycle assessment and environmental life cycle costing analysis of lignocellulosic bioethanol as an alternative transportation fuel, Renew. Energy 89 (2016) 578–587.
[14] W. Gang, S. Wang, F. Xiao, D. Gao, Robust optimal design of building cooling systems considering cooling load uncertainty and equipment reliability, Appl. Energy 159 (2015) 265–275.

[15] R. Karki, R. Billinton, Cost effective wind energy utilization for reliable power supply, IEEE Trans. Energy Convers. 19 (2004) 435–440.
[16] P. Georgilakis, Y. Katsigiannis, Reliability and economic evaluation of small autonomous power systems containing only renewable energy sources, Renew. Energy 34 (1) (2009) 65–70.
[17] W. Gang, S. Wang, D. Gao, F. Xiao, Multi criteria sustainability assessment of biogas production in Kenya, Appl. Energy 93 (2012) 496–506.
[18] A. Neely, Performance measurement system design: a literature review and research, Int. J. operations Prod. Manag. 15 (4) (1994) 80–116.
[19] A. Koontz, H. Weihrich, Administración: una perspectiva global. México: McGraw-Hill/Interamericana de México, 2003.
[20] M. Guillemette, M. Laroche, J. Cadieux, Defining decision making process performance: conceptualization and validation of an index, Inf. Manag. 51 (2014) 618–626.
[21] J. Chai, E. Liu, W. Ngai, Application of decision-making techniques in supplier selection: a systematic review of literature, Expert Syst. Appl. 40 (2013) 3872–3885.
[22] ISO/DIS 14224: petroleum, petrochemical and natural gas industries, Collect. Exch. Reliab. maintenance data Equip. (October 2004).
[23] P. Baraldi, M. Compare, E. Zio, Component ranking by Birnaum importance in presence of epistemic uncertainty in failure event probabilities. IEEE transactions on Reliability, Inst. Electr. Electron. Eng. 62 (2013) 37–48.
[24] F. Kristjanpoller, P. Viveros, A. Crespo, T. Grubessich, R. Stegmaier, RAM-C: a novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations, in: The Annual European Safety and Reliability Conference (ESREL), Switzerland, Zurich, September 2015, pp. 7–10, 8-84-92970-17-9.
[25] M. Rausand, A. Hoyland, System Reliability Theory: Models, Statistical Methods, and Applications, third ed., Wiley, New York, 2003.
[26] H. Guo, X. Yang, A simple reliability block diagram method for safety integrity verification, Reliab. Eng. Syst. Saf. 92 (2007) 1267–1273.
[27] Dhillon B. Maintainability, Maintenance, and Reliability for Engineers, Taylor & Francis Group, Boca Raton, 2006.
[28] C. Bunea, T. Mazzuchi, S. Sarkani, H. Chang, Application of modern reliability database techniques to military system data, Reliab. Eng. Syst. Saf. 93 (2008) 14–27.
[29] J. Caldeira Duartea, P. Cunhaa, Craveiroc J.Maintenance database, Procedia CIRP 13 (2013) 551–556.
[30] R. Baheti, H. Gill, Cyber-physical systems, Impact Control Technol. 1 (2011) 161–166.
[31] J. Lee, B. Bagheri, H. Kao, A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems, Manuf. Lett. 3 (2015) 18–23.

Special Issue Article

Advances in Mechanical Engineering

Advances in Mechanical Engineering
2016, Vol. 8(10) 1–13

DOI: 10.1177/1687814016674845
aime.sagepub.com
SAGE

Expected impact quantification–based reliability assessment methodology for Chilean copper smelting process: A case study

Fredy Kristjanpoller[1,2], Adolfo Crespo[2], Pablo Viveros[1,2] and Luis Barberá[2]

Abstract
Currently, a lack of interpretation tools and methodologies hinders the ability to assess the performance of a single piece of equipment or a total system. Therefore, a reliability, availability, and maintainability analysis must be combined with a quantitative reliability impact analysis to interpret the actual performance and identify bottlenecks and improvement opportunities. This article proposes a novel methodology that uses reliability, availability, and maintainability analysis to quantify the expected impact. The strengths of the failure expected impact methodology include its ability to systematically and quantitatively assess the expected impact in terms of reliability, availability, and maintainability indicators and the logical configuration of subsystems and individual equipment, which show the direct effects of each element on the total system. This proposed analysis complements plant modeling and analysis. Determining the operational effectiveness impact, as the final result of the computation process, enables the quantitative and unequivocal prioritization of the system elements by assessing the associated loss as a "production loss" regarding its unavailability and effect on the system process. The Chilean copper smelting process study provides useful results for developing a hierarchization that enables an analysis of improvement actions that are aligned with the best opportunities.

Keywords
Reliability analysis, failure, reliability engineering, maintenance, industrial engineering, life cycle assessment

Date received: 19 May 2016; accepted: 26 September 2016

Academic Editor: Shun-Peng Zhu

Introduction and background

Literature review

The effectiveness of production processes and their associated equipment is an important tool for assessing total system effectiveness,[1] which is generally measured according to the results of reliability and availability indicators and life cycle economic analysis.[2] The total equipment effectiveness indicator measures the productive efficiency using the control parameters as a basis for calculating the fundamentals of industrial production: availability, efficiency, and quality.[3]

In the current literature, several investigations have been performed to identify the principal factors that directly affect the maximization of economic benefits; these factors converge at the empirical consideration of reliability, availability, and maintainability (RAM) indicators. The traditional reliability analyses that are

[1]Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaíso, Chile
[2]Department of Industrial Management, University of Seville, Seville, Spain

Corresponding author:
Fredy Kristjanpoller, Department of Industrial Engineering, Universidad Técnica Federico Santa María, Av. España 1680, Casilla 110-V, Valparaíso, Chile.
Email: fredy.kristjanpoller@usm.cl

based on logical and probabilistic modeling contribute to the improved key performance indicators (KPIs) of a system,[4] which directly influence optimal operation designs.[5] However, many alternatives are available for system reliability analyses that employ analytical techniques, such as Markov models,[6] Poisson models,[7] universal generating function (UGF) and decision diagram.[8] This systematic study is based on techniques such as reliability block diagrams (RBDs),[9,10] fault trees (FTs),[11] reliability graphics (RGs),[12] and Petri nets (PNs);[13] these techniques can be used to determine logical relationships that underlie the behavior or dynamics of a process.

As an example, the productive processes in the mining industry have numerous equipment and systems, rendering a systematic analysis of the plant more difficult.[4] Different analysis methodologies, such as the RBD methodology,[9,10] have been developed and extensively applied in the mining sector due to their adaptability in representing complex arrangements and environments with large amounts of equipment, simplifying reliability analysis. For the correct development of an RAM analysis, a complete scan of the data must be performed to fit the data to a statistical model and to then obtain key indicators.[14] Using a maintenance management support tool, different improvement opportunities can be identified, and recommendations can be offered to develop the most appropriate actions.[15]

The Birnbaum importance measure (IM)[16] ranks the components of the system with respect to the impact of their failure on the overall system's performance; however, its application is primarily related to epistemic uncertainties.

Interpretation tools and methodologies for understanding the performance of a single piece of equipment and a total system are lacking; this deficiency is even more pronounced when the selected analysis process has been disaggregated on many levels, and each level has been disaggregated across several pieces of equipment. Therefore, an RAM analysis must be combined with a quantitative reliability impact analysis to determine the real performance and identify bottlenecks and opportunities for improvement.

Motivation of work

This article proposes an integral and quantitative innovative methodology to analyze the RAM and plant failure expected impact (FEI). The FEI analysis is related specifically to production capacity and the effect of preventive and corrective maintenance intervention on system availability. This proposal designs a novel algorithm to compute an impact index based on the frequency of failures associated, with the reliability and maintainability of the machinery and the expected impact according to different scenarios and configurations. This impact index, based on a probabilistic approach, defines the expected condition of the item in the system from a perspective of evaluation of its possible states (intrinsic behavior) and related to the logical and functional configuration of the system. This approach enables an overall comparison of elements and the prioritization of those elements, as well as a partial effectiveness assessment.

What is the motivation for applying the FEI methodology? In the finance area, for example, when a single stock of the NASDAQ index has a variation price of 10% and this stock represents 5% of the index composition, the NASDAQ index increases by only 0.5%. Developing a similar analysis over an "element" failure and determining the system consequences are simple when the "elements" have a serial configuration. If the configuration employs redundancy logic, the result is uncertain and dependent on the reliability and maintainability of the elements that compose the subsystem. The FEI methodology solves this problem by proposing four steps and applying them to a mining process—specifically, a copper smelting process (CSP) in Chile. Related to failure impact methodology, a novel algorithm is proposed to compute a failure impact index for the total availability performance of the system based on the reliability (frequency of failures), maintainability (downtime), and availability of the elements. This impact index defines the expected condition of the item in the system by evaluating its possible states (intrinsic behavior) and the logical and functional configuration of the system. This analysis enables a total comparison of the elements, their prioritization, and a failure impact evaluation.

Scope of work

The two key indicators of FEI methodology are outlined in Figure 1, which incorporates general formulas for analysis and calculation. This methodology seeks to explain the level of responsibility for a failure in a single piece of equipment (b3) for system inoperability from a historical perspective. Two important steps are included:

1. Explain the effect of a single failure (downtime Ti of equipment b3) in terms of the single downtime propagation in the system (equivalent downtime ti). This indicator is named the expected downtime factor propagation (E-DFP).
2. Explain the effect of a single downtime propagation (equipment b3) on the total downtime of the system (downtime responsibility). This

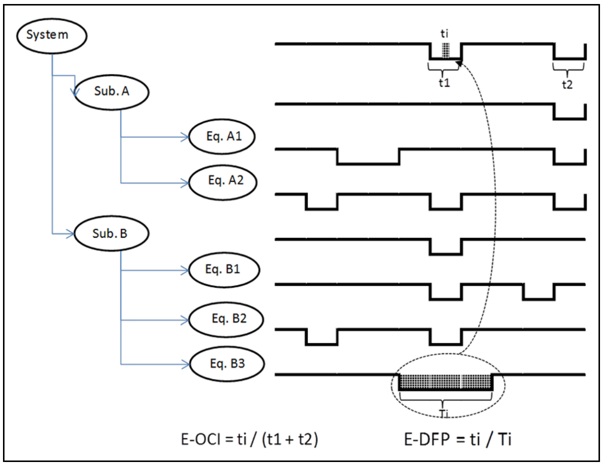


Figure 1. Expected impact scheme.

indicator is named the expected operational criticality index (E-OCI).

A copper smelting plant in Chile is examined as a case study. The smelting process is one of the most important and critical phases in any mineral processing system, especially in copper plants.[1] The selected mining process is divided into four main subsystems: drying, concentrate fusion, conversion, and refining.

This article is structured as follows: section "FEI methodology" describes the reliability assessment based on the FEI methodology and presents its conceptual and mathematical basis, section "Case study" introduces and develops the case study according to the methodology, and section "Conclusion" explains the main results and conclusions.

FEI methodology

The FEI methodology should consider the joint processes that are necessary for identifying improvement opportunities and generating maintenance recommendations. These processes can be summarized in four steps: data cleaning, data management, RAM analysis, and FEI quantification (E-OCI and E-DFP) and decision making.

Data cleaning

The first step is to purge and filter the obtained data to improve the data quality (missing values, usefulness records, and erroneous data).[17]

Data management

To achieve an efficient data management, some methodologies can be considered based on the equipment (historical reparable behavior). A repairable system after a failure scenario can be restored to its functioning condition (perfect and imperfect) by maintenance actions, with the exception of the replacement[18] (nonreparable item). A reparable system is defined as follows: "A system that, after failing to perform one or more of its functions satisfactorily, it can be restored to fully satisfactory performance by any method other than replacement of the entire system."[19] The model and analysis of reparable equipment have high importance, mainly in order to increase the performance oriented to reliability and maintenance as part of the cost reduction in this last item. Depending on the type of maintenance given to equipment, it is possible to find five cases:[20]

- *Perfect maintenance or reparation.* Maintenance operation that restores the equipment to the condition "as good as new."
- *Minimum maintenance or reparation.* Maintenance operation that restores the equipment to the condition "as bad as old."
- *Imperfect maintenance or reparation.* Maintenance operation that restores the equipment to the condition "worse than new but better than old."
- *Over-perfect maintenance or reparation.* Maintenance operation that restores the equipment to the condition "better than new."
- *Destructive maintenance or reparation.* Maintenance operation that restores the equipment to the condition "worse than old."

For a perfect maintenance, the most common developed model corresponds to the perfect renewal process (PRP). In this, we assume that repairing action restores the equipment to a condition as good as new and assumes that times between failures in the equipment are distributed by an identical and independent way. The most used and common model PRP is the homogeneous Poisson process (HPP), which considers that the system neither ages nor spoils independently of the previous pattern of failures. That is to say, it is a process without memory. Regarding case b, "as bad as old" is the opposite case to what happens in case a, "as good as new," since it is assumed that the equipment will stay after the maintenance intervention in the same state than before each failure. This consideration is based on that the equipment is complex, composed by hundreds of components, with many failure modes and the fact that replacing or repairing a determined component will not affect significantly the global state and age of the equipment. In other words, the system is subject to minimum repairs, which does not cause any change or considerable improvement. The most common model to represent this case is through nonhomogeneous Poisson process (NHPP), in this case the most used model to represent NHPP is called "Power Law." In this model, a Weibull distribution is assumed for the first failure and that later, it is modified over time. Although the models HPP and NHPP are the most used, they have a practical restriction regarding its application since a more realistic condition after a repairing action is what we find between both: "worse than new but better than old." In order to find a generalization to this situation and not distinguishing between HPP and NHPP, it was necessary to create the generalized renewal process (GRP).[21] The main objective of this stage is to generate parameters evaluation and basic indicators.

RAM analysis

Reliability analysis. Different alternatives have been proposed for the individual and systemic logical–functional representations of processes.[4] Modeling a complex system using RBDs is a well-known method that has been adopted for different applications in system reliability analysis.[5,22] An RBD is constructed after performing a logical decomposition of a system into subsystems; the RBD is constructed to express reliability logics such as series, redundancy, and standby in a network of subsystems. RBDs are considered to be a modeling tool that is consolidated and available for the normal duties of reliability analysis. The RBD analysis methodology[9,10] is used extensively in the mining sector due to its adaptability for representing complex provisions and environments with large amounts of equipment. An RBD can be applied in addition to other reliability techniques, such as a fault tree analysis (FTA).

Maintainability analysis. Maintainability performance is defined as

> the ability of an item under given conditions of use to be retained in, or restored to, a state in which it can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources.[23]

The "given conditions" refer to the conditions in which the item is used and maintained, for example, climate conditions, support conditions, human factors, and geographical location. The maintainability of equipment can be represented and understood as a probability distribution of the maintenance completion time. Parametric methods have been used to analyze historical time to repair (TTR) datasets in many case studies.[24]

Availability analysis. According to Dhillon,[5] availability is the probability that the equipment is available as required. Assuming that the required equipment must always be operating and that maintenance orders are immediately executed after a failure, the expected availability of the determined equipment can be defined[25]

$$A(t) = \frac{\textit{System uptime}}{\textit{System uptime} + \textit{System downtime}} \approx \frac{MTTF}{MTTF + MTTR} \tag{1}$$

Availability is probably the most important parameter because it is directly related to the equipment performance, especially in a production environment that is based on volume, such as the mining industry. In this environment, the rate of production, among other variables, determines the level of benefit that is derived from the exercises. Monte Carlo simulation is used as a modeling framework to represent the realistic features of the equipment and the complex behavior of high-dimensional systems to obtain the performance indicators for the availability.[4]

FEI quantification and decision making

To implement an efficient asset management, an item classification should be developed based on criteria such as direct and indirect costs, failure rate, and operational impact. The objective is to identify the relevant elements in making priority maintenance decisions and efficiently allocating resources. Many techniques exist for asset hierarchy, and each technique has advantages and disadvantages that depend on the operation context.[4] For this proposal, the authors present a novel quantitative methodology for measurement based on reliability impact using previous results of RAM analysis.

FEI methodology. In this phase, the first indicator is the E-OCI of each element in the system, which is determined by decomposing the global index and each subsystem index[26] on the following levels

$$E\text{-}OCI_{system\ i=0} = 1 \tag{2}$$

Equation (2) represents the start of the process considering the E-OCI as a 100%. Then, the breakdown of each level begins with the following equations

$$\sum_{j=1}^{n} E\text{-}OCI_{i;j} = E\text{-}OCI_{i-1} \quad \forall i: 1, \ldots, r;\ \forall j: 1, \ldots, n \tag{3}$$

In equation (3), the E-OCI of a level is distributed in all the elements that composed it, all this to keep the consistence of the impact quantification. To determine the E-OCI of each element of the lower level, it is necessary to develop equation (4), which considers the distribution by an unavailability factor. In this sense, the most unavailable element of the lower level obtains a bigger proportion of the E-OCI from the upper level

$$\frac{E\text{-}OCI_{i;j}}{E\text{-}OCI_{i;j+1}} = \frac{\left(1 - A_{i;j}\right)}{\left(1 - A_{i;j+1}\right)} \quad \forall i : 1, \ldots, r;\ \forall j : 1, \ldots, n \tag{4}$$

where $E\text{-}OCI_{i;j}$ is the E-OCI for element j (from 1 to n) that is included in decomposition level i (from 1 to r) and $A_{i;j}$ is the expected availability for element j (from 1 to n) that is included in decomposition level i (from 1 to r).

In simple terms, the E-OCI shows the final contribution of each element toward mitigating the system's lack of effectiveness based on the production capacity loss. When considering a lower detail level, such as level r, the sum of all E-OCI values is 100% of the system

$$\sum_{i=1}^{r}\sum_{j=1}^{n} E\text{-}OCI_{i;j} = 1 \tag{5}$$

Once the $E\text{-}OCI_{i;j}$ of each item is known, its level of impact is divided into two main aspects: frequency (by the unavailability of the element) and consequence (by the impact of the element). The consequence is $E\text{-}DFP_{i;j}$, which represents the effect on system j of element i stopping. The effect of stopping element i may have different results on system j depending on the state of the elements that are also on level i. Particularly, equation (7) is deducted from the definition of E-OCI and the relation between the element and system unavailability (equation (6))

$$E\text{-}OCI_{i;j} = \frac{\left(1 - A_{i;j}\right) * E\text{-}DFP_{i;j}}{\left(1 - A_{system}\right)} \tag{6}$$

$$E\text{-}DFP_{i;j} = \frac{E\text{-}OCI_{i;j} * \left(1 - A_{system}\right)}{\left(1 - A_{i;j}\right)} \tag{7}$$

Figure 2 shows the FEI methodology and each phase of the process. Table 1 shows a comparative analysis between the main criticality and the operative impact methodologies.

Case study

For the analytical development of this case study, the selected process and equipment in the analysis are presented to develop the logical–functional sequence RBD due to the complexity of the system with a large amount of equipment. Then, the time to failure (TTF) and the TTR are analyzed to validate and identify trends and correlations. The parameterization is performed according to the most suitable stochastic

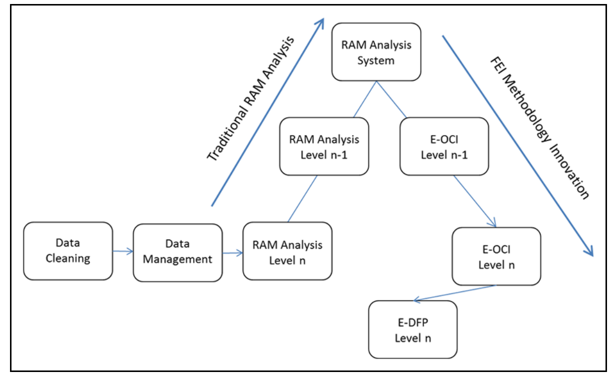


Figure 2. FEI methodology.

model, which represents both the nature of the failure and the process of repairing the equipment. The FEI is individually and systematically developed to obtain the main indicators and identify the equipment with the highest impacts on the process.

The data were collected over a period of 16 months using the Plant Maintenance Module of SAP Enterprise Resource Planning software (SAP-PM) report from the mining industry in Chile. Considering that current automatic capture systems provide rich and complete data with respect to operational parameters, focused on prognosis and health management application, data related to the state of the asset, specific process parameters, and downtimes. This data repository is linked with information related to work notifications and work orders. Accordingly, an enterprise resource planning (ERP) solution permits the complete integration of information flow from all functional areas by means of a single database that is accessible through a unified interface and channel communication. Hence, it is possible to apply the proposed methodology using this consolidated database validating the quality and quantity of the information.

The CSP case study

The case study is the smelting process of a mine in Chile; the first stage of this process is smelting ore, which contains a concentration of approximately 26% copper. The pyro-metallurgical operations, which enable the extraction of metallic copper, are performed in type A converters (the melting process), type B converters (the conversion process), slag cleaning furnaces (the copper recovery process), fire refinement stoves (the refined copper preparation process), and anodic furnaces (the anodic copper preparation process). The nominal production capacity of the smelting process is 60 tons/h. The resulting gases from the fusion conversion process are treated in gas cleaning plants, which also produce sulfuric acid that is primarily marketed in the mining industry in the northern region of Chile.

Table 1. Comparison of operative impact assessment methodologies.

Methodology	Typology	Focus	Failure effect estimation	Flexibility
Failure tree[11]	Qualitative	Individual	Failure analysis	High
US Department of Defense[27]	Qualitative	Individual	Failure analysis	High
Crespo et al.[28] proposal	Quantitative	Systemic	Expert criteria (1–5)	Medium
FEI[26]	Quantitative	Systemic	Probabilistic impact analysis	High

FEI: failure expected impact.

Table 2. CSP information.

Equipment	Label	Basic function	Capacity (ton/h)	
			Nominal	Maximum
Dryer 1	D1	Drying	30	60
Dryer 2	D2		30	60
Type A converter 1	CA1	Conversion type A	30	60
Type A converter 2	CA2		30	60
Type B converter 1	CB1	Conversion type B	20	30
Type B converter 2	CB2		20	30
Type B converter 3	CB3		20	30
Refining anode furnace 1	RAF1	Refining A	30	60
Refining anode furnace 2	RAF2		30	60
Anode furnace 1	AF1	Refining B	30	60
Anode furnace 2	AF2		30	60

CSP: copper smelting process.

Therefore, the portfolio of products obtained through these processes includes copper plates with 99.7% purity, fire refined copper ingots with 99.9% purity and sulfuric acid derived from the processing of smelter gases (Table 2). The analytical development of the case study uses the main operational flow of the concentrate in the smelting process, which is represented by the equipment and subprocesses shown in Figure 3. The mining subprocesses that are considered in this article are drying, concentrate fusion, conversion, and refining.

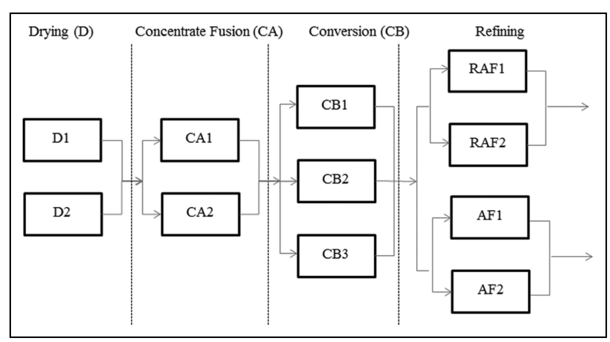


Figure 3. Case study process diagram.

Modeling the system

The logic behind the process operations can be represented using FT diagrams, which enable the subsequent development of the RBD configuration. According to Table 1, the FT is constructed as shown in Figure 4:

According to Figure 2, the smelting process is composed of four subsystems arranged serially: the drying subsystem (DS), which consists of two dryers in full redundancy; the concentrate fusion subsystem (CFS), which consists of two type A converters in full redundancy; the conversion subsystem (CS), which consists of three type B converters in a 3-2 configuration with partial redundancy; and the refining subsystem (RS), which consists of two work lines that separate the refining anode furnace (RAF) production from the anode furnace (AF) plate production, with a load distribution of 60% and 40%, respectively. Each subprocess is composed of two elements in total redundancy. The classification for the reliability analysis of the CSP is presented in the FT diagram.

The quantitative analysis of the CSP considers the operating conditions, failure data, maintenance times, and other functional information needed to estimate the RAM indicators for each piece of equipment, each subsystem, and the total system. Reliability analysis was performed using traditional algorithms.[26]

Data analysis

The collected data include TTF and TTR for each equipment. The next step in data management is to

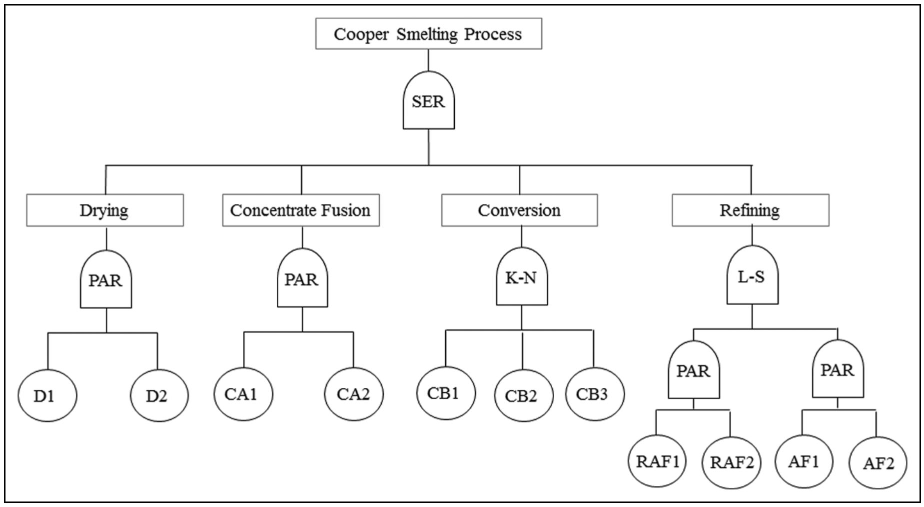


Figure 4. FT representation of the process.

Table 3. Statistical results for TTF and TTR data.

Subsystem	Equipment	Dataset	Degrees of freedom	Statistic U	Rejection of null hypothesis at a 5% level of significance
DS	D1	TTF	96	97.25	Not rejected (>76.11)
		TTR	96	82.21	Not rejected (>74.40)
	D2	TTF	66	57.32	Not rejected (>52.34)
		TTR	66	51.31	Not rejected (>47.85)
CFS	CA1	TTF	62	47.56	Not rejected (>39.65)
		TTR	62	45.44	Not rejected (>40.67)
	CA2	TTF	56	46.17	Not rejected (>38.95)
		TTR	54	45.76	Not rejected (>38.65)
CS	CB1	TTF	62	49.13	Not rejected (>33.56)
		TTR	62	50.17	Not rejected (>34.55)
	CB2	TTF	70	54.23	Not rejected (>47.36)
		TTR	70	49.95	Not rejected (>42.72)
	CB3	TTF	92	89.34	Rejected (<92.71)
		TTR	90	87.36	Not rejected (>70.23)
RS	RAF1	TTF	70	52.14	Rejected (<53.11)
		TTR	70	56.22	Not rejected (>52.34)
	RAF2	TTF	68	49.76	Not rejected (>42.57)
		TTR	68	47.66	Not rejected (>43.54)
	AF1	TTF	62	58.27	Rejected (<59.56)
		TTR	62	60.22	Not rejected (>53.33)
	AF2	TTF	54	41.56	Not rejected (>39.44)
		TTR	52	41.75	Not rejected (>37.72)

TTF: time to failure; TTR: time to repair; DS: drying subsystem; CFS: concentrate fusion subsystem; CS: conversion subsystem; RS: refining subsystem; RAF: refining anode furnace; AF: anode furnace.

determine the nature of the equipment that is involved in the process. In this case, all of the equipment uses the dynamics of serviceable equipment, and its subsequent distribution must be selected using relevant stochastic models[29] according to the behaviors of the data in terms of trend and independence.

Trend and correlation analysis. Analyzing the data of the equipment that is involved in the process, the independence and trend indicators are calculated. The calculated values of the test statistics for all of the equipment failures and repair data are listed in Table 3. Using the null hypothesis of an HPP, in which the test statistic U is χ^2 distributed with $2(n-1)$ degrees of freedom, the null hypothesis is not rejected at a 5% level of significance in most of the equipment. The statistical results show that the datasets for the majority of the equipment, with the exceptions of the TTF data for CB3, RAF1, and AF1, show no trends or serial

Table 4. Fitting distributions of the TTF and TTR data.

Equipment	Best fit (TTF data)				
	Distribution	p value (K-S)	Parameter 1	Parameter 2	MTTFi
D1	Weibull	0.29	$\alpha = 238$	$\beta = 1.13$	228
D2	Weibull	0.17	$\alpha = 224$	$\beta = 1.2$	211
CA1	Exponential	0.14	$\alpha = 253$	$\beta = 1.6$	227
CA2	Weibull	0.43	$\alpha = 330$	$\beta = 1.4$	300
CB1	Exponential	0.32	$\alpha = 256$	$\beta = 1$	256
CB2	Weibull	0.29	$\alpha = 792$	$\beta = 1.34$	722
CB3	NHPP-PLP	0.31	$\alpha = 402$	$\beta = 1.32$	269
RAF1	NHPP-PLP	0.28	$\alpha = 351$	$\beta = 1.27$	211
RAF2	Weibull	0.40	$\alpha = 144$	$\beta = 1.30$	133
AF1	NHPP-PLP	0.23	$\alpha = 324$	$\beta = 1.31$	203
AF2	Exponential	0.61	$\alpha = 315$	$\beta = 1$	315
Equipment	**Best fit (TTR data)**				
	Distribution	p value (K-S)	Parameter 1	Parameter 2	MTTRi
D1	Lognormal	0.57	$\mu = 0.478$	$\sigma = 2.24$	4.94
D2	Lognormal	0.24	$\mu = 0.731$	$\sigma = 1.3$	3.97
CA1	Lognormal	0.71	$\mu = 0.940$	$\sigma = 1.8$	6.29
CA2	Normal	0.61	$\mu = 4.8$	$\sigma = 1.2$	4.84
CB1	Lognormal	0.66	$\mu = 1.31$	$\sigma = 1.57$	8.12
CB2	Lognormal	0.35	$\mu = 1.45$	$\sigma = 2.02$	11.71
CB3	Normal	0.69	$\mu = 7.33$	$\sigma = 1.4$	7.33
RAF1	Lognormal	0.21	$\mu = 1.44$	$\sigma = 1.1$	7.31
RAF2	Lognormal	0.61	$\mu = 0.872$	$\sigma = 1.24$	4.41
AF1	Lognormal	0.45	$\mu = 1.31$	$\sigma = 1.45$	7.65
AF2	Lognormal	0.24	$\mu = 0.91$	$\sigma = 1.7$	5.82

TTF: time to failure; TTR: time to repair; MTTF: mean time to failure; MTTR: mean time to repair; K-S: Kolmogorov–Smirnov; RAF: refining anode furnace; AF: anode furnace.

correlation. Therefore, the independent and identically distributed (i.i.d.) assumption is rejected for these equipment. Identical results were obtained from the graphical trend analysis.[14]

Distribution fitting and calculation of basic indicators. The definition of the probability distributions is commonly used to describe the equipment failure and repair processes. Different types of statistical distributions were examined, and their parameters were estimated using MATLAB.[30] A statistical goodness-of-fit test was performed to define the distributions of the operating times and TTR. In particular, Kolmogorov–Smirnov tests[25] at a significance level of $a = 0.1$ were required to be satisfied for $p = 0.1$ at each setting. The null hypothesis H0 is as follows: the data follow a normal, log-normal, exponential, or Weibull distribution.

The equipment trend data should be analyzed using a stochastic model for reparable elements. The NHPP model used in this study is based on the power law process (PLP). The χ^2 test and the Kolmogorov–Smirnov test were classically encountered to validate the best-fit distribution.[31] The parameters that were estimated from the failure data are listed in Table 4.

Table 4 also lists the basic indicator of reliability, which is the mean time to failure (MTTF), the basic indicator of maintainability, which is the mean time to repair (MTTR), and the respective parameters of the fitted curves.

According to the traditional setting (no trend), the reliability parameters of the fitted curves (α, β), which are based on the life cycle theory,[31] show that the equipment are in different phases of the bathtub curve. $\beta = 1$ is related to a constant failure rate or "useful" life phase; $\beta > 1$ is the phase in which the failure rate typically increases, and additional service and maintenance are needed. In the "wear-out" life phase, a technical and economic assessment is required to determine the need for possible replacement, and in the $\beta < 1$ phase, the component failure rate decreases over time. Early life cycle problems are often due to failures in design, incorrect installation, and operation by poorly trained operators. Therefore, the statistical information obtained from the curve fitting should be used to estimate the system performance instead of explaining individual equipment behavior.

The probability distribution that is commonly used to represent repair times is the normal-logarithmic

Table 5. Reliability evaluation of the CSP.

	R(0)	R(50)	R(100)	R(150)	R(200)	R(250)	R(300)	R(350)	R(400)
System	1.000	0.948	0.785	0.568	0.360	0.196	0.088	0.031	0.009
DS	1.000	0.976	0.901	0.794	0.674	0.556	0.449	0.356	0.278
D1	1.000	0.842	0.687	0.552	0.440	0.347	0.273	0.213	0.166
D2	1.000	0.848	0.684	0.539	0.418	0.320	0.242	0.181	0.135
CFS	1.000	1.000	0.999	0.987	0.943	0.833	0.643	0.412	0.218
CA1	1.000	0.928	0.797	0.648	0.503	0.375	0.269	0.186	0.125
CA2	1.000	1.000	0.993	0.964	0.885	0.732	0.512	0.278	0.106
CS	1.000	0.987	0.942	0.869	0.778	0.679	0.580	0.486	0.401
CB1	1.000	0.823	0.677	0.557	0.458	0.377	0.310	0.255	0.210
CB2	1.000	0.979	0.946	0.907	0.864	0.820	0.773	0.727	0.681
CB3	1.000	0.953	0.882	0.802	0.721	0.640	0.564	0.492	0.426
RS	1.000	0.984	0.925	0.834	0.728	0.622	0.523	0.436	0.360
RAF subsystem	1.000	0.981	0.911	0.801	0.677	0.556	0.449	0.359	0.284
RAF1	1.000	0.917	0.807	0.694	0.588	0.491	0.405	0.331	0.268
RAF2	1.000	0.777	0.537	0.348	0.216	0.129	0.075	0.042	0.023
AF subsystem	1.000	0.988	0.948	0.884	0.806	0.721	0.635	0.551	0.473
AF1	1.000	0.917	0.807	0.694	0.588	0.491	0.405	0.331	0.268
AF2	1.000	0.853	0.728	0.621	0.530	0.452	0.386	0.329	0.281

CSP: copper smelting process; DS: drying subsystem; CFS: concentrate fusion subsystem; CS: conversion subsystem; RS: refining subsystem; RAF: refining anode furnace; AF: anode furnace.

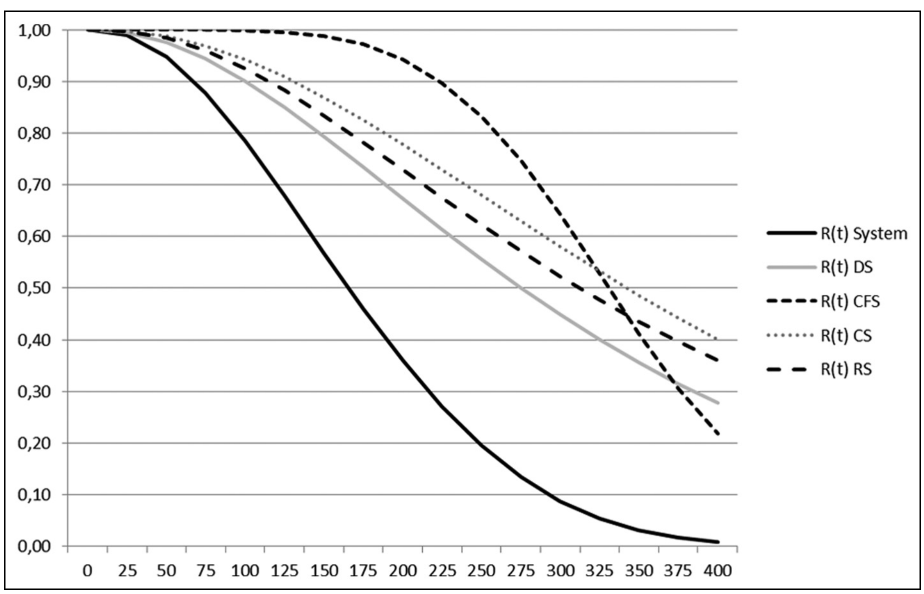


Figure 5. Reliability curves for the main subsystems in the CSP.

distribution, which explains the variability of repair by two phenomena:[32] the variation of the time associated with accidental factors (negative exponential distribution) and the factors related to typical repair (normal distribution).

System reliability analysis. CSP is divided into four subsystems, which comprise a logical–functional configuration series, that is, all subsystems must be operating to ensure that the process performs properly. Subsystem and system reliability is generally calculated using the standard RBD formulas.[5,22]

Table 5 presents the main reliability results for different operating times. The reliability results for the main subsystem and total system are shown graphically in Figure 5.

Through numerically and graphically analyzing the reliability results, the DS and RS subsystems show an accelerated decrease in reliability compared with the other subsystems (exponential behavior). The CS subsystem presents the best condition due to the redundant configuration of the subsystem and the distinctly reliable behavior of the equipment. During the first 300 h, the CFS subsystem presents the most reliable behavior

Table 6. Expected availability calculation.

	MTTF (h)	MTTR (h)	Availability (%)	Subsystem availability (%)	System availability (%)
System					95.17
DS				98.66	
D1	227.69	4.94	97.88		
D2	210.71	3.98	98.15		
CFS				98.62	
CA1	226.83	6.30	97.30		
CA2	299.95	4.80	98.42		
CS				99.83	
CB1	256.00	8.13	96.92		
CB2	721.85	11.70	98.40		
CB3	269.38	7.33	97.35		
RS				97.99	
RAF subsystem				97.77	
RAF1	211.13	7.32	96.65		
RAF2	133.00	4.45	96.77		
AF subsystem				98.31	
AF1	202.94	7.58	96.40		
AF2	315.00	5.81	98.19		

MTTF: mean time to failure; MTTR: mean time to repair; DS: drying subsystem; CFS: concentrate fusion subsystem; CS: conversion subsystem; RS: refining subsystem; RAF: refining anode furnace; AF: anode furnace.

due to its redundancy; after this time, the reliability decreases exponentially (wear-out behavior).

To identify opportunities to improve the reliability, processes should focus on subsystems with less reliability over time, that is, DS and RS. This information is the key for defining the intervals for preventive interventions. For example, if the reliability defined by an organization to develop the preventive intervention of critical equipment ranges between 75% and 80%, the planning activities for the DS subsystem should range between 75 and 100 h of operation. However, the examined system presents an important level of redundancy in three of its subsystems, which should also be considered when evaluating and defining future maintenance policies. In practical terms, a corrective policy is generally assumed in redundant systems. However, to reach this conclusion, individual assessment and identification of critical subsystems and equipment as well as the real costs of preventive and corrective interventions are required.[5]

System maintainability analysis. In terms of individual analyses, the maintainability has an important effect on the equipment and systemic availability results.[23] For each element, TTR and $MTTR_i$ are required for the next analysis. Table 5 lists the parametric information for computing the $MTTR_i$.

System availability analysis. With the information obtained from the curve adjustments, the expected availability[5,22,33] was analyzed. Table 6 presents the results of the expected availability calculations for the equipment, subsystems, and system.

According to the results, the subsystem with the least expected availability is RS, while CS has more availability. For this particular case, the availability results are consistent with the reliability results. Therefore, a practical mechanism is needed for identifying the highest E-OCI and integrating the RAM results.

According to the procedure in section "FEI methodology" and equations (2)–(6), the impacts of each piece of equipment, each subsystem, and the system are presented in Table 7.

Table 7 shows that D1 explains 14.57% of the lack of effectiveness of the system, which is expressed as the E-OCI; each D1 failure results in an expected 33.09% loss of production capacity for the total system, which is expressed as the E-DFP. Both impact indices are dependent on the behavior of the equipment in terms of the RAM results, operational context, and logical dependencies as well as the indicators for the other pieces of equipment in their subsystem (immediately higher level). The E-DFP values for each subsystem are equal, which is attributed to the serial configuration of the system.

Using this analysis, the equipment and subsystems that generate the highest impact on the availability or production of the main system can be grouped together. However, the results are not distinct. Therefore, continuity with a dispersion analysis is proposed in which the X-axis corresponds to the unavailability and the Y-axis corresponds to the E-DFP. In this manner, the generated curves correspond to the expected operational criticality iso-impact curves.

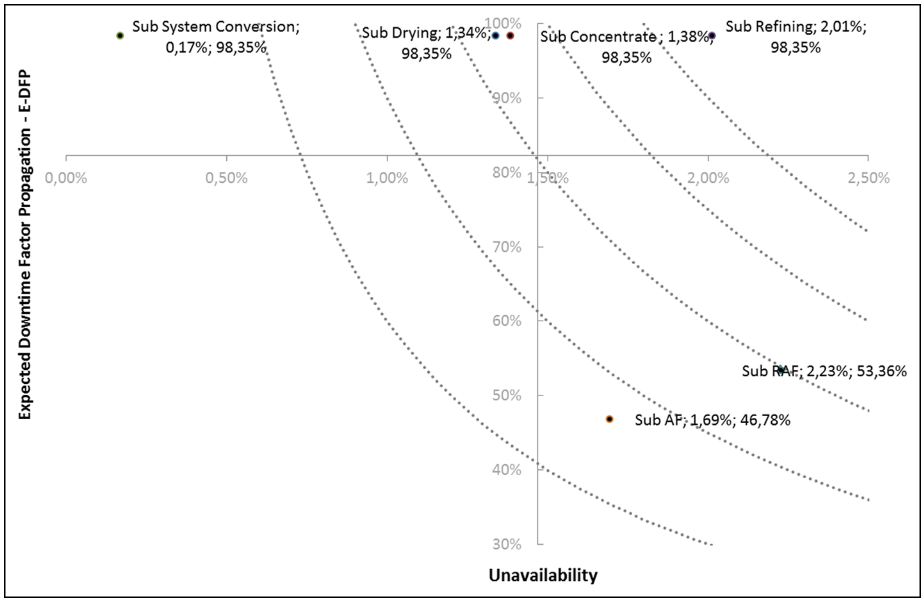


Figure 6. FEI methodology dispersion analysis for the subsystems.

Table 7. Calculation of E-OCI and E-DFP.

	E-OCI (%)	E-DFP (%)
System	100.00	100.00
DS	27.27	98.35
D1	14.57	33.09
D2	12.71	33.09
CFS	28.22	98.35
CA1	17.82	31.85
CA2	10.39	31.85
CS	3.47	98.35
CB1	1.46	2.29
CB2	0.76	2.29
CB3	1.26	2.29
RS	41.04	98.35
RAF subsystem	24.62	53.36
RAF1	12.53	18.05
RAF2	12.10	18.05
AF subsystem	16.42	46.78
AF1	10.92	14.65
AF2	5.50	14.65

E-OCI: expected operational criticality index; E-DFP: expected downtime factor propagation; DS: drying subsystem; CFS: concentrate fusion subsystem; CS: conversion subsystem; RS: refining subsystem; RAF: refining anode furnace; AF: anode furnace.

First, an analysis is performed at the subsystem level (Figure 6); DS, CFS, CS, and RS have the same level of E-DFP because they are in series. Therefore, the unavailability of each subsystem creates a different E-OCI. The subsystems RAF and AF have a smaller E-DFP because they employ a load-sharing configuration (60% of the load and 40% of the load, respectively) in the RS subsystem.

Figure 7 shows the relatively low E-DFP for the equipment, which is attributed to the redundancy in each of the subsystems. Due to the serial configuration of all subsystems, the E-DFP values are all identical, with the exception of the RAF and AF subsystems, which have different capacities and operational contexts. The order of the subsystems in terms of operational effectiveness is RS, CFS, DS, and CS. At the individual level, the order of the equipment is as follows: CA1, D1, D2, RAF1, RAF2, AF1, CA2, AF2, CB1, CB3, and CB2.

Conclusion

The reliability impact study is a relevant analysis to develop a decision-making process. Considering the standard methodologies, it is possible to establish that there are no formal criteria to identify the impact of each asset and its behavior or failure. So, it is necessary to define a KPI oriented to establish a hierarchy and determine the effectiveness of the KPI's impact on the elements.

A deep reliability analysis requires quality and quantity of data; therefore, this article shows the importance of the quality of information that is available for analysis; the existing data should be audited to validate the previous analysis.

The FEI methodology has significant potential applications in several engineering problems, industrial realities, and productive sectors. FEI is a powerful tool for analysis and decision making for the various phases of an industrial project via life cycle cost (LCC) for design-oriented operations, such as capital expenditures

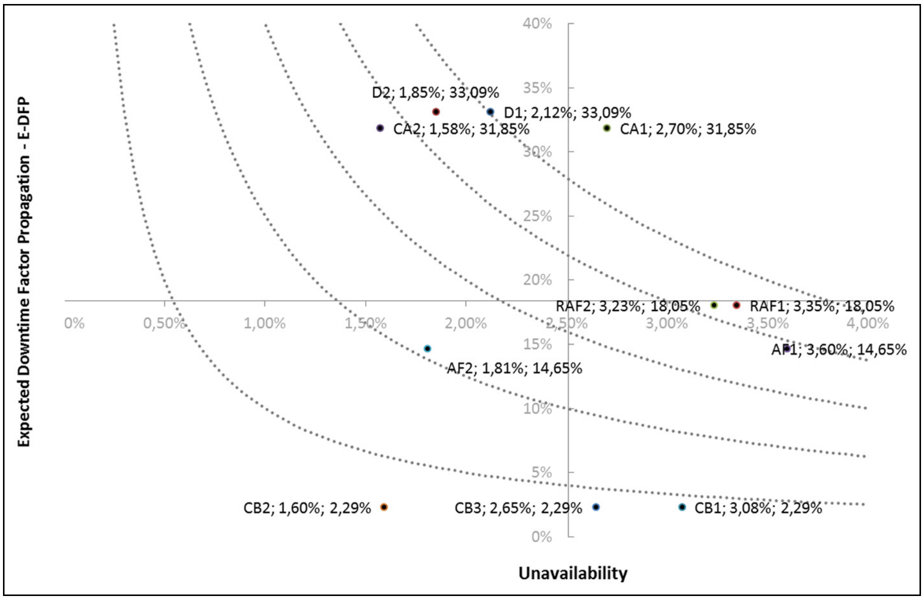


Figure 7. FEI methodology dispersion analysis for the equipment.

(CAPEX) and operational expenditures (OPEX), which are associated with the improvement process.

The strengths of the FEI methodology include its ability to systematically and quantitatively assess the operational criticality in terms of the RAM indicators and the logical configuration of subsystems and individual equipment, which directly affect each element in the total system. This proposal complements plant modeling and analysis, from traditional methodologies. The E-OCI is the final result of the computation process, which enables the quantitative and unequivocal prioritization of the system elements to assess the associated loss as "production loss" regarding its unavailability and effect in the process. The latter concept enables estimating the E-DFP of the equipment to determine the individual effects of the detention and assess complex and redundant scenarios.

The case study provides useful results for developing a hierarchization that enables an analysis of improvement actions that are aligned with the best opportunities.

Considering the FEI methodology structure, it is possible to conclude that it is replicable in different application fields and can be easily automated. Rankings that are based on the expected impact in the operation are effective, recognize weaknesses and opportunities, and serve as the basis for action plans based on reliability and maintainability.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

1. Asaki Z. Kinetic studies of copper flash smelting furnace and improvements of its operation in the smelters in Japan. *Miner Process Extr M* 1992; 11: 163–185.
2. Parra C. *Desarrollo de modelos de cuantificación económica del factor Fiabilidad en el coste total de ciclo de vida de un sistema de producción*. Tesis Doctoral, Universidad de Sevilla, Sevilla, 2009.
3. Pham H (ed.). *Handbook of reliability engineering*. Piscataway: NJ: Springer, 2003.
4. Viveros P, Zio E, Arata A, et al. Integrated system reliability and productive capacity analysis of a production line. A case study for a Chilean mining process. *Proc IMechE, Part O: J Risk and Reliability* 2012; 226: 305–317.
5. Dhillon BS. *Maintainability, maintenance, and reliability for engineers*. Boca Raton, FL: Taylor & Francis Group, 2006.
6. Welte TM. A rule-based approach for establishing states in a Markov process applied to maintenance modeling. *Proc IMechE, Part O: J Risk and Reliability* 2009; 223: 1–12.
7. Heinrich L. Goodness-of-fit tests for the second moment function of a stationary multidimensional Poisson process. *Statistics* 1991; 22: 245–278.
8. Peng R, Zhai QQ, Xing LD, et al. Reliability of demand-based phased-mission systems subject to fault level coverage. *Reliab Eng Syst Safe* 2014; 121: 18–25.
9. Rausand M and Hoyland A. *System reliability theory: models, statistical methods, and applications*. 3rd ed. New York: Wiley, 2003.

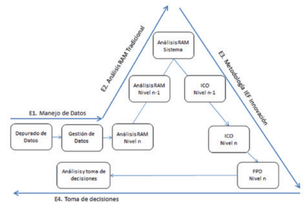
10. Guo H and Yang X. A simple reliability block diagram method for safety integrity verification. *Reliab Eng Syst Safe* 2007; 92: 1267–1273.
11. Rauzy AB, Gauthier J and Leduc X. Assessment of large automatically generated fault trees by means of binary decision diagrams. *Proc IMechE, Part O: J Risk and Reliability* 2007; 221: 95–105.
12. Distefano S and Puliafito A. Reliability and availability analysis of dependent-dynamic systems with DRBDs. *Reliab Eng Syst Safe* 2009; 94: 1381–1393.
13. Volovoi V. Modeling of system reliability Petri nets with aging tokens. *Reliab Eng Syst Safe* 2004; 84: 149–161.
14. Jiang W, Xie C, Wei B, et al. A modified method for risk evaluation in failure modes and effects analysis of aircraft turbine rotor blades. *Adv Mech Eng*. Epub ahead of print 22 April 2016. DOI: 10.1177/1687814016644579.
15. Barberá L, Crespo A, Viveros P, et al. The graphical analysis for maintenance management method: a quantitative graphical analysis to support maintenance management decision making. *Int J Reliab Qual Saf Eng* 2013; 29: 77–87.
16. Baraldi P, Compare M and Zio E. Component ranking by Birnbaum importance in presence of epistemic uncertainty in failure event probabilities. *IEEE T Reliab* 2013; 62: 37–48.
17. Chapman AD. Principles of data quality, version 1.0. Report for the Global Biodiversity Information Facility. Copenhagen: GBIF, 2005.
18. Gámiz ML and Lindqvist BH. Nonparametric estimation in trend-renewal processes. *Reliab Eng Syst Safe* 2016; 145: 38–46.
19. Ascher H and Feingold H. *Repairable systems reliability: modeling, inference, misconceptions and their causes*, vol. 7. New York: CRC Press, 1984.
20. Veber B, Nagode M and Fajdiga M. Generalized renewal process for repairable systems based on finite Weibull mixture. *Reliab Eng Syst Safe* 2008; 93: 1461–1472.
21. Kijima M and Sumita N. A useful generalization of renewal theory: counting processes governed by non-negative Markovian increments. *J Appl Probab* 1986; 23: 71–88.
22. Macchi M, Kristjanpoller F, Arata A, et al. Introducing buffer inventories in the RBD analysis of production systems. *Reliab Eng Syst Safe* 2012; 104: 84–95.
23. Moreu P, Gonzalez-Prida V, Barberá L, et al. A practical method for the maintainability assessment in industrial devices using indicators and specific attributes. *Reliab Eng Syst Safe* 2012; 100: 84–92.
24. Barabady J. Reliability and maintainability analysis of crushing plants in Jajarm Bauxite Mine of Iran. In: *Proceedings of the annual reliability and maintainability symposium*, Alexandria, VA, 24–27 January 2005, pp.109–115. New York: IEEE.
25. Sundararajan CR. *Guide to reliability engineering*. New York: Van Nostrand Reinhold, 1991.
26. Kristjanpoller F, Viveros P, Crespo A, et al. A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations. In: *Proceedings of the annual European safety and reliability conference (ESREL)*, Zurich, 7–10 September 2015, ISBN: 978-1-138-02879-1. London: Taylor & Francis Group.
27. US Department of Defense. *Procedures for performing a failure mode and effects analysis, MIL-STD-1629A*. Washington, DC: Department of Defense, 1977.
28. Crespo A, Moreu P, Sola A, et al. Criticality analysis for maintenance purposes: a study for complex in-service engineering assets. *Qual Reliab Eng Int* 2015; 32: 519–533.
29. Viveros P, Crespo A, Kristjanpoller F, et al. Mathematical and stochastic models for reliability in repairable industrial physical assets. In: Gonzalez-Prida V and Raman A (eds) *Promoting sustainable practices through energy engineering and asset management*. Hershey, PA: IGI Global, 2015, pp.287–310.
30. Dogan I. Engineering simulation with MATLAB: improving teaching and learning effectiveness. *Procedia Comp S* 2011; 3: 853–858.
31. Levitin G. Block diagram method for analyzing multi-state systems with uncovered failures. *Reliab Eng Syst Safe* 2007; 92: 727–734.
32. Barlow R and Proschan F. *Mathematical theory of reliability*. Philadelphia, PA: Society for Industrial and Applied Mathematics, 1996.
33. Lisnianski A. Extended block diagram method for a multi-state system reliability assessment. *Reliab Eng Syst Safe* 2007; 92: 1601–1607.

Appendix 1

Notation

A	availability
α	scale parameter of Weibull distribution
β	form parameter of Weibull distribution
Γ	gamma function
λ	failure rate

Propuesta metodológica para la evaluación del impacto esperado de fallos en equipos complejos. Caso aplicado a una planta de trituración de mineral de cobre



Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant

Fredy Kristjanpoller[1,2], Adolfo Crespo[1], Mónica López-Campos[2], Pablo Viveros[1,2]

[1] Universidad de Sevilla. Escuela Superior de Ingeniería. Dpto de Organización y Gestión de Empresas I. Avda. Camino de los Descubrimientos, s/n - 41092 Sevilla (España). Tfno: +34 954 487215.

[2] Universidad Técnica Federico Santa María. Departamento de Industrias. Valparaíso (Chile). Tfno: +56 322654905.

DOI: http://dx.doi.org/10.6036/8088 | Recibido: 20/06/2016 • Aceptado: 05/09/2016

ABSTRACT

- Analysis of the reliability and maintainability of a production process is relevant to the determination of availability and the capacity of the plant. In order to quantify the importance of each equipment in the systemic availability and improve decision-making related to asset management, it is proposed a new analysis tool: the methodology of the Expected Impact of Fault (IEF). It has as main novelty quantifying indicators of the real influence of each element in the total reliability/availability of the productive system. This is applicable in any logical functional configuration. In this way the importance of the equipment is set and is quantified more accurately the impact of his possible unavailability. The methodology starts with the management of the process data to analyze, and then proceeds to develop an analysis based on the classical technique of block diagram of reliability (RBD), which structure the teams according to their functional configuration by levels, in ascending order, to determine the availability of each item and of the system in general. Subsequently, IEF methodology makes descendant analysis, from the availability of the system to the impact of each element in particular in the expected availability of the system. This impact is expressed through indicators of Propagation of the Time of Failure (FPD) and the index of Expected Impact of Operational Criticality (ICO) of an element on the whole of the system. The use of these indicators has shown important results to evaluate the design and performance of a plant. In this case the methodology is applied to the actual data of a plant's crushing of a mining process.
- **Keywords:** reliability, availability, operational efficiency, criticality, physical assets.

RESUMEN

El análisis de la fiabilidad operacional y de la mantenibilidad de un proceso productivo es relevante para la determinación de la disponibilidad y de la capacidad de la planta. Con el fin de cuantificar la importancia de cada equipo en la disponibilidad sistémica y mejorar la toma de decisiones relacionadas con la gestión de activos, se propone una nueva herramienta de análisis: la metodología del Impacto Esperado de Fallos (IEF). Esta tiene como principal novedad el cuantificar mediante indicadores la influencia real de cada elemento en la fiabilidad/disponibilidad total del sistema productivo, siendo aplicable en cualquier configuración lógico funcional. De esta forma se establece la importancia de los equipos y se cuantifica con mayor precisión el impacto de su posible indisponibilidad. La metodología inicia con la gestión de los datos del proceso a analizar, posteriormente se procede a desarrollar un análisis basado en la técnica clásica de diagrama de bloques de fiabilidad (RBD), la cual estructura los equipos de acuerdo a su configuración funcional por niveles, para llegar a determinar la disponibilidad de cada elemento y del sistema en general. Posteriormente, la metodología IEF hace el análisis descendiente, a partir de la disponibilidad del sistema hasta el impacto de cada elemento en particular en la disponibilidad esperada del sistema. Este impacto se expresa a través de los indicadores de Propagación del Tiempo de Detención (FPD) y del índice de Impacto Esperado de Criticidad Operacional (ICO) de un elemento sobre el conjunto del sistema. El uso de estos indicadores ha demostrado resultados importantes para evaluar el diseño y el rendimiento de una planta. En este caso la metodología es aplicada a los datos reales de una planta de triturado de un proceso minero.

Palabras clave: fiabilidad, disponibilidad, eficiencia operacional, criticidad, activos físicos.

1. INTRODUCCIÓN

La aplicación de técnicas de fiabilidad con el fin de apoyar la toma de decisiones, es una tarea fundamental para la gestión eficiente y precisa de los activos y recursos en cualquier organización industrial. Es conocido que la capacidad productiva real de una planta, depende fuertemente de la disponibilidad sistémica, la cual a su vez está determinada por la configuración lógica en la que se encuentran los equipos. Equipos dispuestos en serie o con alguna clase de redundancia tendrán de por sí, distinto impacto en la disponibilidad del sistema, independientemente de su propia fiabilidad y disponibilidad individual. Es decir, el tiempo de indisponibilidad del sistema no tiene porqué corresponder con el tiempo de indisponibilidad de los equipos en fallo, pues cada equipo tiene un distinto "factor de propagación" de su tiempo de detención en el tiempo de detención del sistema. Sin embargo, a pesar de la utilidad y relevancia de conocer esta información, durante la ejecución de la mayoría de los planes de gestión de activos, el análisis del mencionado "factor de propagación" y del impacto de cada equipo en la disponibilidad sistémica no es común. Esta carencia no es menor, ya que el conocer el impacto real de cada activo en la configuración del sistema total proporciona ventajas en la planificación de la producción y mantenimiento.

En general, se reconoce que la teoría de la fiabilidad, junto con el análisis de ciclo de vida de los activos, es un apoyo importante para el análisis y mejora en plantas industriales [1]. La evaluación de la fiabilidad y disponibilidad, involucrando parámetros técnicos y de costos, es crucial en la evaluación del desempeño de un proceso industrial, específicamente en procesos productivos intensivos en capital [2]. Por otro lado, es conocido que el análisis de los KPI (*Key Performance Indicators*), es una forma efectiva para medir cuantitativamente los resultados y el desempeño de un proceso [3]. De aquí, se infiere que el contar con KPI que arrojen información relacionada con la cuantificación de la disponibilidad y del peso relativo de cada equipo en el sistema, por lo que es indispensable estudiar la criticidad de los activos para poder priorizar y focalizar las actividades de control del riesgo operacional [4].

A pesar de las ventajas de conocer el impacto esperado de fallo de cada elemento en la disponibilidad del sistema, se ha encontrado un vacío en este sentido. En la práctica industrial, frecuentemente se recurre a enfoques semi-cuantitativos como matrices de criticidad basadas en factores ponderados y flujogramas de análisis de riesgo, o bien se utilizan herramientas más bien genéricas desde el punto de vista de la toma de decisiones, como es el caso del *Proceso de Análisis Jerárquico* (AHP), las cuales necesariamente deben ser contextualizadas y adaptadas a cada caso, por consecuencia no necesariamente proporcionan resultados homogéneos y comparables entre procesos o instalaciones físicas. En la literatura científica exclusiva para la gestión de activos, solo se ha encontrado el *Índice de Birnbaum* [5] que permite la evaluación del impacto de equipos bajo una visión de riesgo epistémico, permitiendo un análisis directo, pero focalizado en procesos específicos. Este método compara los elementos entre sí, en función de la incertidumbre de fiabilidad que poseen y de la propagación de esta incertidumbre, con el objetivo de ordenarlos por nivel. Sin embargo dicho índice depende altamente de la calidad de los datos históricos, no considera directamente el efecto de la configuración lógica del sistema y es difícil de aplicar en sistemas compuestos por una cantidad considerable de elementos. Por otra parte Wang et al.[6] se basan en el índice Birnbaum y proponen una técnica de evaluación complementaria desde un enfoque probabilístico dependiente de una simulación.

El objetivo de este artículo es proponer una nueva metodología genérica, es decir aplicable sobre cualquier configuración lógico-funcional, cuantitativa e integral para el análisis de la disponibilidad, y del impacto esperado de fallos (IEF) [7]. Esta propuesta diseña un nuevo algoritmo para calcular dos índices de impacto, el Índice de Criticidad Operacional esperado (ICO) y el Factor de Propagación del tiempo de Detención esperado (FPD), basados en la fiabilidad y capacidad de mantenimiento de los elementos; y el impacto esperado de cada uno de acuerdo a diferentes escenarios y configuraciones. Estos índices de impacto, basados en un enfoque probabilístico, definirán las condiciones previstas en el sistema, desde el punto de vista de la evaluación de sus posibles estados (comportamiento intrínseco), y en relación con la configuración lógica y funcional en el sistema. Permitiendo la comparación global de los elementos, su priorización y evaluación parcial de su efectividad.

2. DECLARACIÓN DEL PROBLEMA

El análisis de la bibliografía y la experiencia práctica han puesto a la luz la inexistencia de una metodología de utilización sencilla y aplicable a cualquier configuración lógica funcional, que cuantifique el impacto de un fallo en la disponibilidad general de un sistema complejo. En la mayoría de las empresas industriales, no existe un criterio formal para identificar el impacto de cada activo y de su comportamiento de fallo considerando su fiabilidad y la de su subsistema, por lo que las decisiones de reemplazo de los equipos se realizan ad hoc y no de acuerdo a los procesos de negocio. Lo que hace necesario definir una propuesta metodológica que incluya el uso de indicadores clave de rendimiento (KPI) orientados al análisis del impacto de cada elemento en la disponibilidad sistémica, haciendo posible una jerarquización útil para la toma de decisiones estratégicas y operativas.

La propuesta desarrollada, consiste en una metodología para la cuantificación del impacto esperado del fallo de cada elemento sobre la disponibilidad de un sistema complejo, a la cual se le ha denominado Metodología de Impacto Esperado de Fallos (IEF). La estructura de esta metodología, la hace aplicable en sistemas complejos con una gran cantidad de elementos, tomando especialmente en cuenta la configuración lógico-funcional de cada uno como parte del cálculo de los índices de impacto. La metodología IEF parte con la gestión de los datos provenientes del proceso industrial y posteriormente determina dos indicadores clave

Notación	
IEF:	Metodología de Impacto Esperado de Fallos
RBD:	Reliability Blocks Diagram – Diagrama de Bloques de Fiabilidad
FPD:	Factor de Propagación del Tiempo de Detención
ICO:	Impacto Esperado de Criticidad Operacional
KPI:	Key Process Indicator – Indicador Clave del Proceso
MTTF:	Mean time to failure – Tiempo medio para fallar
MTTR:	Mean time to repair – Tiempo medio para reparar
MTBM:	Mean time between maintenance – Tiempo medio entre mantenciones
A:	Disponibilidad
RAM:	Reliability, availability, maintainability methodology – Metodología de evaluación de fiabilidad, disponibilidad, mantenibilidad
α	Parámetro de escala de Distribución Weibull
β	Parámetro de forma de Distribución Weibull
CMMS	Computerized Maintenance Management System – Sistema informático de gestión de mantenimiento

Tabla 1: Notación

de proceso (KPI) relevantes en el análisis de la disponibilidad. El primero es el índice ICO y el segundo es el factor FPD. El cálculo y seguimiento de estos indicadores y de la metodología propuesta, pretende desenvolverse en estrecha relación con el control de la gestión a través la definición de estrategias y toma de decisiones [8, 9].

La metodología propuesta IEF, tiene como reto principal, dotar de información relevante para la mejora en la gestión de activos. Uno de los puntos más importantes es conocer el efecto operacional, medido sobre la pérdida de la capacidad de producción, de cada elemento sobre el sistema que lo contiene. El impacto de un elemento debe ser definido como dinámico, ya que depende tanto del rendimiento individual del elemento en cuanto a su fiabilidad y capacidad de mantenimiento, como del estado de funcionamiento de todos los elementos presentes en el mismo subsistema, y de su configuración funcional. En la metodología IEF, este análisis se logra mediante los KPI propuestos: el factor FPD que cuantifica la propagación del impacto que tiene el desempeño de un componente, especialmente una detención no programada, sobre el desempeño total del sistema (pudiendo este factor ser cercano a cero por ejemplo, si debido a una redundancia total, la propagación del fallo sobre el desempeño del sistema es despreciable en términos de disponibilidad) y el ICO que, para un desempeño sistémico conocido, cuantifica la proporción de cada elemento componente del sistema sobre el desempeño sistémico (a partir de la disponibilidad de cada elemento y de su factor FPD en relación a los demás elementos que afectan al sistema).

Después de llevar a cabo un análisis IEF completo, se debería ser capaz de contestar las siguientes preguntas: ¿Cuáles son los cuellos de botella del sistema? ¿Cuáles son los principales factores que explican la pérdida de la producción del sistema? ¿Cuál es el nivel de disponibilidad del sistema? ¿Dónde están las principales oportunidades de mejora?

3. METODOLOGÍA PROPUESTA

Esta metodología se estructura en cuatro etapas que se resumen en la Figura 1. La primera etapa gestiona y prepara los datos e información del proceso sujetos a análisis. La segunda etapa se encarga del cálculo de la fiabilidad y disponibilidad de cada elemento individual hasta obtener datos sistémicos de disponibilidad. La tercera etapa toma los datos de disponibilidad del sistema y con ellos encuentra la influencia real de cada elemento en el sistema, es decir su ICO y su FPD. La cuarta y última etapa corresponde al análisis de los indicadores para la toma de decisiones.

3.1. ETAPA 1: DEPURADO Y GESTIÓN DE DATOS

Sin un suministro de información adecuado, el análisis de datos es tiempo perdido. Por tanto el primer paso de esta metodología implica la depuración y filtrado de los datos industriales con el fin de mejorar sus atributos, detectando la ausencia de valores y datos erróneos, discriminando datos correspondientes a distintos elementos y condiciones operacionales y evaluando en general la calidad de los registros [10].

En vista de lo anterior, es necesario diseñar un procedimiento para recabar los datos útiles del proceso, con el fin de tener datos fiables y representativos de cada elemento a analizar. Posteriormente el uso de técnicas estadísticas como el análisis de dominancia y percentiles significativos puede ser útil para filtrar los datos y lograr una base de datos depurada [11].

3.2. ETAPA 2: ANÁLISIS ASCENDENTE. ANÁLISIS CLÁSICO RAM DESDE EL ELEMENTO MÁS PEQUEÑO HACIA EL SISTEMA

Para llevar a cabo esta etapa, se desarrolla un análisis clásico de Diagrama de Bloques de Fiabilidad (RBD) [12,13] en el que se realiza un análisis de fiabilidad y disponibilidad del proceso por niveles. Comenzando con el cálculo de la fiabilidad y disponibilidad de cada elemento y dada su configuración lógico-funcional se asciende para el cálculo de la disponibilidad sistémica. Este proceso puede ser entendido como ir de "abajo – arriba" ya que parte del cálculo de los indicadores RAM del elemento de nivel más bajo y posteriormente estos indicadores se utilizan para construir los índices de todo el sistema complejo, bajo el uso de las relaciones lógicas de RBD [14, 15].

La disponibilidad corresponde a una proporción de tiempo que podría ser expresada como la probabilidad de que el equipo está disponible, cuando se requiere. De esta manera, y suponiendo que el equipo requerido siempre debe ser utilizado y que las órdenes de producción se inician inmediatamente después de un fallo, es posible definir la disponibilidad prevista de un elemento específico, como por ejemplo [14]:

$$A = \frac{MTTF}{MTTF + MTTR} \qquad (1)$$

Para la generación del análisis sistémico RBD, y para la obtención de la disponibilidad del sistema, se utilizan los modelos desarrollados por Dhillon [14] para las configuraciones de serie, redundancia total, *stand by*, redundancia parcial y fraccionamiento.

3.3. ETAPA 3: ANÁLISIS DESDE EL SISTEMA HASTA EL ELEMENTO. DETERMINACIÓN DEL DESEMPEÑO SISTÉMICO Y DEL IMPACTO DE LOS ELEMENTOS

Esta fase corresponde a un análisis de "*arriba - abajo*", proceso para el cálculo de los indicadores de impacto, a partir de la disponibilidad del sistema

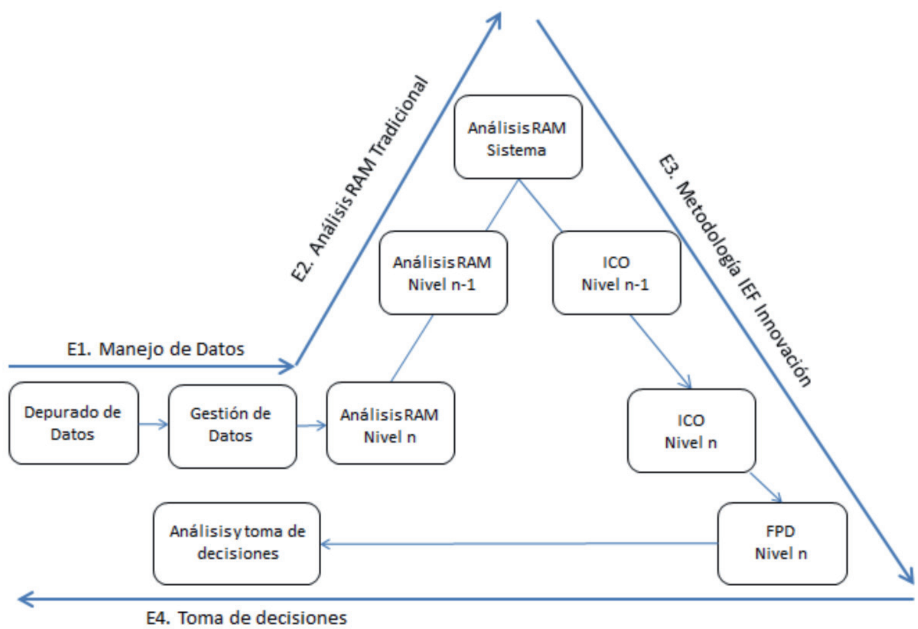


Fig. 1: Etapas de la Metodología IEF

hasta el elemento de nivel inferior. Así, es posible calcular el ICO (impacto esperado de criticidad operacional) que permite conocer la contribución del fallo de cada elemento a la pérdida de producción del sistema debido a su indisponibilidad, siendo la sumatoria de los ICO de todos los elementos el 100%.

Dado un sistema complejo compuesto por *I* niveles, desde *i=0* hasta *i= r*, donde el *i*=0 corresponde al nivel del sistema en general, *i*=1 al nivel de los elementos "padres" en que inicialmente se divide el sistema (subsistemas), *i*=2 al nivel de los elementos "hijos" o sub-elementos del nivel anterior y así hasta el nivel *r*. Sea *J* el conjunto de elementos mantenibles del sistema; habrá desde *j=1* hasta *j=n* elementos en cada nivel *i* del sistema. El factor ICO de cada elemento en el sistema se determina a través de la descomposición del índice global y de cada uno de los subsistemas. El desglose del ICO de cada nivel se expresa con las ecuaciones 2, 3 y 4:

$$\textit{Impacto de Criticidad Operacional}\ (ICO)_{sistema\ \ i=0} = 1 \tag{2}$$

$$\sum_{j=1}^{n} ICO_{i;j} = ICO_{i-1} \quad \forall\, i: 0, \ldots, r;\ \ \forall\, j: 1, \ldots, n \tag{3}$$

$$\frac{ICO_{i;j}}{ICO_{i;j+1}} = \frac{(1-A_{i;j})}{(1-A_{i;j+1})} \quad \forall\, i: 0, \ldots, r;\ \ \forall\, j: 1, \ldots, n \tag{4}$$

Dónde:

ICO i; j: Es ICO para el elemento *j* (de 1 a *n*) que se encuentra en el nivel de descomposición *i* (de 1 a *r*).

Ai;j: Es la disponibilidad esperada para el elemento *j* (de 1 a *n*) que se encuentra en el nivel de descomposición *i* (de 1 a *r*).

En términos simples, el ICO muestra el resultado final de la contribución de cada elemento sobre el sistema, exponiendo el posible impacto de un fallo en la pérdida de capacidad de producción. Al considerar el nivel de detalle más bajo, esto es el sistema en su totalidad o nivel *i=0*, la suma de todos los ICO es 100% del sistema (ecuación 5).

$$\sum_{j=1}^{n} ICO_{i;j} = 1 \qquad \forall\, i: 0, \ldots, r; \tag{5}$$

Por último, una vez conocido el $ICO_{i;j}$ de cada elemento, su nivel de impacto se puede descomponer en dos aspectos principales: la frecuencia (por la falta de disponibilidad del elemento) y la consecuencia (a través del impacto del elemento según su configuración lógico funcional). Este último índice se llamará Factor de Propagación esperado de Detención $FPD_{i;j}$ el cual representa el efecto que causa una parada del elemento *i; j* en el sistema (ecuación 6). El efecto de detener un elemento *j* puede tener diferentes resultados, dependiendo del estado de los demás elementos que se encuentran en el mismo nivel *i*.

$$FPD_{i;j} = \frac{ICO_{i;j} * (1 - A_{system})}{(1 - A_{i;j})} \tag{6}$$

Considerando una estructura sistema-subsistema-equipo, el algoritmo de cálculos para esta etapa sería el siguiente:

1. Calcular la suma de la indisponibilidad total de todos los subsistemas de cada nivel *i*: $\sum_{j=1}^{n} 1-A_{sub}\ \ \forall\ i{:}1,\ldots,r\text{-}1$
2. El ICO del sistema será ICO_{sis} = 100% (*i=0*)
3. El ICO del subsistema ICO_{sub} será la proporción de impacto del subsistema con respecto al total de indisponibilidades, multiplicado por el ICO_{sis} lo que quedaría: $1-A_{sub}/ \sum_{j=1}^{n} 1-A_{sub}\ \ \forall\ i{:}1,\ldots,r\text{-}1$
4. Calcular la suma de la indisponibilidad de los equipos pertenecientes a un subsistema: $\sum_{j=1}^{n}(1-A_{equ})\ \forall\ r$. En caso de fraccionamiento, dicha indisponibilidad deberá multiplicarse por la capacidad de cada elemento.
5. El ICO del equipo ICO_{equ} será la proporción de impacto del equipo con respecto al total de indisponibilidades para el subsistema en análisis, multiplicado por el ICO_{sub} lo que quedaría: $1-A_{equ}/ \sum_{j=1}^{n} 1-A_{equ} * ICO_{sub}\ \ \forall\ r$. En caso de fraccionamiento, es necesario multiplicar la indisponibilidad del equipo por la capacidad,
6. El FPD del equipo FPD_{equ} se calcula con la ecuación 6.

3.4. ETAPA 4: ANÁLISIS DE INDICADORES Y RESULTADOS

Esta fase recoge los resultados numéricos obtenidos en las etapas anteriores y los analiza para la toma de decisiones estratégicas. Los primeros análisis pueden ir enfocados en la cuantificación de la indisponibilidad del sistema. Dicha indisponibilidad será el elemento de análisis para determinar el aporte de cada equipo y subsistema, en términos de consecuencia de posibles fallos. Posteriormente, el análisis de los subsistemas y equipos con mayor ICO indican cuáles son los elementos más críticos y sobre los que debería enfocarse la gestión de activos con mayor énfasis. En esta etapa se propone la elaboración de un Gráfico de Dispersión IEF, el cual relaciona en su eje X la indisponibilidad de los equipos y en el eje Y su FPD. De acuerdo a la localización de los equipos dentro del gráfico es posible hacer una clasificación de los equipos para enfocar diversas acciones de mejora.

4. APLICACIÓN DE LA METODOLOGÍA IEF: PROCESO DE TRITURACIÓN DE MINERAL DE COBRE

4.1. ANTECEDENTES DEL CONTEXTO INDUSTRIAL

Una planta de trituración es una instalación compleja, que consta de una variedad de elementos. La elección del tipo y el diseño de una planta de trituración se determina principalmente por su importancia en el proceso de producción del cobre.

El proceso de obtención del cobre, comienza con la extracción del material desde la mina, el que se transporta a través de camiones al proceso de trituración primario, posteriormente a través de correas transportadoras es derivado al triturador secundario, para culminar el proceso de conminución en el triturador terciario. Una vez finalizado el proceso de trituración, el material es tratado con el curado ácido en correas transportadoras, para culminar el proceso en las pilas de lixiviación. El presente estudio, se focalizará en el proceso de trituración, en particular para la fase más crítica del proceso que es el de trituración secundaria.

- Trituración Primaria: este proceso tiene como objetivo el reducir el tamaño del material a un diámetro inferior a 8 pulgadas, de manera homogénea. En la fase previa al triturador primario, se encuentra un equipo Picador de Rocas, que facilita la entrada de las rocas de mayor tamaño. Este proceso tiene una capacidad de 15.000 ton/h. El material triturado es trasladado por una Correa Transportadora de 1 km hacia el proceso de trituración secundaria.

- Trituración Secundaria: este proceso es alimentado por la producción del triturador primario y se compone por cuatros líneas independientes, cuyo objetivo es obtener un 100% de la granulometría bajo 1 pulgada, la cual es seleccionado por un harnero; todo el material que no cumple es procesado en el triturador secundario, con un proceso de retroalimentación repetitivo, hasta lograr el cumplimiento del objetivo.

Cada una de las líneas de trituración secundaria se compone por cuatro equipos: Alimentador, Correa, Harnero y Triturador. La capacidad de cada una de las líneas es descrita en la Tabla 2.

Trituración Secundaria	Capacidad [ton/h].
Línea 1	5.250
Línea 2	6.000
Línea 3	4.500
Línea 4	4.500

Tabla 2: Capacidad Líneas de Trituración Secundaria

Al observar las capacidades de las líneas y la forma independiente de operación entre ellas, se puede establecer que la configuración de este proceso es la de un fraccionamiento con capacidad ociosa [15], permitiendo operar en condiciones excepcionales, a menos carga de la requerida ya que la capacidad nominal del proceso de trituración secundaria corresponde a 20.250 [ton/h]. Tales sistemas pueden representar configuraciones de carga compartida con exceso de capacidad y niveles de trabajo flexibles, permitiendo asimismo que los equipos presenten diferente comportamiento de fallos.

4.2. APLICACIÓN DE LA METODOLOGÍA IEF

Para el desarrollo de este artículo, se han utilizado los datos reales de mantenimiento de los equipos principales de una línea de trituración secundaria, de una planta de trituración minera situada en Chile.

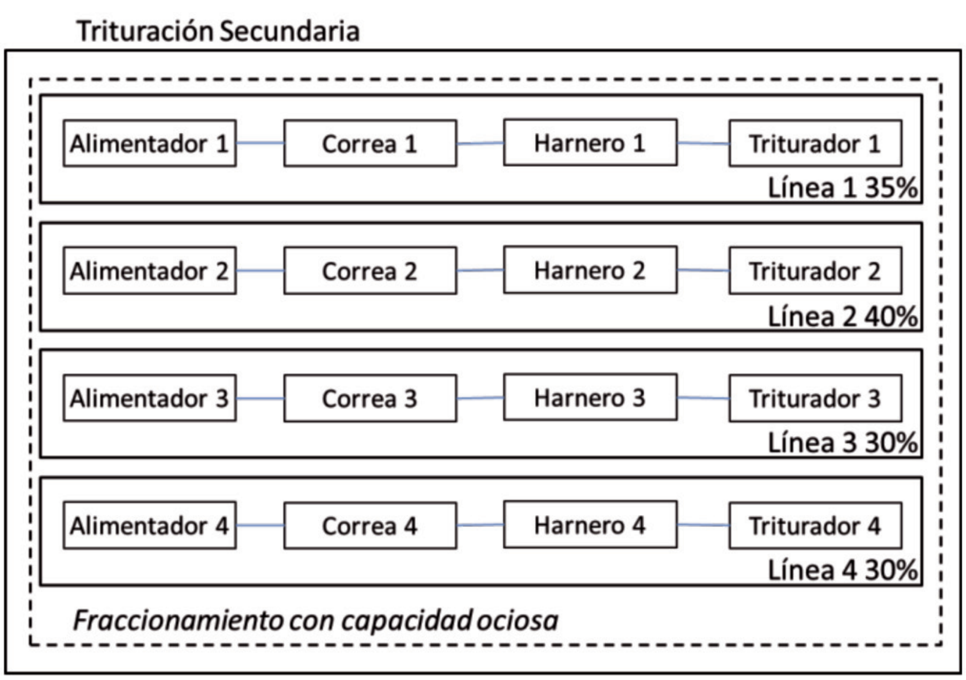


Fig. 2: Diagrama del proceso de Trituración Secundaria

4.2.1. Etapa 1. Depurado y gestión de datos

Los datos del proceso a analizar han sido recopilados utilizando una metodología estructurada propuesta por Ballou et al [16]. Posteriormente, los datos han sido limpiados para trabajar solamente con información de calidad asegurada, eliminando datos no significativos e incompletos, con el soporte de los expertos de la empresa. Analizando la data histórica de intervenciones de mantenimiento de los equipos del proceso de trituración, se pudo verificar en la mayoría el concepto de independencia y análisis de tendencia (descartar envejecimiento). Se determinó bajo la hipótesis nula de homogeneidad de Poisson, utilizando el estadístico X^2 (chi cuadrado) distribuido con 2 (n-1) grados de libertad, donde la hipótesis no es rechazada con un 5% de nivel de significancia. Esto se cumple para todos los equipos, indicando los parámetros de la distribución de Weibull respectivos en la Tabla 3.

4.2.2. Etapa 2. Análisis clásico RAM ascendente

El proceso de trituración secundaria se ha descompuesto en cuatro subsistemas, de acuerdo con la lógica del proceso global (configuración de fraccionamiento con capacidad ociosa). Debido a que la suma de las capacidades de las líneas excede un 35% de la capacidad requerida, la cual queda definida por la trituración primaria, 15.000 toneladas por hora. La Figura 2, muestra la configuración lógica del proceso de trituración secundaria. Donde el porcentaje indicado representa la capacidad de cada línea o subsistema, sobre la capacidad requerida.

La Tabla 3, muestra los datos iniciales de fiabilidad, mantenibilidad y disponibilidad para cada uno de los 16 equipos del proceso. La base para la determinación de los modelos de fiabilidad, es a través de los parámetros α y β de la distribución de Weibull. Estos parámetros fueron obtenidos desde los sistemas de información de mantenimiento de la empresa en estudio. Aplicando los modelos de RBD [14, 15] para el cálculo de la disponibilidad de las líneas (A líneas) y el de fraccionamiento con capacidad ociosa [17] para la disponibilidad del sistema (A sist), se obtiene:

Del análisis RAM ascendente se observa que la disponibilidad esperada de todo el sistema de trituración secundaria corresponde a casi un 96%; destacando la línea 3 por ser el subsistema de menor disponibilidad (83,13%) y dentro de la misma línea 3, el triturador se aprecia como el equipo más indisponible.

4.2.3. Etapa 3. Análisis descendente y cálculo de indicadores FPD e ICO

Se calcula el impacto de cada equipo, entendido como el porcentaje de pérdida de disponibilidad, producción o capacidad operativa, en el nivel superior *i=0*, siendo este equipo un componente de un subsistema o un subsistema $i \neq 0$. Este impacto es descrito por los indicadores FPD e ICO. Por la lógica descrita, el ICO y el FPD del sistema (nivel superior máximo o *i=0*) será siempre 100%. El ICO es la contribución de cada elemento *j* en la disponibilidad del sistema, a causa de una falta de eficacia reflejada en una posible pérdida de producción; el Factor de Propagación de Detención (FPD) es el efecto esperado de una deten-

	Configuración	α	β	MTTR	A eq	A líneas	A sist
Trituración Secundaria	Fraccionamiento con ociosa						**95,93%**
Línea 1 CH2	35%					**85,52%**	
Alimentador 1 CH2	Serie	414,75	1,97	11,92	96,86%		
Correa 1 CH2	Serie	188,22	1,86	4,13	97,59%		
Harnero 1 CH2	Serie	1.727,09	1,56	6,93	99,56%		
Triturador 1 CH2	Serie	210,85	1,57	19,00	90,88%		
Línea 2 CH2	40%					**85,55%**	
Alimentador 2 CH2	Serie	343,97	1,91	14,42	95,49%		
Correa 2 CH2	Serie	230,49	1,57	7,68	96,42%		
Harnero 2 CH2	Serie	1.236,10	1,49	6,85	99,39%		
Triturador 2 CH2	Serie	214,35	1,39	13,62	93,49%		
Línea 3 CH2	30%					**83,13%**	
Alimentador 3 CH2	Serie	369,36	1,56	8,02	97,64%		
Correa 3 CH2	Serie	189,75	1,42	6,83	96,20%		
Harnero 3 CH2	Serie	1.413,29	1,48	6,29	99,51%		
Triturador 3 CH2	Serie	143,92	1,98	15,86	88,94%		
Línea 4 CH2	30%					**85,88%**	
Alimentador 4 CH2	Serie	629,60	1,79	7,28	98,72%		
Correa 4 CH2	Serie	113,58	1,42	5,24	95,17%		
Harnero 4 CH2	Serie	1.116,12	1,46	4,73	99,53%		
Triturador 4 CH2	Serie	136,73	1,87	10,79	91,83%		

Tabla 3: Análisis de disponibilidad por equipos, líneas y sistema de trituración secundaria

Nivel *i*		ICO Sist	ICO líneas	ICO Eq	FPD Eq
0	**Trituración Secundaria**	**100,00%**			
1	Línea 1 CH2		**25,15%**		
2	*Alimentador 1 CH2*			5,23%	6,77%
2	*Correa 1 CH2*			4,01%	6,77%
2	*Harnero 1 CH2*			0,74%	6,77%
2	*Triturador 1 CH2*			15,17%	6,77%
1	Línea 2 CH2		**28,69%**		
2	*Alimentador 2 CH2*			8,51%	7,67%
2	*Correa 2 CH2*			6,75%	7,67%
2	*Harnero 2 CH2*			1,15%	7,67%
2	*Triturador 2 CH2*			12,28%	7,67%
1	Línea 3 CH2		**25,12%**		
2	*Alimentador 3 CH2*			3,35%	5,77%
2	*Correa 3 CH2*			5,40%	5,77%
2	*Harnero 3 CH2*			0,69%	5,77%
2	*Triturador 3 CH2*			15,68%	5,77%
1	Línea 4 CH2		**21,03%**		
2	*Alimentador 4 CH2*			1,83%	5,80%
2	*Correa 4 CH2*			6,89%	5,80%
2	*Harnero 4 CH2*			0,66%	5,80%
2	*Triturador 4 CH2*			11,65%	5,80%
	Sumatoria		**100%**	100%	

Tabla 4: Cálculo ICO y FPD

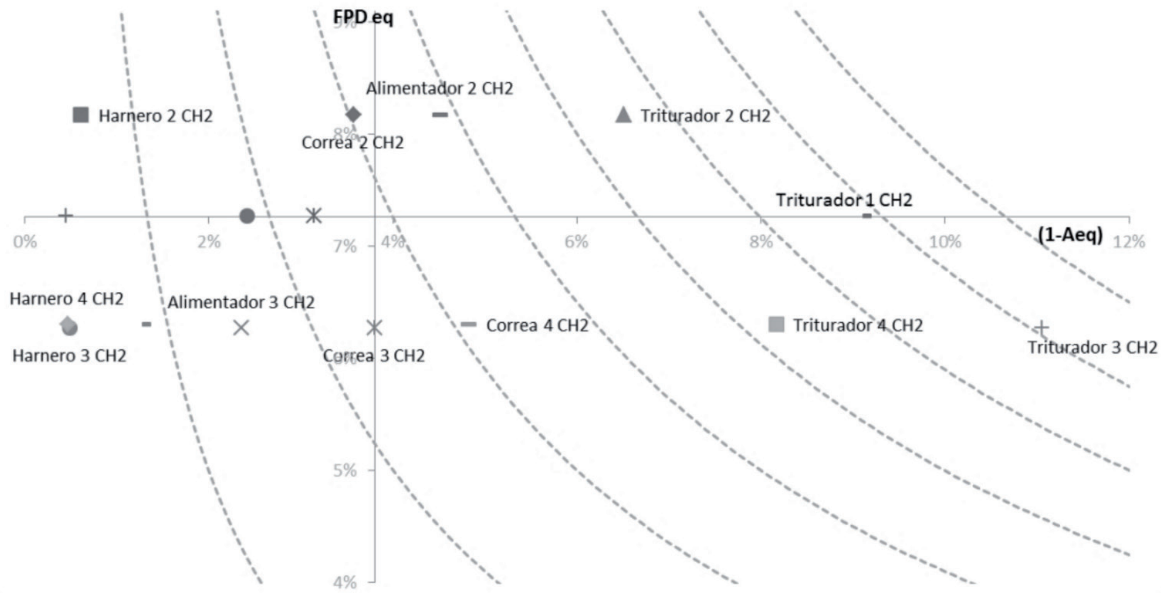


Fig. 3: Gráfico Dispersión para Metodología IEF

ción de cada elemento sobre el sistema. A partir de las ecuaciones 2-6 y de los algoritmos expuestos en la sección 3.2 y en 3.3 se hace el cálculo de los indicadores ICO y FPD para el caso de estudio, los cuales se muestran en la Tabla 4.

Los resultados de la Tabla 4 muestran que, aunque la línea 2 es la línea de trituración con mayor ICO, como equipo es el triturador 3, de la línea 3 el que tiene mayor ICO o impacto esperado de criticidad. Este equipo posee la mayor indisponibilidad de todo el sistema (A=88,94%), sin embargo su capacidad es menor que la de los trituradores de las líneas 1 y 2 (ver Tabla 2). La línea con el menor ICO es la 4, que además tiene el equipo con el menor ICO del sistema (harnero) y el triturador con menor ICO con respecto a los trituradores de las otras líneas.

4.2.4. Etapa 4. Análisis de indicadores y resultados

Una vez que se cuenta con los datos de disponibilidad e indisponibilidad globales y por elemento, así como con los valores de los indicadores ICO y FPD es posible analizar las implicancias de esta información para la toma de decisiones.

La Figura 3 a través del Gráfico de Dispersión IEF, facilita la interpretación de los conceptos y del índice ICO, teniendo en cuenta en el eje *X* la falta de disponibilidad de equipos (indisponibilidad) y en el eje *Y* el FPD. El motivo de esta disposición es la evaluación estándar que se realiza de un riesgo operacional, que considera el producto de dos factores: frecuencia y consecuencia. Quedando los equipos más críticos para el funcionamiento sistémico por su factor de propagación e indisponibilidad, en el área más noreste posible del diagrama. Es fácil de confirmar, a través de las curvas de Iso ICO, que los trituradores ocupan los primeros lugares de mayor impacto en el sistema (en el orden por número de triturador 3, 1, 2 y 4), el quinto lugar es para el alimentador de la línea 2 y el sexto para la correa de la línea 4.

Respecto del FPD se puede establecer claramente que los factores más altos están en las líneas de mayor capacidad (2 y 1 respectivamente). Al estar en presencia de una configuración con cierto grado de redundancia (fraccionamiento con capacidad ociosa) el FPD es de suma utilidad, ya que por ejemplo el triturador 2 representa un 40% de la capacidad productiva requerida, pero si falla y las otras tres líneas se mantienen operativas, el sistema de trituración secundaria solo pierde un 5% de su capacidad, obviamente al fallar más equipos de otras líneas de manera simultánea, la capacidad del sistema desciende, pero siempre de manera suavizada al contar con capacidad ociosa. EL FPD explica todas estas situaciones, estableciendo que en términos esperados una detención de cualquier equipo de la línea 2, implicará la pérdida un 7,67% promedio para el sistema.

Teniendo en cuenta las cuestiones clave que se presentan en la sección Planteamiento del problema, es fácil dejar claro que el subsistema con mayor ICO (subsistema 2) es el que tiene mayor impacto en la operatividad del sistema, siendo referido éste a más del 28% de la indisponibilidad esperada. Sin embargo como equipo individual es el triturador 3 el que más influye en la indisponibilidad sistémica, correspondiendo ésta en más del 15% a interrupciones en dicho triturador.

Ahora con la disponibilidad esperada de cada equipo, subsistema y del sistema en general, así como con el conocimiento del impacto de cada elemento es posible hacer un pronóstico más exacto de la capacidad del sistema para desarrollar un plan y control de la producción. Posteriormente, es posible aplicar otras metodologías de mejoras de procesos, tales como la propuesta de Eguren et al. [17].

5. CONCLUSIONES

En relación con los objetivos planteados al inicio, orientados a proponer una metodología que cubra un vacío de aplicación práctica y científica, se puede concluir que la metodología propuesta (IEF) es capaz de generar indicadores útiles para el análisis y posterior mejora en el desempeño de los sistemas productivos. Esto en términos de la disponibilidad de sus equipos. Así como para la priorización, focalización de las actividades y toma de decisiones relacionadas con la gestión de activos, todo independientemente del tipo de industria del que se trate y de la disposición lógico-funcional de los componentes del sistema.

La propuesta metodológica IEF consta de cuatro etapas: la primera que gestiona y prepara los datos a analizar, la segunda que de forma clásica calcula la fiabilidad y disponibilidad operacional de cada elemento y del sistema general, la tercera que encuentra el impacto en la criticidad operacional (ICO) y el factor de propagación del tiempo de detención esperado (FPD) de cada uno de los equipos sobre el sistema y la última que obtiene mediante un gráfico de dispersión "indisponibilidad vs FPD" la interpretación de los resultados para la toma de decisiones. Cada una de las mencionadas etapas se ilustra con el caso de análisis a un sistema de trituración de cobre, cuyos resultados finales arrojan información relevante para evaluar el diseño y el rendimiento de la planta, lo cual por supuesto se puede posteriormente traducir en beneficios económicos.

En general, después de aplicar la metodología es posible obtener los siguientes elementos de información:

- Identificar los activos que tienen el ICO más alto, lo cual es relevante para concentrar los esfuerzos en ellos dado su impacto potencial. Recordemos que el ICO descubre cuál es el subsistema o equipo con mayor impacto en la operatividad del sistema, asignando el % de la indisponibilidad total correspondiente
- Identificar los equipos de mayor criticidad en el sistema (frecuencia x consecuencia), entendiendo en este caso particular que la consecuencia medida es netamente operacional, por ende basada en la indisponibilidad individual y sistémicamente impactada de cada equipo. Este análisis se facilita por medio de un gráfico de dispersión, que relaciona en su eje X la indisponibilidad de los equipos (interpretada como la frecuencia) y en el eje Y el FPD (entendido como la consecuencia). En dicho gráfico es posible apreciar que para una misma configuración lógica, los elementos del mismo subsistema tendrán un mismo FPD, siendo la indisponibilidad esperada de cada elemento el factor diferenciador para priorizar un equipo sobre otro. También es posible visualizar que para una misma indisponibilidad entre equipos, la configuración lógico-funcional, representada por el FPD hace la diferencia en su criticidad.

Dado lo anterior, las acciones del plan de gestión de activos que emanen de esta metodología pueden ser dirigidas a la fiabilidad y mantenibilidad de los elementos presentes en la zona de la derecha (eje X) del gráfico, es decir los más indisponibles. Lo que implicaría la redefinición de su estrategia de mantenimiento, de los procedimientos de mantenimiento, y el análisis de piezas de repuesto. En tanto, para los elementos situados en la zona más alta (eje Y) del gráfico de dispersión, es decir para aquellos con mayor FPD, las acciones pueden estar relacionados en reducir el impacto del elemento, por ejemplo: incluyendo mejoras en el diseño, la incorporación de redundancia y de exceso de capacidad, cuando sea posible.

La contribución de esta metodología tiene un alto componente económico, ya que el determinar adecuadamente la disponibilidad de un sistema industrial ayuda a conocer su capacidad real de producción y por lo tanto los beneficios potenciales. Por otro lado, el identificar las oportunidades de mejora y asignar los recursos de mantención a los equipos y sistemas más críticos (y no sólo a aquellos de mayor capacidad productiva) genera ahorros en el presupuesto de mantención, pero además en la consecuente disminución en tiempos de ineficiencia, producción defectuosa, pérdidas y mermas. Finalmente, es importante destacar que por su carácter genérico, la metodología de IEF se podría incorporar en cualquier base de datos de un Sistema informático de gestión de mantenimiento - CMMS para tener una evaluación de impacto automatizada.

BIBLIOGRAFÍA

(Endnotes)

1 Daylan B, Ciliz N. "Life cycle assessment and environmental life cycle costing analysis of lignocellulosic bioethanol as an alternative transportation fuel". Renewable Energy 2016. Vol.89 p.578-587. DOI: http://dx.doi.org/10.1016/j.renene.2015.11.059
2 Gang W, Wang S, Xiao F, Gao D. "Robust optimal design of building cooling systems considering cooling load uncertainty and equipment reliability". Applied Energy 2015. Vol159 p.265–275. DOI: http://dx.doi.org/10.1016/j.apenergy.2015.08.070.
3 Koontz A, Weihrich H. Administración: una perspectiva global. México: McGraw-Hill / Interamericana de México 2014. ISBN 978-607-15-0759-4.
4 Crespo A, Moreu P, Sola A and Gómez J. "Criticality Analysis for Maintenance Purposes: A Study for Complex In-service Engineering Assets". Quality and Reliability Engineering International 2015. Published online in Wiley Online Library. DOI: http://dx.doi.org/10.1002/qre.1769
5 Baraldi P, Compare M, Zio E. "Component ranking by Birnaum importance in presence of epistemic uncertainty in failure event probabilities". IEEE. DOI: http://dx.doi.org/10.1109/TR.2013.2240885.
6 Wang, W., Loman, J., Vassiliou, P. "Reliability importance of components in a complex system". Proceedings of the Annual Reliability and Maintainability Symposium. Los Angeles, California, USA, January 26-29, 2004. DOI: http://dx.doi.org/10.1109/RAMS.2004.1285415
7 Kristjanpoller F, Viveros P, Crespo A, Grubessich T and Stegmaier R. "RAM-C: A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations". In: The Annual European Safety and Reliability Conference (ESREL), Zurich, Switzerland, 7 – 10 September 2015.8-84-92970-17-9
8 Guillemette M, Laroche M, Cadieux J. "Defining decision making process performance: Conceptualization and validation of an index". Information & Management 2014. Vol 51 p.618-626. DOI: http://dx.doi.org/10.1016/j.im.2014.05.012
9 Chai J, Liu E, Ngai W. "Application of decision-making techniques in supplier selection: A systematic review of literature". Expert Systems with Applications 2013. Vol. 40 p.3872–3885. DOI: http://dx.doi.org/10.1016/j.eswa.2012.12.040
10 Chapman AD. "Principles of Data Quality", version 1.0. Report for the Global Biodiversity Information Facility. Copenhagen: GBIF, 2005.
11 Carnero M. "The control of the setting up of a Predictive Maintenance Programme using a system of indicators". Omega-International Journal of Management Science 2004, Vol. 32, p. 57-75.
12 Rausand M, Hoyland A. "System reliability theory: models, statistical methods, and applications". 3rd ed. New York: Wiley; 2003.
13 Guo H, Yang X. "A simple reliability block diagram method for safety integrity verification". Reliability Engineering System Safety 2007. Vol. 92 p.1267–1273. DOI: http://dx.doi.org/10.1016/j.ress.2006.08.002
14 Dhillon B. " Maintenance Engineering a Modern Approach". Boca Raton: CRC Press LLC; 2002. ISBN 1-58716-142-7. p. 78.
15 Kristjanpoller F, Crespo A, Viveros P, Mena R, Stegmaier R. "A novel methodology for availability assessment of complex load sharing systems". The Annual European Safety and Reliability Conference (ESREL). Wroclaw, Poland. Sept 14-18, 2014.
16 Ballou D, Madnick S, Wang R. "Assuring Information Quality". Journal of Managemente Information Systems 2003, Vol. 20, p.9-11.
17 Eguren-Egiguren J, Goti-Elordi A, Pozueta-Fernandez L. "Design, application and evaluation of a model for process improvement in the context of mature industrial sectors. Case study." DYNA 2011 Vol.86-1 p.59-73. DOI: http://dx.doi.org/10.6036/3734

2. INFORME DE LA RELEVANCIA CIENTÍFICA DE LAS PUBLICACIONES

INFORME DE LA RELEVANCIA CIENTÍFICA DE LAS PUBLICACIONES

1. F. Kristjanpoller, A. Crespo, L. Barberá, P. Viveros. Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy. Renewable Energy 101C (2017) pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

Renewable Energy

Impact Factor: 3.404 (2015); 4.068 (5 años)

Categoría de JCR ®	**Clasificación en la categoría**	**Cuartil en la categoría**
ENERGY & FUELS	24 de 88	Q2
GREEN & SUSTAINABLE SCIENCE & TECHNOLOGY	10 de 29	Q2

JCR Year	**ENERGY & FUELS**			**GREEN & SUSTAINABLE SCIENCE & TECHNOLOGY**		
	Rank	Quartile	JIF Percentile	Rank	Quartile	JIF Percentile
2015	24/88	Q2	73.295	10/29	Q2	67.241
2014	20/89	Q1	78.090	NA	undefined	
2013	23/83	Q2	72.892	NA	undefined	
2012	18/81	Q1	78.395	NA	undefined	
2011	21/81	Q2	74.691	NA	undefined	
2010	22/79	Q2	72.785	NA	undefined	

Fuente: Web of Knowledge. Thomson Reuters.

2. F. Kristjanpoller, A. Crespo, P. Viveros, L. Barberá. Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

Advances in Mechanical Engineering

Impact Factor:0.64 (2015); 0.766 (5 años)

Categoría de JCR ®	**Clasificación en la categoría**	**Cuartil en la categoría**
ENGINEERING, MECHANICAL	104 de 132	Q4
THERMODYNAMICS	48 de 58	Q4

JCR Year	**ENGINEERING, MECHANICAL**			**THERMODYNAMICS**		
	Rank	Quartile	JIF Percentile	Rank	Quartile	JIF Percentile
2015	104/132	Q4	21.591	48/58	Q4	18.103
2014	96/130	Q3	26.538	44/55	Q4	20.909
2013	99/128	Q4	23.047	44/55	Q4	20.909
2012	43/125	Q2	66.000	26/55	Q2	53.636

Fuente: Web of Knowledge. Thomson Reuters.

3. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. Accepted 5 September 2016. http://dx.doi.org/10.6036/8088.

DYNA

Impact Factor: 0.302 (2015); 0.234 (5 años)

Categoría de JCR ®	**Clasificación en la categoría**	**Cuartil en la categoría**
ENGINEERING, MULTIDISCIPLINARY	77 de 85	Q4

JCR Year	**ENGINEERING, MULTIDISCIPLINARY**		
	Rank	Quartile	JIF Percentile
2015	77/85	Q4	10.000
2014	84/85	Q4	1.765
2013	82/87	Q4	6.322
2012	81/90	Q4	10.556
2011	84/90	Q4	7.222
2010	76/87	Q4	13.218

Fuente: Web of Knowledge. Thomson Reuters.

3. ACEPTACIÓN DE LOS COAUTORES DE LA PRESENTACIÓN DE LOS TRABAJOS COMO TESIS

<u>Aceptación de la presentación de trabajos como tesis</u>

Yo **Luis Barberá Martínez**, Doctor de la Universidad de Sevilla, declaro mi aceptación a la presentación de los siguientes trabajos, como parte del trabajo de Tesis de **Fredy Kristjanpoller Rodríguez** en el Programa de Doctorado en Ingeniería Mecánica y de Organización Industrial de la Universidad de Sevilla

Trabajos:

1. F. Kristjanpoller, A. Crespo, L. Barberá, P. Viveros. Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C (2017) pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

2. F. Kristjanpoller, A. Crespo, P. Viveros, L. Barberá. Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

Luis Barberá Martínez

Sevilla, 20 de diciembre de 2016

<u>**Aceptación de la presentación de trabajos como tesis**</u>

Yo **Mónica López Campos**, Doctora de la Universidad de Sevilla, declaro mi aceptación a la presentación de los siguientes trabajos, como parte del trabajo de Tesis de **Fredy Kristjanpoller Rodríguez** en el Programa de Doctorado en Ingeniería Mecánica y de Organización Industrial de la Universidad de Sevilla

Trabajos:

1. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088.

Dra. Mónica Alejandra López Campos.

Mónica López Campos

Valparaíso, 20 de diciembre de 2016

<u>Aceptación de la presentación de trabajos como tesis</u>

Yo **Pablo Viveros Gunckel**, Candidato a Doctor de la Universidad de Sevilla, declaro mi aceptación a la presentación de los siguientes trabajos, como parte del trabajo de Tesis de **Fredy Kristjanpoller Rodríguez** en el Programa de Doctorado en Ingeniería Mecánica y de Organización Industrial de la Universidad de Sevilla

Trabajos:

1. F. Kristjanpoller, A. Crespo, L. Barberá, P. Viveros. Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C (2017) pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

2. F. Kristjanpoller, A. Crespo, P. Viveros, L. Barberá. Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

3. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088.

Pablo Viveros Gunckel

Valparaíso, 20 de diciembre de 2016

4. RENUNCIA DE LAS PERSONAS QUE COMPARTAN AUTORÍA QUE NO SEAN DOCTORES A PRESENTARLOS COMO PARTE DE OTRA TESIS

<u>Renuncia de las personas que compartan autoría que no sean doctores a presentarlos como parte de otra tesis</u>

Yo **Pablo Viveros Gunckel**, Candidato a Doctor de la Universidad de Sevilla, declaro mi renuncia a presentar los siguientes artículos como parte de mi tesis doctoral, aceptando la presentación de los mismos como parte del trabajo de Tesis de **Fredy Kristjanpoller Rodríguez** en el Programa de Doctorado en Ingeniería Mecánica y de Organización Industrial de la Universidad de Sevilla

Trabajos:

1. F. Kristjanpoller, A. Crespo, L. Barberá, P. Viveros. Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C (2017) pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

2. F. Kristjanpoller, A. Crespo, P. Viveros, L. Barberá. Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

3. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088.

Pablo Viveros Gunckel

Valparaíso, 20 de diciembre de 2016

5. PUBLICACIONES EN CONGRESOS INTERNACIONALES

5.1 F. Kristjanpoller, A. Crespo, M. Lopez-Campos, P. Viveros, T. Grubessich. Reliability assessment methodology for multiproduct and flexible industrial process. The Annual European Safety and Reliability Conference (ESREL). Glasgow, Scotland. Sept 25-29, 2016. ISBN: 978-1-138-02997-2.

5.2 F. Kristjanpoller, M. López, A. Crespo, P. Viveros. Reliability assessment based on energy consumption as a failure rate factor. 6th IESM Conference, October 2015, Seville, Spain.

5.3 F. Kristjanpoller, P. Viveros, A. Crespo, T. Grubessich, R. Stegmaier. RAM-C: A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations. The Annual European Safety and Reliability Conference (ESREL). Zurich, Switzerland. Sept 7-10, 2015.

5.4 F. Kristjanpoller, A. Crespo, P. Viveros, R. Mena, R. Stegmaier. A novel methodology for availability assessment of complex load sharing systems. The Annual European Safety and Reliability Conference (ESREL). Wroclaw, Poland. Sept 14-18, 2014.

Risk, Reliability and Safety: Innovating Theory and Practice – Walls, Revie & Bedford (Eds)

Reliability assessment methodology for multiproduct and flexible industrial process

F. Kristjanpoller
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile
Department of Industrial Management, School of Engineering, University of Seville, Seville, Spain

A. Crespo
Department of Industrial Management, School of Engineering, University of Seville, Seville, Spain

M. López-Campos
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile

P. Viveros
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile
Department of Industrial Management, School of Engineering, University of Seville, Seville, Spain

T. Grubessich
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile

ABSTRACT: Experience reveals that reliability vary depending on the characteristics of system operation. The multi-product production lines give a usual case of variation in operating conditions (Nourelfath and Yalaoui, 2012). However, in the literature there are not reported studies that systematically confront the problem of reliability on multi-product lines. This work presents a methodology for the reliability analysis of multiproduct processes, using the RCM approach, and a modification of the Universal Generating Function (UGF) (Levitin, 2005). The result of applying the proposed methodology is a characterization of reliability, for each equipment and for the production system in general. From this analysis, operating guidelines can be generated based on the knowledge of how certain production conditions impact on the reliability and systemic availability. The methodology is applied in a production line of the bakery industry, where there is prior evidence that the failure behavior varies according to the type of product which is processed.

1 INTRODUCTION

The theory of reliability is especially important under the competitive global scenario, since it is essential to determine and optimize the real productive capacity and economic convenience of a plant short and long term (Stenström et al, 2016). The failure behavior of plants and equipment is not explained with exact causes assigned to preset conditions, but varies depending on the characteristics of use of each element within the system (Yuan et al, 1987). The failures by own causes of the component, equipment or system recognize the time as the main variable influencing this behavior. However, empirical studies have shown that the behavior of the failure rate of an equipment and / or its components depends on the workload and the characteristics of the products (or raw material) which is produced or processed (You et al, 2011, Decò et al, 2012, Burciu & Grabski, 2011, Barberá et al, 2014). Moreover, the industrial technological advance, flexibility and customization make increasingly common manufacturing lines of multi product type. The different operating conditions demanded by each particular type of product on the same production line make suppose that the reliability of the multi-product system depends on the mixture scheduled to produce (Nourelfath and Yalaoui, 2012). Therefore, it is interesting to model this behavior, using for this the support of the existing reliability theory, taking into account the difference in the intrinsic properties of the multi production. Since the study of reliability in multi-product systems is not currently developed in the literature area, it is proposed to address studies related to the analysis of multistate systems (MSS) (Lisnianski, 2007, Lisnianski et al, 2010), and, by suitable adaptation, to achieve a common and widespread valid approach for a multi-product production logic.

One of the classic tools for the analysis of systemic reliability is the RCM approach (Reliability Centered Maintenance), which describes the operation of equipment arranged in a logical configuration and that, by probabilities, it allows its modelling and understanding, enabling to formulate convenient maintenance policies (Moubray, 1997). Given the magnitude typical of the multi-product problem with multiple states and transitions, a methodology for the analysis of multi-product reliability is developed under the RCM approach and applying mathematical procedures such as the Universal Generating Function (UGF) to reduce the problem of dimension (Levitin, 2005), which allows to find the distribution performance of an entire MSS based on the performance distributions of its elements using algebraic procedures (Youssef and Mohib, 2006). In this article, the proposed methodology is applied to a case study in the food sector.

2 PROBLEM STATEMENT

The components used in production systems often work in operation modes that are essentially different, characterized by varying loads and speeds work, product management of a different nature or different environment conditions. These modes result in different failure rates and life distributions. However, in terms of reliability analysis, this is a problem that has not been formally addressed, with no previous proposals that quantify the effect of the multiproduct in the systemic reliability. For this reason, it is interesting to develop and propose a methodology for reliability analysis in multi-product processes, taking as theoretical basis existing previous studies in reliability for MSS, adapting them conveniently. A binary logic of operation of equipment is then considered, either when functioning properly (UP) or total failure (DOWN), since by defining multiple operating states it is sought to differentiate the type of product to be processed. Being $J = \{1, 2, \ldots, n\}$ the whole production system equipment and $H = \{1, 2, \ldots k\}$ the set of products to be manufactured or states. An MSS composed by n different repairable elements, where each element j has k_j different levels of performance, has a model with $K = \prod_{j=1}^{n} kj$ estates. This number can be quite large even for a relatively small MSS, so the methodology proposed here uses tools like UGF to simplify the problem.

3 PROPOSITION FOR METHODOLOGY

Below there is a proposed methodology to study the reliability of multiproduct processes that serve for decision-making and study of the technical and economic effects. The methodology focuses on the analysis of reliability, so that data such as product demand, manufacturing quantities and probabilities associated with these items shall be considered as given, for example, by the production planning. It should be emphasized that this is a methodology and not an algorithm, so its application is not one hundred percent accurate and tight end to stringent rules. The steps of the methodology proposed are the following:

1) To identify a system or production line that has a proper multi product nature. To manufacture different products is a necessary condition, but not sufficient to satisfy this point, since it is essential that the equipment have the tendency to react differently (or support different loads, for example) depending on the product they are processing.
2) To focus the methodology on a system or production line that processes a common set of products. In the case of several sets depending on the line, the methodology should be applied separately on each form.
3) To focus the analysis on the parts of the line which satisfy the multiproduct condition. However, the parties that not meet this condition should also be considered since they all make an impact on the reliability of the system.
4) To analyze the normal conditions of the operation of the j equipments of the system when they are processing each product h, and to determine a measure of performance of its various components, depending on the nature of the process. This can be represented by a workload g_{jh} given by the production planning. The set $g_j = \{g_{j1}, g_{j2}, \ldots, g_{jk}\}$ represents the standard load or performance of the element$j$ in the state h. G_j is a random variable of each item j and represents the load (product type) that that equipment is manufacturing. This also involves knowing the respective probabilities of process according to each equipment or knowing them generally for the entire line according to each product. The probabilities associated to the different states of the element j can be represented by the set: $p_j = \{p_{j1}, p_{j2}, \ldots, p_{jk}\}$ where $p_{jh} = Pr\{G_j = g_{jh}\}$ y $\sum_{h=1}^{k} pjh = 1$.
5) To make an analysis of operational flexibility that describes the process attributes related to the programming of production of the equipment directly related to their working standard time interval (minimum time during which only one type of product is processed).
6) To illustrate the logical configuration RBD of the system and understand the size and behavior of product flows circulating on the line.
7) To obtain the possible output values of each product and the probability of occurrence of each of these states to the line, by the modified UGF tool, the equation of the u-function (equation 1) and the polynomial $U(z)$ of the entire system (equation 2), taking into consideration the polynomial $U_{disp}(z)$ that includes the availability (A) (equation 3).

$$u_j(z) = \sum_{h=1}^{k} p_{jh} z_h^{g_{jh}} \tag{1}$$

$$U(z)=\otimes_{\varphi}(u_1(z),\ldots,u_n(z))$$
$$=\otimes_{\varphi}(\sum_{h=1}^{k}p_{1h}z_h{}^{g_{1h}},\ldots,\sum_{h=1}^{k}p_{nh}z_h{}^{g_{nh}})$$
$$=\sum_{h=1}^{k}(\prod_{j=1}^{n}p_{jh}z_h{}^{\varphi(g_{1h},\ldots g_{nh})}) \quad (2)$$

$$U_{disp}(z)=\sum_{h=1}^{k}(\prod_{j=1}^{n}p_{jh}z_h{}^{\varphi(g_{1h},\ldots,g_{nh})*A_h}) \quad (3)$$

8) Once known the polynomial $U(z)$ of the line, it is possible to obtain indicators for the analysis of reliability conditions of the system, from an acceptability function $f(V,\phi)$, which represents the desired relation between the performance of the system V and some limit value ϕ called system demand ($f(V,\phi)=1$, if the performance of the system is acceptable and $f(V,\phi)=0$ if it does not). The MSS reliability is defined as its expected acceptability. Given the probability mass function of the q_i system, v_i, $1\leq i\leq K$, where $q_i=Pr\{V=v_i\}$, it is possible to obtain its reliability as shown in equation 4.

$$R(\theta)=E[f(V,\theta]=\sum_{i=1}^{K}q_i f(v_i,\theta) \quad (4)$$

9) Once known the information from step 4, to perform a procedure of data recording of equipment failure of the production line under study, while processing the same type of product. This step should be performed for each type of product manufactured by the line and may include data such as type of event (corrective, preventive), average load, repair times and good performance, etc. The collected data should be properly arranged in tables that allow a good read and the grouping of data.
10) Get output data from the previous step that serve for reliability analysis of product processes, such as mean time between failures (MTBF) and mean time to repair (MTTR).
11) With these, to estimate the different availability of system according to the processed product, and, by polynomial $U_{disp}(z)$ (ecuación 3) (equation 3), to determine the output quantities of each product h, depending on the availability and the probabilities associated with each state.
12) To perform an appropriate parameterization with the equipment failure data according to the product they process, to adjust the data to probability density curves of representative failures of the case under study and to show the modeling the reliability of equipment.
13) Through a mathematical tool, which can be stochastic simulation, to define a probabilistic reliability assessment scenario, which depends on the odds of developing each product and on the operational flexibility of the production line.
14) To perform a simulation with multiple iterations that change the processed products at each minimum time interval of processing, whose transition probabilities depend on the product made in the previous time interval. To determine expected values of reliability for the equipment of the production line, in other words, reliability values that together consider all the processed products and, thus, to build an expected reliability curve for each equipment.
15) To add the reliability analysis at the level of the production line, by performing mathematical operations required to reach the global values from those thrown by the equipment.
16) To consolidate the information obtained from the study and to facilitate the decision-making from the research added. If desirable, with the results already obtained, to apply complementary analysis tools.

4 CASE STUDY

Consider the production process of an automated production line of vanilla cake (product A), nuts cake (product B) and chocolate cake (product C), in the plant of a manufacturer of numerous bakery products. There is collected information of failure data of a period of five years.

4.1 *Process description*

The production line under study is typical of its kind and it consists of numerous work stations integrated in series as a single system and with a common control system.

Each work station contains one or more machines and each machine may present various failure modes. The movement of material between work stations is carried out automatically by mechanical means. There are six different stages (work stations) for the manufacturing of these products: 1. kneading, 2. molding, 3. coverage, 4. baking, 5. cooling, and 6. packaging.

4.2 *Identification of multi product components in the production line*

In the experience of the staff, the failure behavior of some workstations of the line depends more on the operation than on the operating time (although it never stops depending on the latter, of course). In this case the three products made (vanilla, nuts and chocolate cake) have processing conditions that make them different to the operation of some stations (especially differences in density for kneading, in coverage, and for packaging in different forms). All other stations have no evidence of being influenced by the multi-product (molding, baking and cooling).

4.3 *Analysis of normal operation conditions*

The stations have a different processing capacity in units per hour for each product type. The production planning determines the type of product to be manufactured per shift. The probability of switching between products and proportion of each product relative to the total elaborated, are stationary at the long term. Modeling reliability will depend on the specific long-term behavior.

4.4 *RBD system configuration*

For this case study the system is known with 6 work stations connected in series with each other, and wherein the first station is formed as a subsystem with partial redundancy (three stations of kneading, from which two are required).

4.5 *Universal Generating Function (UGF) in the production line*

By using the equations (1) and (2), it is possible to know the polynomial $U(z)$ of the production line performance, according to its RBD configuration. This polynomial shows the stationary probabilities that are associated with the production rate, per hour, of each product. Per property of the function for elements in series, it is considered the minimum production rate in each composition. In this case, the station that acts as a bottleneck for the product A and the product C is number 2 (molding), so the production rate of the system matches with that station. In the case of product B, the bottleneck is station 3 (coverage), so the system adopts that global production rate. The polynomial given by the UGF is valid for this case, since it is habitual to work with the logic of the bottleneck in the food industry.

4.6 *Failure data collection*

There has been access to records of failure that the line technicians maintained during each shift, for a total of 1825 days, i.e. five years of operations. During this period, the line operated for 24 [h/day], with three shifts of eight hours per day, for a total of 1224 working days. The records included the failure modes that occurred in each shift, the action taken to repair, the delay time of repair and the time between failures (TBF). The latter was obtained per shift rather than per hours, i.e. the registration is made in amounts that are multiples of one shift of eight hours. Furthermore, the time to repair (TTR) was recorded in minutes. During this period a total of 1843 failures was recorded all along the line, which were classified into 46 different failure modes. In the case of work stations that have a multi-product nature have registered their failures according to the product were processing.

4.7 *Parameter calculation*

With the values of time between failures (TBF) and time to repair (TTR) a curve fitting to find the one that best explains the behavior of failures of each work station was performed by means of stochastic simulation. This was done separately for each product in the case of the stations with a multi-product nature, and in the case of station 1 it was carried out separately for each substation. In the case of TBF the adjustment chosen was Weibull, from which scaling (α) and form (β) parameters were obtained. Meanwhile the TTF are better fit to a lognormal distribution, whose parameters are the mean (μ) and the standard deviation (σ). For TTF, besides, there is no evidence that shows a variation depending on the product whose process has led to the failure, so its modeling is the same for all products.

4.8 *Availability in static state*

With the information of failure behavior of each station it is possible to obtain values of availability (A) of the line according to the processed product. The calculation of the system availability depends, of course, on the TBD system configuration.

4.9 *Polynomial U(z) according to the availability of the production line*

By using equation (3) it is possible to calculate the amount produced per hour, depending on the availability of the production line at steady state by adding the system availability to the manufacturing probabilities of each product already known. This represents a performance indicator to the expected output per hour in an undefined instant, however, it does not consider that this influence a short-term scenario in which the probability of transition between the manufacturing of a product and another, and where the elaborate proportions are not the ones from the static scenario.

4.10 *Reliability Analysis*

4.10.1 *Failure density and failure rate functions*

Defined as f_{jh}(t) the density failure function of station j when processing product h, and as $\lambda_{jh}(t)$ the failure rate of station j when processing product h. By plotting both f_{jh}(t) and $\lambda_{jh}(t)$ for each product that passes through each workstation, it can be appreciated the failure behavior that each product causes in each station. In addition, the parameters calculated in 4.7 report on differences in times of good performance for each case. For this case study, the differences in the values obtained for the parameter β throw that the failure rate in the multi-product stations is growing when processing product C, increasing to a lesser extent when processing B and close to be constant when processing A. Regarding the times of good performance, largely determined by the parameter α, for this case they show a statistical tendency to be higher when processing product B in the case of all multi product stations. Meanwhile, the process of product A is the next one with longer good performance, and product C is shorter in this sense, which is met again in the case of all the stations described. The parameters calculated for non-multi product stations do not change depending on the product they are processing.

All three of them have parameters β close to 1, so its failure density function takes a similar way to a negative exponential distribution (and its failure rate is slightly increasing). The α parameter determines that the times of good performance of the station 4 (baking) are widely larger than those of the other two stations and, in fact, makes it the station with the longest times of good performance of all the ones from the line.

4.10.2 *Reliability curves per station and reliability line when producing a type of product*

By using the classical formula of reliability function from Weibull it is possible to derive the equations of the reliability curves per station and manufactured product, where $R_{jh}(t)$ is the reliability function of station j when processing product h. In these curves it is possible to assess whether in a moment of time, the reliability decreases faster when processing a particular product. In this case, the reliability function of the system when processing a determined product being in series is the product of all the reliability functions. In static state it is possible to obtain a reliability curve of the line, which is different for each product.

4.10.3 *Calculation of the expected reliability with multi-product*

Once obtained the reliability curves for each processed product, it is possible to analyze the multiproduct scenario. The reliability of the stations will then be variable depending on the type of processed products in a determined time horizon and on the order these are made. In order to get reliability curves expected for both the stations and for the complete production line, it is necessary to understand the behavior of the system production. The scenario to be analyzed depends on the shift schedule, provided by the production planning of the company. The first step then is to define a stochastic model that shows the possible scenarios of the production line over time. These scenarios can be generated by simulation, considering a horizon of working days and shifts. For this case it is defined as it follows: for each shift it is possible either to manufacture product A, product B or product C, depending on the transition probabilities between the development of products, which were previously calculated in 4.3. Taking into account that during one shift a single type of product is produced, the reliability function of each of the stations is built depending on which product has been produced during all the shifts on the horizon of analysis. For this, the parameters in the reliability function change depending on this last condition. Therefore, the reliability when processing product j and during a shift m decreases in the proper proportion to the length of time to process that product, but since the case is integrated with the other products, the "initial" availability of that shift depends on the production configuration adopted during the $m - 1$ previous shifts. Hence, the curves are formed section by section, and they take countless forms through the iterations.

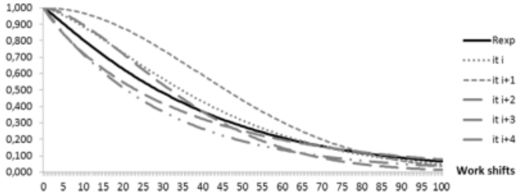


Figure 1. Expected reliability curve of the production line and reliability curves of the production line in iterations.

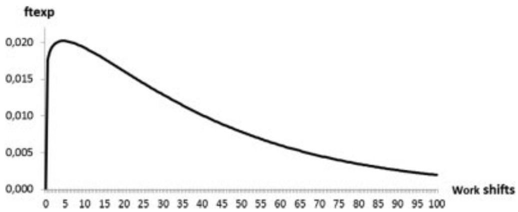


Figure 2. Expected failure density function of the production line.

4.10.3.1 Reliability curves per station and for the production line with multi-product

A simulation was performed with 200.000 iterations that make the processed product change shift by shift and they produce changes in the reliability values of each station. The expected reliability value was obtained in every single instant of time t, between 0 [h] and 900 [h] (100 shifts of operation), and from that information the expected failure density curves, the expected failure rate and the expected reliability per station were built, all of them under the multi production conditions. The expected reliability function of the station j is denoted as $Rexp_j(t)$. From this function the reliability parameters of the three stations were estimated, iterating with credible Weibull parameters according to the situation and looking for a coefficient of determination value (R^2) as high as possible. It was also calculated and plotted a $fexp_j(t)$ as an expected failure density function of the station j, and a $\lambda exp_j(t)$ as an expected failure rate of the station j, both considering multi production. Subsequently, the expected values of reliability of the entire line are calculated, as the product of the stochastic reliability of all the stations. The expected reliability curve of the entire line is denoted as $Rexp(t)$. As an example, Figure 1 shows the expected reliability curve of the entire production line in the case under study, besides the reliability curve of the same in some of many iterations performed. Each iteration generates a different curve according to the production planning per shift.

Furthermore, just as in the analysis done for each station, from the expected values of reliability of the line, the Weibull parameters are estimated and it is obtained *fexp(t)* as an expected failure density function for the entire system (Figure 2) and λ*exp(t)* as an expected failure rate function for the line (Figure 3). For the case under study based on this information, the expected failure rate of the system is not as markedly increasing as the ones from the multi-product stations.

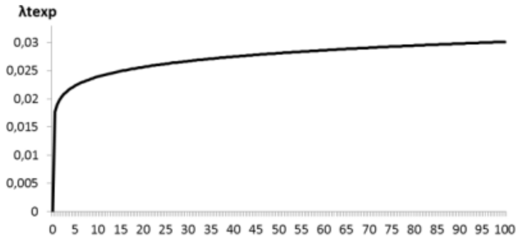


Figure 3. Expected failure rate function of the production line.

This because the parameter β is very close to 1 in stations that are not multi product, which mitigates the global impact caused by the first ones. It is then a failure density function with form close to the negative exponential that defines the useful life spam of equipment and systems.

4.10.4 *Calculation of MTBF, MTTR and expected availability with multi-product*

After obtaining the Weibull parameters of the expected failure behavior of the stations that make up the production line, it is possible to obtain their values of mean time between failures (MTBF), mean time to repair (MTTR) and availability (A), being the latter both at a disaggregated level and a total for the line. By using the equations of the reliability curves obtained for each station and the expression (5), it is possible to obtain the mean time between failures of the stations for multi-product stochastic scenario.

$$MTBF = \int_0^\infty R(t)dt \tag{5}$$

Since the values of MTTR are known in advance to all the equipment and since it is assumed that they do not vary depending on the product being processed, the availability for both each station and for the line as a whole is calculated, throwing a value for this case study of $Aexp = 0.9145$.

4.11 *Results analysis*

Now it is possible to elaborate an analysis that facilitates the understanding of the failure behavior and the decision-making related to the productive process, as the following:

The calculation of the failure parameter corroborates the multiproduct nature of stations 1, 3 and 6, because its failure behavior is visibly different according to the product they are processing. Overall, the failure rate when producing product C (chocolate cake) is increasing more steeply than for the other products. In turn, the time of good performance when baking chocolate cakes is the worst. So the chocolate cake is the most complex product for the production line. This is explained given the properties of the chocolate mass, which lower the kneading process performance, because the chocolate coating is heavier and it contains more ingredients than the other products. As for availability, the highest value is obtained when elaborating the product B (nuts cake), followed by the process of elaborating product A (vanilla cake). However, although the properties of the vanilla mass produce failures more often over time at the kneading station than the ones from the mass of nuts, their failure rate is rather constant, while the times of proper functioning of these equipment when producing croissant are more widespread, but its failure rate has shown an increasing trend over time; similarly occurs in coverage and packaging.

As for the expected behavior at line level, the stations that are not multi product (with stable failure rates) mitigate the trend of increasing failure rate that the multi stations transmit to the model, reaching a relatively intermediate pattern that shows a failure rate only slightly increasing. Due to this, the expected reliability function of the line is not far from a failure density function that follows a negative exponential distribution.

Since the logical configuration of the line is of elements in series, the inefficiency costs per unit of time attributed to the detention time are the same, so that criticality is rather determined by the expected availability of the stations. By this criterion, out of all the stations that are not multi product, the most critical station is number 2 (molding), while out of the multi-product stations, the proper result is accomplished by station 6 (packaging).

5 CONCLUSIONS

It is common in manufacturing industries of a varied nature that their equipment participate in the process of elaboration of different products, even if they have significantly different properties from each other. The reliability analysis of this scenario has not been fully explored, nor a general solution to this problem has been raised, at least in the most accessible state of art of the study done here. An emphasis is then made on how useful a reliability evaluation approach based on this need is, that considers the characteristics of both the studied industry and its operating conditions, equipment used and processed products, and that is capable of providing a generalized approach of analysis. The proposal developed here consists on the adapted model of the Universal Generating Function and the model that studies the influence of the feed load on the reliability, conditioned to a multi-product logic. All the methodology proposed is sustained theoretically on the classical RCM reliability approach.

Through a real case study, consisting of the analysis and evaluation of reliability in a plant of automated production of vanilla, nuts and chocolate cake, the use of the methodology proposed was shown as an explanatory manner. The analysis was able to show that the nature of this line of food production is multiproduct, since the failure behavior of some of its equipment varies depending on the product they are processing. Through analysis of the operating conditions of the line, and the analysis of operational flexibility, it was defined the stochastic scenario of production, whose product that was being processed at a certain period of time depended on the one that had been processed in a period of time immediately above. Leaving aside the stochastic scenario and by the Universal Generating Function and the classical tools of reliability, it was possible to determine the failure behavior of the line according to each product it processes. This is useful for the decision making in a static scenario, and it also shows the odds of making products on a long-term horizon.

Subsequently, numerous iterations were executed that show possible scenarios of shifts programming in the production line. Through them, and through the expected values of reliability for each instant of time, the expected reliability of each line station was modeled, and an aggregate analysis of the system was performed. Same idea for the graphic display of failure density functions and the failure rate functions. Through the joint analysis of results, and studying the impact that each work station has on the failure behavior of the line, it was possible to reach to conclusions about the reliability of the whole process and about the criticality of the elements it is made of.

Some recommendations for possible future studies that seek to resolve this problem are: it would be helpful to develop approaches that beyond analyzing reliability and related attributes, consider other areas of interest in the industry as the costs of analysis, maintenance strategies, equipment sizing and problems of demand satisfaction, among others. For this, an algorithmic formulation could be posed to develop a stochastic scenario of reliability evaluation that is generalized and applicable in a systematic way to any case of multi product study, and even beyond, a multi-state study. It is also possible to recommend posteriori some analysis of complementary type as a support to the study performed with additional points of view, such as those that the Markov chains can provide for the evaluation of reliability in multistate systems and a model of optimization of global cost that integrates load distribution decisions and tactical production planning, considering the costs of switching the equipment capacity and the idle capacity costs.

REFERENCES

Barberá, L., Viveros, P., González-Prida, V., & Mena , R. (2014). Influencia de la carga de alimentación en la fiabilidad de líneas de molienda. Caso de estudio. DYNA (89), 560–568.

Burciu, Z., & Grabski, F. (2011). The experimental and theoretical study of life raft safety under strong wind. *Reliability Engineering and System Safety*, 96(11), 1456–1461. doi:10.1016/j.ress.2011.06.001

Decò, A., Frangopol, D. M., & Zhu, B. (2012). Reliability and redundancy assessment of ships under different operational conditions. *Engineering Structures*, 42, 457–471. doi:10.1016/j.engstruct.2012.04.017

Levitin, G. (2005). The universal generating function in reliability analysis and optimization (p. 442). London: Springer.

Liberopoulos, G., & Tsarouhas, P. (2005). Reliability analysis of an automated pizza production line. *Journal of Food Engineering* (69), 79–96.

Lisnianski, A. (2007). Extended block diagram method for a multi-state system reliability assessment. *Reliability Engineering and System Safety* (92), 1601–1607.

Lisnianski, A., Frenkel, I., & Ding, Y. (2010). Multi-state system reliability analysis and optimization for engineers and industrial managers. Multi-state system reliability analysis and optimization for engineers and industrial managers (pp. 1–393) doi:10.1007/978-1-84996-320-6

Moubray, J. (1997). *Reliability centered maintenance*. Industrial Press.

Nourelfath, M., & Yalaoui, F. (2012). Integrated load distribution and production planning in series-parallel multi-state systems with failure rate depending on load . *Reliability Engineering and System Safety* (106), 138–145.

Stenström, C., Norrbin, P., Parida, A., & Kumar, U. (2016). Preventive and corrective maintenance – cost comparison and cost–benefit analysis. *Structure & Infrastructure Engineering*, 12(5), 603–617. doi:10.1080/15732479.2015.1032983

You, M. -., Li, H., & Meng, G. (2011). Control-limit preventive maintenance policies for components subject to imperfect preventive maintenance and variable operational conditions. *Reliability Engineering and System Safety*, 96(5), 590–598. doi:10.1016/j.ress.2010.12.015

Youssef, A., & Mohib, A. (2006). Availability Assessment of Multi-State Manufacturing Systems Using Universal Generating Function. CIRP Annals – Manufacturing Technology (55), 445–448.

Yuan, J., Lin, C., Chang, S. J., & Lai, S. (1987). Reliability modeling and evaluation for networks under multiple and fluctuating operational conditions. *IEEE Transactions on Reliability*, R-36(5) Retrieved from www.scopus.com

Reliability assessment based on energy consumption as a failure rate factor

(presented at the 6th IESM Conference, October 2015, Seville, Spain) © I^4e^2 2015

Fredy Kristjanpoller*†, Mónica A. López-Campos*, Pablo Viveros*†, Adolfo Crespo Márquez†
*Department of Industrial Engineering
Universidad Técnica Federico Santa María
Valparaíso, Chile
E-mail: fredy.kristjanpoller@usm.cl
†Industrial Management Department
School of Engineering
Universidad de Sevilla
Sevilla, Spain
E-mail: adolfo@etsi.us.es

***Abstract*— The present study defines a methodology to analyze the relationship between the failure rate of any component and the factors that can influence it, in order to link time independent operating variables to the reliability study. Characterizing the failure rate using these variables is especially useful for changing time operational contexts. To do this, a study of traditional and modern methods of analysis, together with the assumptions that must be fulfill for its implementation and the methodology for testing the assumptions is performed. Specifically, the methodology proposed in this paper is used to develop a complete study of the influence of the energy consumption of a component, at the rate of engine failure. As can be inferred, there is a relationship between energy consumption and the rate of failure; the practical experience reveals that companies frequently use the energy expenditure variable, but documented studies that corroborate their decision are not found in the literature**

Keywords—failure rate, reliability, energy, maintenance, methodology

I. INTRODUCTION

Knowledge about the reliability of a system, takes a very important role, as it provides the availability for the exploitation that can be performed over a manufacturing equipment, a mining asset, etc. Having a clear knowledge of the amount of time the equipment will be available, it is possible to determine the actual production capacity, the amount of products to be manufactured and therefore, the potential income received by the company. Understanding the impact of reliability in production and operations, the importance of estimating the time that the component will fail (behavior of the failure rate) is understood, as well as for plans of preventive and corrective maintenance to run [1].

The study of the failure rate of the systems, composed of arrangements of elements, depends on the reliability of their components. Systems consist of a large number of components, and in many cases, it is enough that one of them fails to make the system becomes disabled, creating opportunity costs and other associated losses [1].

Due to the importance of studies in this area and knowing that there are a number of factors that can affect the reliability of systems, this paper proposes a methodology to develop a model of the failure rate, based on all the variables in the system that affect their performance. Historically, the variable used to study the behavior of the failure rate has been time [1], so it has been detected a gap in the literature regarding models that consider the impact of other variables that characterize the operational differences between equipments [28]. Specifically, this study focuses on a methodology to study the relationship between the energy consumption of a system and the failure rate of the components. In many cases, the reliability is correctly explained by the operation time, and the operation time is directly correlated with the energy consumption. However, there are several cases, such as the large mining trucks, included in the case of study, where this correlation is not as straightforward because of the large variability of the operational conditions in different mining sites. In some open-cast mines, the maximum slope is 12°, while in other mines it exceeds 35°. There are also factors such as altitude, which in some cases is near 4,000 meters above sea level, the characteristics of the manufacturing process, the presence of moisture and oxygen in the air, etc. These factors make that the operation interval measured in time on a task, it could be not necessarily comparable to the same period in another location. This justifies the search for measuring other variables, beyond time, to model wear and reliability of the elements. The proposed methodology, involves the analysis of operational energy consumption variables under the different methods used for the calculation of the elements that determine the failure rate: Traditional Methods and Modern Methods [1]. The proposal gives special emphasis on the latter, given the flexibility they present to the detailed study of the variables in the behavior of the failure rate.

The methodology proposed in this article involves the application of the following models: proportional hazards model of Cox, extended and stratified Cox models, accelerated failure model and the non parametrized model of Kaplan-Meier [10, 3, 6, 26]. The ultimate goal of the methodology developed here, is to follow a flow of decisions to guide for the study of the failure rate of various components according to their behavior. Specifically, the methodology makes possible to analyze the effect of energy consumption on the failure rate of the component under consideration. This is dealt with a case study for a component which its operating time, energy consumption and required load operation are known.

Summarizing, regarding the factors that may affect the time in which a component fails, a series of queries are generated, this research responds to these questions by applying the methodology proposed:

- Does the energy consumption of the system have a relation to the failure rate?
- Does the failure rate of a component must be based on the time of use of it?
- Is it correct to express the failure rate according to energy consumption?

II. PROBLEM STATEMENT

For many years, the main and only basis for measuring the reliability of the systems has been the failure time of the components of a system [1, 8]. However, it is important to ask: if a component has a failure probability at t hours, the fault is always given in a neighborhood of t? From a simplistic view, it is reasonable to think so, but practice shows that there are other factors that influence at the time of component fails, so uncertainty is generated, especially if the operating conditions of the system are variable, increasing the complexity of any decision on the matter.

For example, the rate of overload that any component can suffer. If any workpiece is used with twice the load in a process, versus the same part used with a normal load, it would be expected the most required to fail first. Although this is as expected, it is not possible to confirm it to launch preventive plans without a studio involved.

The technological advances of recent years now make possible the inclusion, analysis and control of a greater number of factors that change the durability of a component, such as: conditions of temperature, pressure, overload, type of material with which you work, etc. [2]

The existence of external and operational factors that change the time in which a component of a system fails, is a problem that is insufficiently treated, as an input element for modeling the failure rate. In order to generally classify different operating conditions, we can distinguish different types of systems:

- Overload Systems
- Systems with normal load
- Systems with below normal loads
- Systems with mixed loads

While for the first three systems, to estimate the failure time can be relatively simple by using traditional statistical methods, the failure rate in the fourth becomes somewhat more complex. Systems with mixed loads refer to those systems in which it involves the first three stages, without necessarily being temporarily defined at the moment of its transition to another stage. To improve the understanding, we might think about a truck that performs their tasks in any mining industry. The speed in which their components wear a sloping path, fully loaded is different from the return path where the same unloaded truck back and down the slope. Nowadays, for the recently exposed case, companies consider the time of failure based on the distance covered by the vehicle, as an alternative to operating time measurement; but usually aspects such as overload are not considered, or the slope of each trip [15]. In this paper, we propose the existence of a relationship between the changes in the system and the energy consumption of it. From a practical point of view, the truck in question, when it travels uphill and loaded, it consumes a greater amount of oil compared to the return trip, which is done unloaded and downhill. This is a tangible example of the failure rate behavior of a component, it does not only depends on a variable, but it can have a number of influential factors, which may be dependent or not of the operation time.

Although for the condition based maintenance (CBM) it is not surprising to consider similar variables to execute proactive maintenance actions [2, 11, 21, 22], the statistical account of energy expenditure for modeling the failure rate, is an issue generally not addressed in the literature.

According to the above problem, the present study aims to contribute by proposing a methodology for calculating the failure rate by analyzing the variables that are independent of the operating time. This aspect is especially useful for determining the rate of failure in systems operating with a mixed load. Specifically, the proposed methodology uses a structure of classical and modern analysis models, with the aim of analyzing the relationship between the failure rate, and a complex variable as it is the power consumption of components, among other variables that can influence equally in the life of the system.

III. BACKGROUND

A. Classical reliability methods

Classical methods for the reliability of the system components are developed based on time. This is simply because the reliability is defined as "the probability that an item will work flawlessly for a time *t* determined under certain known conditions" [1]. The various traditional methods have similar characteristics to obtain the reliability of the analyzed component, the main difference between them is the probability distribution method used to model failures. The most used probability distributions used to model the reliability function are the negative exponential distribution, Normal distribution and Weibull [14] distribution. However, regardless of the used distribution, the basic concepts for calculating the reliability are similar. Traditional methods base its analysis on the behavior of the systems, particularly based on the parameters for the calculation of failure rates [1, 4, 5, 8].

In general, the behavior of assets in terms of their failure recurrence can be modeled by the survival function [9,23], which is defined generally as the probability of a component failure to be produced immediately after a certain time, that is to say:

$$S(t) = Pr(T > t) = \int_t^{\infty} f(u)du \tag{1}$$

At the same time, the survival function is complementary to the distribution function, since:

$F(t) = P(T \leq t) = 1 - S(t)$ it satisfies that: $S(0) = 1$ y $S(t) \rightarrow_{t \rightarrow 0} 0$

Although as mentioned above, some probability distributions are especially useful for this modeling, there are occasions where a previous model is unknown and it proceeds to use non-parameterized methods to estimate the survival function. One of the most reliable methods to do this, is the Maximum Likelihood, which it considers the existence of not of censored data, and what type of censorship data report (on the right, the left or intervals) [25].

B. Modern reliability methods

The main difference between traditional methods and modern methods, lies in the flexibility that allows each model, it from the point of view of previous requirements to be used. In traditional methods, rigid requirements are observed; while it greatly facilitates the process of calculation, not quite correspond to reality. Traditional methods provide for the use of parametric distributions as Weibull, Exponential, Normal, Log-Normal, Exponential Negative, among others [24].

Modern methods can be classified as semi-parametric and nonparametric. As for the semi-parametric methods a sub-difference is made, this differentiates those models used to study variables that fulfill the proportionality assumption of Cox, such as Proportional Hazards Model (PHM), from those methods that violate this assumption [11, 12, 18]; in the latter category we can mention 3 important models: Extended Cox method, the Stratified Method of Cox and Accelerated Method of Failure [7,26].

In 1972, the English statistician David Roxbee Cox developed one of his greatest contributions to the field of survival analysis with his called Cox Regression. In the beginning, the Cox Regression was developed as a contribution to the field of medicine, to study whether the actions of treatments influence extend the life of a patient, observing the symptoms and possible health improvements [23, 27]. Today, this model is applicable in a variety of fields of knowledge, including the analysis of failure times of components from various systems [25].

The proportional hazards model of Cox considered a constant failure rate λ_0 (*t*) which does not assume parametric distribution and depends only on time. On the other hand, it has a parametric part Φ (z, β), which is independent of time and incorporates the effect of other variables that may affect component failure. Here is the vector z as variables and β as column vectors associated with the system; this contains regression parameters that define the effect of the variables on the failure rate [12, 13].

Finally, we can observe that the effect of exogenous variables has a multiplicative effect on the failure rate base, both to increase (in the case of decreasing the maintenance) or to decrease (with the addition of a new component to the system) compared to the base rate. The assumption shows the multiplier effect of the variables on the base rate risk, it implies that the ratio of any two elements Z_1 and Z_2 it respectively, will be constant over time and proportional to each other, hence the name Proportional Hazards Models [12, 19, 20].

As an alternative to the above explained proportionality, the Extended Model of Cox was born from the desire to analyze components using time dependent and independent factors simultaneously. The Stratified Cox model proposes the existence of proportionality, but at certain periods over all *t*. Finally, the Accelerated Method of Failures seeks to adjust the curve of a component failure, accelerating the time that its failure occurs [3, 5, 6, 7].

Easing further data required to determine the behavior of the failure rate, the Non-parameterized Models appear, which need no known distributions or parameters for its calculations, being the most well-known model, the Kaplan-Meier Method [10, 26].

This method has a greater flexibility compared to the above mentioned, however, while presenting fewer known data, it becomes a much more complex and greater uncertainty, especially for data with censure per interval [10].

C. *Previous calculations*

The application of semi-parameterized methods involves running some previous estimates. In summary these are: selection of variables for survival analysis, hypothesis test for the chosen variables, where test overall and individual significance of the model is made, calculating the β vector and finally, determining the behavior of the failure rate [10, 23].

The behavior of the failure rate was initially described by calculating the base failure rate. Which it corresponds to the value of the failure rate when the effect of all covariates is null, in other words, it happens when the exogenous variables have no influence on the pattern of failure. For the calculation, there are two ways to model the base failure rate. The first, is to assume the form of any of the above mentioned probability distributions in the classical methods. However, most times the form of distribution is not known and there is where it proposes a second method of calculation, precisely Modern semi-parameterized methods. To do this, the estimation of β vector must be known [10, 11, 12, 13].

It is here, where the general assumptions of the models that consider the effect of the variables on the failure rate are developed. How to check these assumptions, is based on graphical analysis of Martingale Residuals, Deviance Residuals, Score Residuals and Residuals of Schoenfeld. And finally, the variant of each of the models against the overall failure rate [18, 19, 20].

Once the characteristics of traditional and modern methods are analyzed, it has been considered that the semi-parametric and non-parametric methods are best dimensioned to solve the problem in analysis, because they have the ability to incorporate time independent variables to the model failure rate.

IV. PROPOSED METHODOLOGY

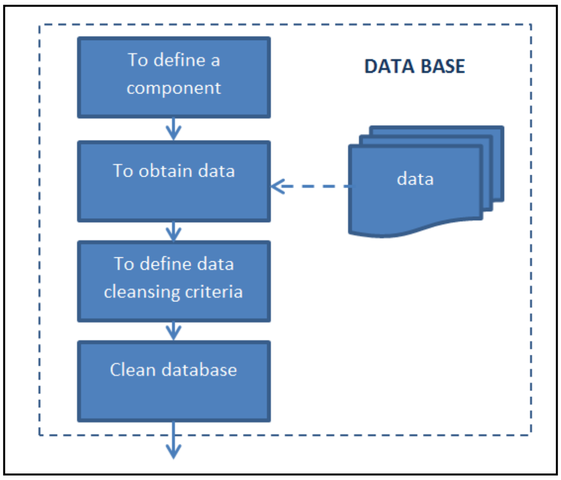
This methodology is proposed in order to develop a model that faithfully represents the failure rate of a component and therefore, it performs a correct estimation of reliability curves. The methodology is divided into 5 stages: 1. Database, 2. Analysis of Variables, 3. Model Estimation, 4. Residual Analysis, and 5. Conclusions and Recommendations.

A. *Database*

The flow of suggested elements for the proper management of databases containing historical time and operational conditions information is presented below (Fig.1).

a) *Step1. Define components*: Once the system has been chosen to be analyzed, we must define the component to be studied. Based on this choice, the study of the rate of failure and reliability analysis will be performed.

Fig. 1. Stage 1: Data base flow process.



b) *Step 2. Data collection:* Once it is defined the component to be studied, we proceed to the data request. These must be requested from experts in the field or the selected component suppliers. Generally, these data will be historical and it is not always complete, as they are records made by employees in the area and therefore, they are subject to human error.

c) *Step 3. Defining Cleaning Criteria*: Because in most cases the data will not be complete, data must be analyzed and a cleanup criteria must be defined, such as elimination of incomplete data.

d) *Step 4. Clean Database:* Once defined cleaning criteria, we proceed to implement this, either manually or automated by a specialized software.

B. *Analysis of variables*

Using the already collected, defined, and error-free database, the variables to study must be analyzed. To do this, the following decision flow has been defined (Fig.2).

a) *Step 5. Determine variables in the model:* Once the database is clean, the analysis of the variables that influence the failure rate of the component must be done. For this, the data are analyzed and variables must be observed and measured for its analysis of influence.

b) *Step 6. Global Docimo*: Using the data variables, the Global Docimo is analyzed, where it has the Null hypothesis H_0: All Betas of the variables are equal to 0, and the Alternative Hypothesis H_a: there is at least one Beta other than 0, so at least one variable represents the model.

Fig. 2. Stage 2: Variable analysis process.

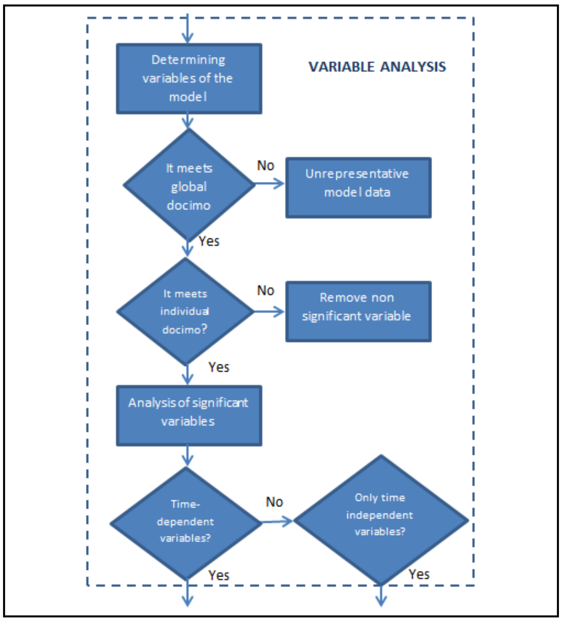
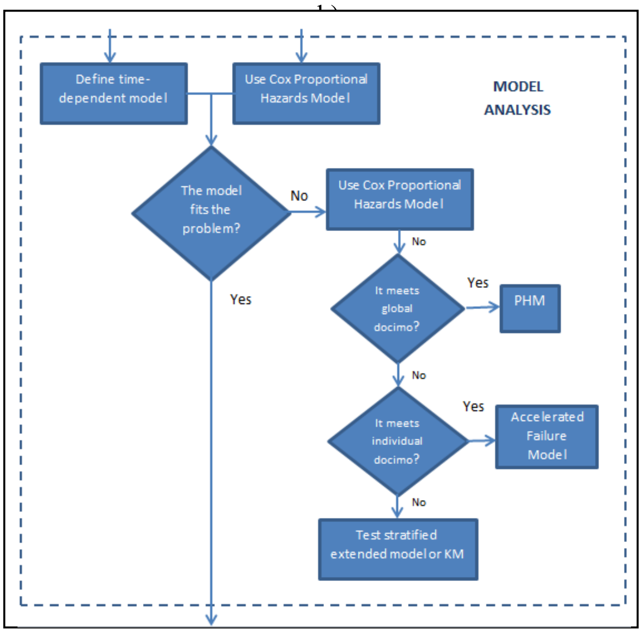


Fig. 3. Stage 3: Model analysis process.



It is advisable, to assess Docimo per value P. If Docimo value is Not Significant, H_0 is rejected and H_a accepted, therefore we must make a new data collection and proceeding with the exposed methodology.

c) *Step 7. Individual Docimo*: If in the Global Docimo there is at least one significant variable representing the model, so that should analyze the variables one by one through the Single Docimo. Where we have H_0: The Beta of the variable under study is 0,and H_a: The Beta of the variable under study is different from 0. It is possible to observe their significance through the P value.

d) *Step 8. Dependence of the Variables*: Once we already have discriminated the variables representing the model, we proceed to an analysis of them, which is important to characterize whether they are time-dependent or not. This is based on expert judgment in the area. With this in mind, we proceed to define the model to be used.

C. Model Estimation

Once defined the variables involved in the model and its data collected, we proceed to analyze the best model that represents the component failure rate, later to calculate their reliability. It is therefore recommended to follow the following decisions flow (Figure 3).

a) *Step 9. Types of Models*: If all the already defined variables are time independent, we recommend using the Cox Proportional Hazards Method (PHM). Otherwise, if the variables are time-dependent, it must be analyzed using the Stratified Model of Cox, Extended of Cox or Accelerated Failure Model.

t) *Step 10. Model Adjustment*: Once the model is defined, we must assess if it fits with the problem to be solved, otherwise it is recommended to use a graph of survival curves. This analysis allows us to decide whether to use PHM or Accelerated Model of Failure, depending if these curves are parallel horizontal or vertical, respectively. If none of them complies, an analysis of the other 3 models is recommended.

D. Residual analysis

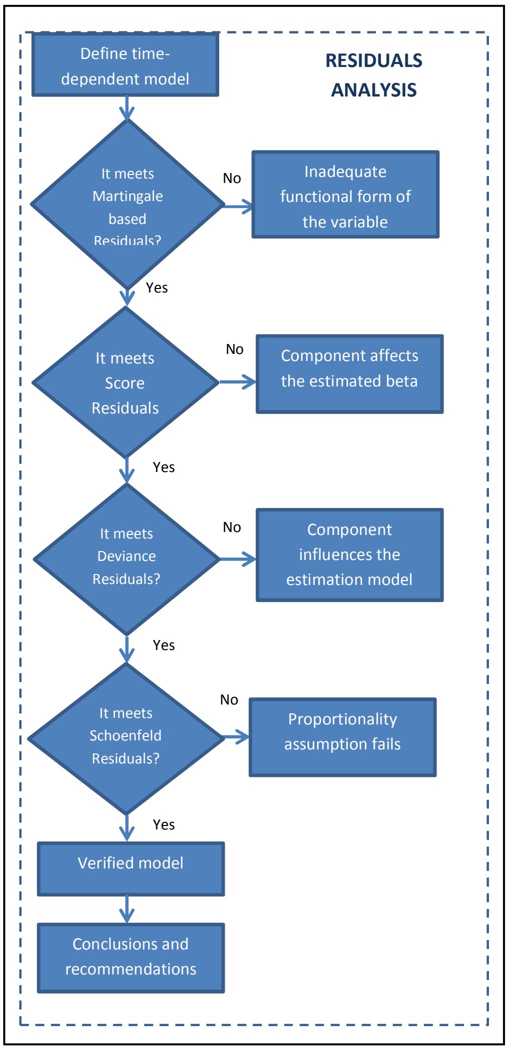
Once we have selected the best model that represents the problem under study, we proceed to analyze and test their assumptions by studying the Residual Graphs. For this we recommend the following sequence (Fig.4).

a) Step 11. Analysis of Residual Graphs: In this stage, we must examine four graphs, which are:

1.Martingala Residual Analysis: The analysis of the graph of Martingale allows us to define if the functional form of the variables is correct. The question is whether the data is formed around a straight line, or assimilated to it, and if so the assumption is true.

2. Deviance Residual Analysis: In a Deviance Residuals graph, we examine whether the current model deviates from the ideal or theoretical model, in this graph

Fig. 4. Stage 4: Residuals Analysis process.



we expect a trend close to 0 to the axis. If the graph fulfills this, it means that the component under study is affecting on the estimation model

3. Score Residual Analysis: The Score graph is to determine if the component under study influences on the estimation of each β, so we should analyze a graph for each variable. To determine this, we must observe the existence of extreme values on the y axis.

4. Schoenfeld Residual Analysis: The graph of Schoenfeld seeks to verify the proportionality of the failure. This assumption will not be fulfill for those time-dependent variables, however, in the case of stratified model, it fulfills by segments. In this graph it should be noted that there is no trend in the data, conforming randomly above and below the axis.

b) Step 12. Confirm the model: Once the assumptions have been accomplished, it is possible to say that the model is confirmed.

E. Conclusions and Recommendations

Once we have done the above steps, it is possible to obtain the best model that represents the component failure rate. With this model is now possible to construct the reliability curve and reach the necessary conclusions.

V. CASE STUDY

To test the methodology outlined above, we proceed with the development of an example case, based on the study of the reliability behavior of an electric motor of a mining truck, operating in a Copper Mine in the north of Chile. The R software was used, to obtain the parameters and the development of Residuals graphs [16, 17, 24].

A. Database

To start, we have a table that records the following information (Table I):

- Censorship: Type I censorship data are presented, in which the components are observed until a certain time. In this case, it has the value 1 for those censored data from the right, recalling that this data corresponds to those where at time of observation, it has not failure presented yet. And the value 0 for data that have presented a failure at the time of observation.
- Time: Displays the time of inspection, measured in hours.
- Consumption: Represents the energy consumption of the component until the inspection period; measured in fuel liters.
- Load: Represents the load carried by the component, measured in kilograms.

Following the methodology, it should be made a criterion for cleaning and then run the analysis. However, the database prepared for this case study has all accurate data and cleaning is not needed to be applied.

Now, we proceed to an initial analysis of the variables. It should be observed for those variables in the database and define whether they are time-dependent or not. In this particular case, we have that both energy consumption, and the load are independent of time. To load the data and start the analysis, we continue with the use of the R software.

B. Analysis of variables

Once we have the data in Table I it is possible to develop a graph that shows the behavior of the survival curve at different times, with their respective upper and lower limits. The existence of censored data means that the survival function cannot be taken probable, therefore, it should be considered using some estimates, being the most used the Kaplan Meier model.

In survival analysis, we tend to a climbing and descending curve, with upper and lower ranges covering uncertainty. It should be recalled that the analysis of survival at a given time depends on the survival in all prior periods, however, the possibility of it, over a period of time, is independent of the probability of survival in other periods.

So it is possible to generate a table of survival curves, and it is possible to develop a comparative analysis between a model with or without the Energy consumption and Load variables respectively.

For this analysis, the software reports a result for $p \lll 0.05$ value, so the null hypothesis of equality of the survival functions is rejected (considering a significance level of 5%), thus concluding the energy consumption should be included in the model.

The same analysis of the load variable gives as a result the value $p \lll 0.05$ per 1, in this way we can confirm that the Null Hypothesis is rejected, that is to say, the idea that both survival functions are the same is rejected, considering a level of trust of 5%. So concluding, that we should consider incorporating the loader variable.

TABLE I. CASE STUDY DATA

Censoring	Time	Energy cons.	Load
1	552	1659	133
0	786	945	111
1	685	633	92
1	581	1015	55
1	575	654	157
1	761	1244	144
1	691	1101	119
0	675	1577	96
0	745	1256	157
1	675	1300	62
0	547	1377	143
1	617	1658	131
0	670	1465	54
1	592	1043	116
0	797	783	126
1	582	842	166
1	559	1391	114
1	533	1302	118
1	502	1001	103
0	624	528	86
0	791	1538	157
1	667	1574	88
0	765	577	157
1	530	1057	95
0	585	1344	84
1	562	1688	156
0	617	684	139
1	650	1677	57

C. *Model Estimation*

Once clear survival analysis and having confirmed that both energy consumption and load are part of the model as independent variables of time, one proceeds to perform the calculation model.

Now, knowing that the options discussed depend on the characteristics of that variables, specifically on the dependence on them to time, we proceed to use the proportional hazards model of Cox, better known as PHM, since this is used for a model having only independent variables of time.

There are three hypothesis tests to verify the significance of the model, these are asymptotically equivalent, these are: Likelihood Ratio Test, the Test of Wald, and the Test of Scores.

In this case the R software determined as significant the three test: (*T est > p value*). Thanks to this, we can conclude that the model is significant. Then, a graph of the Cox model is generated, represented by the solid line and the Kaplan Meier estimator represented by the dashed line in Fig 5. It is possible to observe that the Cox model is above the Kaplan Meier estimator. This means that it is closer to reality model, thus better.

D. *Residual analysis*

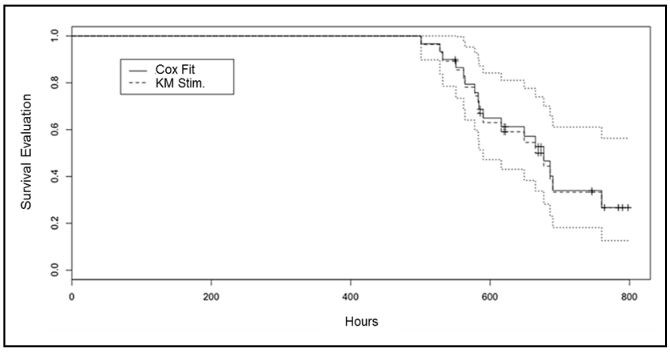
Once proving that the proportional hazards model of Cox fits better to the problem, than the Kaplan Meier estimator, we proceed to a more detailed analysis of the former, through a study of its overall significance, though it may seem redundant, along with an analysis of Residuals. The results show that in the overall analysis, the model is significant and a more detailed analysis of the co-variables graphs of their betas are generated.

Through the graphs of Schoenfeld it is possible to check the proportionality of the variables. These, being independent of time, should be kept constant as time passes.

To generate Schoenfeld curves, betas curves behavior over time, both the energy consumption and load are plotted. Noting the graphs developed, we can see that there is a trend in the behavior of the betas of the variables over time, and formed randomly around the 0-axis. Thanks to this, it can be concluded that the proportionality holds for both co-variables.

For the analysis of Deviation Residuals, it should be analyzed that there are influential values on the estimation of the model and this is done through the graph of Deviation Residuals versus the component. The objective here it is to determine the absence of influence of the component of the model estimation. To this, it should be noted the graph and confirm that the data randomly conform closer to 0 to the *y* axis.

Fig. 5. Stage 4: Residuals Analysis process.



Once verified the assumptions of proportionality and influence on the estimation component model, we proceed to analyze the residues of rate or Score. This analysis seeks to determine the lack of influence of the component on the estimation of each of the respective betas to each variable. To determine this, it should be noted that there are extreme values in the graph. Through the developed graphics it is possible to conclude that the assumption is true and there is no influence of the component on the estimated betas.

Finally, we proceed to the analysis of residues of Martingale. This graph allows to confirm that the way we have considered the behavior of the variables was correct. Thanks to graphical analysis of Martingale, in this case we can see a linear trend, although its linearity is not perfect, it does exist and therefore the assumption meets.

E. Case study conclusions

The study of factors that affect the behavior of the rate of failure of a component has been made, specifically the variables of energy consumption and load. Thanks to the database obtained it has been observed the existence of right-censored data and others that are not censored. Moreover, through R program used for the calculation model, the survival curves are developed affirming its downward trend over time. Then, we analyzed a graph of survival variables energy consumption and load independently, by means of which it has been concluded that the PHM model is better than the Kaplan Meier estimator, therefore the mentioned variables are considered important for the model, as both variables are independent of time. Similarly, analysis of the Likelihood Test, Test of Walds and Test of Score are developed, through which it is found that the model obtained is significant and therefore is a solution to the presented problem. These tests are delivered by the R program, to request details of the exponents.

Once confirmed that the model to be used is the Cox proportional hazards, we proceed to checking the four assumptions proposed in studies, by analysis of 4 residuals, along with their respective conclusion:

- Schoenfeld Residual Analysis: Meets proportionality assumption.
- Deviation Residual Analysis: There is no influence on the estimation of the component model.
- Score Residual Analysis: No component influence on the estimation of betas model.
- Martingala Residual Analysis: The shape of the variables is correct.

It is thanks to all the above, that the methodology presented is checked in this study, where a sequence is proposed to determine the effect that variables have on the failure rate of a component. Similarly, through the case example presented is achieved confirms its operation.

VI. General Conclusions

From the beginning, it has been observed the importance that has for companies, to make a correct plan of preventive and corrective maintenance, which it should be based on the behavior of the failure rate associated with items. But nowadays, many of the companies base their maintenance plans solely on the recommendations given by the manufacturers, generating enough economic losses to the organization, because such planning does not consider the particularity of different operational conditions.

For the analysis of the failure rate, regarding traditional methods, it is concluded that they are a good approximation, but it is not recommended to use them for detailed analysis, because they are far from the real rate of failure. Semi-parametric models are quite useful for the calculation of failure rates that aim to consider the effect that various factors that influence in it. However, for a correct estimation of the failure rate, we should have some considerations:

- Selecting Variables: variable selection is key in determining a good model, if we want to use semi-parametric models, because to exclude a significant variable can generate bias, turning significant a variable that is not really.

- Data Collection: As stated in the selection of variables, data collection is primordial. Having a strong database with as many variables that may affect the failure rate, able to generate a better approximation. But while the database is complete, the existence of censored data will be a reality, so the survival analysis using the Kaplan Meier estimator is a good way to analyze the behavior of the component in time.

Once the variables are defined and their data characterized according to the type of censorship the data possess, the dependence which have over time is determined. Then it is possible to determine which is the most appropriate method to use for modeling rate failure. In general, the recommendation is the following:

- Proportional Hazards Model (PHM) is recommended if all variables are independent of time.
- Stratified Model of Cox: It is recommended when there are time dependent variables, however, seen that the proportionality of the variables changes slowly.
- Extended Cox Model: Its use is recommended when we want to analyze simultaneously dependent and independent variables of time.
- Model Accelerated Failure: Its use is recommended when we have knowledge that the variable speeds up or slows significantly the failure rate. It is possible to observe through the graph of survival curves, noting that parallels horizontally.

After defining the model to use, we must proceed to confirm the significance of the model. A simple and reliable way to check the model is through the Likelihood Test, Test of Wald and Test Scores, simultaneously. Finally, we proceed to conclude about the assumptions of the Cox model, independent of the extensions used. The recommended way to do this, it is through the analysis of Residuals graphs.

Thus, it is possible to generate a methodology for studying the effect it can have any variable on the failure rate of a component and therefore on its reliability. The methodology developed here allows determining the correct functioning of the failure rate, considering the main influential factors.

In the case study the 5 stages newly exposed are exposed, with the help R. Program. Finally, the methodology is proposed as a general method for calculating the rate of failure of a component, specifically for the study of energy consumption as an important factor for the calculation of failure rate. The main recommendations proposed after the development of this study are:

- Study nonparametric alternatives for calculating the failure rate. While Semi-parametric methods are the most advisable by the balance between complexity and efficiency of their estimates, nonparametric methods have less requirements, making them more flexible, but are far more complex to calculate.
- It is proposed to study in more detail the Accelerated Failure Model, since it can be a real alternative in case of having knowledge of the behavior of certain components.
- It is recommended to delve into alternatives for selection of variables. It is known that Docimo Global and Docimas Single are a good option, but there are other tests that could become more specific.
- It is recommended to seek alternative math methods to the confirmation of the assumptions of the Cox model. It has chosen the option graph of Residuals as it is fast more reliable alternative, however the mathematical option will always be more accurate but slower.

REFERENCES

[1] B. Dhillon, S. Balbir, Maintainability, maintenance, and reliability for engineers, CRC Press, 2006.

[2] M. López-Campos, A. Crespo Márquez, J. Gómez Fernández, "Modelling using UML and BPMN the integration of open reliability, maintenance and condition monitoring management systems: an application in an electric transformer system", Computers in Industry 2013; 64, pp. 524-542. (ISSN: 0166-3615).

[3] K. Dhananjay, and B. Klefsjö, "Proportional hazards model: a review." Reliability Engineering & System Safety 44.2, 1994, pp. 177-188.

[4] A. Montesinos López, Análisis estadístico de datos de vida. Tesis Universidad Autónoma de Chapingo. Estado de México, 2009.

[5] B. Abbas, J. Barabady, and T. Markeset, "Maintainability analysis considering time-dependent and time-independent covariates." Reliability Engineering & System Safety 96.1, 2011, pp. 210-217.

[6] C. Huber, M. Nikulin, Extended Cox an Accelerated Models in Reliability, with General Censoring and Truncation en Statistical Models and Methods for Biomedical and Technical Systems, Editors: Filia Vonta, Mikhail Nikulin, Nikolaos Limnios, Catherine Huber-Carol ISBN: 978-0-8176-4464-2 (Print) 978-0-8176-4619-6 2006, (Online)

[7] Zhao, Yichuan. "Empirical likelihood inference for the accelerated failure time model", Statistics & Probability Letters 81.5 (2011), pp. 603-610.

[8] A. López Montoya Antonio, Comparación de dos modelos de regresión en fiabilidad, Tesis Universidad de Granada, España, 2011.

[9] Manual IBM SPSS Advanced Statistics 22. En ftp://public.dhe.ibm.com/software/analytics/spss/documentation/statistics/22.0/es/client/Manuals/IBM_SPSS_Advanced_Statistics.pdf

[10] Y. Ming-Yi, L. Lin, M. Guang, N. Jun, "Two-Zone proportional hazard model for equipment remaining useful life prediction", Journal of manufacturing science and engineering, ISSN 1087-1357 Source / Source 2010, vol. 132, no4, [Note(s): 041008.1-041008.6]

[11] D. Lin, D. Banjevic and A. K. S. Jardine, "Using principal components in a proportional hazards model with applications in condition-based maintenance". The Journal of the Operational Research Society. Vol. 57, No. 8, Aug., 2006, pp. 910-919.

[12] J. Fox, "Cox proportional-hazards regression for survival data", An R and S-PLUS companion to applied regression, 2002, pp. 1-18.

[13] D.R Cox, "Regression models and life-tables", Journal of the Royal Statistical Societ,. Series B (Methodological), Vol. 34, No. 2, 1972.

[14] M. Febrero, P. Galeano, J. González, B. Pateiro, Prácticas de Estadística en R. Universidad de Santiago de Compostela, 2008.

[15] J. Urquiza, Apoyo Asignatura de Econometría I, 2012, unpublished.

[16] D. Diez, Survival analysis in R, 2008, en http://anson.ucdavis.edu/~hiwang/teaching/10fall/R_tutorial%201.pdf

[17] R. Borges Peña, Análisis de sobrevivencia utilizando el lenguaje R, 2005, unpublished.

[18] A. Antoniadis, P. Fryzlewicz, F. Letué, "The Dantzig Selector in Cox 's Proportional Hazards Model", Scandinavian Journal of Statics 37(4), 2009, pp.531-552.

[19] M. Sarnrout, E. Chátelet, R. Kouta, N. Chebbo, "Optimization of maintenance policy using the proportional hazard model", Reliability Engineering and System Safety 94(1), 2009, pp. 44-52.

[20] B. Kash, H. Baround, “Proportional hazards models of infrastructure system recovery”, Reliability Engineering & System Safety 124, 1014, pp. 201-206.

[21] Zhigang Tian, Haitao Liao, “Condition based maintenance optimization for multi-componente systems using proportional hazards model”, Reliability Engineering & System Safety 96(5), 1011, pp. 581-589.

[22] Q. Zhang, C. Hua, G. Xu , “A mixture Weibull proportional hazard model for mechanical system failure prediction utilising lifetime and monitoring data”, Mechanical Systems and Signal Processing, 2014, DOI: 10.1016/j.ymssp.2013.10.013

[23] K.A.H. Kobbacy, B.B. Fawzi and D.F. Percy, “A full history proportional hazards model for preventive maintenance scheduling”, Quality and Reliability Engineering International 13, 1997, pp. 187-198.

[24] A.M. Hernández, Análisis Estadístico de Datos de Tiempo de Fallo en R, Tesis Universidad de Granada. España, 2010.

[25] M. Ayala, R. Boges y G. Colmenares, Verificación de los supuestos de Cox. Caso de estudio: Banca Comercial venezolana 1996-2004, 2007.

[26] K. Devarajan, N. Ebrahimi, “A Semi-parametric generalization of the Cox proportional hazards regression model: Inference and applications”, Journal of Computational Statistics & Data Analysis, Volume 55 Issue 1, January, pp.667-676, 2011.

[27] P. Rebasa, Conceptos Básicos del análisis de supervivencia. AE Cirujanos 2006 en http://www.aecirujanos.es/revisiones_cirugia/2005/Octubre2_2005.pdf

[28] H. Li, Z. Zhang, X. Li, X. Y. Ren, “Reliability prediction method based on state space model for rolling element bearing”. Journal of Shanghai Jiaotong University (Science), 20(3), 317-321, 2015.

Safety and Reliability of Complex Engineered Systems – Podofillini et al. (Eds)
© 2015 Taylor & Francis Group, London, ISBN 978-1-138-02879-1

RAM-C: A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations

F. Kristjanpoller & P. Viveros
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile
Department of Industrial Management, School of Engineering, University of Seville, Seville, Spain

A. Crespo
Department of Industrial Management, School of Engineering, University of Seville, Seville, Spain

T. Grubessich & R. Stegmaier
Department of Industrial Engineering, Universidad Técnica Federico Santa María, Valparaiso, Chile

ABSTRACT: Today, the critical analysis is the main challenge to identify the opportunities for an improvement process of asset management. One of the most important points is to know what is the effect of each element over the system that contains it, mainly when the logical configuration are not in serial dependency. The impact of one element in complex configuration (total redundancy, partial redundancy, stand by or load sharing) must be defined as dynamic, because it depends of the element individual performance on reliability and maintainability, as well of the performance of all of the elements that are in the same subsystem.

The RAM-C methodology, develop the analysis based on a RBD configuration, and structuring the process analysis by levels, ascending for availability analysis (from the element to system) and descending for the impact analysis (from the system to the smallest element). Therefore, to complement the Critical analysis and the related tools, the authors have designed and applied a novel algorithm, enhancing the traditional RAM analysis interpretation.

Finally, a case study based on Chilean copper mining process, will be developed to demonstrate the application and strengthens of RAM-C methodology.

1 INTRODUCTION

Production processes have broad opportunities for improvement, by increasing their Reliability rates, Availability, and Maintainability (RAM) based on an analysis of Life Cycle Cost. (Parra 2009, Parra et al. 2012). The analysis of these opportunities emerges as a requirement for prioritizing and evaluating them. The criticality assessment methodologies stand for allowing this evaluation process, in a standardized and standardized manner (Moss & Woodhouse 1999), which is why its use has amassed over the years.

The first aspect to evaluate to start with a criticality analysis, focuses on reliability analysis, for which there are various techniques such as Markov chains (Welte 2009), Poisson (Heinrich 1991). In consideration of the study of system-level reliability, one of the techniques used is the Reliability Block Diagram—RBD (Gou & Yang 2007, Rausand & Hoyland 2003), which allows to develop an individual and systemic analysis considering the effect of each of the components in the system or production process (Viveros 2011), it also highlights: Fault tree Analysis (FTs) (Rauzy et al. 2007), Reliability Graphics (RGs) (Distefano & Puliafito 2009), Petri Nets (PNs) (Volovoi 2004).

Regarding criticality techniques, the US Department of Defense (1977) developed a document where description of the main techniques related to failure mode are found. For equipment or assets analyze, recently Crespo et al. (2015) developed an applied model for a criticality analysis of complex in-engineering assets. This paper describes an efficient and rational working process and a model resulting in a hierarchy of assets, based on risk analysis and cost–benefit principles, which will be ranked according to their importance for the business to meet specific goals.

The concept of complex logical configuration is related to productive process that contains many functions and some of them are composed by groups of elements (subsystems). The relationship between the elements grouped in subsystems, depends of the required capacity, the specific performance and capacity of the elements and the

Table 1. Comparison of criticality methodologies.

Methodology	Typology	Focus	Failure effect estimation	Flexibility
Failure tree	Qualitative	Individual	Failure analysis	High
US Department	Qualitative	Individual	Failure analysis	High
Crespo et al. proposal	Quantitative	Systemic	Expert criteria (1 to 5)	Medium
RAM-C	Quantitative	Systemic	Probabilistic impact analysis	High

redundancy level, so is impossible to stablish in a first analysis the impact of each element over the specific subsystem and the system. The determination of impact of the elements is a vital indicator to hierarchize the elements by a criticality analysis.

The Table 1 shows a comparative analysis, between the main criticality methodologies, with the proposal of RAM-C.

The productive processes in the mining industry have, as an additional complexity, a large amount of equipment and systems, which make the systematic analysis of the more difficult plant (Viveros et al. 2011). Because of this, different analysis methodologies have been developed, like for example the RBD methodology (Gou & Yang 2007, Rausand & Hoyland 2003), widely used in the mining sector for its adaptability of representation in complex arrangements and environments with large amounts of equipment, where they look to simplify the reliability analysis through the use of diagram blocks under systemic configurations mainly in serial and parallel.

2 PROBLEM STATEMENT

When considering a complex production process, the relationship between each of its component equipment is not linear, given the dependence and grouping into logical subsystems, defined according RBD configurations (Gou & Yang 2007, Rausand & Hoyland 2003). In this sense, these settings, especially those associated with redundant systems prevent direct criticality analysis, since it is not possible to determine the impact of a detention of a unit beforehand. In fact, if two units are considered in a standby configuration, the arrest of one of the units has no impact as long as the second unit is available for operation; if the second one is not available, the system stops and the original detention has a 100% effect on the system. On this basis the criticality assessment model that considers the frequency of failures associated with the reliability of the elements and their ability to be maintained, maintainability defined; and the expected impact according to different scenarios and configurations, they have about the complex system. On this basis the criticality assessment model is defined, which considers the frequency of failures, associated with the reliability of the elements and their ability to be maintained, maintainability; and the expected impact according to different scenarios and configurations, that have about the complex system.

This impact index will define the expected condition of the item on the system, from a perspective of evaluation of its various states and the elements of the same logical subsystem and share the same function. This allows the overall comparison of elements, their prioritization and criticality evaluation.

3 PROPOSITION FOR METHODOLOGY

The methodology considers the development of an evaluation process, "bottom—up" for calculating the indicators RAM from the lowest level element, to build indexes of the entire complex system under the use of the usage of logical relationships of RBD (Gou & Yang 2007, Rausand & Hoyland 2003). The second phase corresponds to the "up-bottom" process for the calculation of impacts and criticalities, starting from the system to reach the lower level element. Thus it is possible to know the "Critical Impact" that allows to find out the contribution of each element to the system and clear the "Real Impact" which describes how does it affect in expected terms the arrest of each element of the system, evaluating all scenarios and the likelihood of them for complex configurations.

3.1 *Phase 1: Bottom–up. RAM analysis from smallest element to complete system*

This phase takes place under the RBD methodology, considering the following functional relationships and expressions to calculate the reliability and availability.

According to (Dhillon 2006), availability corresponds to a proportion of time that could be expressed as a probability that the equipment is available as it is required. In this way, and assuming the equipment required must always be operated and that the orders are initiated immediately following a failure, it is possible to define expected availability of determined equipment, such as (Sundararajan 1991):

$$A_i = \frac{MTTF}{MTTF + MTTR} \tag{1}$$

Regarding the series configuration, based on the total dependence of the elements on the subsystem that brings them together, the subsystem analysis is performed as follows:

$$A_{serial} = \prod_{i=1}^{n} A_i \tag{2}$$

For a subsystem in a logical full redundancy configuration (parallel), characterized by the simultaneous operation of the elements of the subsystem and by the fact that each element can withstand 100% of the load required for the same, the following analysis will be used for a redundant no repairable system:

$$MTBF_{parellel} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} - \frac{1}{\lambda_1 + \lambda_2} \tag{3}$$

where λ_i represents the average failure rate of each of the equipment that participate in the system. Generalizing for a Weibull model, this is represented by:

$$\lambda_i = \frac{1}{\alpha * \Gamma\left(1 + \frac{1}{\beta}\right)} \tag{4}$$

$$MTTR_{parellel} = average\left(MTTR_i\right) \tag{5}$$

Finally,

$$A_{parallel} = \frac{MTBF_{parallel}}{MTBF_{parallel} + MTTR_{parallel}} \tag{6}$$

For a subsystem in a stand by configuration, a cold standby will be considered, that is to say, that at every moment only one unit operates and to the failure of it is replaced by the following item. With regard to the maintainability, both units are maintained simultaneously. In this case, it is used the following analysis:

$$MTBF_{standby} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} \tag{7}$$

$$MTTR_{standby} = minimum\left(MTTR_i\right) \tag{8}$$

Finally,

$$A_{standby} = \frac{MTBF_{standby}}{MTBF_{standby} + MTTR_{standby}} \tag{9}$$

The partial redundancy subsystem characterized by the ability to respond to load requirement at a fraction of the items available, but with the obligation to meet 100% of the request, the model to be used is an extension of the reliability model:

$$A_{partial} = \sum_{j=r}^{n} \binom{n}{j} A^j \left(1 - A\right)^{n-j} \tag{10}$$

where:
n: total number of elements.
r: minimum number of elements to meet the required load.

Regarding load sharing configuration, characterized by the possibility to operate within the required load, evaluating the loss caused, the ratio of capacities to determine the equivalent subsystem availability is used.

$$A_{loadsharing} = \sum_{i=1}^{n} \left(A_i * \frac{Q_i}{Q_T} \right) \tag{11}$$

where:
Q_i: capacity of the element *i*
Q_T: total capacity of the subsystem.

3.2 *Phase 2: Up–Bottom. Impact determination and criticism analysis from complete system to smallest element*

In this phase the relative impact of each element in the system is determined, through the decomposition the global index and each of the subsystems, these, at the same time, on the following levels:

$$Critical\ Impact\left(Crt.Imp\right)_{system\, i=0} = 1 \tag{12}$$

Then begins the breakdown for each level, with the following expressions:

$$Crt.Imp_{i;j} = \frac{\left(1 - A_{i;j}\right)}{\sum_{j=1}^{n}\left(1 - A_{i;j}\right)} * Crt.Imp_{i-1} \tag{13}$$

$$Crt.Imp_{i-1} = \sum_{j=1}^{n} Crt.Imp_{i;j}\ \ \forall i: 1, \ldots, r \tag{14}$$

where:
$Crt.Imp_{i;j}$: It is the critical impact for element *j* (from 1 to n) that is found in the decomposition level *i* (from 1 to *r*).

In simple terms, the Critical Impact shows the final result of the criticality of each element of the system. When considering the lower detail level, level r, the sum of all *Crt.Imp* is 100% of the system.

$$\sum_{j=1}^{n} Crt.Imp_{r;j} = 1 \tag{15}$$

Finally, known *Crt.Imp* of each item, you may break its level of criticality in two main aspects: frequency (through the unavailability of the element) and consequence (through the impact of the element). The latter index will be called by Real Impact (*Real.Imp*) and in expected terms represent the effect that causes a stop element $i; j$ on the system. As the effect of stopping an element i noted above, j can have different results, depending on the state of the elements that are at the same level i.

$$Real.Imp_{i;j} = \frac{Crt.Imp_{i;j} * 1 - A_{system)}}{(1 - A_{i;j})} \tag{16}$$

4 CASE STUDY

The mine site is located in far north Chile and it has an annual production of about 1,200,000 metric tons of copper. The applied case study developed in the concentrator plant. This material has a law that exceeds 1.25% copper, moving up more than one million metric tons of material composed of mineral and ballast in a 3: 1. This last aspect that is relevant to understanding the importance of studying the truck system that does this job. The site is located at an altitude of over 3,000 meters above sea level. The productive process is composed by two sub process: SAG Milling and Ball Milling.

Four feeders can be appreciated at the entrance of the milling plant SAG/Balls. Only two of them are needed for the correct functioning of the system, therefore, partial redundancy configuration (4:2) is applied in this case; configuration implies that the system of nourishment does not operate with less than 2 available elements. Later, the mill SAG the Mill SAG (MOL001), have a conveyor belt of nourishment, properly such in configuration Series. This implies that the detention of anyone of either elements or both simultaneously generates a detention of the Plant.

At the exit of the Mill SAG there exist two Sieves, which fulfill the function to classify, in accordance to the size, the tried material to be re-circulated or for the nourishment of the second process of Milling (Balls). In this particular case, one sieve produces and the other remains in reserve, in case of detentions of the principal element, applying in this case the Stand By configuration. Downstream in the process two bombs (BM001 and BM002) can be appreciated. One of them it is operating and the other remaining in reserve, therefore in this case Stand By configuration it is applied, sequentially Hydrocyclone 1 (HID 001) can be found in configuration Series.

The section of Ball milling consists of two independent lines. Every line has a Ball Mill like a constituent element, two bombs in Stand By configuration and a Hydrocyclone in series. It is supposed in this case that each of the lines has an

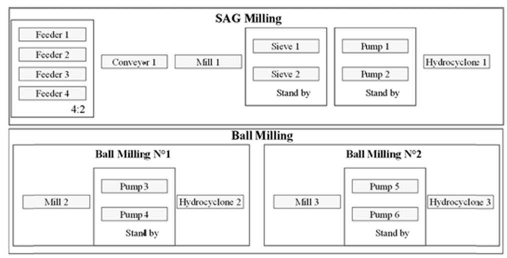


Figure 1. Logical functional diagram of the plant.

Table 2. Equipment data.

Equipment	MTTF	MTTR
0. Milling system		
1;1 Milling SAG		
2.1;1 Conveyor belt 1	585,2	8,4
2.1;2 Feeding		
2.1.2;1 Feeder 1	346,7	12,4
2.1.2;2 Feeder 2	560,7	18,3
2.1.2;3 Feeder 3	474,2	14,5
2.1.2;4 Feeder 4	439,8	18,2
2.1;3 Mill 1	385,9	9,3
2.1;4 Hydrocyclone 1	1.980,3	8,3
2.1;5 Sieves		
2.1.5;1 Sieve 1	852,3	7,4
2.1.5;2 Sieve 2	642,3	5,8
2.1;6 SAG pumps		
2.1.6;1 Pump 1	608,9	12,4
2.1.6;2 Pump 2	542,4	14,6
1;2 Ball milling		
2.2;1 Ball mill N°1		
2.2.1;1 Mill 2	462,7	8,3
2.2.1;2 Ball pumps 3 y 4		
2.2.1.2;1 Pump 3	693,6	13,3
2.2.1.2;2 Pump 4	585,1	12,8
2.2.1;3 Hydrocyclone 2	2.274,2	6,9
2.2;2 Ball mill N°2		
2.2.2;1 Mill 3	438,9	9,7
2.2.2;2 Ball pumps 5 and 6		
2.2.2.2;1 Pump 5	651,9	12,8
2.2.2.2;2 Pump 6	672,6	12,3
2.2.2;3 Hydrocyclone 3	2.023,8	7,2

Table 3. Phase 1: Availability analysis.

Equipment	5° level avail.	4° level avail.	3° level avail.	2° level avail.	1° level avail.
Milling syst.					91,42%
Milling SAG			94,46%	94,46%	
Conv. belt 1	98,58%	98,58%			
Feeding		99,99%			
Feeder 1	96,55%				
Feeder 2	96,84%				
Feeder 3	97,03%				
Feeder 4	96,03%				
Mill 1	97,65%	97,65%			
Hydro. 1	99,58%	99,58%			
Sieves		99,61%			
Sieve 1	99,14%				
Sieve 2	99,11%				
SAG pumps		98,93%			
Pump 1	98,00%				
Pump 2	97,38%				
Ball milling				96,78%	
Ball mill N°1			96,97%		
Mill 2	98,24%	98,24%			
B. pumps 3–4		99,01%			
Pump 3	98,12%				
Pump 4	97,86%				
Hydro. 2	99,70%	99,70%			
Ball mill N°2			96,59%		
Mill 3	97,84%	97,84%			
B. pumps 5–6		99,08%			
Pump 5	98,07%				
Pump 6	98,20%				
Hydro. 3	99,65%	99,65%			

impact of 50% in the process availability. Therefore, in the section top level it is applied breaking down configuration with a 50% of impact associated with every line.

Naturally, in order that the plant can be available, the systems of Milling SAG and Balls must be also prepared. Therefore, in the top level a configuration Series can be found between both systems.

It is important to remember that the functional logician configuration delivers relevant information of the possible critical element and can be considered an approach in the determination of these. About this it is expected that the critical equipment are those that do not have built-in redundancy (Series), nevertheless this analysis is incomplete if there are not born in mind the detentions carried out in the analyzed equipment, which definitively delivers the availability levels in every stage of the process, allowing to identify the elements that generate major fault costs.

To begin the process of analysis, MTTF and MTTR values are obtained for each of the grinding system units.

Then through the RBD methodology, the availability analysis Phase 1; Bottom-up, was constructed. Given the system architecture, 5 levels are constructed, corresponding to level 5 units and level 1 system.

Subsequently develops Phase 2: Up—bottom, to calculate the Critical Impact of each subsystem and equipment (Table 4), which represents the criticality analysis. Additionally, Real Impact estimation is performed for each element (Table 5), which added to the effect of unavailability builds the criticality chart completely.

Analyzing the Impact Critical information, it is possible to establish that the most critical equipment is the Mill 1, followed by the Conveyor Belt 1, the Mill 3 and Mill 2. It is important to note that between these 4 units, explain more than 64% criticality of the system, expressed through loss of production.

Commonly and erroneously, criticality analysis is performed only based on the assessment of the unavailability of each element due to the implementation of a RBD analysis. For example, the

Table 4. Phase 2: Critical Impact determination.

Equipment	1° Level *Crt.Imp*	2° Level *Crt.Imp*	3° Level *Crt.Imp*	4° Level *Crt.Imp*	5° Level *Crt.Imp*
Milling syst.	100,00%				
Milling SAG		63,26%	63,26%		
Conv. belt 1				15,85%	15,85%
Feeding				0,17%	
Feeder 1					0,04%
Feeder 2					0,04%
Feeder 3					0,04%
Feeder 4					0,05%
Mill 1				26,33%	26,33%
Hydro. 1				4,67%	4,67%
Sieves				4,32%	
Sieve 1					2,12%
Sieve 2					2,20%
SAG pumps				11,92%	
Pump 1					5,15%
Pump 2					6,77%
Ball milling		36,74%			
Ball mill N°1			17,30%		
Mill 2				9,97%	9,97%
B. pumps 3–4				5,61%	
Pump 3					2,62%
Pump 4					2,99%
Hydro. 2				1,71%	1,71%
Ball mill N°2			19,44%		
Mill 3				12,23%	12,23%
B. pumps 5–6				5,21%	
Pump 5					2,69%
Pump 6					2,51%
Hydro. 3				2,01%	2,01%

Table 5. Phase 2: Real Impact determination.

Equipment	*Real.Imp*
Conv. belt 1	95,99%
Feeder 1	0,11%
Feeder 2	0,11%
Feeder 3	0,11%
Feeder 4	0,11%
Mill 1	95,99%
Hydro. 1	95,99%
Sieve 1	21,14%
Sieve 2	21,14%
Pump 1	22,15%
Pump 2	22,15%
Mill 2	48,57%
Pump 3	11,97%
Pump 4	11,97%
Hydro. 2	48,57%
Mill 3	48,54%
Pump 5	12,00%
Pump 6	12,00%
Hydro. 3	48,54%

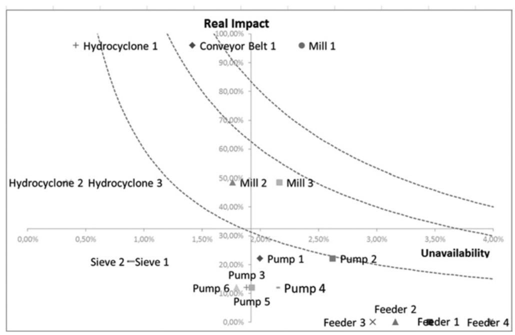


Figure 2. RAM-C plotter graph.

availability of Mill 1 (97.65%) is in the same range as the Pump 2 (97.38%) and the Pump 4 (97.86%). Certainly the situation of the three elements is very different. The Mill 1 is a single unit, a process that owns 100% of the required load, whereas the Pump 2 is in a standby configuration with Pump 1, processing 100% of the required load.

While Pump 4 also is in a standby configuration along with Pump 3, process only 50% of the load required by the line Ball Milling 1. These considerations are clearly reflected in the Critical Impact, since the index of Mill 1 (26.33%) is much higher than the Pump 2 (6.77%) which in turn is higher than the Pump 4 (2.99%). This relationship is explained by the Real Impact, which estimates the effect of the arrest of an item on the system, considering the configuration they have. Indeed, in this case. Real Impact is 95.99% for Mill1; 22.15% for Pump 2 and 11.97% for Pump 4.

The concept of Critical Impact Index is possible to understand more directly considering that it is the result of the unavailability and Real Impact of an item. This can be seen by the construction of a scatter plot.

With this graph it is confirmed clearly and precisely the four highest criticalities (Mill1, Conveyor Belt 1 Mill 3 and Mill 2). Likewise you can see the effect of the Real Impact on Mill 1, Pump 2, and Pump 4 who are located in a similar horizontal position (unavailability) but different vertical position (Real Impact), which explains its different critical level.

5 CONCLUSIONS

Throughout this paper a new methodology has been presented, for determining the criticality of components by calculating the Critical Impact and the Real Impact. This methodology has a great strength in its application because it allows comparing elements found in different logical configurations, assessing the characteristics and properties of each subsystem. The method presented can be applied in many engineering problems, industrial realities and productive sectors, resulting from its application a powerful tool for analysis and decision making for the various phases of an industrial project through Life Cycle Cost—LCC, from design oriented operation CAPEX to OPEX associated with, and process improvement thereof.

To understand the strength of the methodology, it is essential to compare their results with those obtained with more qualitative techniques, as described in the introduction, or more limited techniques such as those that serve only to elements in serial configuration. While the methodology requires accurate and quality for RAM analysis, the results are clear and objective, excluding criteria or opinions that often add subjectivity to the evaluation.

The case allowed to analyze the process of the great Chilean mining, using the RAM-C methodology, obtaining clear results regarding the criticality and impact of the elements of the production process, meeting the objectives.

REFERENCES

Crespo, A., Moreu, P., Sola, A. & Gómez, J. 2015. Criticality Analysis for Maintenance Purposes: A Study for Complex In-service Engineering Assets. *Quality and Reliability Engineering International*. Published online in Wiley Online Library.

Dhillon, B.S. 2006. *Maintainability, Maintenance, and Reliability for Engineers*. Boca Raton: Taylor & Francis Group, LLC.

Distefano, S. & Puliafito, A. 2009. Reliability and availability analysis of dependent-dynamic systems with DRBDs. *Reliability Engineering and System Safety* 94: 1381–1393.

Guo, H. & Yang, X. 2007. A simple reliability block diagram method for safety integrity verification. *Reliability Engineering System Safety* 92: 1267–1273.

Heinrich, L. 1991. Goodness-of-fit tests for the second moment function of a stationary multidimensional, Poisson process. *Statistics* 22: 245–278.

Moss, T.R. & Woodhouse, J. 1999. Criticality analysis revisited. *Quality and Reliability Engineering International* 15: 117–121.

Parra, C. 2009. *Desarrollo de modelos de cuantificación económica del factor Fiabilidad en el coste total de ciclo de vida de un sistema de producción*. Sevilla: Universidad de Sevilla.

Parra, C., Crespo, A., Kristjanpoller, F. & Viveros, P. 2012. Stochastic model applied to evaluate the economic impact of the failure in the cycle cost analysis (LCCA). Case Study for the Rail Freight and Oil Industries. *Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability* 226(O4): 392–405.

Rausand, M. & Hoyland, A. (3rd Ed) 2003. *System reliability theory: models, statistical methods, and applications*. New York: Wiley: IEEE.

Rauzy, A.B., Gauthier, J. & Leduc, X. 2007. Assessment of large automatically generated fault trees by means of binary decision diagrams. *Proceeding of the Institution of Mechanical Engineers, Part O: Journal of Risk and reliability* 221(2): 95–105.

Sundararajan, C.R. 1991. *Guide to Reliability Engineering*. New York: Van Nostrand Reinhold.

US Department of Defense. 1977. *Procedures for performing a failure mode and effects analysis, MIL-STD-1629A*. Washington: Department of Defense.

Viveros, P., Zio, E., Arata, A. & Kristjanpoller, F. 2011. Integrated system reliability and productive capacity analysis of a production line. A Case Study for a Chilean Mining Process. *Proceeding of the Institution of Mechanical Engineers, Part O: Journal of Risk and reliability* 226(O3): 315–317.

Volovoi, V. 2004. Modeling of system reliability Petri nets with aging tokens. *Reliability Engineering and System Safety* 84: 149–161.

Welte, T.M. 2009. A rule-based approach for establishing states in a Markov process applied to maintenance modeling. *Proc. IMechE: Journal of Risk and Reliability* 223: 1–12.

A novel methodology for availability assessment of complex load sharing systems

F. Kristjanpoller & P. Viveros
Universidad Técnica Federico Santa María, Department of Industrial Engineering, Valparaiso, Chile.

Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n. 41092, Seville, Spain.

A. Crespo
Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n. 41092, Seville, Spain

R. Mena
European Foundation for New Energy-Electricity of France at Central School of Paris-Supelec, Paris 92295, France.

R. Stegmaier
Universidad Técnica Federico Santa María, Department of Industrial Engineering, Valparaiso, Chile.

ABSTRACT

In last years, the process flexibility and productivity is a goal to improve the process efficiency and the overall company results. In this context, the dynamic systems have reached a great level of importance for the productive process modelling. The dynamic systems are those which change in time. In the case of components and its configuration in a system, dependencies, redundancies and the load they bear, which can be shared, varies in time, that is to say, its dependency relations can change with the environment or change its ability to function in different scenarios. Transport systems are characterized usually for its flexibility, huge quantity of equipment and application. In effect the feature of load sharing, allows obtaining the required capacity on the basis of the sum of the available equipment even operating in a lower load than required. The case of overcapacity is characterized by having more capacity installed than required, by which there exists a series of combinations that allow satisfy the required capacity. The above condition requires that the equipment can operate at different work levels. As a conclusion of this problem, we can set up that the impact of each component is variable and depends on its required load as well as its reliability and maintainability behavior, as so also of the characteristics of each one of the equipment that constitutes the system. For the previously situation mentioned above, the availability assessment is a complex system to carry out and follow up it is proposed a methodology for its validation. These concepts justify the methodology for availability assessment of complex systems accounting for load sharing configurations with overcapacity and flexible work levels, allow the possibility that all the equipment have different failure behavior. This methodology is based on event space method, considering the matrix modeling for multistate and dynamic impact evaluation, and the result is expressed as an equivalent availability. The case study based on mining trucks availability modeling to optimize the fleet sizing, show the benefits and summarizes the application, obtaining relevant results to develop a expedite decision making process over reliability and availability indicators. The usage of the simulation model, as a bench tool, validated the proposed methodology.

A novel methodology for availability assessment of complex load sharing systems

F. Kristjanpoller & P. Viveros
Universidad Técnica Federico Santa María, Department of Industrial Engineering, Valparaiso, Chile.
Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n. 41092, Seville, Spain.

A. Crespo
Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n. 41092, Seville, Spain

R. Mena
European Foundation for New Energy-Electricity of France at Central School of Paris-Supelec, Paris 92295, France.

R. Stegmaier
Universidad Técnica Federico Santa María, Department of Industrial Engineering, Valparaiso, Chile.

ABSTRACT: The methodology for availability assessment of complex systems accounting for load sharing configurations with overcapacity and flexible work levels, allow the possibility that all the equipment have different failure behavior. This methodology is based on event space method, considering the matrix modeling for multistate and dynamic impact evaluation, and the result is expressed as an equivalent availability. At the literature there are models that develop the overcapacity problem, but only for identical equipment and without the multistate work level; others allow the modeling of multistate characteristic but avoid the overcapacity evaluation. This situation is commonly present in continuous process industries with important transportation systems, like mining, steel, paper and wood. The case study based on mining trucks availability modeling to optimize the fleet sizing, show the benefits and summarizes the application, obtaining relevant results to develop a expedite decision making process over reliability and availability indicators. The usage of the simulation model, as a bench tool, validated the proposed methodology.

1 INTRODUCTION AND BACKGROUND

In last years, the process flexibility and productivity is a goal to improve the process efficiency and the overall company results. In this context, the dynamic systems have reached a great level of importance for the productive process modelling.

The dynamic systems are those which change in time. In the case of components and its configuration in a system, dependencies, redundancies and the load they bear, which can be shared, varies in time, that is to say, its dependency relations can change with the environment or change its ability to function in different scenarios. The modelling methods like Reliability Block Diagram (RBD) [1-2] and Failure Tree (FT) [2] have different limits to represent these systems, in the case of RBD it presents restrictions with respect to the dependencies and the large complex systems [3].

For the representation of the dynamic systems, different methodologies will be shown below.

Macchi et al. [4] presents a special analysis for buffer (RBD) showing the possibility to make flexible the structure for a dynamic system. Although some of these restrictions are treated by the method of Dynamic Fault Tree (DFT), particularly the shared load case is not modelled through the FT neither through the DFT[5], although have appeared tools that have enriched them, they are not represented appropriately.

A new named model dynamic reliability block diagram (DRBD), is presented by two publications, S. Distefano, L.Xing [6] and by Xu, L. Xing and R. Robidoux 2009 [3] both of them present two ways of applying and schematize the DRBD, though in both is L. Xing, the last one presents a simpler way than the first work.

S. Distefano, L. Xing [6], introduce some features that may be of special interest, as three patterns of state stand-by and three types of dependency. If one component depends on various other components it can produce an attendance conflict which is solved

by a discrimination manner due to a hierarchical level of priorities.
For the analysis of one DRBD there are various alternatives within the literature [7-9]:
1) Markov Chains: Where the limit are the few reliability distributions that can be analyzed.
2) Petri nets: Where the redundancies and shared load are tailored.
3) Simulations: Where any distribution can be tailored, Montecarlo technique is one of the most explored.
The other way to present DRBD is one introduced by H.Xu, L. Xing and R.Robidoux 2009 [3] previously worked only by the first ones in 2007 [10] where show the DRBD as a system that tailor and catch the dynamic relations between components as dependence states as well as redundancy state, they suggest a simple way and tailor a particular case. For checking, it is transferred to a Petri net model colored by a software support which certifies the correct design of the DRBD.
With respect to works related with resolutions of systems availability of shared load, solved by Markov chains, we can find Shendao et al. [11], where though there are variable failure rates in time, we find again the explosion state-space. It is calculated the availability of a charge load system with variable failure rates solving different equations, however it is required algebraic operations that depend of the size of the system, since for large systems it becomes a huge problem.
Akthar [12] also contributes respect to this same resolution method, although he considers identical equipment, he adds a new feature, cover the failure in an imperfect manner (that is to say there are failures that are impossible to repair).
Due to the inexistence of description of divided systems, it will be used as basis the system k-out-of-N:G/Load Sharing described in the bibliography and that will have the divided load characteristic.
One of the advances in the model system with DRBD and its validation it is made by Distefano and Puliafito [13] where they analyze three study cases, however, although they make great advances, these must be translated to the OPENSesame system to be validated, where some features cannot be introduced and there appears the lack of a special software.
Similar to the above is what considers Scheuer [14], who studies the reliability for a k-out-of-n:G system where he holds that in basis to previous studies made by Kapur and Lamberson [15] that when there is a component failure, then there is a higher failure in the surviving ones, however it is for identical components with constant failure rates, similar to made by Shao & Lamberson [16] where it is also used identical components but with an imperfect switching and it is used for few components due to it is carried out in Markov chains basis.
Jenab y Dhillon [17] grant a form to analyze not only the reliability and availability of a k-out-of-n system but also for reversible multi-state systems, that is to say they can change from state i to i+1 in addition it gives the suggestion that all the compo-nents are identical and independent. Something at a short rate but similar to the former study is made by Hasset, Dietrich and Szidarovsky [18] who investigated the reliability and availability of systems 1 of 2 reparable, both components statistically identical with variable failure rate.
On the other hand, Liu [19] introduces a pattern to calculate the reliability of shared load systems k-out-of-n, with non-identical components and general distributions (Weibull, Gaussian, lognormal and Gamma), something similar to intended to do, however due to complex scenario and suggested solution, is not possible the resolution for n>=5 and with k n-3, however taking these elements, is probable to have some results for higher n.
Amari et al. [20] develop a solution through Markov chains where it is indicated that the maximum of the components must be 16, nevertheless they analyze a problem of maximum three components, although tips are given to increase the efficiency of the computational resolution. It applies for exponential distributions and for general distributions, is possible to indicate the suggestion that all failure rates are the same when these vary with t time when elements j fails. Nevertheless this choice can be viable with respect to the problem set up, it considers that the load is delivered in the same way on the surviving elements, something that is not sure to happen due to the capacity of each one and though certain rules of the shared load could relax, we can indicate that when the components are not identical each sequence of failure must be analyzed separately and yet this must be studied for the general case.

2. PROBLEM STATEMENT

Transport systems are characterized usually for its flexibility, huge quantity of equipment and application. In effect the feature of load sharing, allows obtaining the required capacity on the basis of the sum of the available equipment even operating in a lower load than required. The case of overcapacity is characterized by having more capacity installed than required, by which there exists a series of combinations that allow satisfy the required capacity. The above condition requires that the equipment can operate at different work levels. As a conclusion of this problem, we can set up that the impact of each component is variable and depends on its required load as well as its reliability and maintainability behavior, as so also of the characteristics of each one of the equipment that constitutes the system. For the previously situation mentioned above, the availability assessment is a complex system to carry out and follow up it is proposed a methodology for its validation.

3. PROPOSITION FOR METHODOLOGY

Here is present the proposed methodology together with defined variables

i. Variables and Nomenclature

Table 1. Glossary

Id	Description
	set of equipment
	$\lvert E\rvert$ total number of equipment
	index of equipment $\in \{1,...,n_E\}$
	set of operating states of the system
	$\lvert S\rvert$ total number of possible operating states of the system
	index of operating states $\in \{1,...,n_S\}$
	Availability
	system required capacity
	maximum capacity
	Available capacity
	Operating capacity
	Availability-based probability
	Impact
δ	Matrix of possible combinations of operating states
n_{zeros}	Number of zeros $\in \{1,...,n_E\}$

i. Modeling

Assumption 1:

All equipment in the systems has two possible operating states, (1) operating, (0) unavailable. Under the assumption 1, the first step is to obtain all the possible combinations of operating states, given the total number of equipment in the system. As the operating states are binary, the total number of operating states of the system is 2^{nE}.

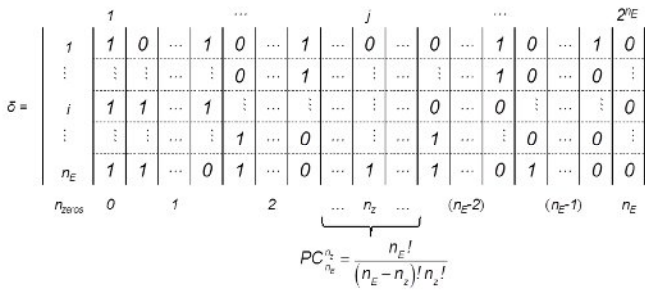


Figure 1. Possible combinations of operating states

Considering one operating state combination $j \in \{1,...,2^{nE}\}$ of the system, the corresponding binary variables to visualize the individual operating state of each equipment are defined as follows:

$$\delta_{ij} = \begin{cases} 1 & \text{if equipment i is in operating state} \\ 0 & \text{if equipment i is unavailable} \end{cases} \quad \forall i \in \{1,...,n_E\} \tag{1}$$

From the matrix δ, we obtain the available capacity for each operating state combination:

$$C^A{}_j = \sum_{i=1}^{n_E} \delta_{ij} \times C^{\max}{}_i \quad \forall j \in \{1,...,2^{n_E}\} \tag{2}$$

Assumption 2:

Given a systemic operating state j, the proportion between the operating capacities of the corresponding equipment C^O_{ij} and the maximum equipment capacity $C^{\max}{}_i$ must be the same for all equipment.

To determine the final impact of each equipment, we need to identify the systemic operating states j for which the available capacity of the equipment is less or equal than the required capacity of the system (otherwise the impact is defined *0* since the system is able to satisfy the requirement of capacity).

Then, we define the binary variable ω_j as follows,

$$\omega_j = \begin{cases} 1 & C^A{}_j \geq C^R{}_S \\ 0 & Otherwise \end{cases} \quad \forall j \in \{1,...,2^{n_E}\} \tag{3}$$

Then, the operating capacities of the equipment C^O_{ij} are:

$$C^O{}_{ij} = \frac{\left(\omega_j \times C_S{}^R + (1-\omega_j) \times C^A{}_j\right) \times \delta_{ij} \times C_i^{\max}}{C_i^{\max} + \sum_{k=1 \wedge k \neq i}^{n_E} \delta_{kj} \times C^{\max}{}_k} \quad \forall i \in \{1,...,n_E\}, j \in \{1,...,2^{n_E}\} \tag{4}$$

When the calculation of the impacts is applicable ($C^R_S > C^A_j$), the systemic operating state $j=1$ for which all the equipment are in operating state is considered as the state of reference. The objective is to determine the loss of capacity that the unavailable equipment produces over the system as a function of the operating capacity if that equipment were operating. The formulation of the impact is:

$$I_{ij} = \begin{cases} \frac{\left(C^R{}_S - C^A{}_j\right) \times (1-\delta_{ij}) \times C^O{}_{i1}}{C^R{}_S \times \sum_{k=1}^{n_E} (1-\delta_{kj}) \times C^O{}_{k1}} & C^R{}_S > C^A{}_j \\ 0 & Otherwise \end{cases} \quad \forall i \in \{2,...,n_E\}, j \in \{2,...,2^{n_E}\} \tag{5}$$

Assumption 3:

Under systemic operating state $j=1$ the required capacity is always satisfied.

Then, the availability-based probability of each systemic operating state is defined as follows:

$$P_j^A = \prod_{i=1}^{n_E} A^{\delta_{ij}}{}_i \times \left(1 - A_j\right)^{\left(1-\delta_{ij}\right)} \quad j \in \left\{1,\ldots,2^{n_E}\right\} \quad (6)$$

Finally, the weighed impact for each equipment, considering all the possible combinations for the system operating state is:

$$I_i^W = \sum_{j=1}^{2^{n_E}} P_j^A \times I_{ij} \quad i \in \left\{1,\ldots,n_E\right\} \quad (7)$$

4. CASE STUDY

A company of the great copper mining in Chile requires a transport of an average of 5,200 tons each hour ( ), from the mine to the concentrated plant. This material has between 0.5 - 1.1% of copper. The transportation system is composed by 20 trucks, of 4 different models, for capacity, manufacturer and antiquity. For each truck, in an independent way, it has obtained its reliability and maintenance data, calculating its main maintenance indexes like: MTBF (Mean Time Between Failure) and MTTR (Mean and Time to repair) respectively.

The expected Availability (A_i) is calculated as shown on equation 8. [21]:

$$= \frac{\qquad}{\quad + \quad} \quad (8)$$

The Table 2 summarizes the information obtained for each truck and includes the analysis of the individual availability.

Table 2. Reliability and availability data.

Truck	Type	Capacity (tons)	MTBF	MTTR	Ai
1	A	300	156,4	23,2	0,8708
2	A	300	173,2	26,4	0,8677
3	A	300	168,4	22,5	0,8821
4	A	300	177,3	19,8	0,8995
5	B	350	116,3	27,3	0,8099
6	B	350	125,9	24,1	0,8393
7	B	350	148,7	26,5	0,8487
8	B	350	112,6	30,8	0,7852
9	B	350	151,8	28,5	0,8419
10	B	350	127,3	34,1	0,7887
11	C	220	188,4	14,3	0,9295
12	C	220	178,3	17,5	0,9106
13	C	220	182,9	12,6	0,9355
14	C	220	167,2	11,6	0,9351
15	C	220	159,3	18,4	0,8965
16	C	220	174,2	15,9	0,9164
17	C	220	183,3	9,6	0,9502
18	D	250	203,6	14,6	0,9331
19	D	250	208,5	17,4	0,9230
20	D	250	210,6	13,7	0,9389

As deducted from the information presented, the maximum capacity of the system is of 5.590 tons, corresponding to the addition of each individual capacity, which indicates that there is a load sharing system with overcapacity. Additionally, checking the reliability information we can establish that all the equipment has different data and its capacity is in relation with the type classification.

As mentioned above, it can be validated that we are in presence of a load sharing system, overcapacity and flexible work level.

To (Availability-based probability) determination will use the methodology proposed on point 3.

As first step, the total number of operating states is 1,048,576 states. For example, the state number 96,800 is characterized by 12 available trucks (1, 2, 3, 4, 5, 7, 9, 11, 13, 15, 17, 19), that appears with “1”; and 8 unavailable trucks (6, 8, 10, 12, 14, 16, 18) that appears with “0”. In this step, the available capacity is 3,380 tons, that represents an equal to 0.6047, as the system has an availability of 60.47% of the time, but this state has only a 3,428E-09 of occurrence probability.

Consolidating the results of each of the 1,048,576 states, the global results obtained indicates an equal to 0.8955, as the system

in each impact over .

Scenario1: Base case has an equivalent availability of 89.55%.

4.1.Sensibilization analysis

- To evaluate and sensibilize the results of the base case, 4 scenarios of improvement will design through the acquirement of new equipment, evaluating
- Scenario2: Acquisition of 2 new Trucks-Type A (the data given is of the best of the type, which is Nº4)
- Scenario3: Acquisition of 2 new trucks Type B (the data given is of the best of the type which is Nº7)
- Scenario 4: Acquisition of 3 new trucks type C (the data given is one of the best of the type, which is Nº17)

- Scenario 5: Acquisition of 3 new trucks Type D (the data given is one of the best of the type which is Nº20)

The results obtained are shown as follows:

Table 3. Scenarios results for the indicator .

Id	Esc 1	Esc 2	Esc 3	Esc 4	Esc 5
	5,200	5,200	5,200	5,200	5,200
	5,590	6,190	6,290	6,250	6,340
	0.8955	0.9247	0.9220	0.9336	0.9408

The analysis of the results is very interesting, it is established that the only important is not the number of trucks and the for the increasing of , but also the specific values of the Ai of the added equipment, have a relevant impact over the system indicator.

To validate the results obtained for the , it was developed a simulation method Montecarlo in order to calculate the availability [22]. The base for simulations is the states that equipment can take, as described in the Modeling Assumption 1. For this effect, simulations with 100,000; 200,000; and 300,000 iterations are developed with the objective of evaluate the impact of each model over the analytic resolution.

As we can appreciate in the Fig.2 the deviations obtained respect to the analytic value are extremely low, the maximum deviation is for the Scenario 1 with the model of 100.000 iterations achieving only 0.067% which indicates a high grade of precision of the availability values

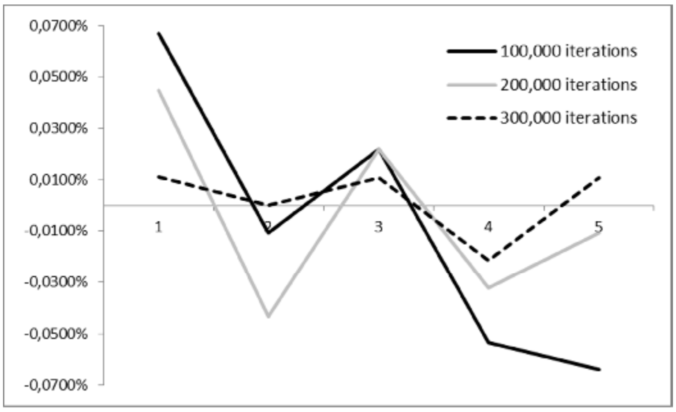


Fig 2. Bench Tool Deviation from Analytical System Availability

To evaluate each one of the models in a more precise way, it is developed the analysis of the absolute deviation, in this case the mean values are:

Table 4. MAD evaluation for simulation

Test	Mean Absolute Deviation MAD
100,000 iterations	0.043%
200,000 iterations	0.031%
300,000 iterations	0.011%

As we can appreciate in the Fig.3, increasing the number of iterations the MAD decreases, which implies that the proposed value for as also its methodology of calculus have been validated.

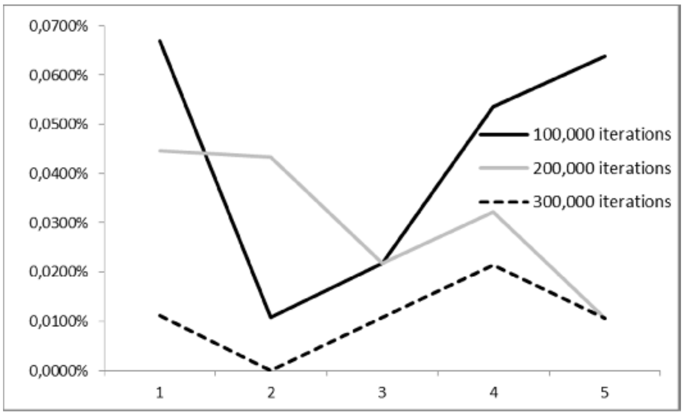


Fig. 3 Bench Tool Absolute Deviation from Analytical System Availability

5. CONCLUSIONS AND DISCUSSION

It was effectively generated a methodology for the availability assessment of complex systems accounting for load sharing configurations with overcapacity and flexible work levels, presenting its understanding and proving its application in a practical case obtaining positive results in both cases.

In order to implement and compare the results it was developed the analytic application of the methodology with a sensible analysis and with improvement scenarios.

As a result of the earlier, we can establish that the proposed methodology has been validated through the comparison with simulation model such as bench tool since the detected differences between both models exceed a MAD 0.011% for the model with 300.000 iterations.

The case study through the evaluation of the five scenarios (basis case and four of improvements) permits the evaluation of the real impact of rising up the quantity of trucks for the process. The comparison between the scenario 2 and scenario 3 shows that not always the increasing of capacity obtains results in the availability assessment of the system.

In that case there is more impact about the quality of improvement, associated to the availability of the trucks, than the quantity associated to the capacity of the trucks.

Indubitably, we can conclude that the methodology developed is a contribution to model the availability of systems of transport, suggesting an analysis of the evaluation of her, flexible and precise.

As a future step, is thought the possibility to incorporate economic variables to evaluate the scenarios and in this way to determine the profits in the OPEX through the improvement of the availability, versus the costs included in the CAPEX in order to finance these projects.

REFERENCES

[1] Barlow R, Proschan F. Mathematical Theory of Reliability. Philadelphia: Society for Industrial and Applied Mathematics; 1996.

[2] Birolini A. Reliability Engineering: Theory and Practice. Berlin: Springer-Verlag; 2004.

[3] H. Xu, l. Xing, R. Robidoux. DRBD: Dynamic reliability block diagrams for system reliability modelling. International journal of computers and applications, 2009, international journal of computers and applications, 202.

[4] Marco Macchi, Fredy Kristjanpoller, Adolfo Arata, Marco Garetti, Luca Fumagalli. Introducing buffer inventories in the RBD analysis of production systems. Reliability Engineering & System Safety 2012;104; 84-95

[5] R. Manian, J. B. Dugan, D. Coppit, & K. J. Sullivan. Combining various solution techniques for dynamic fault tree analysis of computer systems. Proc. of the IEEE International High-Assurance Systems Engineering Symposium, 1998.

[6] Distefano S, Xing Liudong. A New Approach to Modeling the System Reliability: Dynamic Reliability Block Diagrams. Reliability and Maintainability Symposium. RAMS Annual, Newport Beach, CA, USA. 2006.

[7] R. Manian, J. B. Dugan, D. Coppit, K. J. Sullivan. Combining Various Solution Techniques for Dynamic Fault Tree Analysis of Computer Systems. Proc. IEEE Int. High-Assurance Systems Engineering Symp. 1998

[8] K. Trivedi, S. Hunter, S. Garg, R. Fricks. Reliability Analysis Techniques Explored Through a Communication Network Example. China. Int. Workshop on CAD, Test & Evaluation for Dependability, 1996.

[9] K. Trivedi, M. Malhotra. Reliability and Performability Techniques and Tools: A Survey. MMB, 1993. pp 27-48.

[10] Haiping Xu, Liudong Xing. Formal semantics and verification of dynamic reliability block diagrams for system reliability modeling. Proceedings of the 11th IASTED international conference, november, 2007. Cambridge, MA, USA.

[11] Shengdao T., Fengquan W. Reliability analysis for a repairable parallel system with time-varying failure rates. Appl. Math. J. Chinese Univ. Ser. B, 2005,20(1):85-90.

[12] Akhtar, Shaki. Reliability of k-out-of-n: G Systems with imperfect Fault-Coverage. IEEE Transactions on reliability, vol. 43, no. 1, 1994.

[13] Salvatore Distefano, Antonio Puliafito. Reliability and availability analysis of dependent–dynamic systems with DRBDs. Reliability Engineering and System Safety 94(2009)1381–1393.

[14] Scheuer, E.M. Reliability of an m-out-of-n system when component failure induces higher failure rates in survivors. IEEE Trans. Reliability, vol 37, pp 73-74, 1988.

[15] K.C. Kapur, L.R. Lamberson. Reliability in Engineering Design. s.l. : John Wiley & Sons., 1977.

[16] J. Shao, L.R. Lamberson. Modeling a shared-load k-out of n:g system. IEEE Trans. Reliability, 1991, Jun, pp 205-209, Vol. 40.

[17] K. Jenab, B.S. Dhillon. Assessment of reversible multi-state k-out-of-n:G/F/Load-Sharing systems with flow-graph models. Reliability Engineering and System Safety 91 (2006) 765–771.

[18] T.F. Hassett, D.L. Dietrich, F. Szidarovszky. Time varying failure rates in the availability and reliability analysis of repairable system. IEEE Duns. Reliability, 1995, Mar, pp 155 - 160, Vol. 44.

[19] Huamin, Liu. Reliability of a Load-Sharing k-out-of-n:G System: Non-iid Components with Arbitrary Distributions. IEEE Transactions on Reliability. Vol. 47, no. 3, 1998 September

[20] V. Amari, K. B. Misra, H. Pham,. Tampered Failure Rate Load-Sharing Systems: Status and Perspectives. Chapter 20 in Handbook on Performability Engineering. Springer, 2007.

[21] Sharma RK, Kumar S. Performance modeling in critical engineering systems using RAM analysis. Reliability Engineering and System Safety 2008; 93:891–7.

[22] Khan MRR, Kabir ABMZ. Availability simulation of an ammonia plant. Reliability Engineering & System Safety 1995; 48: 217–27.

6. CURRICULUM VITAE

FREDY KRISTJANPOLLER RODRÍGUEZ
fredy.kristjanpoller@usm.cl
Académico, Universidad Técnica Federico Santa María
Magíster en Gestión de Activos y Mantenimiento, Universidad Técnica Federico Santa María
Candidato a Doctor Ingeniero de la Universidad de Sevilla

C. Identidad:	13.191.020-7.
Fecha de Nacimiento:	24 de marzo de 1977.
Nacionalidad:	Chilena.
Estado Civil:	Casado.
Residencia:	Viña del Mar, Chile.

CARGOS

1. Académico Jornada Completa. Departamento de Industrias. Universidad Técnica Federico Santa María. (2016 hasta la fecha).
2. Ingeniero de Estudios. Departamento de Industrias. Universidad Técnica Federico Santa María. (2001 hasta 2016).
3. Coordinador Académico Magíster en Gestión de Activos y Mantenimiento. (2004 hasta la fecha).
4. Investigador en proyecto internacional Universidad de Sevilla. Desarrollo de procesos avanzados de operación y mantenimiento sobre sistemas. Referencia: DPI2015-70842-R Universidad de Sevilla. (2015 a la fecha).
5. Coordinador Académico Diplomado en Ingeniería del Mantenimiento. (2004 hasta 2011).
6. Coordinador Académico Diploma en Gestión de Activos y Mantenimiento (2011 hasta la fecha).
7. Coordinador Nacional Proyecto iMaPla Integrated Maintenance Planning - European Union. (2008 – 2013).
8. Coordinador Nacional Proyecto Interlink - Italian Ministry for Education, University and Research (2007 – 2009.)
9. Member of the IPC of IFAC A-MEST Workshop. (2010 hasta la fecha).
10. Miembro del Comité Técnico del Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA. (2010 hasta la fecha).

DOCENCIA EN CÁTEDRAS DE PREGRADO

1. Profesor Ingeniería de Plantas Industriales.
2. Profesor Ingeniería Económica.
3. Profesor Proyectos.
4. Profesor Gestión de Operaciones.

DOCENCIA EN CÁTEDRAS DE POSTGRADO Y POSTÍTULOS

1. Profesor Ingeniería en Confiabilidad. Magíster en Gestión de Activos y Mantenimiento.
2. Profesor Ingeniería en Mantenimiento. Diploma en Gestión de Activos y Mantenimiento.
3. Profesor Estrategias de Mantenimiento. Diploma en Gestión de Activos y Mantenimiento.
4. Profesor Ingeniería de Proyectos. Diplomado en Ingeniería Industrial.

DIRECCIÓN DE MEMORIAS Y TESINAS

1. 120 memorias de pregrado. Ingeniería Civil Industrial – Ingeniería Comercial.
2. 70 tesinas de postgrado. Magíster en Gestión de Activos y Mantenimiento.

DISTINCIONES

1. **Maestro de Excelencia 2006**. Universidad Técnica Federico Santa María.
2. **Maestro de Excelencia 2008**. Universidad Técnica Federico Santa María.
3. **Maestro Destacado 2009**. Universidad Técnica Federico Santa María.
4. **Maestro de Excelencia 2010**. Universidad Técnica Federico Santa María.
5. **Maestro de Excelencia 2012**. Universidad Técnica Federico Santa María.
6. **Maestro de Excelencia 2013**. Universidad Técnica Federico Santa María.
7. **Maestro de Excelencia 2015**. Universidad Técnica Federico Santa María.

PUBLICACIONES

A. PUBLICACIONES ISI

1. Marco Macchi, Fredy Kristjanpoller, Adolfo Arata, Marco Garetti, Luca Fumagalli. Introducing buffer inventories in the RBD analysis of production systems. Reliability Engineering & System Safety 2012; 104; 84-95. DOI: 10.1016/j.ress.2012.03.015

2. Pablo Viveros, Enrico Zio, Fredy Kristjanpoller, Adolfo Arata. Integrated system reliability and productive capacity analysis of a production line. A Case Study for a Chilean Mining Process. Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability. Volume: 226 Issue: O3 Pages: 305-317. June 2012. DOI: 10.1177/1748006X11408675

3. Carlos Parra, Adolfo Crespo, Fredy Kristjanpoller, Pablo Viveros. Stochastic model applied to evaluate the economic impact of the failure in the cycle cost analysis (LCCA). Case Study for the Rail Freight and Oil Industries. Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability Volume: 226 Issue:O4. Pages: 392-405. August 2012. DOI: 10.1177/1748006X12441880

4. Mónica A. López-Campos, Adolfo Crespo Márquez, Pablo Viveros Gunckel, Fredy Kristjanpoller Rodríguez, Raúl Stegmaier Bravo. Methodology for auditing the resources allocation of critical maintenance activities. Dyna. Volume 89, Pages: 89-97, January 2014. DOI: 10.6036/5819

5. Viveros P, Crespo A, Tapia R, Kristjanpoller F, González-Prida V. Reliability stochastic modeling for repairable physical assets. Case study applied to the Chilean mining. DYNA. Volume 91. Pages: 423-431, Julio-Agosto 2016. DOI: 10.6036/7863

6. F. Kristjanpoller, A. Crespo, L. Barberá, P. Viveros. Biomethanation plant assessment based on reliability impact on operational effectiveness. Renewable Energy 101C (2017) pp. 301-310 DOI: 10.1016/j.renene.2016.08.065

7. F. Kristjanpoller, A. Crespo, P. Viveros, L. Barberá. Expected Impact Quantification based Reliability Assessment Methodology for Chilean Copper Smelting Process – A Case Study. Advances in Mechanical Engineering. Volume 8 (10). Pages: 1-13. DOI: 10.1177/1687814016674845

8. F. Kristjanpoller, A. Crespo, M. López, P. Viveros. Methodological proposal for the evaluation of reliability impacts in complex systems. Applied case to a crushing copper plant. Dyna. http://dx.doi.org/10.6036/8088.

B. PUBLICACIONES SCIELO

1. Pablo Viveros, Raúl Stegmaier, Fredy Kristjanpoller, Luis Barberá , Adolfo Crespo, Proposal of a Maintenance Management Model and its Mains Tools Support. Revista Chilena de Ingenieria, vol. 21 Nº 1, 2013, pp. 125-138.

C. LIBROS

1. Carlos Parra, Adolfo Crespo, Vicente González-Prida, Fredy Kristjanpoller, Pablo Viveros & Gabriel Llort. "Case study on a maintenance and reliability management model proposal: A third set of locks project in the Panama Canal". Chapter 1. Optimum Decision Making in Asset Management. An imprint of IGI Global. USA, 2017. ISBN: 9781522506522 (ebook).

2. José Contreras, Carlos Parra, Adolfo Crespo, Vicente González-Prida & Fredy Kristjanpoller, Pablo Viveros. "Model of a performance measurement system for maintenance management". Chapter 9. Optimum Decision Making in Asset Management. An imprint of IGI Global. USA, 2017. ISBN: 9781522506522 (ebook).

3. Pablo Viveros, Fredy Kristjanpoller, Adolfo Crespo, René Tapia & Vicente González-Prida. "Mathematical and Stochastic Models for Reliability in Repairable Industrial Physical Assets". Chapter 12. Practices through Energy Engineering and Asset Management. Engineering Science Reference (an imprint of IGI Global). USA, 2015.

4. Pablo Viveros, René Tapia, Fredy Kristjanpoller, Luis Barberá, Vicente González-Prida. "Functional stockpile analysis in complex productive systems". Advanced Maintenance Engineering, Services and Technology. 2012. Elsevier Science. (Ed.) Marquez, C. ISBN: 9781622769254

5. <u>Colaborador</u>: Adolfo Arata, "Ingeniería y Gestión de la Confiabilidad Operacional en Plantas Industriales". Ril Editores, Santiago, Chile. Julio 2009.

6. <u>Co-autor del Capítulo 4</u>: Adolfo Arata, Luciano Furlanetto "Manual de Gestión de Activos". Ril Editores, Santiago, Chile. Mayo 2005.

D. JOURNALS CIENTÍFICOS Y OTRAS REVISTAS

1. Vicente González-Prida, Luis Barberá, Adolfo Crespo, Pablo Viveros, Fredy Kristjanpoller. Root-cause analysis in the aftersales management. Revista Técnica de Ingeniería de la Universidad de Zulia. Vol. 37, Nº 2, 1 - 10, 2014. ISSN 0254-0770. SCImago Journal Rank (SJR): 0.118.

2. Rodrigo Mena, Enrico Zio, Fredy Kristjanpoller, Adolfo Arata. Availability-Based Optimization and Simulation Model to Open-Pit Mine Truck Allocation Problem. International Journal of Mining Science and Technology, Volume 23, Issue 1, January 2013, Pages 113-119. http://dx.doi.org/10.1016/j.ijmst.2013.01.017. Source Normalized Impact per Paper (SNIP): 2013: 1.409. SCImago Journal Rank (SJR): 0.693

3. V. González-Prida, L. Barberá, A. Crespo, P. Viveros, F. Kristjanpoller. 2013. Approach to Analyzing Root Causes in the Management of Warranty Support. International Journal of E-Business Development 3 (1), 1-9. ISSN: 2226-7336.

4. Vicente González-Prida, Luis Barberá, Adolfo Crespo, Pablo Viveros, Fredy Kristjanpoller, "Implementing the Balance Scorecard for the Improvement of the Warranty Management: The Strategic Alignment". International Journal of E-Business Development. IJED Vol. 1 Iss. 1, PP. 15-21, Nov. 2011.

5. F. Kristjanpoller, A. Arata, V. González, A. Crespo. "Caso de estudio sobre el análisis de la fiabilidad en una planta de triturado de mineral en Chile". Revista Ingeniería y Gestión de Mantenimiento. Vol. Abril/Mayo/Junio 2010 España 2010.

6. Arata A., Kristjanpoller F, Arata B A., “Asset Management. Un factor necesario para el logro de la competitividad empresarial“. Trend Management, V.11 N°4, mayo 2009. Santiago, Chile.

7. A. Arata, L. Furlanetto, F. Kristjanpoller “Maintenance Engineering System: An opportunity for maintenance function evolution”. China Plant Engineering 2006 Nº2. Páginas 48-51.

8. A. Arata, L. Furlanetto, F. Kristjanpoller “Maintenance Engineering System: Una oportunidad para la evolución de la función mantenimiento”. Mantenimiento: Ingeniería Industrial y de Edificios, ISSN 0214-4344, Nº. 187, 2005. Asociación Española de Mantenimiento. Páginas 24 – 30.

9. A. Arata, F. Kristjanpoller, R.Madrid. “Le competenze professionali per lo sviluppo dell’ingegneria di manutenzione” Manuntenzione Tecnica e Management. Anno XII – Nº6 Giugno 2005. Associazione Italiana Manutenzione. Páginas 27 – 33.

10. Arata, F. Kristjanpoller “El ingeniero de mantenimiento y sus desafíos profesionales”, Revista Mantenimiento, Noviembre 2007, Costa Rica. 8 páginas.

PRESENTACIONES EN CONFERENCIAS & PROCEEDINGS

1. F. Kristjanpoller, A. Crespo, M. Lopez-Campos, P. Viveros, T. Grubessich. Reliability assessment methodology for multiproduct and flexible industrial process. The Annual European Safety and Reliability Conference (ESREL). Glasgow, Scotland. Sept 25-29, 2016. ISBN: 978-1-138-02997-2.

2. P. Viveros, A. Crespo, F. Kristjanpoller, R. Stegmaier, E. Johns, T. Grubessich, L. Barberá. General framework about graphical analysis for overall effectiveness management. The Annual European Safety and Reliability Conference (ESREL). Glasgow, Scotland. Sept 25-29, 2016. ISBN: 978-1-138-02997-2.

3. T. Grubessich, P. Viveros, R. Stegmaier, F. Kristjanpoller, V. González-Prida, F. Pérès. General framework methodology to increase organizational learning in the field of asset management. The Annual European Safety and Reliability Conference (ESREL). Glasgow, Scotland. Sept 25-29, 2016. ISBN: 978-1-138-02997-2

4. F. Kristjanpoller, M. López, A. Crespo, P. Viveros. Reliability assessment based on energy consumption as a failure rate factor. 6th IESM Conference, October 2015, Seville, Spain.

5. F. Kristjanpoller, P. Viveros, A. Crespo, T. Grubessich, R. Stegmaier. RAM-C: A novel methodology for evaluating the impact and the criticality of assets over systems with complex logical configurations. The Annual European Safety and Reliability Conference (ESREL). Zurich, Switzerland. Sept 7-10, 2015.

6. P. Viveros, A. Crespo, L. Barberá, F. Kristjanpoller, R. Stegmaier, E. Johns, T. Grubessich. General Framework about Graphical Analysis for Operation Management. The Annual European Safety and Reliability Conference (ESREL). Zurich, Switzerland. Sept 7-10, 2015.

7. T. Grubessich, R. Stegmaier, E. Johns, P. Viveros, F. Kristjanpoller. A Methodological Proposal to meet analysis requirements with purified information through a logical work sequence and a decision tree in the field of maintenance management. The Annual European Safety and Reliability Conference (ESREL). Zurich, Switzerland. Sept 7-10, 2015.

8. F. Kristjanpoller, A. Crespo, P. Viveros, R. Mena, R. Stegmaier. A novel methodology for availability assessment of complex load sharing systems. The Annual European Safety and Reliability Conference (ESREL). Wroclaw, Poland. Sept 14-18, 2014.

9. T. Grubessich, E. Johns, P. Viveros, R. Stegmaier, F. Kristjanpoller. A framework proposal to analyse the performance of assets under complex system. The Annual European Safety and Reliability Conference (ESREL). Wroclaw, Poland. Sept 14-18, 2014.

10. P. Viveros, A. Crespo, F. Kristjanpoller, R. Stegmaier, E. Johns, V. Gonzalez-Prida. Probabilistic Performance Assessment for Crushing System. A Case Study for a Mining Process. In: PSAM14 - Probabilistic Safety Assessment and Management. June 22 – 27, 2014. Honolulu, Hawaii, USA.

11. P. Viveros, C. Nikulin, A. Crespo, R. Tapia, R. Stegmaier, E. Johns, F. Kristjanpoller. A Support System for Selecting the most suitable Spare Parts Strategy. In: 8th World Congress on Engineering Asset Management & 3rd International Conference on Utility Management & Safety. 30 Oct – 1 Nov 2013, Hong Kong.

12. E. Johns, R. Stegmaier, J. Cea, F. Kristjanpoller, P. Viveros. Career employability development through a specialized Asset Management's degree: An exploratory analysis for a Chilean Program. In: 8th World Congress on Engineering Asset Management & 3rd International Conference on Utility Management & Safety. 30 Oct – 1 Nov 2013, Hong Kong.

13. P. Viveros, R. Tapia, E. Johns, F. Kristjanpoller, C. Nikulin. A Creative Risk Analysis Algorithm to Support the Spare Part Decision. In: The Annual European Safety and Reliability Conference (ESREL). Holland, Amsterdam. Sept 29- Oct 02, 2013.

14. F. Kristjanpoller, A. Crespo. "Desarrollo de Ingeniería de Mantenimiento, a través de Técnicas de Simulación. Caso aplicado modelado de capacidad y disponibilidad de stockpile" XIV Encuentro de Activos Físicos. Pontificia Universidad Católica de Chile. Junio, 2013.

15. L. Barberá, A. Crespo, P. Viveros, F. Kristjanpoller. "RAM Analysis of Mining Process: A Case Study of a Copper Smelting Process in the Field of Mining, Chile". 2nd IFAC Workshop on Advanced Maintenance Engineering, Services and Technology, A-MEST '12, through the Conference Paper Management System of the IFAC. November 21-23 2012, Sevilla, Spain.

16. P. Viveros; René Tapia; Fredy Kristjanpoller; L. Barberá, V. Gonzalez-Prida. "Functional Stockpile Analysis in Complex Productive Systems" 2nd IFAC Workshop on Advanced Maintenance Engineering, Services and Technology, A-MEST '12, through the Conference Paper Management System of the IFAC. November 21-23 2012, Sevilla, Spain.

17. R. Mena, E. Zio, P. Viveros, F. Kristjanpoller, A. Arata. Simulation and Multi-Objective Optimization of an Open-Pit Mine Truck-Shovel System by the Cross-Entropy Method. In: Proceedings of the 11th international Probabilistic Safety Assessment and Management Conference and The Annual European Safety and Reliability Conference. Helsinki, Finland. June 25-29, 2012

18. R. Mena, E. Zio, P. Viveros, F. Kristjanpoller and A. Arata. Stochastic Modeling and Simulation of an Open-Pit Mine Truck-Shovel System. 4th meeting of the EURO (The Association of European Operational Research Societies) Working Group on Stochastic Modeling, May 30 - June 1, 2012, Paris , France.

19. Raúl Stegmaier, Fredy Kristjanpoller, Edith Carolina Carmona, Marco Macchi. "A methodology to assess software tools for reliability and maintenance engineering". 24th International Congress on Condition Monitoring and Diagnostics Engineering Management (COMADEM2011). Stavanger, Noruega. Junio, 2011

20. Alessio Arata, Esteban Heidke, Adolfo Arata, Fredy Kristjanpoller. Comminution process optimisation through reliability & maintainability modelling and simulation. Eighth International Seminar on Mineral Processing – PROCEMIN 2011. Santiago.

21. Adolfo Arata, Pablo Viveros, Fredy Kristjanpoller, Vicente González, Luis Barberá y Adolfo Crespo. "Aplicación del cuadro de mando integral para la mejora de la gestión de garantía—alineación estratégica". VIII Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2011. Antofagasta.

22. Rodrigo Mena, Fredy Kristjanpoller, Adolfo Arata, Marco Macchi y Luca Fumagalli. "Calidad en la Información de Indicadores de Desempeño KPI para Análisis de

Confiabilidad, Disponibilidad y Mantenibilidad”. VIII Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2011. Antofagasta.

23. Adolfo Arata, Fredy Kristjanpoller, Rodrigo Mena, Enrico Zio. “Availability-based optimization for open-pit mine truck allocation under dynamic constraints”, Workshop on simulation modeling for performance improvement in operations and service management, Milán, Italia. Febrero 2011.

24. Adolfo Arata, Fredy Kristjanpoller, Pablo Viveros, Enrico Zio “Integrated analysis of system reliability and productive capacity of a production line”, ESREL 2010. Rhodes – Grecia.

25. Carlos Parra , Adolfo Crespo, Juan Gómez, Vicente González, Adolfo Arata, Fredy Kristjanpoller, “Non- homogeneous Poisson Process (NHPP), stochastic model applied to evaluate the economic impact of the failure in the life cycle cost analysis (LCCA). Case of study in the oil industry”. ESREL 2010. Rhodes – Grecia.

26. Adolfo Arata, Fredy Kristjanpoller “Economical equipment replacement based on risk analysis”. Euromaintenance 2010. 146-148. European Federation of National Maintenance Societies – EFNMS. Verona, Italia

27. Edith Carmona y Fredy Kristjanpoller, “Estudio de Percepción y Preferencias por Software de Mantenimiento en la Industria Chilena” VII Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2010. Santiago

28. F. Kristjanpoller, E. Carmona, “Selección y Comparación de Software de Ingeniería en Mantenimiento.”. VI Encuentro Internacional de Mantenedores de Plantas Mineras, Congreso MAPLA 2009, Antofagasta, Chile. Noviembre 2009

29. A. Arata, F. Kristjanpoller, A. Arata B., J. Villarroel, P. Viveros, “Confiabilidad Operacional: Factor de Maximización del Beneficio Económico de Proyectos de Inversión”. Congreso: VI Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2009. Antofagasta, Chile. Noviembre 2009

30. A. Arata, F. Kristjanpoller, A. Arata B., J. Villarroel. “Análisis de riesgo para reemplazo económico de equipos: aplicación de Simulación Montecarlo”, V Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2008. Santiago

31. A.Arata, F.Kristjanpoller . Conferencia Latinoamericana de Gestión de Mantenimiento y Confiabilidad Operacional. GMC 2007. “Modelamientos basados en confiabilidad para determinar políticas de mantenimiento”

32. A.Arata, F.Kristjanpoller. “El MES, un herramienta para el desarrollo de la ingeniería de mantención” Congreso Iberoamericano de Mantenimiento 2005. Santiago.

33. Adolfo Arata, Fredy Kristjanpoller, Luciano Furlanetto. “Maintenance Engineering System: An opportunity for maintenance function evolution”. Euromaintenance 2004. 373-381. European Federation of National Maintenance Societies – EFNMS. Barcelona - España

34. A.Arata, F.Kristjanpoller, “Las competencias para el desarrollo de la ingeniería de mantención” Congreso Mundial de Mantenimiento 2004. Curitiba - Brasil.

35. A.Arata, F.Kristjanpoller,“Le competenze professionali per lo sviluppo dell’ingegneria di manutenzione” Congreso Asociación Italiana de Mantenimiento – AIMAN 2004. Milán – Italia

36. A. Arata, F.Kristjanpoller. “Maintenance Engineering System: Una oportunidad para la evolución de la función mantenimiento”, I Encuentro Internacional de Mantenedores de Plantas Mineras, MAPLA 2004. Iquique

PROYECTOS INDUSTRIALES

1. Estudio de Capacidad y Confiabilidad en líneas de Molienda. Minera Doña Inés de Collahuasi. 2012.

2. RAM Simulation for Sierra Gorda Project. 2010.

3. Estudio Sensibilización de Emisiones de As y S para Fundición Proyecto MMH. 2009.

4. Estudio Confiabilidad Proyecto MMH. Codelco. 2009.

5. Servicio de ingeniería para el desarrollo de un modelo de sistema de trenes de producción para establecer la estrategia de Mantenimiento de carros metaleros Ferrocarril Teniente 8. Codelco 2008.