

Tactical Business-Process-Decision Support based on KPIs Monitoring and Validation

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Key Performance Indicators (KPIs) can be used to evaluate the success of an organization, facilitating the detection of the deviations and unexpected evolution of the behaviour of a company. The difficulty for enterprises is to ascertain what to do when a deviation is detected. In this paper, we propose a modelling approach to improve the operational business-level and to ascertain the possible actions that can be executed to maintain the right direction in a company. For business process-oriented companies, it entails knowing how KPIs can be affected by the business processes. It implies not only pointing out that a system malfunction exists, but also to know what to do when a deviation is detected. Our proposal presents a methodology that covers: (1) an extension of the existing models in order to combine KPIs, goals of the companies, and the decision variables together with business processes; (2) a methodology based on data mining analysis to verify the correctness of the enriched proposed model according to the data stored during business evolution, and; (3) a framework to simulate the evolution of the business according to the decisions taken in the governance process, thereby supporting governance activities to achieve the defined objectives by exploiting goals and KPIs from the proposed model.

1. Introduction

The IT Governance Institute (2001) defines enterprise governance as the “set of responsibilities and practices exercised by the Board and Executive management Team (BET) with the goal of providing strategic direction, ensuring that objectives are achieved, ascertaining that risks are managed appropriately and verifying that the enterprise's resources are used responsibly” [4].

A business plan is a document that details the activities of an organization and examines how and when the objectives can be achieved [26]. A business plan contains a set of sections that details every aspect of the company, in which the BET apply foundations of the Theory of Organization [44] and related techniques, to describe how the company and how to achieve its objectives. The sections of a business plan contain, amount others, operational section (operational plan) and strategic section (strategic plan). Operational plans describe in detail all the actions that can be performed

in the company, meanwhile strategic plans describe the objectives (the right direction), and how to achieve them.

In order to support the operational plan, companies are able to incorporate a commercial Business Process Management System (BPMS). BPMSs represent software that supports the implementation, coordination and monitoring of the business process execution, allowing companies to manage the entire process life-cycle of the business processes. BPMSs operate as orchestrator that can be integrated with other systems existing in the company, such as Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM), which allows reaching a better automation to the operational plans. The information related to the status of the business keep stored in these systems, for this reason, in order to analyse the status of the business and his alignment with the right direction, companies can incorporate Business Intelligence (BI) techniques that monitoring their data values and the satisfiability of the indicators.

However, BI tools are not aligned with the whole life-cycle of the decisions made in the companies to satisfy the strategic plan. This misalignment makes difficult to know what to do if a functional deviation is detected, or how the business can evolve according to the operational decisions that can be made. At the management level, the BET does not make the low-level decision in

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actions under-performing [54], at management level, they must make decisions about what action perform to maintain and follow the agreed business strategy, thus the right direction. In order to make the best decisions, three aspects must be analysed: (i) model the relation between the elements of the organization (i.e., measurements, goals, processes) by the business experts; (ii) verify the correctness of the expected model with the real values extracted from the behaviour of the company; and, (iii) simulate how the decisions can affect the evolution of the organization in the future.

The execution of each business process is able to contribute towards achieving one or more business goals. In order to gain information about the business process efficiency according to the desired business objectives, activities represented in controlling mechanism are performed, and Key Performance Indicators (KPIs) of business processes are determined [51]. Performance Management Systems (PMSs) are concerned with defining, controlling and managing both the achievement of outcomes or ends and the means used to achieve these results at a societal and organisational [5]. One of the objectives of a traditional PMSs is to create a consistent approach to extract, analyse and report information about the performance of the company. PMSs are used to know if systems are working as expected, comparing the expected model with the observed information. For this reason, we need to have the capacity to create a model that represents the expected behaviour (achieve the defined goals according to the KPIs and KRIs). It is, therefore, necessary to create a combined model of influences where processes, goals and measurements are able to be combined. Meanwhile, the BI lets analysis of the information stored in the systems of the organization to evaluate the achievement of the strategic plans, our proposal creates the model according to these plans to help BET making decisions aligned with them. The ability to analyse extracted information and help in decision-making is being associated with PMS frameworks [52], therefore our proposal could also be categorized as a PMS framework that analyses the data according to the defined model and simulating how each action can affect the evolution of the system.

In this paper, the approach deals with the older modelling in management science [40], such as systems dynamics. It includes how the execution of the business processes used by the

organizations can affect the indicators and goals. In process orientation, business processes are the main instrument for the organization of the operations of an enterprise [16]. This implies that the overall organization can be seen as a set of business processes, working together to achieve the objectives of the company. Organizations can incorporate various types of business processes, and they are influenced by the strategic plan that defines the objectives and goals, but they are also influenced by the stakeholders and the information systems that support them.

When business process models are included in the decision making, new challenges must be faced derived from the decisions related to the input data introduced in the business process models, and that affects to the achievement of the objectives of the organisation. In this paper, the business management helps to decide which operation has to be carried out. It is typically a human and manual task, the BET of the enterprise uses indicators, frequently shown on dashboards, to decide which actions to take to improve the indicators in the future. The relation between the operations and how they can affect the measures and indicators is not always clear, since it depends on the background of the particular decision-maker and the complexity of the relations. Thereby, it is necessary to verify the correctness of the model in accordance with the history of the company. To create a model that fits with the reality allows for simulating how the decisions might influence to the indicators, and reduces the errors produced by incorrect decisions that fail to follow the strategy defined in the organization.

In order to extend the management of the strategic plans with business processes (i.e., modelling, verification and simulation), we propose a methodology consisting of 5 steps, as shown in Fig. 1 used as guide to present our proposal:

- 1. Creation of enriched models by Business Experts:** In this paper we propose the use of model-based fuzzy logic graphs that represent the relation between KPIs, Goals, Measures and the processes of the companies. Fuzzy Governance Maps (FGMs) were introduced in [42], but in the current proposal the types of elements are extended. Since there are several factors involved in the decisions of an organization, FGMs are able to be defined by parts, from different points of view and from various business experts as shown in Fig. 1.(1). Different KPIs can be defined from

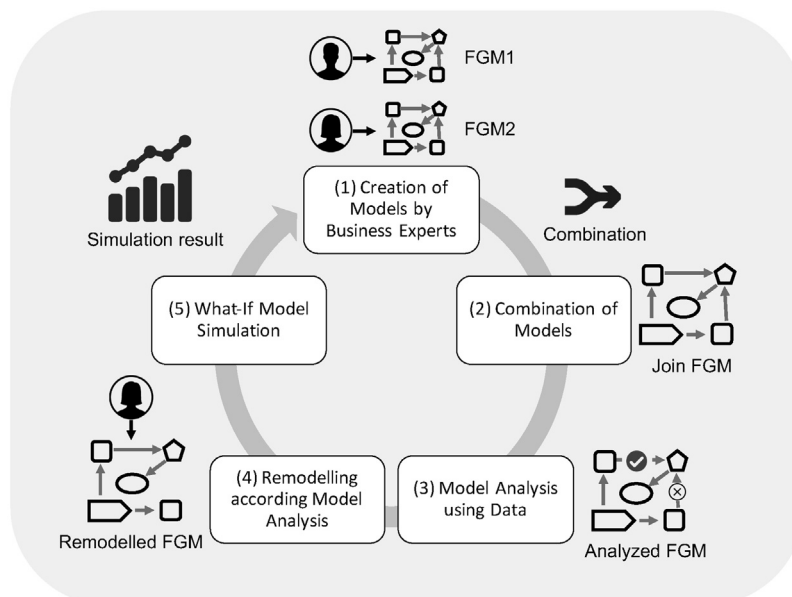


Fig. 1. Life-cycle proposal for improving Decision-Making based on Business Models and Measurements.

different points of view and organizations [31], giving the possibility to the various business expert can modify them according to the prospects.

2. **Combination of FGMs:** Business processes, measurements (KPIs, Key Result Indicators (KRIs) [28,36] and measures) and objectives involved in the various FGMs are combined automatically in a single model (Fig. 1.(2)), in order to tackle the problem analysis in a joint way. These concepts are further described in Section 4.2.
3. **The model is validated using the data extracted from previous instances:** Sometimes the models defined by the experts are not working as they were envisaged for. An analysis is necessary to confront the data obtained in the former activities of the companies, and the models described by the experts (Fig. 1.(3)). This analysis lets the detection of possible incorrect assumption done by the experts during the modelling of the FGMs [29].
4. **Remodelling according to the Model Analysis:** A business expert needs to study the incorrect assumptions and the result of the combination for remodelling, if necessary, the FGM of the organization. A new FGM (FGM*) might be created, closer to the real behaviour of the company (Fig. 1.(4)).
5. **What if Model Simulation:** The model is able to be simulate to ascertain the evolution of the KPIs and the goal achieved during a potential execution. These decisions help the BET during decision-making processes, completed with a framework to simulate automatically the different scenarios in a what-if analysis [24] supported by a dashboard (Fig. 1.(5)).

In this paper, the main objective fulfilled using the FGMs is the capacity to simulate them, in order to help to the BET to make better and strategic-aligned decisions. However, FGMs are also a useful tool to share a vision of how the entire company works, and how the actions that can be done in the company affects the different elements involved.

The paper is organized as follows: Section 2 analyses an overview of related work found in the literature. Section 3 introduces an illustrative real example. Section 4 presents the extension of the existing model in the literature to combine KPIs, goals and business processes in a company. Section 5 tackles now the FGMs described by parts can be combined to help the BET maintaining the correct direction. Section 6 describes how model correctness is verified based on the data extracted from former instances. Section 7 describes the possible actions that can be carried out in the remodeling process (i.e., eliminate relation, aggregate relation, modify label). Section 8 introduces how the improved FGM is used to develop a what-if analysis. Finally, conclusions are drawn and future work is proposed.

2. Related work

Modelling in management science is a key aspect, since it is not possible to derive knowledge about elements whose influences are not included in the model. In the management area, there exist several types of models to describe the influence of the elements (e.g., causal/flow graphs [37], stock and flow diagrams [2], influence models [1], casual-loop diagrams [43]). The failures of these proposals reside in business processes cannot be incorporated. Goal-Oriented techniques [18,55] facilitate the detection of the actions in an organization that facilitate fulfill the objective, but they do not permit the inclusion of the input data for business processes in the analysis. In previous work [9], the organization goals are modelled using User Requirements Notation (URN) [19], but they do not allow for integrating indicators and business processes as part of the user requirements.

The verification of the model is fundamental to reduce uncertainty in a company, since organizations must invest large quantities of time and money to ensure Business Process Compliance (BPC) with policies, regulations, and legislation. A systematic selection and characterization of the literature that focuses on BPC was published in [45]. Other studies have expanded on how it is possible to utilize tactical information, knowledge, and experience concerning business activities for the BPC. Business Process Intelligence techniques (BPI) integrate BPMS and Business Intelligence systems [15]. Shollo [46] proposes applying "hard facts" provided by BI in the IT governance context, as a foundation for rendering arguments more convincing during decision-making discussions. In the case of Goal-Oriented techniques, they extend URN to include the validation of business processes by considering performance issues as compliance, such as [41]. However, the tactical point of view applied to BPC is missed in the works found in the literature.

In addition to these techniques, there has been extensive research focused on improving business performance by means of modeling and monitoring performance through KPIs in business models. They combine strategic business models with business process data to reason and calculate performance indicators, detecting deviations in the processes from what decision makers expect. Unfortunately, the correctness of the models and reasoning results depends entirely on the knowledge and accuracy of domain experts when building the models. This means that they must be knowledgeable not only about the strategic level, but also about the tactical level and all the fine-grained details that may influence the outcome of processes and goals. The specialization of BIM to the tactical level (TBIM) has partially addressed these issues [8], by focusing on the tactical level and adding necessary constructs to represent processes and their related elements. However, aside from incipient works, such as [28], there are still no techniques that allow decision makers to contrast their models against hard facts in order to validate them.

Once the simulation model is known, the decision-making can be faced. Decision-making processes have been studied previously [13] to settle the values of the inputs of the processes, but it is not oriented to decide both business process and input data to achieve the goals of the organization.

In order to know how decisions can affect the evolution of the system, simulation techniques are able to be used. The simulation is hard-linked to the characteristics and components of the used model. Some examples of those simulation techniques for management science have been summarized by Pidd in [39]. Our proposal extends [25], where the authors present a combination of fuzzy techniques with cognitive maps, to facilitate the modelling and performing the what-if analysis. In [34], the authors also consider time relationships, that allow simulating the delays between the actions and the effects. Mentioned proposals allow for simulating the evolution of the system, but business processes and input data are neither included nor aligned with goals and KPIs. Simulations in business process area is an important issue [17], frequently used for predicting the system performance. The analysis of the input data determines the branches and paths to execute [50,22], but there are no solutions that relate how these executions can affect to the business indicators and strategic goals.

Unfortunately, in the mentioned techniques input data are not available to model the systems, and therefore cannot be simulated to observe the behaviour of the system under input data changes using simulation techniques.

Summarizing, many previous studies use reasoning and techniques to improve some phases of the development of the strategic plan, but there is not an integrated solution that covers the whole life-cycle in the strategic decisions, and how they can affect the defined goals. Techniques listed above do not provide

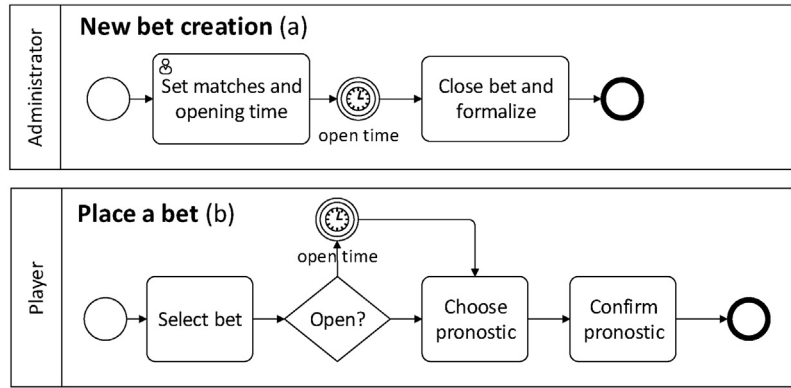


Fig. 2. Tutiplay business process for the users of the platform.

sufficient support dealing with business goal models and business process executions in an integrated and efficient manner. They do not offer a framework where revised models can be obtained applying data mining techniques, and where process and data are able to be included in the simulation.

3. A real-world example

The used example used in the proposal is based on a real-world scenario of a collaborative platform to play a football pool called Tutiplay™ [48]. This is a web platform oriented towards collaborative betting, where people buy betting ticket together. In each bet, each person fills in an independent row and permits the Tutiplay platform to collect every row together in one betting ticket, and formalizes the bet using the corresponding administration. In the case of economic reward, the platform also collects the winnings and divides the quantity of the participants. More than one bet can be opened for placing at the same time.

Fig. 2 shows two business process models implemented to support the platform. The first model “New bet creation (a)” shows how a bet is managed by the person who administers the platform, from the creation to the close and final formalization of the bets. The second model “Place a bet (b)” shows the steps that a player must follow to place a specific bet.

The business objective of the platform is to formalize as many bets as possible in order to (i) maximize the profits, but also (ii) maximize the active users. To achieve these goals, the organization has the business processes shown in Table 1 which allow the BET to implement certain strategies that contribute to this end. Table 1 also shows a small explanation regarding the business processes available, with the business aim that each one follows.

The correct direction of the company is based on the business strategy defined: The BET observes the evolution of the business using a dashboard, and when necessary or desired, they can settle to perform any action, that implies executing some processes.

Table 1
BET strategy process.

Business process	Consists of	Strategy aim
Send tweet	Select a generic tweet from a repository and send it with the aim of stimulating the social networks, and to connect players and followers	Increase the forecasts to get followers
Execute a “miss you” campaign	Send an emails to every lost user, inviting them to use the platform again	Decrease the number of lost users, trying to reactivate users.
Execute a ranking campaign	Send an individual email to every user, including indicators of the evolution of the player	Gain more bets and decrease the number of lost users
Execute a reminder campaign	For a determinate round of fixtures, send an email to players that have not yet placed a bet, when the deadline is near.	Increase the number of bets for a determinate round of fixtures
Invest in online publicity	Invest money on social networks, to enrol new users to the platform	Increase the number of users

The problem involves ascertaining which process or processes can improve the competitiveness of the company, and how they can affect the other KPIs. In the following Section we describe how our proposal covers this aspect.

4. Business process and business strategy

The relation between certain types of processes and the capacity to modify the goals of an organization was detected by Smith et al. [33], and depicted in Fig. 3. The alignment between the processes of an organization, and the goals to be achieved are depicted in strategic plans, and his achievement implies performing three steps. The first (1) consists of taking measurements, which are taken from the indicators observed from the processes defined as relevant for the organization. (2) It is then necessary to make an analysis of these measurements in order to (3) perform possible actions that will affect the goals of the organization. As mentioned earlier, measurement, analysis and response actions are oriented towards improving the business strategy defined, which is affected by the evolution and the status of the organization itself, and by the external environment.

Certain measures may be directly influenced by the decision-making process or business process executions, but others are affected by external actions in an indirect way. For example, a company can change the price of a product (variable directly determined in a decision-making process) but cannot determine the number of products sold (variable affected by the execution of other actions). However, organizations usually have a set of mechanisms that can help to achieve their goals, for example, when the price is decreased or an advertising campaign is deployed, more products will likely be sold. The actions do not always modify the measures directly, but they can stimulate the indicators of the company in the desired direction. The execution of a business process (e.g., Execute a marketing campaign) might influence in the indicators.

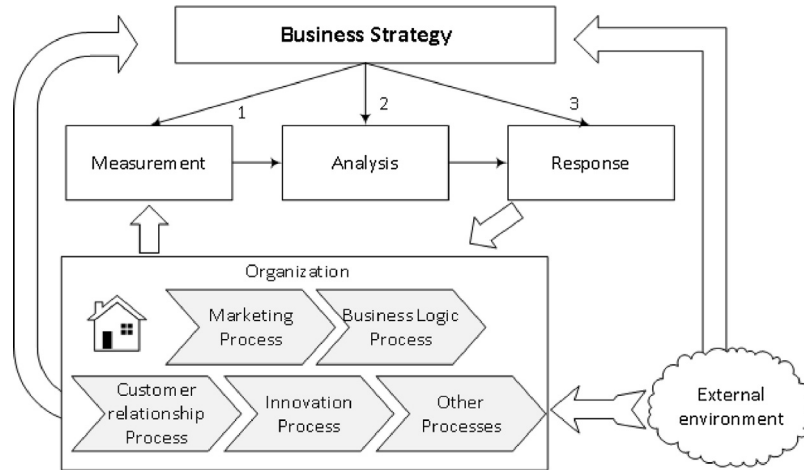


Fig. 3. Performance management process.

The principal aspects described above can be implemented and automated in an easy way by using BPMSs. The main aspect supported by BPMSs involves the handling of the business processes of the organization. This aspect is represented in Fig. 3 in the box labelled as *Organization*. Furthermore, the *External Environment*, including the relationship with *Stakeholders*, manages input knowledge obtained from external information systems and other important sources.

In order to obtain measurements from the status of the business (edge 1 of Fig. 3), the Business Activity Monitoring (BAM) or Process Performance Measurement (PPM) tools are employed. These tools allow the expert to evaluate the defined KPIs that permit the status of the business to be ascertain at each moment. These tools require intervention from IT personnel in order to be automated. The visualization and monitoring of the status of the business by means of observations of the KPIs can easily be created through using the dashboards of these tools.

The remaining aspect to be automated, the definition of business strategy and the specific KPIs to measure, is the responsibility of the BET, as it depends on the particular strategies that the organization wants to follow. Since we are focusing on the tactical level, this step is guided by the processes related to the target markets that the company wants to cover, the product and services offered, and how they are tailored for each particular market.

Once the BET obtains the status of the business by evaluating the KPIs that can be observed on a dashboard (edge 1 in Fig. 3), the team must decide whether the status of the business is correct based on the business strategy defined (edge 2 in Fig. 3), and they must also decide whether to act (edge 3 in Fig. 3). A response can involve doing nothing, or performing a set of actions in order to archive the objectives defined as strategy. Here is where the contributions of this paper take place, by helping to model action-reaction knowledge in the process governance, and by contributing a method for the computation of this knowledge in order to make better reasoned decisions that steer the computing in the right direction to achieve its business goals.

4.1. Fuzzy Governance Maps (FGM): processes and measures

Analysing the strategic plans of a company, it is possible to extract the existing business processes and their descriptions, as presented in Table 1. In order to help in the governance decision points, this information needs to be modelled and related to the objectives defined by the company. The first challenge is the detection of the possible elements that can be involved in a

strategic plan, as analysed in Section 4.2. The second challenge is to ascertain how the elements are related and how the expert can combine them. For strategic plan description, we propose the use of Fuzzy Governance Maps (FGMs) as an extension of Fuzzy Cognitive Maps (FCMs) [23], providing new elements to cover the needed semantics for strategic plans. FCMs have been used as a mechanism to model the relationship with the model, but they do not have enough expressivity to represent strategic plan needs. FGMs contribute to towards the effort for more intelligent governance control methods and for the development of systems that help in the governance decision process. FGM representation is a formal method that allows the BET to describe the expected behaviour of the organization itself, as well as how the environment will evolve by means of stimulations of business processes, measures and KPIs. As FCMs, the success of the construction of FGMs is strongly dependent on the degree of expertise held by those involved in the FCM construction [47]. However, unlike FCMs, our method includes a data-driven analysis step, sold out in Section 6, that softens this dependency.

To model every relation between the business components is a very hard task, since several elements must be combined. A FGM is composed of (N, E) , being N a set of Nodes, and E a set of Edges that link N . Fig. 4 shows the meta-model of the FGM, the meta-class “FGM” is the root meta-class of the meta-model.

4.2. Concepts in FGMs: nodes

The set of nodes N is composed of $\langle G, IN, BP, DV \rangle$, being G the Goals, IN Indicator Nodes, BP the Business Process, and DV Decision Variables. The details of each type of node is described bellow.

Goals (G) are desired states of affairs. They are used in the language to represent business objectives that companies aim to achieve (e.g., “Increase profits”). Goals are used as first-class citizens in the model, which drive the construction of the strategic model while making no distinction on their nature (usually categorized as strategic, operational, or tactical).

Indicator Nodes (IN) model the set of indicators that represent the status of the organization. Indicators are defined to provide quantitative information and insights about both data mining techniques and decision makers. IN can be classified into three types: $[M, KRI, KPI]$. First, **Measures (M)** are the simplest form of indicators (IN) represented by means of formulas for measuring business activities. Measures provide performance information without a clear cut criteria and, thus, they do not have associated targets or thresholds. The lack of a clear cut criteria renders them unable to be used to make statements regarding goal satisfaction.

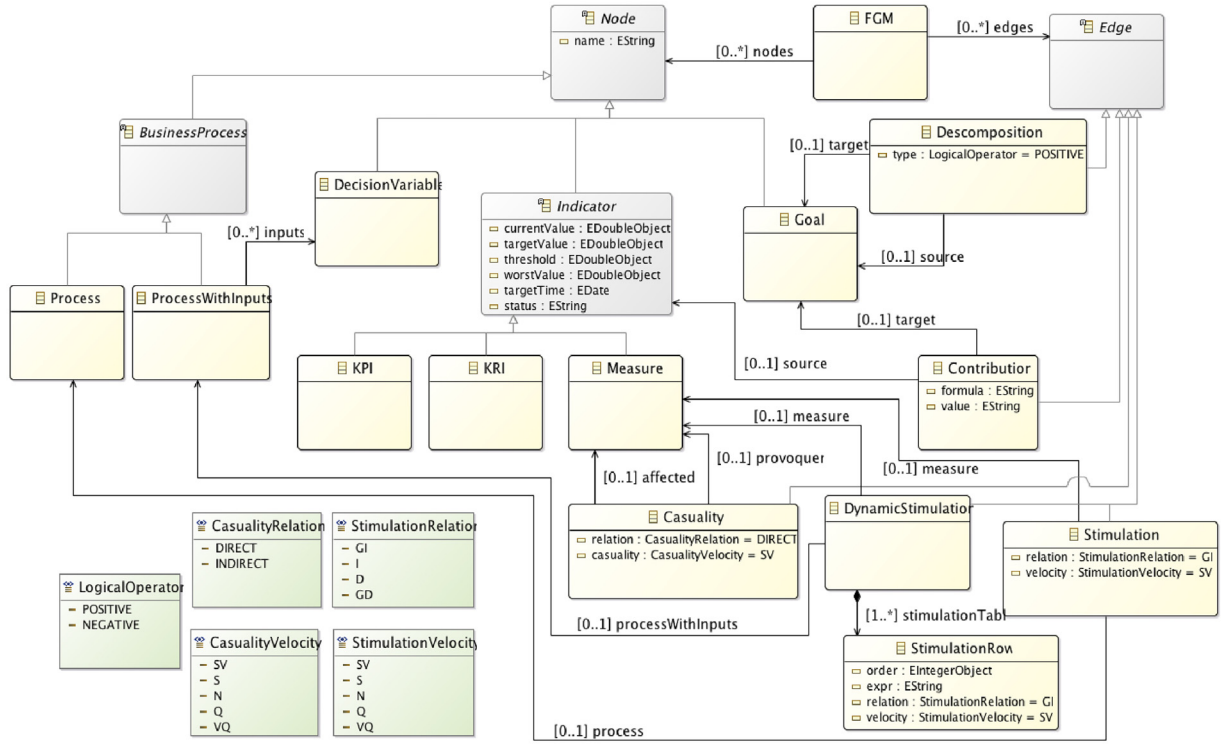


Fig. 4. FGM metamodel.

For example, given the measure “profits”, we cannot argue whether the associated objective has been filled or not. Measures are mainly relevant as components to explore potential KPI and KRI candidates. Second, **Key Result Indicators (KRIs)** [28,36] are indicators directly correlated with the satisfaction of a business goal. For example, “Increment in profits by 5%” is a KRI, it provides information about the results of the business objective “Increase profits”. The main added value of KRIs is their thresholds. They allow decision makers to define and evaluate business goals using clear-cut terms of satisfaction levels. However, the values of KRIs need to be either measured or estimated at the point in time when their business goals are to be fulfilled, and thus are sometimes referred as “lag” indicators [21,30,49]. Otherwise, the information they provide cannot be used as an input. Finally, third, **Key Performance Indicators (KPIs)** [20,32] are indicators that measure the performance of key activities and initiatives that lead to the success of goals measured by KRIs. Similarly to KRIs, KPIs have clearly defined thresholds, but they may or may not have a target time, since they can also monitor continuous tasks. For example, “Average response time under 3 days” is a continuous task. KPIs are important for the company due to the ability to affect them directly and, thus, indirectly effect KRIs. Therefore, if KRIs change, the set of KPIs to monitor is also likely to change.

Business Processes (BP) represent mechanisms that organizations have into place in order to improve their daily activities improving the status of the enterprise (e.g., “Invest in online publicity”, “Send a miss you campaign”). According to the type of relationship that the process has with the environment where it is executed, two types of BP are defined, [P, PI]:

- **Processes (P)** represent business processes that can be executed by themselves. They do not require any specific input variable, e.g., “Send a miss you campaign”.
- **Processes with Inputs (PI)** represent business processes that require the specification of a set of decision variables (DV) to be

executed. DV represent the input values that must be provided to the process. The majority of the business process contains input data, however, the input data modelled as DV are just the input data whose values can affect the achievements of the defined goals. For example, the process “Invest in online publicity” is a PI, since the amount to invest is essential to know how it can affect the expenses and benefits. However, the process ‘Write a tweet’ has also as input the text to white, but it is not model how a specific sentence can affect the PKIs.

4.3. Relationships between the nodes of FGMs: edges

The set of edge E is composed of $\langle SE, DSE, CaE, DE, ICoE, GCoE \rangle$, being SE Stimulation Edges, DSE Dynamic Stimulation Edges, CaE Casuality Edges, DE Decomposition Edges, CoE Indicator Contribution Edges, and $GCoE$ Goal Contribution Edges.

As defined following, some components of E are quantified with a value that represents the type of relationships or velocity. Determining a specific value is not an easy task, or even impossible even for an expert since not always systems work exactly equal. For this reason, in order to facilitate the modelling, we propose the use of fuzzy logic, which is indicated for these environments [53].

The specification of each component of E is:

SE (Stimulation Edges) represents a stimulation edge between a process node (P) and a measure (M), being $SE = \{i, j, SR_{ij}, SV_{ij}\}$, where $i \in P, j \in M, SR_{ij}$ is a stimulation function (SR_{ij}), and SV_{ij} is a stimulation velocity:

- **Stimulation Relation (SR)** represents the degree in which the measure is affected by the execution of the business process. In order to facilitate the modelling, four fuzzy set have been defined, $SR \in \{GI, I, D, GD\}$, where GI “Greatly increase”, I “Increase”, D “Decrease”, and GD “Greatly decrease”.

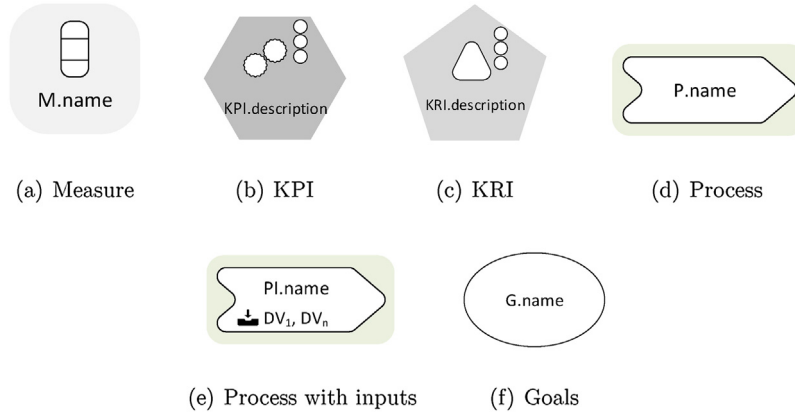


Fig. 5. Graphical representation of nodes.

- **Stimulation Velocity (SV)** represents the velocity of the stimulation using discrete values, $SV \in [VS, S, N, Q, VQ]$, which represent “very slowly”, “slowly”, “normally”, “quickly” and “very quickly” stimulation velocities, respectively.

DSE (Dynamic Stimulation Edges) represents an stimulation edge between a process with inputs node (PI) and a measure (M). DSE is formed by $\langle pi, m, stim \rangle$, where $pi \in PI, m \in M$, and $stim$ a sorted list of conditional stimulations $\{stim_1, \dots, stim_n\}$. Each conditional stimulation $stim_i$ is formed by the tuple $\langle expr, SR, SV \rangle$, where $expr$ is an expression that relates DV of pi , $SR \in [GI, I, D, GD]$ and $SV \in [VS, S, N, Q, VQ]$. $expr$ is able to be evaluated to ascertain the concrete value of SR and SV en each case. If more than one expression is *true*, the first one of the sorted list $stim$ is used.

The main difference between SE and DSE is that in DSE the value of SR and SV can change according to the values of the DV in each PI . In an opposite way, in SE the values of SR and SV are statics.

CaE (Causality Edges) represent the set of causality relations between measures (M). Each CaE is described by $\langle i, j, CaR_{ij}, CaV_{ij} \rangle$, where $i, j \in M$, CaR_{ij} is a causality relation, and CaV_{ij} is a causality velocity:

- **Causality Relation (CaR)** represents the type of relationship, and it can have a positive (+) or negative (−) relation. A positive relation describes when both nodes involved in the edges increase/decrease in the same direction, and an negative (−) relationship when the destination increases/decreases in the opposite direction to the origin.
- **Causality Velocity (CaV)** is used to mitigate the complexity defining the velocity of action-reaction between two values with accuracy. We have defined five fuzzy sets, denoted as “very slow” (VS), “slow” (S), “normal” (N), “quick” (Q), and “very quick” (VQ).

Decomposition Edges (DE) represent the decomposition or simplification of goals into subgoals, due to complex goals can be decomposed in other simpler goals. Each decomposition edge is represented by $\{i, j\}$, where $i, j \in G$ and j is a subgoal of i .

Indicator Contribution Edges (ICoE) are relations between measures (M) and Key Indicators (KI), and represent that the indicator source contributes to the consequence of the Key Indicator as target. $ICoE$ is a set of pairs $\{i, j\}$, where $i \in M, j \in KI$.

Goal Contribution Edges (GCoE) are relations between Indicators (IN) and Goals (G), and represent that the indicator source contributes to the consequence of the Goal as target. $GCoE$ is a set of pairs $\{i, j\}$, where $i \in G, j \in IN$.

4.4. Graphical representation

In order to facilitate the modelling of FGM by business experts, a graphical representation of the previous elements involved is proposed. Fig. 5 shows the representation of the types of presented nodes, meanwhile the representation of the defined types of edges can be seen in Fig. 6. This representation facilitates that business experts could adapt the FGMs to the evolution of the company, because of the graphical notation and the definition by parts that are combined in a single one.

Fig. 6a shows the graphical representation of Causality edges (CE), as can be seen in the figure, the values of Causality relation (CaR) and Causality Velocity (CaV) are represented as attributes of the arrow. Fig. 6b shows the representation of Decomposition Edges, in that case, there is no information associated to the edge. Fig. 6c shows the Stimulation Edges (SE), where source elements can be Business Processes (BP), and target elements can be Measures (M). As can be seen in the figure, the values of Stimulation Relation (SR) and Stimulation Velocity (SV) are represented as labels in edge. Fig. 6e shows the representation of the Goal Contribution Edges ($GCoE$). Finally, Fig. 6f shows an example of graphical representation of Indicator Contribution Edges ($ICoE$).

Those elements are combined by BETs with the objective of create the FGM that will be later analysed in order to help making better decisions.

4.5. An illustrative real world example

Following with the example of TutiplayTM, the two departments involved in this example are the financial and marketing department. Each department has the knowledge of their areas needed to design a partial FGM based on their knowledge. Our proposal affords the possibility to model each part of the knowledge in an isolated way, being possible a later combination. Following subsections show the partial FGM provided by each department, being Section 5 where the combination is explained.

4.5.1. Financial department

Financial department of TutiplayTM is focused on the management of incomes and expenses, being the main goal of this department to maximize the profits. Fig. 7 shows the partial FGM provided by this department.

As can be seen, there is several measures involved: *Number of users registered on the platform with at least one bet placed within the last month*; *Number of visits on the web page of the company*

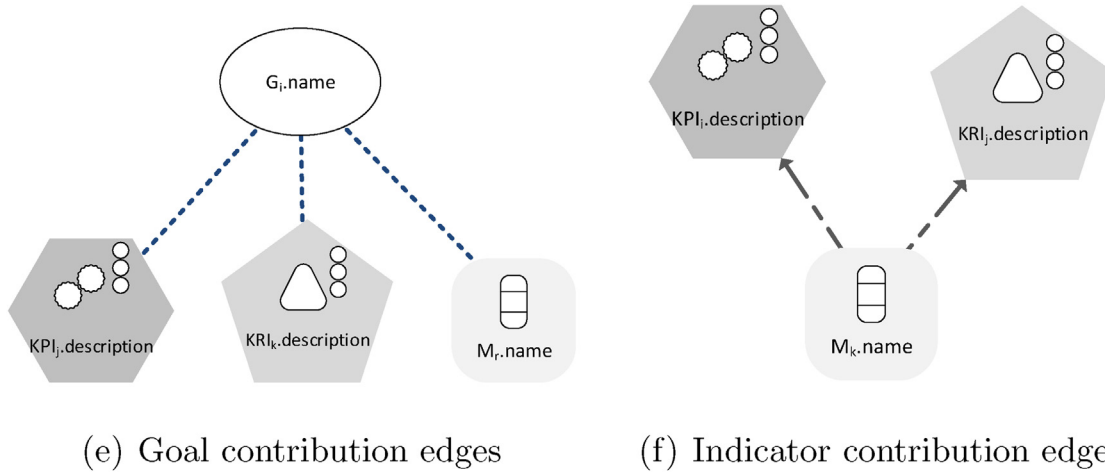
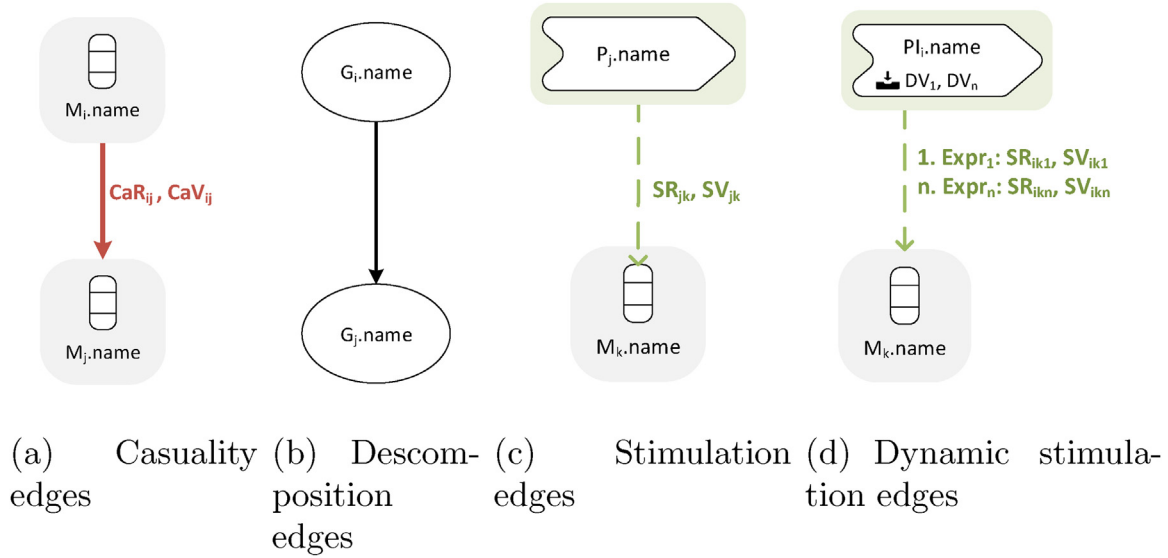


Fig. 6. Graphical representation of edges.

(including landing page and application); *Forecasts* realized by the users registered; *Ad revenues* for the ad inserted in the webpage, and; *Expenses* of the company in the context of the FGM (not including office costs, servers costs, etc.).

Based on the knowledge of financial department, following CaE are examples of related measures:

- *(Number of users, Forecasts, +, Q)*: *Number of users* is positively related with the number of *Forecasts*. In the case of the first indicator increases, the second is also increased with *Quick* velocity.
- *(Number of users, Number of visits, +, VQ)*: Every week the users are able to access to the web platform in order to forecast, for this reason, if there is more users, there will be more number of web visits. The relation is *positive* and the effect can be seen *very quickly*.
- *(Number of visits, Ad revenue, +, VQ)*: Those two measures are positively related due to the ad revenue depends on the number of visits to the webpage, and therefore visualizing the ads. This relation is *positive* and the effects can be seen *very quick*.

In order to stimulate the measures exposed below, the financial department has a business process, whose execution can stimulate

the *Forecasts* measure. This business process is “*Send mail*”, and consists of sending a reminder email to the users that have not forecasted when the time to forecast is near to end. The execution of this process stimulates *Greatly Increase* and *Very Quick* the measure number of *Forecasts*.

On the other hand, the financial department has defined the goal of *Increase the profits*. This objective is decomposed into another tree: (1) *Increase the forecast*, that implies to achieve the KPI *Increase forecast by 45%* evaluated by using the measure *Forecasts*; (2) *Decrease expenses* with the KPI associated *Decrease expenses by 2%*, evaluated by using the M *Expenses*, and; (3) *Increase Ad revenue*, which is reached if the KPI *Increase revenue by 5%* is satisfiable by using the measure *Ad revenue*.

4.5.2. Marketing department

Marketing department of Tutipay™ are focused on manage the users and the publicity, and the main goal of this department is to maximize the number of active users. Fig. 8 shows the partial FGM provided by this department.

The Measures (M) used for this department are: *Number of users*, that models the number of users registered on the platform, with at least one bet placed within the last month. *Lost users* represents the number of users registered on the platform, that

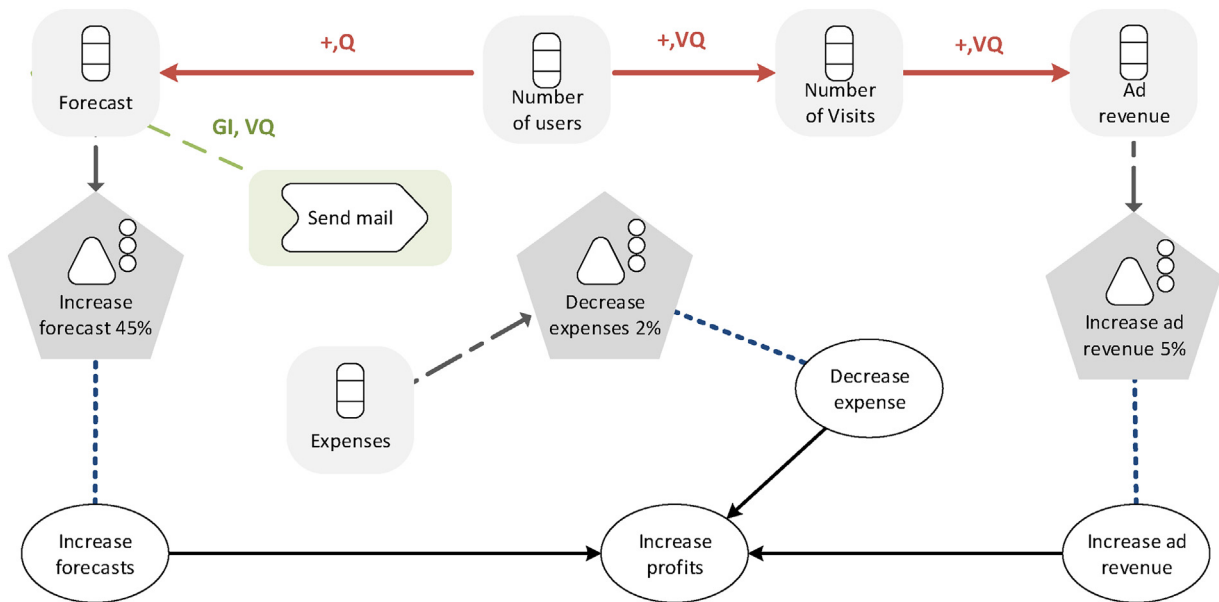


Fig. 7. FGM provided by financial department.

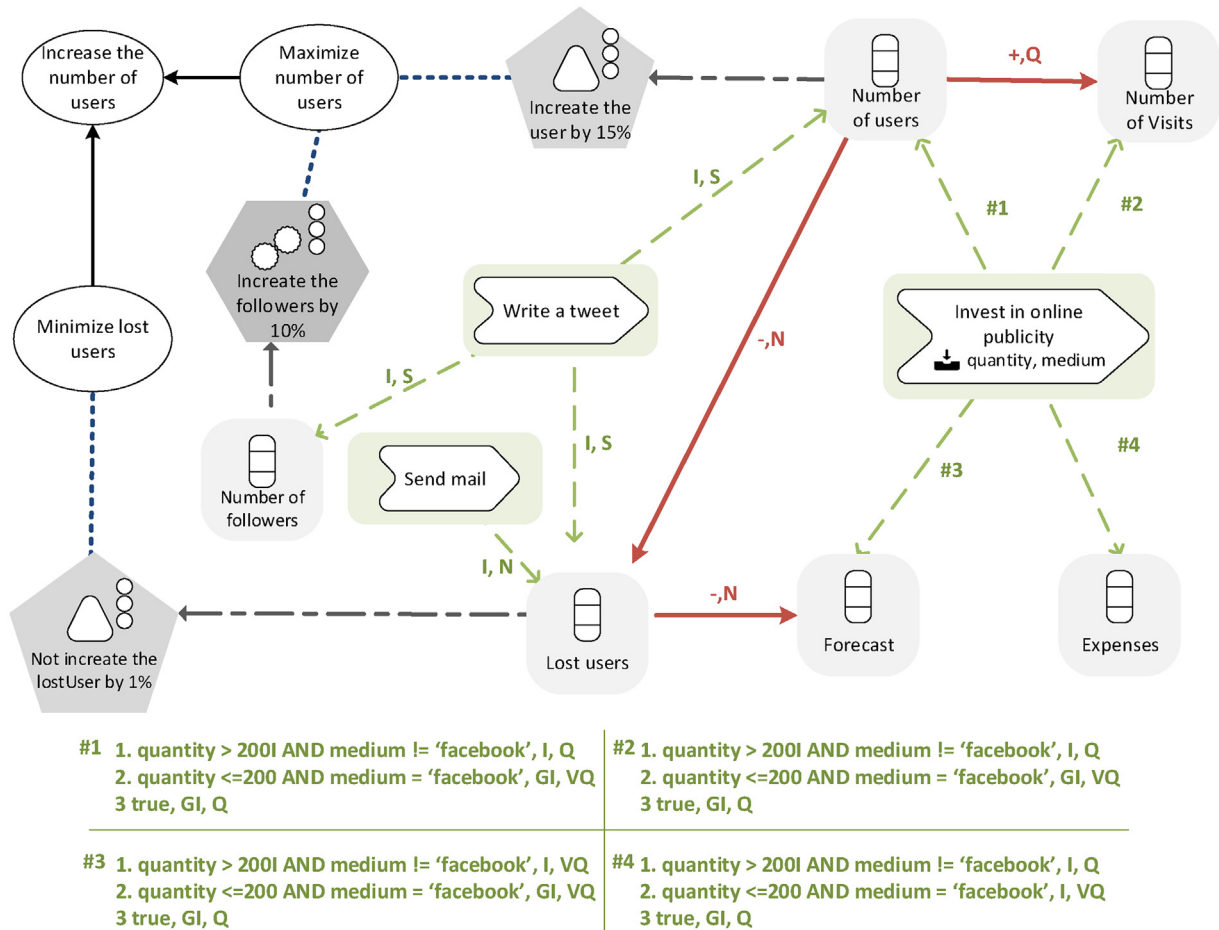


Fig. 8. FGM provided by marketing department.

have not placed a bet in the last month. The *Number of followers* measure the users that are followers of the Twitter™ account of the company. *Number of visits* is the visits in the web page of the company. Including landing page and application. *Forecast* is the number of forecasts realized by the users registered.

Based on the knowledge of the BET, some example of CaE added are:

- (*Number of users*, *Lost users*, -, *N*): In the case that the *Number of users* is increased the number of *Lost users* is decreased, it means

that users that have not forecast for a while, start to forecast again. On the other hand, the opposite can be also possible, in the case that the *Number of users* decreased, the reason can be that the number of *Lost users* is increased. Therefore, this relation is *negative* and the effects can be seen with *normal* velocity.

- $\langle \text{Lost users, forecast, } -, N \rangle$: In the same way that the above CaE, the number of *Lost users* are *negatively* related with the number of *Forecasts*, due to if the number of *Lost users* is increased, the number of *Forecasts* will be decreased.
- $\langle \text{Number of users, Number of visits, } +, Q \rangle$: Every week the users might access to the web platform in order to forecast, for this reason, if there is more users, there will be more number of visits. Therefore the relation is *positive* and the effect can be seen *quickly*.

In order to stimulate the measures exposed below, this department has a set of business processes available, whose execution can modify the value of the measure. In that case, the set of business processes are: “Write a tweet”, “Invest in online publicity” and “Send mails”.

Write a tweet process, consists on writing a message with the aim of create noise in social networks, to give information about the forecasts, matches, and another relevant information to the users. By executing this process attract new users, therefore the *Number of users* is increased *Slowly*. The *Number of followers* is also *increased slowly*, due to some of them share the publication that reach new people, and they start follow the twitter account of the company. Finally, the number of *Lost users* is also increased slowly, this is due to some may consider the tweet account as a spam, and leave the platform.

Another important business process with input parameters is *Invest in online publicity*. This business process consists on spending money in social ads, with the aim of reach potential players. This business process has two decision variables (DV) associated: *quantity*, that represents the amount to invest, and; *medium*, that represents the provider in which the ads will be contracted. The execution of this process has relations with the measures *Number of users*, *Number of visits*, *Forecasts* and *Expenses*, but the degree and velocity in which those indicators are affected for the execution of this business process depends on the decision variables. The concrete values and the conditions can be seen in the table of Fig. 8.

Finally, this department also includes considerations over the execution of *Send mail* that is used by the financial department. They believe that the execution of this business process *increases* with a *normal* velocity the number of *Lost users*, due to some of users may consider the platform as spammer.

The marketing department has defined the following objectives, decomposition of objectives and indicators to reach those them:

- Goal *Increase the number of users* with two subgoals:
 - Subgoal *minimize the number of lost users* that is monitored with the KRI *not increase the number of lost users by 1%*, which uses the value of *Lost users*.
 - Subgoal *maximize the number of users* that is monitored by the KPI *Increase the number of followers by 10%*, which is evaluated by the *Number of followers*, and the KPI *increase the users by 5%* which is evaluated by using the *Number of users*.

5. Combination of FGMs

The combination of FGM consists on creating a new combined $FGM_c = \langle N_c, E_c \rangle$, given the set of partial $PFGM = \langle FGM_1 \dots FGM_n \rangle$, provided by the different areas in an organization.

The people in charge of designing the FGM are tightly related to the business, but they can come from different departments. In order to use the same terms for the same meaning, and the same level of abstraction, the modellers use the business plan which establishes a common language. The concepts that can be used are defined in the business plans.

The combination consists on the join of every elements of all sets, without repeated elements of PFGM, this is:

The set of nodes is composed of the union of the sets of nodes of each PFGM. $N_c = \langle G_c, IN_c, BP_c, DV_c \rangle$, where:

- Goals (G): $G_c = G_1 \cup \dots \cup G_n$
- Indicator nodes (IN): $IN_c = \langle M_c, KRI_c, KPI_c \rangle$
 - Measures (M): $M_c = M_1 \cup \dots \cup M_n$
 - Key Result Indicators (KRI): $KRI_c = RKI_1 \cup \dots \cup RKI_n$
 - Key Performance Indicators (KPI): $KPI_c = KPI_1 \cup \dots \cup KPI_n$
- Business Processes (BP): $BP_c = \langle P_c, PI_c \rangle$
 - Processes (P): $P_c = P_1 \cup \dots \cup P_n$
 - Processes with Inputs (PI): $PI_c = PI_1 \cup \dots \cup PI_n$
- Decision Variables (DV): $DV_c = DV_1 \cup \dots \cup DV_n$

The set of edges is composed of the union of the sets of edges of each PFGM. $Edges_c = \langle SE_c, DSE_c, CaE_c, DE_c, ICoE_c, GCoE_c \rangle$, where:

- Stimulation Edge (SE): $SE_c = SE_1 \cup \dots \cup SE_n$. Given two SE, se_{ij} and se_{ks} , they are equals iff $i=k, j=s$ and their Stimulation Relation and Stimulation Velocity (SV) are also equals $SR_{ij} = SR_{ks}$, $SV_{ij} = SV_{ks}$.
- Dynamic Stimulation Edges (DSE): $DSE_c = DSE_1 \cup \dots \cup DSE_n$. Given two DSE $dse_1 = \{pi_1, m_1, stim_1\}$ and $dse_2 = \{pi_2, m_2, stim_2\}$ they are equals iff $pi_1 = pi_2, m_1 = m_2, count(stim_1) = count(stim_2)$ and $\forall stim_p \in stim_1 \exists stim_s \in stim_2$ where $inex(stim_p) = index(stim_s)$, $expr_p = expr_s, sr_p = sr_s$ and $sv_p = sv_s$.
- Causality Edges (CaE): $CaE_c = CaE_1 \cup \dots \cup CaE_n$. Given two CaE $CaE_{ij} = \langle CaR_{ij}, CaV_{ij} \rangle$, $CaE_{pk} = \langle CaR_{pk}, CaV_{pk} \rangle$ those two CaE are equals iff $i=p, j=k, CaR_{ij} = CaR_{pk}$ and $CaV_{ij} = CaV_{pk}$.
- Decomposition Edges (DE): $DE_c = DE_1 \cup \dots \cup DE_n$. Given two decomposition edges $\{i, j\}$ and $\{p, k\}$ they are equals iff $i=p$ and $j=k$.
- Indicator Contribution Edges (ICoE): $ICoE_c = ICoE_1 \cup \dots \cup ICoE_n$. Given two ICoE $\{i, j\}$ and $\{p, k\}$ they are equals iff $i=p$ and $j=k$.
- Goal Contribution Edges (GCoE): $GCoE_c = GCoE_1 \cup \dots \cup GCoE_n$. Given two GCoE $\{i, j\}$ and $\{p, k\}$ they are equals iff $i=p$ and $j=k$.

Given the partial FGM provided by the financial department of Tutiplay™ shown in Fig. 7 and the partial FGM provided by the marketing department, shown in Fig. 8, the combination operations covert these two partial FGMs, as can be seen graphically in Fig. 9.

6. Analysis to evaluate the correctness of the model

Experts' models are invaluable due to the knowledge they encode. They represent how objectives are intended to interact with each other, which are the expected causal relationships, and, overall, guide the analysis of the processes. However, due to the existence of unknown variables, and misleading perceptions, it is rarely the case that all relationships between measures, KRIs, KPIs, and processes hold.

In order to analyze the correctness of the model proposed by domain experts and to test their assumptions, we make use of existing historical data for the different elements in the model, by using a similar approach done in [7], where the authors use event logs to discover the cause of process delays. In our case, data is gathered from the normal operations of Tutiplay across past months, and is stored in the database of the company.

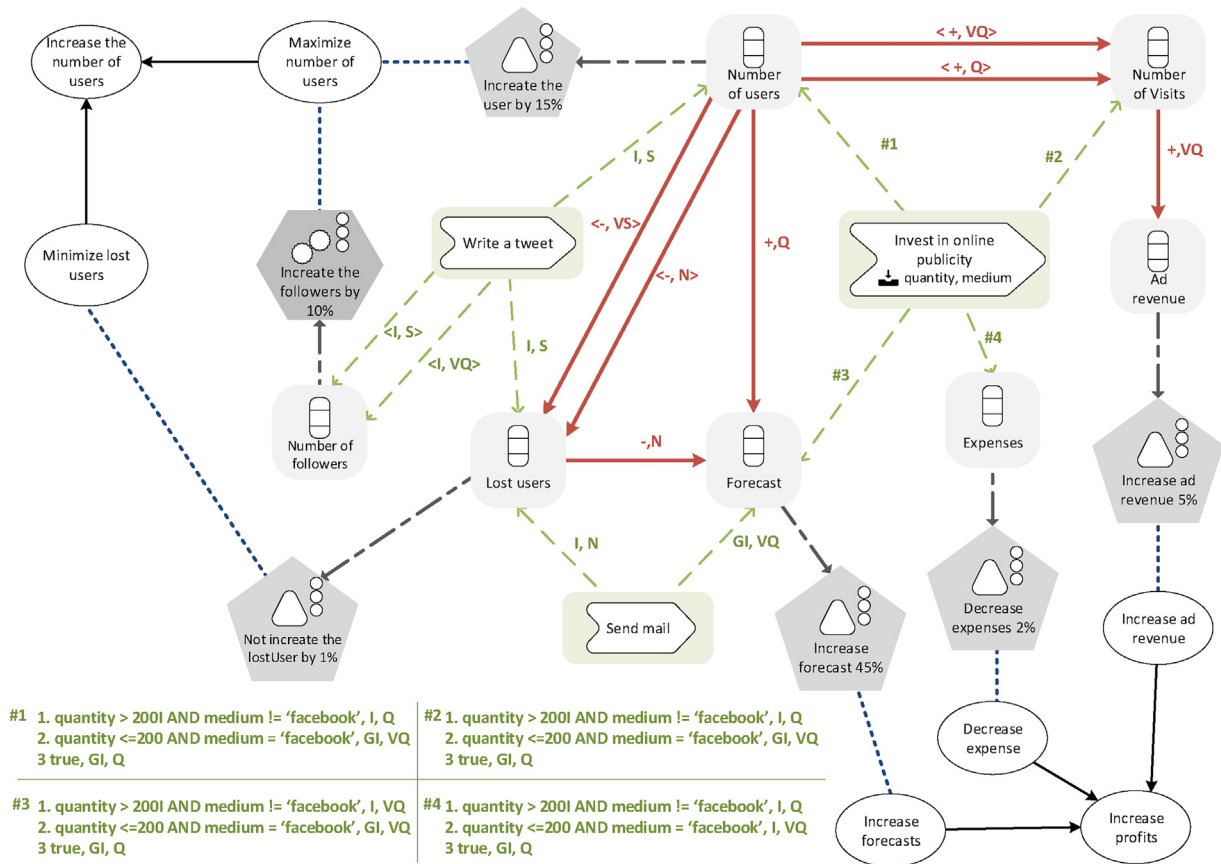


Fig. 9. FGM after combination.

This approach allows us to compare assumptions with hard facts, by means of statistical and mining techniques (without focusing on machine learning which usually requires a larger data sample). However, it is important to note that the purpose of this step is to highlight and help experts to understand the existing discrepancies between observed and expected behaviour. Although proposals as Danglade et al. [6] create a fully data-driven model from scratch, we consider relevant to start from a user-defined model that matches their mental model.

The evaluation process uses as input the model built in the previous section. From this model, a set of relationships between elements for (i) Causality, (ii) Stimulation, and (iii) Dynamic Stimulation edges in the model is extracted. Each of these relationships is then evaluated following an analogous process

to the one described in [28], which has been augmented to provide information about the speed at which the relationship takes effect. For the sake of brevity, we skip the pre-processing and basic statistical analysis of the data.

According to Fig. 9, there are 17 different relationships that must be evaluated. Since our dataset has hundreds of data points (over 800), we can perform the process in two steps. First, we will perform correlation analysis, in order to determine the consistency of the relationship between the source element (mainly processes and measures) over the target element (measures and indicators) and discard weak influence relationships. Weak relationships indicate that the relationship is either non-existent or that the remaining variables (sometimes unknown) have a larger effect on the target than the one represented by domain experts. If we

Table 2
Results of the relationship analysis step.

Relationship (Process/Measure → Measure/Indicator)	Correlation analysis results	Holds?	Effect
1. Write tweets → Followers	0.479	Yes? Weak	+
2. Write tweets → N° of active users	-0.007	No	
3. Write tweets → N° of lost users	0.001	No	
4. Send email → N° of lost users	-0.008	No	
5. Send email → Forecast	0.915	Yes	+
6. N° of active users → N° of lost users	-0.414	Yes? Weak	-
7. N° of active users → Forecast	0.081	No	
8. N° of active users → N° of visits	-0.191	No	
9. N° of lost users → Forecast	-0.003	No	
10. N° of visits → Ad revenue	1	Yes	+
11. Invest in Publicity → N° of active users	-0.105 Facebook; -0.052 Adsense	No	
12. Invest in Publicity → N° of visits	0.699 Facebook; 0.325 Adsense	Yes (Facebook) Yes? Weak (Adsense)	+
13. Invest in Publicity → Forecast	-	Not applicable	
14. Invest in Publicity → Expenses	-	No data about expenses available	

wished to evaluate the magnitude of the effect, we would also perform regression analysis to try and estimate the quantitative effect of a source variable over a target variable.

Second, we will perform cross-correlation to determine the optimal time shift between variables. This will give us an approximate idea of how fast (quick, normal, slow) the source variable influences the target one, if it does. We must highlight however that, because neither of these techniques can determine if a given source is the direct cause of an effect on the target, if the relationship is proven to exist then it is assumed that the model created by the domain experts' is correct.

A summary of the results of the first analysis step in our process is shown in Table 2.

As shown in the table, we can see that several relationships (n° 2, 3, 4, 7, 8, 9, 11) do not hold, which account for half the listed relationships that needed to be evaluated. Additionally, two more relationships (n° 13, 14) cannot be evaluated because time series are completely disjoint in time (n° 13); and there is no data available respectively (n° 14, expenses). Finally, there are several relationships which hold. Relationships close to 1 denote a very strong, direct effect between the source and target processes and indicators (n° 5, 10). Relationship n° 5 denotes a strong effect between sending a reminder and users actively filling in forecasts. Relationship n° 10 on the other hand denotes that both variables behave in exactly the same way. Considering the variables, we can assess that there is a functional dependency between both of them, since Ad revenue is directly dependent on the number of visits. Aside from these relationships, there are relatively strong and weak correlations (n° 1, 6, 12). N° 1 points out that writing tweets helps increasing the number of followers, but their behavior is affected by other factors. N° 6 shows there is an inverse relationship between active users and lost users. While it may seem counter-intuitive that this relationship does not have a very strong correlation (1), analyzing the definition of these variables shows that lost users accumulate over time, whereas active users vary with time. This is important because it may be explained as an underlying problem: the platform is having problems with user retention in the long run. Finally, n° 12 shows that investments in publicity do have an effect on the number of visits, with Facebook being more effective in this case than AdSense. Combined with the results from n° 11, we can confirm that publicity is attracting new visits, but they are not effectively becoming new active users of the platform.

Together with these important findings, relationships that do not hold will need to be reviewed by domain experts, in order to evaluate whether the relationship does not exist at all, or to try and discover hidden variables that are affecting the outcome. This is specially true of correlations tagged as Weak, which are most probably denoting that there are several hidden factors affecting the outcome of the target variable. These hidden factors need to be identified if the company is to adequately control the value of their KPIs and KRIs.

Once we have a clear view of which relationships hold according to the historical data, we proceed to the second step in our process: estimate the span of time required for source process or measure to affect target measures or indicators on each

relationship. The estimation is obtained via cross-correlation analysis of the relationships listed in Table 2. Since cross-correlation looks for the best fit according to the data, it is possible that the results are not always accurate. Therefore, as in the case of existing relationships, they should be contrasted with domain experts. The results of the analysis are shown in Table 3.

As we can see, relationships n° 1 and 5 decrease sharply as time passes between the source and target process and indicators. This means that the effect, if any, of writing a tweet or sending an e-mail is mostly immediate, while dropping significantly in the following days. From a business point of view this behavior makes sense because e-mails contain a reminder link to fill a weekly bet. Therefore, most users are either following the link within the same day or ignoring it. Next, relationship n° 6 presents seemingly an abnormal behavior. Taking a closer look at our previous definition of variables however, we can see that a user remains active for a month after filling a bet, whether he fills more or not later in time. Therefore, changes in the behavior of one variable take a long time to be reflected on the other one, leading to a distorted effect over time. Relationship n° 10 peaks at 0 days of difference between the time series and decreases steadily over time. This result along with the previous one (correlation of 1 between the variables) denotes that the effect is immediate between the variables. Finally, relationship n° 12 presents a soft peak at 0 days, showing that the investments in publicity have a lasting effect for some days after the investment was made.

As a result of this analysis we can conclude the following: (i) the relationship between Write tweets and Followers is confirmed as very quick (VQ) while the slow relationship is discarded; (ii) there is no relationship between Write tweets and Lost users; (iii) the relationship between send email and forecast is confirmed as is; (iv) both relationships proposed by stakeholders between N° of users and N° of visits are rejected by the analysis; (v) the relationship between N° of visits and Revenue is confirmed by the analysis; (vi) among the relationships between N° of users and N° of lost users, the very slow speed (VS) relationship is confirmed while the normal relationship (N) is rejected; (vii) the relationships between N° of users, N° of lost users and Forecast are all rejected; finally, (viii) the relationship between Expenses and N° of visits is confirmed to be Quick, regardless of the channel (Google or Facebook), whereas all the remaining relationships are rejected by the analysis.

While this process could be run directly using the data available, the resulting model would not be easily understood. On the one hand, the result would be a network of indicators with no clear way of identifying which are the objectives pursued or what is the overall logic of the process. On the other hand, many causal relationships would not be correctly identified, as it is almost impossible to guess which is the cause and which is the effect when the time difference between the series is near zero.

The proposed model based on FGM can be applied to both operational and tactical level. However tactical decisions are less usual than operational, being more difficult to recovery data about how the decisions can affect to the goals, and the experts have less knowledge to model the FGMs.

Table 3
Result of the second analysis step: estimated time span between variables.

Relationship (Process/Measure → Measure/Indicator)	Analysis results	Estimated Speed
1. Write tweets → Followers	sharp peak at 0 days	Very Quick
5. Send email → Forecast	sharp peak at 0 days	Very Quick
6. N° of active users → N° of lost users	equally distributed across a 10 day period	Very Slow
10. N° of visits → Ad revenue	peak at 0 days	Very Quick
12. Invest in Publicity → N° of visits	soft peak at 0 days	Quick

As a final remark, it is important to note that generally companies have enough data to perform this process since normal operations of business processes store results and intermediate operations in databases or event logs. However, in cases where no data is available, no data-driven analysis can be carried out. In these cases, this step is skipped and stakeholders need to rely on the models created until enough data is gathered.

7. Remodeling of FGMs according to model analysis

The results of the analysis show two main aspects: the misunderstanding between the different stakeholders that provide different FGMs, and that some relationships between processes and eventually KPIs and KRIs do not hold or are not as impacting as BET expects. However, thanks to the analysis step included in our methodology, decision makers have a complete view of how their assumptions match (or mismatch) with the data available in their processes. In this way, they are able to obtain a much more refined model to be used for simulations (e.g., what-if analysis) and overall making better decisions.

The business experts must remodel the FGM according to the original one and the relationships derived from the previous section. Considering the FGM with inconsistencies to be solved, shown in Fig. 10, the remodeling can imply two types of actions:

- Remove edges with the same source/target and different weight:** As far as the misunderstanding between different stakeholders that provide parts of the FGM, several edges between one source and one target might appear. For instance, in Fig. 10 there are two edges between the indicators *Number of users* and *Lost users*, both with an negative (-) Causality Relation

(CaR), first one with Causality Velocity (CaV) *very slow* (VS), and the second one with *normal* (N) relation. Only one edge between one source and one target is allowed, for this reason, this issue must be mandatory fixed removing one of them.

- Eliminate edges:** Sometimes business experts consider the existence of a relation that is not consistent with the analysis of real data. These relations must be eliminated (e.g., the relation that exists among *Write a tweet* and the *Number of Users*).

Once the remodeling process performed by business experts has finalized, a new FGM is obtained. This new FGM is used in the simulation process, that in our example is the FGM shown in Fig. 11.

8. Framework and evaluation to compare the model simulation and the real measurements

The use of the improved FGM obtained from the combination of data analysis and business expert knowledge is an important mechanism to ascertain how the decisions can affect to the future achievement of the goals. Fig. 12 shows graphically our proposal about how a BET member is able to simulate and observe the evolution of a company according to a set of decisions.

The evaluation process starts when a BET member performs a what-if analysis (step 1 of Fig. 12) using the current state of the company and the improved FGM. The module “Instantiator” (step 2 of Fig. 12) explores the environment and organizational status by means of collecting indicators from: defined by using the Process Instance Query Language (PIQL) [38]; Business Activity Monitoring (BAM) [3]; or Process Performance Measurement (PPM) [14] tools (external sources). The “Instantiator” instances the FGM by calculating the final value for indicators and stimulation edges

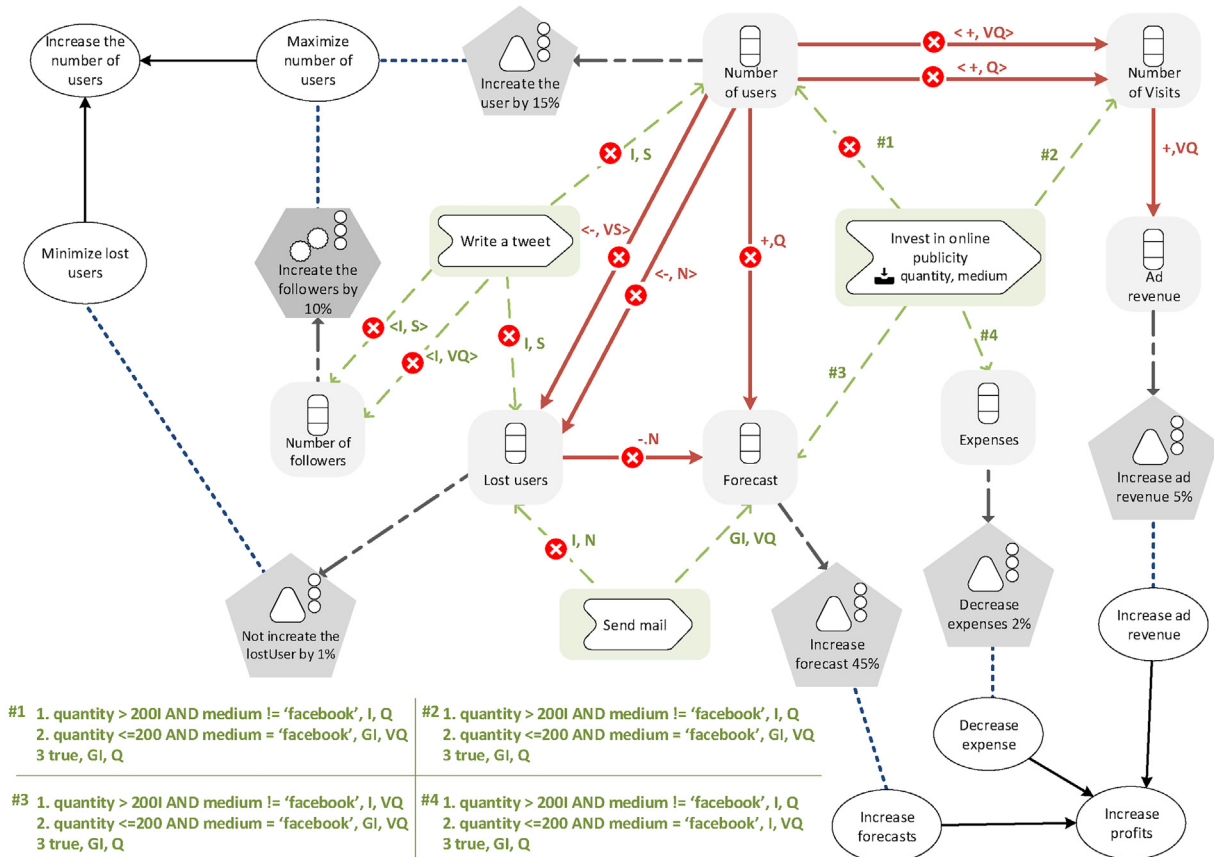


Fig. 10. FGM with inconsistencies to solve.

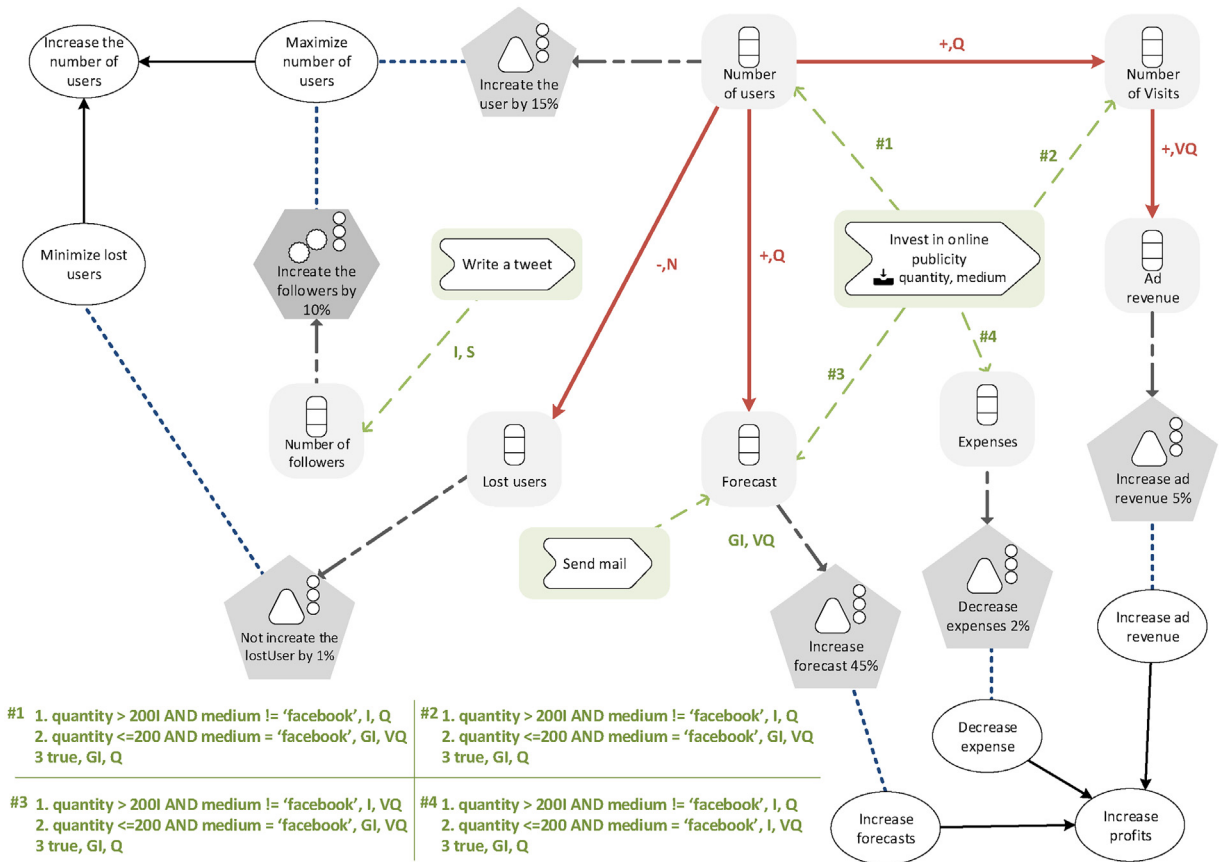


Fig. 11. FGM remodeled by business experts according to data analysis.

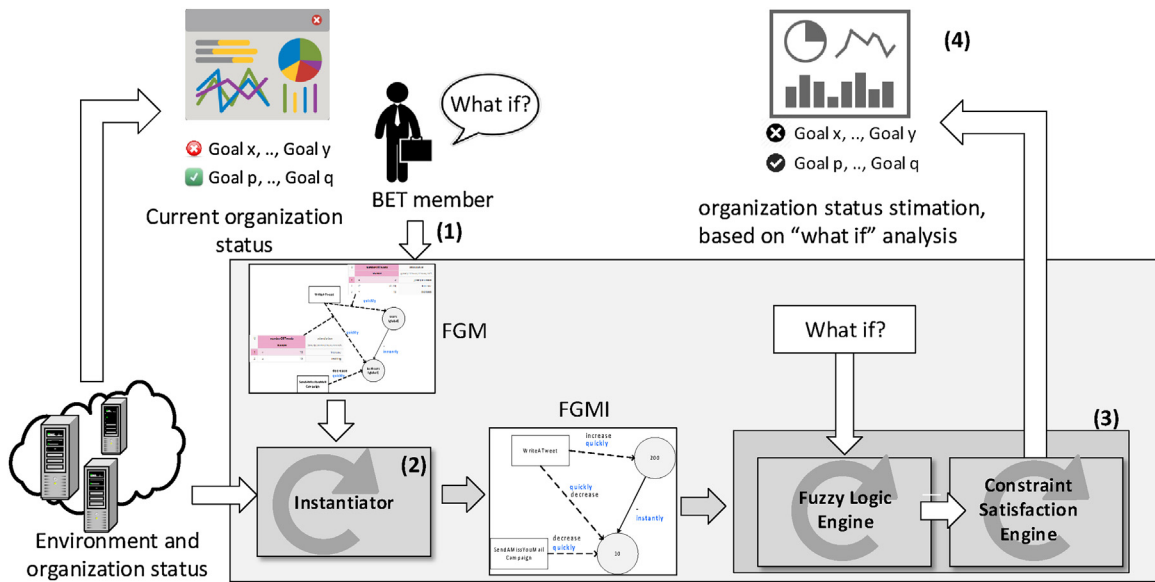


Fig. 12. Simulation process using FGM.

in order to create a Fuzzy Governance Map Instance (FGMI). An FGMI is a FGM where the current values of the IN for the processes, M , KRI and KPI are known. With this information, it is possible to know whether the goals G are satisfied or not.

Once the FGMI is obtained, it is used as the input of the Fuzzy Logic Engine module (step 3 of Fig. 12). This module takes the FGMI and activates the actions according to the “what if” question. An

FGMI is a Fuzzy Cognitive Map that is instantiated in order to obtain a Fuzzy Governance Map Instance (FGMI). Once this is obtained, it can be computed by using fuzzy logic [27].

Finally, the output of the Fuzzy Logic Engine and Constraint Satisfaction Engine (step 4 of Fig. 12) will obtain the estimated values of the different M involved, and the estimated state of the KRI , KPI and G . Fuzzy Logic Engine is able to simulate the values of

the M nodes in through the time, however it cannot evaluate whether KRI or KPI are satisfied, and therefore, cannot evaluate if the G are satisfied as well. To this end, Constraint Database technology [12,10,11] is used, that allows to store and query constraints as basic types in a relational model, ascertain if KRI and KPI are satisfiable.

The proposal has been evaluated for a FGMI and by using two simulation tools, one for the “Fuzzy Logic Engine” module and another “Constraint Satisfaction Engine” module, that have been integrated to work together. This FGMI has been mapped into the integrated simulation tool and time relationships have been considered by introducing intermediate nodes [35]. The simulation tool has the capacity to modify the value of the nodes and propagate the results in order to obtain the degree of stimulation of each indicator. The specific evolution of each M can then be obtained by using these stimulation degrees and an application function, and finally these values of the M have been used to evaluate the KRI , KPI and G .

Fig. 13 shows an example of the estimated output of the dashboard obtained by using the FGM presented in Fig. 11. The simulation works with the evolution of the organization from the

status ($NumberOfUsers = 100$, $lostUsers = 20$, $forecast = 80$, $numberOfVisits = 140$, $adRevenue = 1000$, $Expenses = 600$) and the question “what if we invest more in online publicity (250 euros in facebook) and at the same time, we send an email to the users?”.

Plot (a) of Fig. 13 shows the stimulation degree. The remaining plots describe the evolution of each M and also the limits to satisfy the KPI and KRI . On the other hand, Fig. 13 also shows the goals status at $t = 10$, at the end of the simulation. As can be observed, the two main goals will be achieved.

9. Conclusions and future work

The three main advantages of our proposal are focused on: extend the model of influence including business processes and input data, the verification of the enriched model according to the former data, and the use of the improved model to simulate the evolution of the system according to the possible decisions.

This paper proposes a methodology to improve the decision-making support in organizations. This methodology proposes an iterative life-cycle model that combine the goals of the companies, and how to achieve them by means of the execution of their

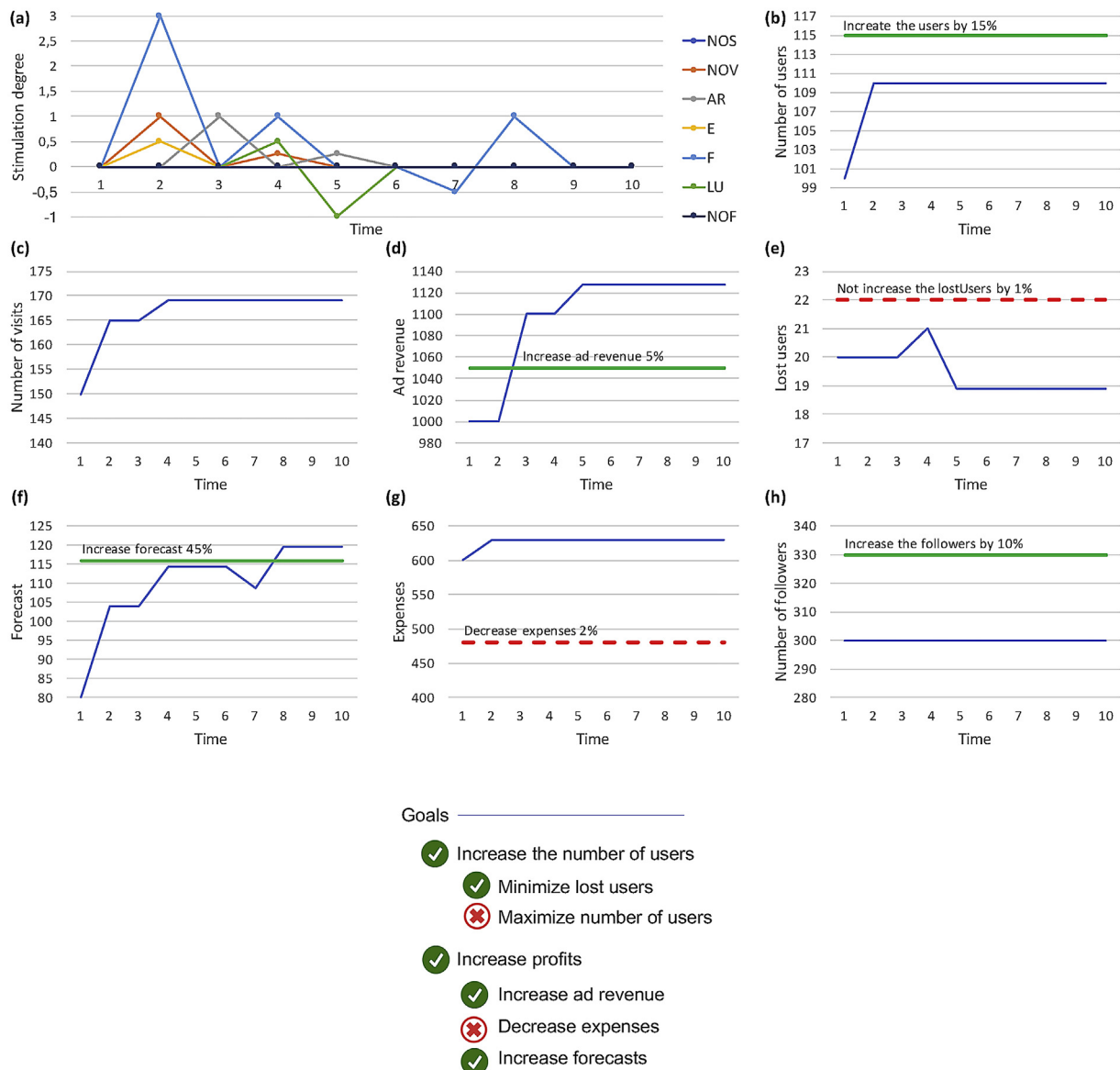


Fig. 13. Sample of our dashboard.

organizational business process. The proposed model is formalized based on Fuzzy Governance Maps (FGM). A FGM allows the Board and Executive Team (BET) to understand how the business works, and how actions can positively or negatively affect the KPIs and KRIs that define the status of the business. A set of data analysis techniques are combined to figure out if the expert knowledge satisfy the real data obtained from the company activities. This data-driven analysis step allows users to validate the assumptions included in their model, identifying potential anomalies and unforeseen behaviors. If the evolution of the business is known according to which actions are performed, then decision-making regarding these actions becomes easier, and this help towards achieving the company's objectives. This refined model is used to ascertain how the decisions can affect to the future achievement of the goal, simulating different scenarios and decisions.

In order to validate the proposal, a real-world example has been used in this paper. Real stakeholders have been involved in the definition and validation. We conclude that the capacity to model the expert knowledge helps to compare what they think with the real behaviour. Also, the use of the validated model helps in decision-making processes, since simulations can be performed. Our proposal puts closer the belief of the expert with the real evidence of the system, justifying the decisions made.

To the best of our knowledge, this paper constitutes the first approach to empower tactical decision making by combining expert knowledge with data-driven analysis, providing a contrasted view of the situation for the decision makers. Our proposal has been applied to a real company, demonstrating its applicability and interest.

As future work, we propose to enlarge the types of analysis applicable to data. New types of analysis could provide mechanisms to discover new edge relations, or even new nodes.

Acknowledgement

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