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A renewable energy optimisation approach with production planning for a real industrial process: An application of genetic algorithms

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ABSTRACT

This article presents the formulation of the optimisation of a manufacturing process, through genetic algorithms, managing the generation and demand of energy in a factory at periodic moments of time. The strategy manages to minimise the daily energy cost and maximise the use of installed renewable energy, also taking advantage of potential battery banks. A time series with a 24-hour horizon of energy production from renewable sources and the electricity supply prices provided by the electricity market operator has been considered. Furthermore, in the simulations, scenarios with different battery capacities have been tested, which has allowed a preliminary study to be carried out for the installation of the electrical storage bank. The results presented in this work show that 6% of energy costs can be saved per day, compared to the current management decided by the manufacturing plant operators.

1. Introduction

According to the latest report of the International Energy Association [1], approximately 41% of global consumption is due to industry and its CO_2 emissions account for 45% of total direct emissions from end-use sectors. The increase in energy consumption is driven by increased production in energy-intensive industrial sub-sectors.

Although energy optimisation techniques in other sectors (buildings, microgrids, etc.) are already well known, a mature technology that takes into account all aspects involved has not yet been established in the industrial field. Energy efficiency is one of the most effective short- and medium-term goals to reduce the carbon footprint of industry and should be taken into account at all levels of the manufacturing process. Industry 4.0's main feature is the digitalisation of manufacturing processes, which is the opportunity to save energy by optimising or transforming technologies.

One of the ways to achieve energy efficiency in industry is by optimising production planning, which, in addition to making the process energy efficient, directly affects the cost of production and, therefore, the cost of the product itself. Planning refers to the order of actions to be carried out on a certain day, concerning the use of machines and operators, to achieve the set production targets. Many research works present various methods to optimise this production planning. In [2], based on the complexity of finding an optimal schedule, a heuristic search approach is presented, based on a simulation-optimisation framework that combines evaluation methods (simulation) and search methods (optimisation), through a reachability (or state space) analysis of timed coloured Petri net models to schedule flexible manufacturing systems (FMS). A different algorithm, based on particle swarm optimisation integrated into a neural network, is presented in [3]. In [4], the use of energy storage with the flexibility of the production plan is considered, in order to achieve lower costs. Some approaches use simulations to minimise grid dependence. In [5], methods of energy flexibilisation of production systems are studied, together with direct (battery) and indirect (thermal, flywheels, etc.) energy storage systems are introduced into planning in [6], as a tool to visualise the improvements that this would entail. In [7] a study is shown on the high power consumption in manufacturing systems and proposes several ways to optimise this consumption. A comprehensive literature review on production planning and scheduling with the aim of improving energy efficiency is provided in [8]. It covers various approaches and mathematical models used in optimising energy efficiency in production.

One of the most widely used algorithms to solve the optimisation problem is genetic algorithms. These algorithms have been widely applied to job order scheduling problems [9]. Some applications are shown in [10–13]

On the other hand, the use of renewable energies has a large share in electricity generation worldwide (29% in 2020) with a year-on-year growth of 10%. The most widely deployed are wind and photovoltaic, which account for 2/3 of this generation [1,14]. The penetration of

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Nomenclature

Abbreviations

BB	Baseline Behaviour
BESS	Battery Energy Storage System
CHP	Combined Heat and Power
CNC	Computer Numerical Control
DENiM	Digital intelligence for collaborative ENergy management in Manufacturing
FMS	Flexible Manufacturing Systems
GA	Genetic Algorithms
IEA	International Energy Association
IEC	International Electrotechnical Commission
MP	Electricity Market
PV	Photovoltaic
RC	Remaining Consumption
RESs	Renewable Energy Sources
SCADA	Supervisory Control And Data Acquisition
SOC	State Of Charge of the battery
WT	Wind Turbine

Variables

η_{CHP}	Electrical Efficiency Rate of CHP
η_c	Charge Efficiency
η_d	Discharge Efficiency
Δt	Sample Time
C^{day}	Daily energy cost
C^k_{CHP}	CHP Production Cost
C^k_{MP}	Obtained Energy Cost from the Grid
DTP	Daily Production Target
$E^{aux,k}_B$	Ideal energy from the battery
E^k_B	Energy charged to/discharged from the battery
E^k_{CNC}	CNC demand
E^k_{RC}	Remaining Consumption or remaining demand
E^k_T	Global demand
E^k_{CHP}	Energy generated by the CHP
$E^{aux,k}_{MP}$	Unsatisfied demand
E^k_{MP}	Purchased energy
E^k_{PV}	Energy generated by the photovoltaic panels
E^k_{RESs}	Total energy obtained from the RESs at each instant
E^k_{WT}	Energy generated by the wind turbine
i	CNC sub-index ID
k	Sample index
M	Number of Manipulable CNCs
n^k_{obj}	Decision variables
n^k_B	Battery operation
n^k_{CHP}	CHP decision variable
n^k_{CHP}	CHP operation
$n^k_{CNC_i}$	CNC number i operation
OH	Optimisation horizon
$P_{B,max}$	Maximum power exchange
P^{max}_{CHP}	Rated power of the CHP
$P^{off,mean}_{CNC_i}$	Average Idle power
$P^{on,mean}_{CNC_i}$	Average Operating power
Pr^k_{gas}	Price per MWh of gas
Pr^k_{MP}	Price per MWh purchased
SOC^k	SOC at k instant
SOC_1	Initial State of Charge
SOC_{max}	Battery capacity
SOC_{min}	Minimum SOC allowed
$T^k_{CNC_i,on}$	CNC run for some time
T_{part}	Production time of one part/Part production time
TPU	Total Produced Units

renewable energy has a great environmental impact, reducing CO_2 and greenhouse gas emissions [15]. Additionally, the lower generation costs of renewable energy sources (RESs) make their deployment in the industry more attractive for supplying energy consumption to the electricity grid. Industries are increasingly opting for the integration of RESs in their different production processes. The implementation and optimisation of RESs allow for an increase in the benefits of production and minimise the consumption of energy produced by fossil fuels.

In a recent research study [16] a summary of relevant research on the integration of renewables is given. The study concludes that the best integration is achieved when the problem is tackled within planning. Some research papers that address the problem of integrating renewable energies in industry within the planning problem are as follows: in [17,18] the focus is on smart planning to solve the problem of overgeneration of renewable energies. In [19–21] other ways of solving the problem of integrating renewables can be seen, taking them into account in planning optimisation.

The literature review always presents a partial view of the problem, i.e. energy optimisation in industry lacks a holistic view, including all the elements involved (use of renewables, production planning, energy storage, etc.). A recent research study [22] shows that the integration of all these elements makes it possible to achieve all the benefits of the above research. Although this study proposes a holistic approach, the power and number of machines, in addition to the optimisation resolution time, would make it impractical for schemes where changes in atmospheric predictions of various renewable sources and machine availability would have to be taken into account.

In the present work, decision variables in generation, storage and demand have been taken into account to address the optimisation problem holistically. The objective of this work is to minimise the energy cost of a real industrial process, indirectly achieving the maximisation of the use of renewable energies in the planning optimisation problem, using a Genetic Algorithm (GA). The real factory where it has been applied does not contain a battery bank, and solutions have been evaluated in various scenarios, in simulation, which include different capacities of electric battery, to see how their inclusion affects the daily energy cost of manufacturing.

The rest of the article is organised as follows. In Section 2 the system where this study is focused is presented. Section 3 shows the modelling carried out for each of the subsystems that make up the real process: both the loads or machines that operate in manufacturing and the energy sources and battery as a storage source that maximises the use of RESs and the loads or machines that operate in manufacturing. The chosen optimisation method and its application to various scenarios are presented in Section 4. Section 5 shows the results of the evaluation. The optimisation strategy followed and the results obtained are improved in Section 6. The article ends with Section 7, dealing with conclusions and future work.

2. Case study: Manufacturing plant

This article proposes a solution for one of the pilot demonstration plants of the DENiM project [23]. This factory produces, 24 h a day, various types of machined parts. It has multiple manufacturing processes. The article focusses on one of the factory's production processes.

From an energy point of view, the factory has renewable energy sources (RESs): a wind turbine (WT) and a photovoltaic panel installation on the roof (PV); in addition, there is a combined heat and power plant (CHP); and the connection to the electricity supplier with prices given by the electricity market (MP).

As mentioned above, only the operation of one of the manufacturing processes will be modified, considering the rest of the factory as non-modifiable energy consumption, which has been referred to as Remaining Consumption. This manipulable process is composed of several computer numerical control (CNC) machines that process the parts in parallel, i.e. only one processing on one machine is necessary for that part to be manufactured. The objective of this research is to minimise the daily energy cost of the factory (C^{day}). For this purpose, the data of a past day will be used, for which all the necessary data are available to know how the production of the manipulable process has been carried out, together with the total demand and energy generation of that day. This particular day has been denoted as *Baseline Behaviour*, as this is the focus against which the optimisation results will be compared. Although the actual plant does not have an electrical storage system, this work will serve as a preliminary design study for the implementation of a battery bank (B).

The daily energy cost (C^{day}) is defined in Eq. (1), focussing on an Optimisation Horizon (OH) of one day.

$$\begin{aligned} C^{day} &= \sum_{k=1}^{OH} C^k_{MP} + C^k_{CHP} \\ &= \sum_{k=1}^{OH} E^k_{MP} \cdot Pr^k_{MP} + E^k_{CHP} \cdot \eta^{-1}_{CHP} \cdot Pr^k_{gas} \end{aligned} \tag{1}$$

Being at each instant k

$$C^k_{MP} \equiv Purchase\ cost,\ C^k_{CHP} \equiv Generation\ cost$$

$$E^k_{MP} \equiv Purchased\ energy,\ E^k_{CHP} \equiv Generated\ energy$$

$$Pr^k_{MP} \equiv Price\ per\ \text{MWh}\ purchased,\ Pr^k_{gas} \equiv Price\ per\ \text{MWh}\ of\ gas$$

$$\eta_{CHP} \equiv CHP\ Electrical\ Efficiency\ Rate$$

To achieve this objective it is necessary to:

1. Maximise the use of RESs because they have the lowest associated costs.
2. Select when to produce energy with CHP, and when to buy energy from the electricity market.
3. Choose the best time to operate each CNC in the manipulable process, concerning the daily production targets, without wasting energy.
4. Decide when and how much to charge/discharge the battery.

The decision variables (n^k) are the only variables whose value can be modified within the OH to achieve the desired objective. To define them, the four previous objectives and some limitations of the system itself have been taken into account: the CNC machines and the CHP operate in on/off mode, so their associated decision variables are of binary type. However, the decision variables of the battery bank are continuous, assuming that converters are installed. Table 1 summarises all decision variables, their type and their limits.

The variable $n^k_{CNC_i}$ indicates whether the machine i is operating at time k. The variable n^k_{CHP} indicates whether the CHP is operating at time k. The variable n^k_B indicates the amount of energy being charged or discharged at time k. If $n^k_B > 0$, the battery is discharging, if $n^k_B < 0$, the battery is charging and if $n^k_B = 0$, the battery is neither charging nor discharging.

Note that RESs have no decision variables because everything that is produced is introduced into the electricity system, maximising the use of RESs. The Remaining Consumption and the MP do not have a decision variable because the first is a non-modifiable demand that must be satisfied, and the second is because all demands not satisfied by other energy sources will be obtained from the MP. Fig. 1 shows all the components of the factory, including the decision variables.

Table 1
Definition of decision variables.

Variable	Symbol	Type	Limits lower	Limits upper
CNC number i operation	$n^k_{CNC_i}$	Binary	0	1
CHP operation	n^k_{CHP}	Binary	0	1
Battery operation	n^k_B	Continuous	−1	1

Table 2
Time-related optimisation parameters.

Parameter	Symbol	Value	Unit
Sample time	Δt	0.5	h
Optimisation horizon	OH	48	samples

The system has constraints that limit the possible values of the decision variables at each time k. The constraints implemented in the system are shown in Eq. (2).

$$\text{Model Constraints} \equiv \begin{bmatrix} TPU \geq DPT \\ SOC_{max} \geq SOC^k \geq SOC_{min} \\ T^k_{CNC_i,on} \geq T_{part} \\ E^k_{consumed} = E^k_{generated} \end{bmatrix} \tag{2}$$

In order of priority, the constraints appearing in Eq. (2) mean:

1. The Total Produced Units (TPU) by the machines must be equal to or greater than the Daily Production Target (DPT). To calculate the TPU, the production time of one part (T_{part}) given in Table 3 is used.
2. The state of charge (SOC) of the battery at any instant (SOC^k) must be less than or equal to the battery capacity (SOC_{max}) and greater than or equal to the selected minimum (SOC_{min}). This restriction drastically increases the lifetime of the battery.
3. For a part to be produced correctly in an interval, the CNC must run for some time ($T^k_{CNC_i,on}$) equal to or longer than the production time (T_{part}) of one part.
4. The energy balance must be zero at each instant k. This implies two things:
   (a) All demands will always be met at all times.
   (b) It is not allowed to sell energy to the grid, so the plant cannot produce more than it consumes.

The values chosen for the time-related parameters are listed in Table 2.

The Sampling Time (Δt) is the period between samples k. In this period, the values of the decision variables remain constant. The Optimisation Horizon (OH) is the total number of k samples that the optimisation algorithm will take into account when making decisions.

To decide the value of both variables, the following information must be taken into account:

1. A daily production plan is developed in the factory. This plan envisages the operation of the factory 24 h a day. To mimic it, the value of the Optimisation Horizon (OH) must be equivalent to one day.
2. The intraday electricity market price Pr^k_{MP} changes every half hour. This variable has a high influence on the final cost of the energy consumed, due to the high variability of prices in the market. Therefore, the value of Δt must be proportional to this variability.

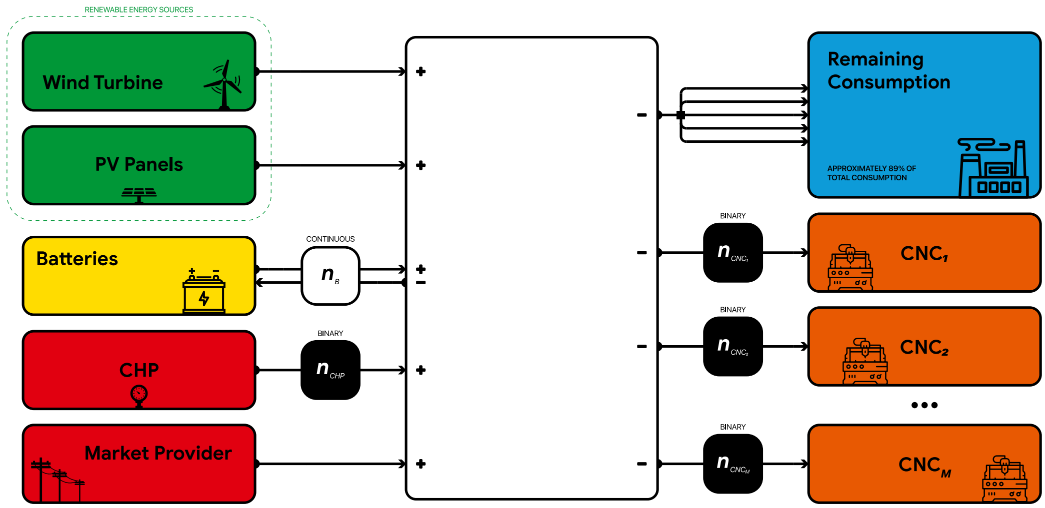

Fig. 1. System setup of the factory.

Table 3
Production process parameters.

Parameter	Symbol	Value	Unit
Daily production target	DPT	378	parts
Part production time	T_{part}	15	min
Number of manipulable CNCs	M	7	machines

3. The smallest time parameter of the system is the production time of each part (T_{part}), fixed at a quarter of an hour. This implies that it contributes nothing if Δt is less than this time.
4. The lower the Δt, the more samples are taken into account in the optimisation horizon, with OH being fixed, as is the case. This implies that the calculation time is inversely proportional to the value of Δt.

Given these issues, two options remain for 0.25 h and 0.5 h. The second option is the one chosen, as it reduces the number of samples in the optimisation horizon, which allows a shorter calculation time, with a negligible loss of accuracy (in the case where one more part is produced than required).

The values of the decision variables of the Base Behaviour have been obtained from the planning executed in the production process during the day to be optimised. The analysis of the recorded history of machine operation with the time data provided the necessary information to reconstruct the production planning decided by the operators. At each instant k, this consumption has been subtracted from the global demand (E_T^k), also recorded over time, to obtain the Remaining Consumption (E_{RC}^k), as can be seen in Eq. (3) and graphically in Fig. 2.

$$E_{RC}^k = E_T^k - \sum_{i=1}^{M} E_{CNC_i}^k \tag{3}$$

The energy consumed by the manipulable process is approximately 11% of global demand (black line with unfilled/filled dots on Fig. 2 respectively), implying that the margin to adjust the demand is reduced.

In Table 3 it can be seen the production process parameters. In particular, it can be seen the production target for that day, the production time for each part and the number of machines that can be handled in the process.

The prices throughout the day for gas (with a conversion for comparison) and the electricity supplier can be found in Fig. 3. The baseline behaviour can be seen graphically in Fig. 4. Knowing that the black lines represent the different demands and that the bars represent the energy generated in each period of duration $\Delta t = 0.5$ h, it is observed that: at each instant the energy balance for each time interval is fulfilled,

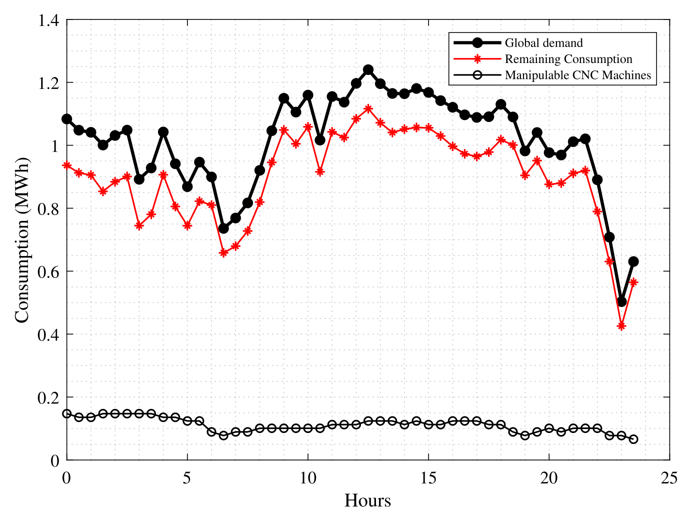

Fig. 2. Comparison of process consumption versus Remaining Consumption.

with an excess of energy in some time intervals, normally produced by the wind turbine; and the power generated by cogeneration is zero, without taking into account the advantage of the price difference between market and gas over time (this usually happens in the planning of the real process).

In the following, all the subsystems that make up the system will be explained.

3. System modelling

This Section will explain how the elements that make up the factory, shown in Fig. 1, have been modelled. As a note, the internal electrical circuit of the factory is assumed to be ideal (lossless), because the value of the losses is small relative to the energy flowing through it.

3.1. CNC machines model

The energy model consists of integrating the average operating ($P_{CNC_i}^{on,mean}$) or idle power ($P_{CNC_i}^{off,mean}$) in one period for each machine. Several real consumption sequences of the CNCs of the process have been analysed to obtain these powers for each machine i. The energy

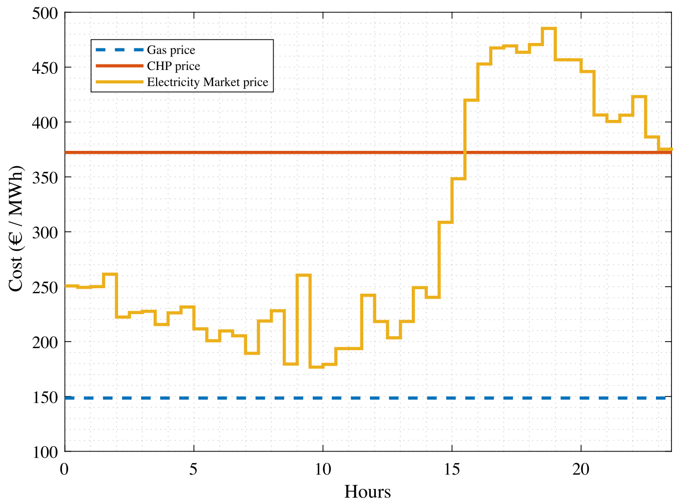

Fig. 3. Prices along the day. The difference between the price of gas and CHP is due to the efficiency of CHP.

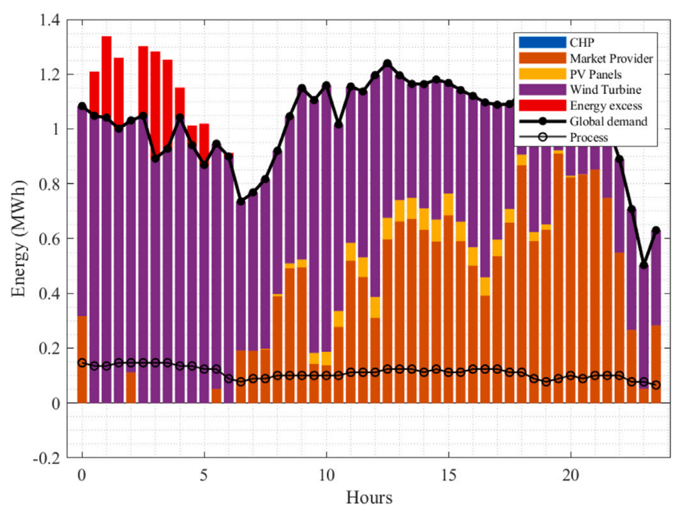

Fig. 4. Energy consumption with the baseline behaviour.

model, to calculate the energy consumed at each instant k by all the machines (E^k_{CNC}), can be seen in Eq. (4).

$$E^k_{CNC} = \sum_{i=1}^{M} \Delta t \cdot \begin{cases} P^{on,mean}_{CNC_i} & \text{if } n^k_{CNC_i} = 1 \\ P^{off,mean}_{CNC_i} & \text{if } n^k_{CNC_i} = 0 \end{cases} \quad (4)$$

Table 3 shows the number of CNC machines (M) that can be handled in the process.

3.2. Battery energy storage system model

A generic battery energy storage system (BESS) model has been implemented to test the different sizes available and to see how battery size influences the energy cost of the process.

The model parameters can be found in Table 4. As their values will change depending on the scenario to be optimised, they have all been referred to as battery capacity (SOC_{max}). The maximum power ($P_{B,max}$) will always be equal to the capacity value divided by one hour, as long as it does not exceed 7 MW since the electrical installation of the factory is not prepared for a power higher than this value. For larger capacities, $P_{B,max}$ = 7 MW. The battery can have different charging and discharging efficiencies. The charge or discharge can reach the maximum value given by the maximum power transmission. The implemented model is described in Eqs. (5), (6) and (7). The auxiliary variable $E^{aux,k}_B$ represents the ideal energy (in the absence of saturations, with perfect efficiency), and E^k_B is the energy charged to/discharged from the battery at each instant k.

Table 4
Battery model parameters.

Parameter	Symbol	Value	Unit
Minimum state of charge	SOC_{min}	$0.2 \cdot SOC_{max}$	MWh
Initial state of charge	SOC^1	SOC_{min}	MWh
Max. power exchange	$P_{B,max}$	$\frac{SOC_{max}}{1h} \leqslant 7$	MW
Charge efficiency	η_c	0.95	–
Discharge efficiency	η_d	0.95	–

Table 5
CHP model parameters.

Parameter	Symbol	Value	Unit
Rated power	P^{max}_{CHP}	435	kW
Electrical efficiency rate	η_{CHP}	39.9	%

$$E^{aux,k}_B = n^k_B \cdot P_{B,max} \cdot \Delta t \quad (5)$$

$$E^k_B = \begin{cases} \text{if } n^k_B \geq 0 & \begin{cases} E^{aux,k}_B \cdot \eta_d & \text{if } SOC^k \geq E^{aux,k}_B \\ SOC^k \cdot \eta_d & \text{in other cases} \end{cases} \\ \text{if } n^k_B < 0 & \begin{cases} \dfrac{E^{aux,k}_B}{\eta_c} & \text{if } SOC^k - E^{aux,k}_B \leq SOC_{max} \\ \dfrac{SOC^k - SOC_{max}}{\eta_c} & \text{in other cases} \end{cases} \end{cases} \quad (6)$$

$$SOC^{k+1} = SOC^k - \begin{cases} \dfrac{E^k_B}{\eta_d} & \text{if } n^k_B \geq 0 \\ E^k_B \cdot \eta_c & \text{if } n^k_B < 0 \end{cases} \quad (7)$$

Recall that, according to Table 1, the decision variable n^k_B contains the sign of the operation to be performed.

3.3. CHP model

CHP stands for *Combined Heat and Power*. That is, heat and electricity are produced from a single device. It is also known as *cogeneration*. In the real scenario, the heat produced is not used. So in the modelled system, it will not be used either.

The data needed for the model are the gas price throughout the day, the efficiency of the CHP (η_{CHP}), the percentage of electrical power that is produced per MWh of gas and the rated power of the CHP (P^{max}_{CHP}). These are all data provided by the manufacturer of the CHP, namely in its datasheet. The value of the parameters can be seen in Table 5.

The CHP installed in the process has only two modes of operation: on, working at rated power; or off. The model implemented in Eq. (8) reflects this behaviour, knowing that the CHP decision variable (n^k_{CHP}) has been defined as binary.

$$E^k_{CHP} = n^k_{CHP} \cdot P^{max}_{CHP} \cdot \Delta t \quad (8)$$

Finally, the cost of this production (C^k_{CHP}) is calculated in Eq. (9).

$$C^k_{CHP} = E^k_{CHP} \cdot \eta^{-1}_{CHP} \cdot Pr^k_{gas} \quad (9)$$

3.4. Electricity supplier at market prices

The electricity supplier, subject to the electricity market, will meet demand when all other energy sources fail to do so. Electricity market prices are obtained from a database of the electricity grid in which the actual plant is located. It follows the curve of a regulated tariff.

In Eq. (10), the total energy obtained from the RESs at each instant (E^k_{RESs}) is described as the sum of the energy generated by the wind turbine (E^k_{WT}) and the photovoltaic panels (E^k_{PV}).

$$E^k_{RESs} = E^k_{WT} + E^k_{PV} \tag{10}$$

The unsatisfied demand ($E^{aux,k}_{MP}$) is given by the energy balance, which is summarised by Eq. (11). This demand can be negative because RESs production covers all demand with its production at some point in time.

$$E^{aux,k}_{MP} = -(E^k_{CHP} + E^k_B + E^k_{RESs}) + E^k_{RC} + \sum_{i=1}^{M} E^k_{CNC_i} \tag{11}$$

The RESs in the original system have no connection to the grid and therefore cannot sell electricity. This constraint has been considered, saturating the grid energy supply (E^k_{MP}), as can be seen in Eq. (12).

$$E^k_{MP} = \begin{cases} 0 & \text{if } E^{aux,k}_{MP} < 0 \\ E^{aux,k}_{MP} & \text{in other cases} \end{cases} \tag{12}$$

The cost of the power obtained from the grid (C^k_{MP}) is calculated in Eq. (13), from electricity market prices (Pr^k_{MP}).

$$C^k_{MP} = E^k_{MP} \cdot Pr^k_{MP} \tag{13}$$

3.5. Renewable energy sources

The generation systems based on renewable energy sources have great penetration and importance in the industry, as they help to replace the energy consumption of the grid, or in turn, supply the energy demand required by the various equipment that make up the process. This Section presents a brief description of two electricity generation systems coupled to the internal electrical grid of the factory. The first uses the wind resource through a wind turbine, and the other uses the solar resource in a photovoltaic installation. The energy generated by both systems is used in the different manufacturing processes within the factory.

3.5.1. Wind turbine

The factory has a 3 MW wind turbine of onshore installation with a windward rotor with a horizontal axis and three blades. The historical data collected by the wind turbine's SCADA contains the measurements made by the sensors of the variables, one of which is the active power generated. Besides, the SCADA stores the data on a day-by-day basis, and the data logging is 10 min as a standard *IEC 61400* wind industry practice.

In this way, it is possible to observe the behaviour of the wind turbine on different days, in this case for an entire calendar year. Therefore, a data-driven approach is applied to analyse the planning production schedule and maximise the use of RESs within the shop floor.

Initially, a process of outliers removal, inconsistent data and an interpolation of data (for missing samples) was carried out for each variable. However, the data show that the active power generated is saturated when there is an excess of renewable resources because the wind turbine does not have a storage unit and is not connected to the external grid. Therefore, these data have been removed by a clustering process in order to capture realistic power behaviour. Fig. 5 shows the data collected from one day of the active power generated by the wind turbine.

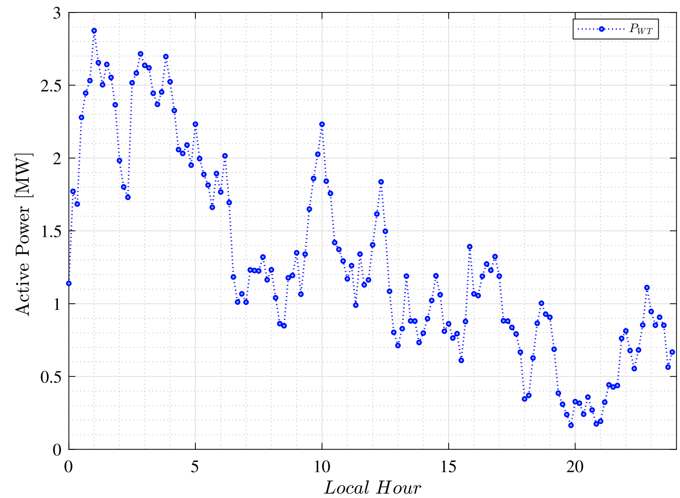

Fig. 5. Data collected by SCADA of the wind turbine: Active power data for a specific day.

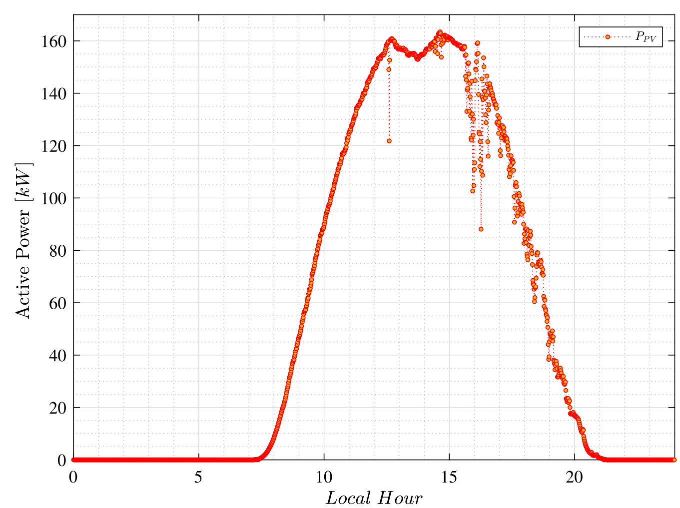

Fig. 6. Data collected by SCADA of the photovoltaic installation: Active power data of a specific day.

3.5.2. Photovoltaic plant

The roof of the workshop building is equipped with a 210 kW photovoltaic installation, with a series-parallel configuration of 688 solar modules and three inverters that can reach an annual energy production of approximately 160 MWh. In addition, each solar module consists of 120 cells and the total PV installation has a surface area of 1107 m^2. The SCADA of the PV plant collects data on the generated power and records it every minute. Also, a data-driven approach is applied to analyse behavioural patterns. In addition, data pre-processing is performed, a process similar to that applied to the wind turbine data. Fig. 6 shows the collected data of one day that is used in planning production to improve energy use.

4. Optimisation solution

The objective of the optimisation is summarised in Eq. (14): to minimise the daily energy cost (C^{day}). To achieve this, the correct value must be selected for the decision variables (n^k_{obj}), as these are the only variables that can be manipulated.

$$\min_{n_{obj}^{k}} C^{day} \quad \text{subject to Eq. (2)} \tag{14}$$

Looking at the Table 1, it can be seen that the problem contains both integer and continuous variables, i.e. it is a mixed problem. To solve this type of problem there are several optimisation algorithms.

Taking into account the type of optimisation problem; the possibility of improving the system model with more complex and realistic descriptions; and looking at other similar works already implemented [10]; genetic algorithms have been chosen among all the optimisation algorithms.

Although genetic algorithms offer no guarantee of finding the global solution in all cases, their advantages in terms of exhaustive exploration, adaptability, flexibility and handling of complex problems make them an attractive and effective option for these optimisation problems.

4.1. Concept of genetic algorithm

The genetic algorithm (GA) is essentially a heuristic search algorithm. The algorithm mimics the process of natural selection, whereby the strongest individuals are chosen for reproduction, resulting in the offspring of the next generation [24].

Natural selection begins with the identification of the most robust individuals within a population, which then produce offspring that inherit their traits and are added to the next generation. If the parents possess superior fitness, their offspring will also be superior and more likely to survive. This cycle repeats itself, ultimately resulting in the emergence of a generation with the most robust individuals. This approach is also applicable to search problems: the genetic algorithm tries to evaluate a set of solutions to a problem and select the best of the group.

The algorithm consists of six stages: initial population, fitness evaluation, selection process, crossover, mutation and termination condition. These six stages will be repeated until the termination condition is met. Each of the stages will be explained below using the nomenclature used throughout this article.

Initial population. A *population* is a set of individuals. An *individual* is a possible combination of values of the decision variables (n_k) of the optimisation problem. Any individual is a possible solution to the problem. These values of the decision variables are called *genes*.

In the first iteration of the process, it is necessary to select a specific population, from which the GA will start searching for the optimal solution.

The size of the initial population is fixed and is given by the number of genes (length of the individual) and the number of individuals desired for each population. The latter is set by the parameter *Population Size*.

Fitness assessment. The ability of an individual to compete with others is determined by the fitness function, which assigns a fitness score to each individual. In this second stage of the process, each individual in the initial population is assessed. The probability of an individual surviving is directly related to this fitness score. Individuals with a higher fitness score are more likely to survive and pass on their genes to the next generation.

Selection process. During the selection phase, the aim is to select the fittest individuals and allow them to pass on their genes to the next generation. This is done by evaluating the *selection function* which has as input the fitness value from the previous step. This function returns a value that is used to select the individuals that will be crossed to form the new individuals of the new population.

The number of individuals selected is given by the parameter *Elite count*. These individuals are the only ones that remain unmodified between the old and the new population.

Table 6
Selected parameters of the genetic algorithm.

Param	Value
Max stall generations	50
Population size	2500
Elite count	500
Selection function	selectionstochunif
Crossover function	crossoverlaplace
Crossover fraction	0.8
Function tolerance	10^{-6}

Crossing. The most important stage in a genetic algorithm is the crossover phase. Here, the evolution of the population takes place through the mixing of pairs of individuals selected in the previous phase. To mix each pair of individuals, a method is selected to mix the genes of the pair. This method is known as the *Crossover function*.

Once the method for mixing individuals has been selected, as many individuals are produced as are derived from the parameter *Crossover fraction*. This parameter indicates the percentage of individuals in a population, excluding those selected in the selection phase, that have been generated through the crossover. The remaining individuals, until the population is complete, are generated through mutation.

Mutation. The purpose of mutation is to ensure that there is a variety of traits within the population and to prevent the population from converging too early.

In the mutation stage, small random changes are made in individuals in the population to create the remaining offspring. The *Mutation Function* is used to make these changes.

Termination condition. The last stage of the process is to decide whether the termination condition has been reached. This condition can be a maximum number of iterations, a maximum number of iterations without improvement, a minimum fitness value, and so on.

In this case, the maximum number of iterations without improvement, given by the parameter *Max Stall Generations*, has been selected as the termination condition. Furthermore, to determine whether an improvement has occurred, the parameter *Function tolerance* is used. This parameter indicates the margin of fitness that the population must improve to consider that an improvement has occurred. If the improvement is not higher than this value, no improvement is considered to have occurred, and the counter of iterations without improvement is incremented. If the improvement is higher, the iteration counter without improvement is reset.

4.2. Selected parameters

In Table 6 it can be seen that the main selected parameters of the GA that are common to the different scenarios will be explained below. These parameters have been empirically adjusted, rewarding values that obtain a better result in terms of the quality of the result and the time spent.

The mutation function is the only parameter that is modified in the different scenarios. A multitude of experiments have been carried out in each scenario by changing the mutation function until the best results were achieved. In these results, two different mutation functions were used:

1. Power mutation [25]: more accurate, but requires more computational burden on mixed problems. It has been implemented only in the scenario without batteries (Scenario 0.0).
2. Uniform mutation [26]: less precision, but less computational burden. It has been used in scenarios with battery, because in these scenarios, where binary variables and continuous are mixed, the GA with the power mutation function is not able to converge to a good solution, in a reasonable time.

Table 7
Battery capacities of each subscenario.

Identification (Scenario.SubScenario)	0.0	1.0	1.1	1.2
Battery capacity (MWh)	0	1	5	10

To initialise the decision variables, a set of values has been taken that make all machines and the CHP on for the entire OH, while at all times the battery (only in scenarios with battery) are kept disconnected. With this set, it is verified that at the start of the optimisation, the initial set of individuals lies within the region created by the constraints, given by Eq. (2).

4.3. Proposed scenarios

Two scenarios have been developed to see how battery consumption affects final cost. The first scenario, compared to Fig. 1, does not have a battery implemented. The second scenario is identical to the first one, with the addition of a battery bank. Within this scenario, three different battery capacities have been tested, resulting in three sub-scenarios. Each subscenario in this scenario varies only in battery capacity. The battery sizes chosen are shown in Table 7. Recall that all battery parameters depend on SOC_{max} for their configuration.

5. Optimisation results

The optimised energy distributions and, if applicable, the state of charge of the battery over the entire optimisation horizon, for each sub-scenario, will be shown below.

The graphs have been scaled as follows: in the graphs referring to the energy sequences, each bar represents the total energy produced/consumed during that period of duration Δt; in the graphs referring to the energy stored in the battery, the SOC of the battery in p.u. at each instant k has been represented. In both figures, the time has been scaled with respect to the sampling period Δt to better visualise the results, maintaining the number of instants, starting at 12:00 AM.

Optimised scenario without battery (scenario v0.0). Fig. 7 shows the optimised energy distribution in the battery-less scenario. It can be seen that throughout the day, the balance of power is always met, that is, at each instant, the overall demand (black line with filled dots) of the factory is covered, first by RESs, i.e, by the WT (purple bars) and/or the PV (yellow bars), and if necessary, additionally by purchasing energy from MP (orange bars) or CHP (blue bars). In addition, it can be seen that surplus energy (red bars) cannot be sold, so it is thrown away.

Compared to Fig. 4 (baseline behaviour), it can be seen that: the sequence of the manipulable CNC machines (black line with unfilled dots) has been optimised, occupying the time instants with the lowest market price and/or the highest amount of renewable energy generated. Due to this, the excess energy (red bars) is lower, as the demand is adjusted to the generation of renewable energy. In addition, the optimiser starts up cogeneration, when deemed appropriate, to cover part of the demand.

Although the utilisation of excess energy is higher, it is not possible to further reduce the amount of wasted energy because the margin of the decision to adjust the demand is very small. To increase this flexibility and to be able to adapt to prices and renewable generation, a battery has been introduced.

Optimised scenario with one battery of 1 MWh *(scenario v1.0).* The optimised energy distribution of the optimised scenario with a 1 MWh battery can be seen in Fig. 8. This shows the energy stored (negative green bars) and supplied (positive green bars) by the battery.

Comparing Fig. 8 with Fig. 7, it can be seen that excess energy is less, because when there is excess energy, it is stored in the battery and is used when there is less renewable energy generation.

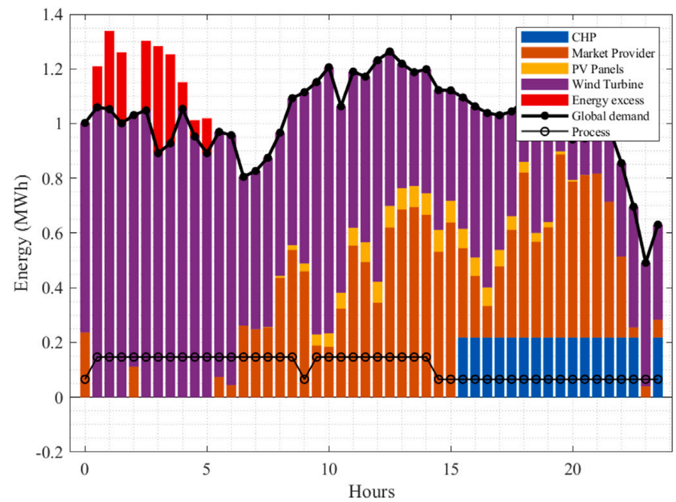

Fig. 7. Energy distribution in the optimised scenario without battery.

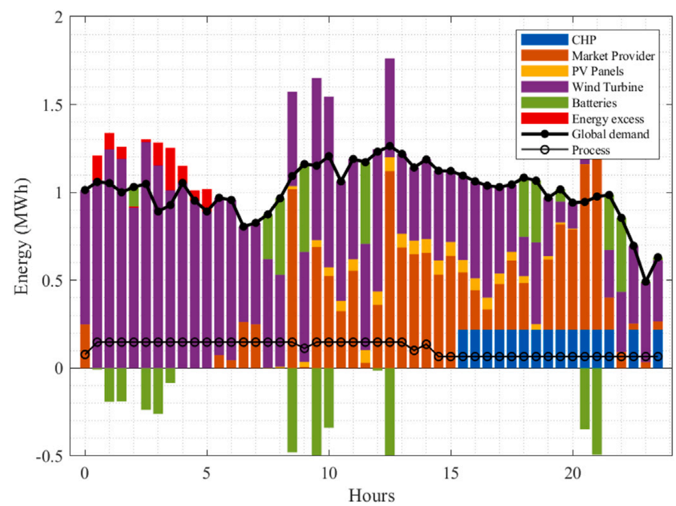

Fig. 8. Energy distribution in the scenario with 1 MWh.

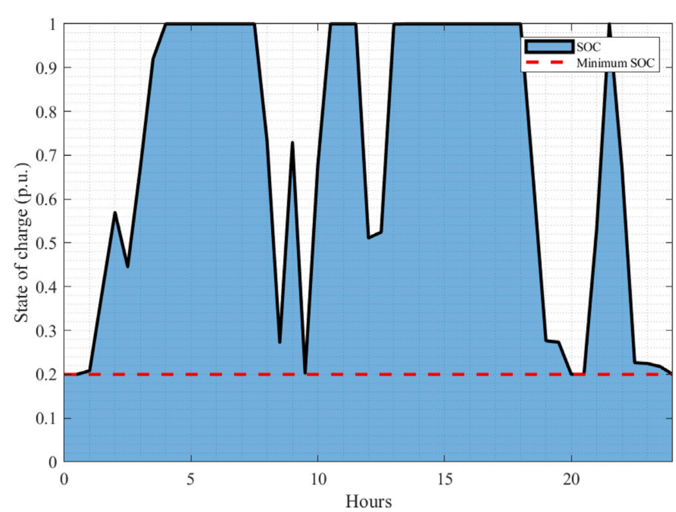

Fig. 9. State of charge of the battery of 1 MWh.

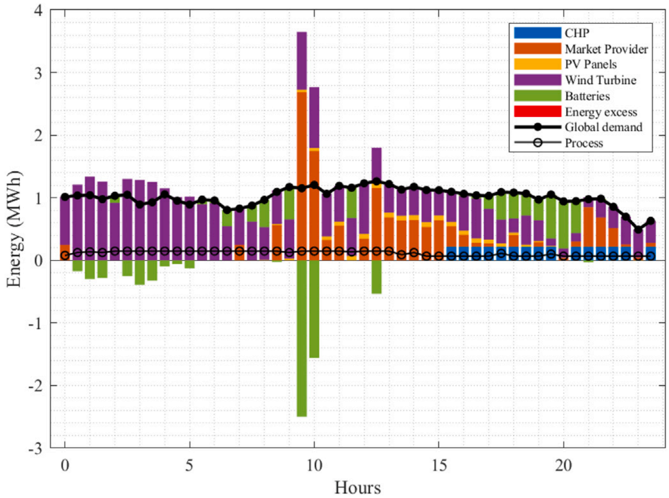

Fig. 10. Energy distribution in the scenario with 5 MWh.

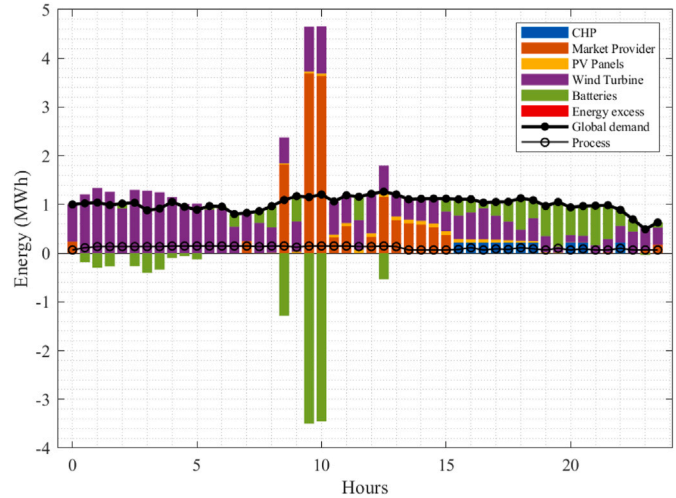

Fig. 12. Energy distribution in the scenario with 10 MWh.

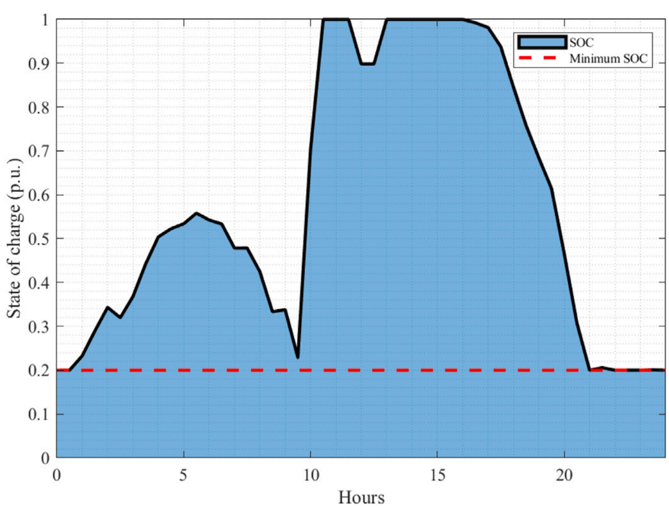

Fig. 11. State of charge of the battery of 5 MWh.

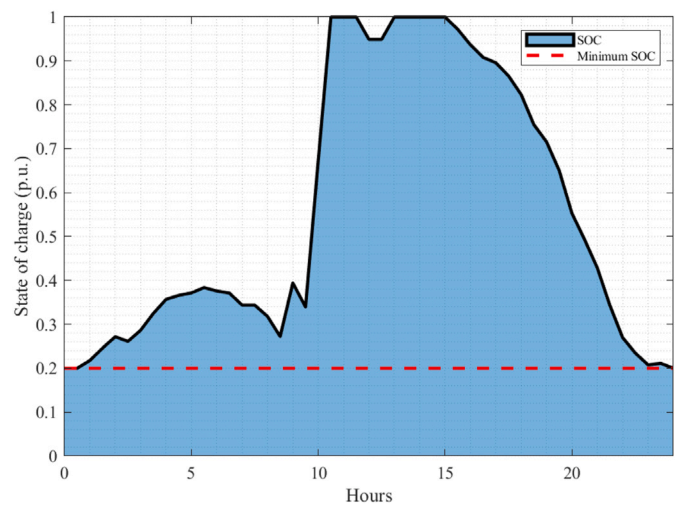

Fig. 13. State of charge of the battery of 10 MWh.

To illustrate this, the SOC of the battery for that day can be seen in Fig. 9: the battery charge is completed several times a day. In addition, in this Figure it can also be seen that saturation is met at the minimum SOC to increase battery life.

In order to be able to use the surplus energy generated to the maximum and thus maximise the use of renewable energies, a larger battery has been introduced in the following scenario.

Optimised scenario with one battery of 5 MWh *(scenario v1.1).* In Fig. 10, the energy distribution for the scenario with a medium-sized battery is shown. In this figure it can be seen that the excess energy (red bars) is zero.

Fig. 11 shows that the battery is fully utilised. To prove that a higher capacity battery does not improve the result, a third scenario with a larger battery was simulated.

Optimised scenario with one battery of 10 MWh *(scenario v1.2).* Fig. 12 shows the energy distribution of this scenario.

In Fig. 13 it can be seen that the improvement over the previous scenario consists in storing all possible electricity from the market when it reaches the minimum daily price, saturating at 7 MW at instant 9.5 h (recall that Fig. 12 is scaled with $\Delta t = 0.5$ h).

All results have been summarised in Table 8. Looking at these results, the following conclusions can be drawn:

Table 8
Summary of the results.

Optimisation Strategy	Daily money saving			
	Battery size			
	–	1 MWh	5 MWh	10 MWh
First	6.2%	12.6%	27.4%	39.2%

1. Although the decision margin on demand is small (11%), the savings achieved are significant, without taking battery into account a daily saving of 6.2% is achieved.
2. Inclusion of a battery considerably reduces the cost of energy; the savings are directly proportional to the capacity of the battery included. To this conclusion, it must be added that when a BESS cost model is added, saturation will appear, limiting this proportionality of capacity and savings.
3. The optimiser, based on GA, is able to find the optimal solution in a reasonable time, even with a large number of variables.

6. Improving the optimisation strategy

Later, to reduce the optimisation time, the number of variables in the CNCs was reduced. In the previous optimisation strategy, for each instant k, there was a binary variable for each CNC. In this

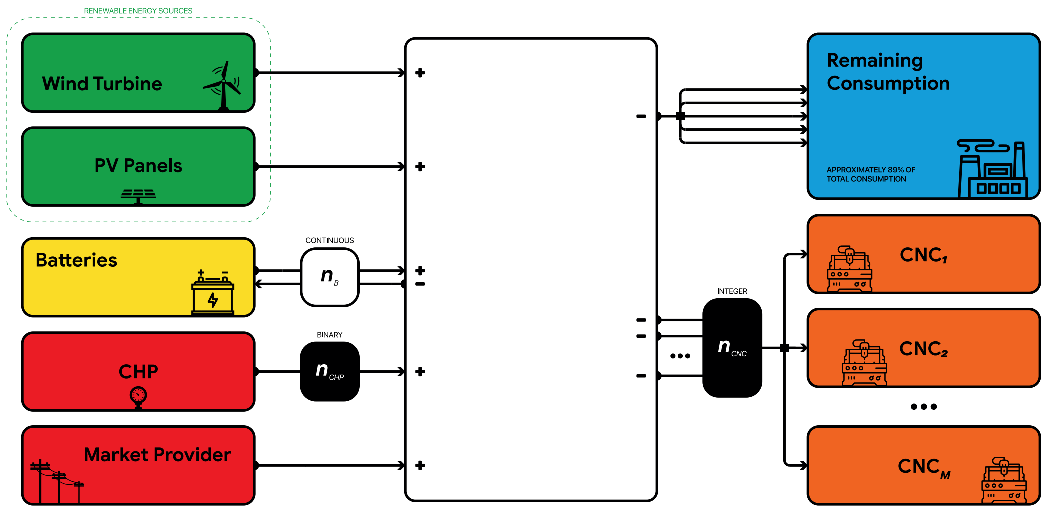

Fig. 14. System setup of the factory with the second strategy decision variables.

Table 9
Free variables of the second strategy.

Symbol	Type	Limits lower	Limits upper
n^k_{CNC}	Integer	0	M
n^k_{CHP}	Binary	0	1
n^k_{B}	Continuous	−1	1

Table 10
Number of variables to optimise.

Optimisation Strategy	Scenario Zero	Scenario One
First	384 variables	432 variables
Second	96 variables	144 variables

second strategy, there is only one integer variable for each instant that indicates how many machines are on at that moment. The decision variables of this strategy can be seen in Table 9.

With this change, two optimisations would be decoupled: how many machines of each type would be turned on at each instant (which depends only on the DPT) and which machines would be turned on to meet the objective first. In Fig. 14 the factory system setup with these decision variables is shown.

As the implemented model of CNCs only takes into account the consumption of the machines, and this is identical for all the machines, this second optimisation will be solved with a rule: the CNCs will be numbered and the first ones will always be started first; for example, if at an instant k there must be 7 machines running, they will be started from 1 to 7. This way of solving the second optimisation may have problems when the sampling time (Δt) is not a multiple of the production time (T_{part}) of one part In that case, another algorithm would be necessary, or the sampling time should be reduced.

The total number of variables to optimise in each of the strategies proportional to the sampling time and optimisation horizon set out in Table 2, is reflected in Table 10. As can be seen in this Table, this strategy achieves a drastic reduction of variables without losing precision in the result.

This reduction of variables makes it possible to take advantage of the precision offered by the mutation function *power mutation*. At the same time, to take advantage of the speed of the mutation function *uniform mutation*, the genetic algorithm has been configured to perform two serial optimisations: the first with the mutation function *uniform mutation*, to obtain a preliminary solution quickly; and the second, with

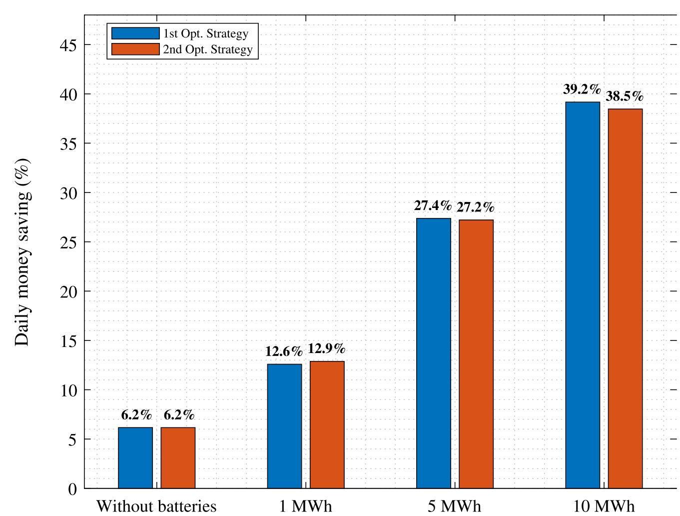

Fig. 15. Comparison of results of the two optimisation strategies.

the mutation function *power mutation*, to obtain a solution closer to the absolute minimum.

To initialise the variables, the same procedure has been followed as in the first strategy, adapting the set of individuals to fit the new representation but complying with all the restrictions to the same extent.

6.1. Comparing results

The results obtained for each scenario for each of the two optimisation strategies are shown in Fig. 15. All data shown in Fig. 15 have been summarised in Table 11, adding the processing times for each optimisation and scenario.

In view of these results, the following conclusion can be drawn: the second optimisation strategy, with its reduction of variables, improves on the first in terms of time, without losing much precision (0.7% at most).

If optimised once a day, this improvement does not justify the temporal improvements obtained. But if it is optimised, as explained

Table 11
Summary of the comparison.

Optimisation Strategy	Daily money saving Battery size/Optimisation time			
First	6.2% –/2 min	12.6% 1 MWh/15 min	27.4% 5 MWh/92 min	39.2% 10 MWh/34 min
Second	6.2% –/2 min	12.9% 1 MWh/5 min	27.2% 5 MWh/11 min	38.5% 10 MWh/7 min

in the next section, in a closed loop, that is, at each instant k the whole system is re-optimised, in order to feedback on all the updated data of the system, the optimisation must be performed in a time shorter than the sampling time (being, in this case, $varDeltat = 0.5; \mathrm{h}$). This is the justification for the need to improve the optimisation time by improving the optimisation strategy.

Finally, it is worth noting that the optimisation method implemented in the system allows the battery size to be decided quite precisely for this factory, being easily replicable for other systems.

7. Conclusion

This article has presented the formulation of the optimisation of a manufacturing process, through genetic algorithms, managing the generation and demand of energy in a factory at periodic moments of time; The strategy manages to minimise the daily energy cost and maximise the use of installed renewable energy, also taking advantage of potential battery banks.

The result of the optimisation for one day decides the work sequence of each machine, as well as the charge and discharge of the potential battery bank and the contribution of an installed CHP.

Another optimisation strategy with fewer variables has also been proposed and tested, obtaining similar results but improving the computation time. In addition, in the simulations, scenarios with different battery capacities have been tested, which has allowed a preliminary study to be carried out for the installation of the electrical storage bank.

The results presented in this work show that 6% of energy costs can be saved per day, compared to the current management decided by the manufacturing plant operators. Furthermore, through the simulation-based study, approximately another 6% additional savings can be achieved by installing 1 MWh of battery, then increasing by approximately 3% for each addition of MWh.

The work has been a study on a real factory, which will serve as an initial framework, where, for future work, more elements can be included to improve the model (uncertainties, other assets, etc.).

This work thus can be extended in several ways. First, because the actual production process involving CNCs is a multi-stage manufacturing process, the whole process could be implemented to improve the accuracy of the optimisation.

In order to solve the problems of errors that may occur in the system model, it is necessary to recalculate the entire optimisation. These errors can be, for example, a machine that breaks down or a weather forecast that is not fulfilled. In this case, continuous closed-loop reprogramming based on genetic algorithms would correct these errors at every k sample without carrying forward errors. In addition, variables could be further reduced to improve the optimisation computation time and improve the accuracy of the optimisation. This future work justifies the search for a fast and accurate solution, since in order to close the loop, the optimisation time needs to be shorter than the sampling time.

Due to the uncertainties associated with the whole system (atmospheric predictions, failures, etc.), the incorporation of stochastic models within the predictive system will improve the accuracy of the prediction, ultimately improving the final cost.

CRediT authorship contribution statement

Javier Gómez: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing – original draft. **William D. Chicaiza:** Methodology, Software, Investigation, Visualization, Writing – original draft. **Juan M. Escaño:** Methodology, Software, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Carlos Bordons:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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