A Performance Estimation Framework for Complex Manufacturing Systems

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Abstract

To cope with today market challenges and guarantee adequate competitive performances, companies have been decreasing their products life cycles, as well as increasing the number of product varieties and respective services available on their portfolio. Consequently, it has been observed an increasing in complexity in all domains, from product and process development, factory and production planning to factory operation and management. This reality implies that organizations should be able to compile and analyze, in a more agile way, the immense quantity of data generated, as well as apply the suitable tools that, based on this knowledge, will supports stakeholders to take decision envisioning future performance scenarios. Aiming to pursuing this vision was developed a proactive performance management framework, composed by a performance thinking methodology and a performance estimation engine. While the methodology developed is an extension of the Systems Dynamics approach for complex systems' performance management, on the other hand, the performance estimation engine is an innovative IT solution responsible by capturing lagging indicators, as well as estimate future performance behaviors. As main outcome of this research work, it was demonstrated that following a systematic and formal approach, it is possible to identify the feedback loops and respective endogenous and exogenous variables responsible by hindering the systems behavior, in terms of a specific KPI. Moreover, based on this enhanced understanding about manufacturing systems behavior, it was proved to be possible to estimate with high levels of confidence not only the present but also future performance behavior. From the combination of both qualitative and quantitative approaches, it was explored an enhanced learning machine algorithm capable to specify the curve of behavior, characteristic from a specific manufacturing system, and thus estimate future behaviors based on a set of leading indicators. In order to achieve these objectives, both Neural Networks and Unscented Kalman Filter for nonlinear estimation were applied. Important results and conclusions were extracted from an application case performed within a real automotive plant, which demonstrated the feasibility of this research towards a more proactive management approach.

1. Context

Nowadays, manufacturing is being shaped by the paradigm shift from mass production to on demand dictated, customer-driven and knowledge-based proactive production [1]. Consequently, shorter product life cycles, an increased number of product varieties, high performance processes and flexible machines and production systems result in an increased complexity in all domains, from product design, process development, factory and production planning to factory operations [2]. Furthermore, from operations performance point-of-view, companies need to be more assertive in order to decrease the ramp-up time when they are introducing new products or modifying the existing ones, and thus decrease the time-to-market, aiming at monetizing the product development as quickly as possible. They also need to implement continuous improvement approaches over the management and manufacturing processes in order to reduce costs and consequently increase profit.

With this in mind, managers are continuously looking for design and conceive new efficient production processes, aligned with the company's strategy and market needs [3]. However, although industrial companies have a set of information systems that generate huge quantities of data, their capability to use it to build performance information in a short time and with low effort is still weak or inexistent. Thus, managers of complex manufacturing systems are dependent of their own experience and knowledge about the system to take important strategic decisions and implement initiatives

Indeed, if in the past this issue was not a problem of pivotal importance, currently, due to the volatile market conditions and short life cycle of products, this constraint has proven to be a strong restriction concerning the success

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performance management solutions implementation. Indeed, the lower the frequency of KPIs calculation, the bigger is the time interval between the moment that a bottleneck/problem arises until some corrective actions are performed. This means that during this time interval companies are losing money and competitive advantage.

In addition to the gaps previously described, it is observed that current performance management solutions are only capable of supporting decision makers with regard to decision taken and implemented in the past. This means that, due to weak and inappropriate performance analytics tools, decision makers only are capable to realize what is happening in the present, as response to decisions taken in the past, and after a specific feedback time. Indeed, this reality has a direct consequence on the effectiveness of the decisions taken, since without the support of a proper global vision of the system behavior, organizations deeply rely on the individual expertise of stakeholders involved, when analyzing the causes, risks, trade-offs and impacts of current decisions into the future behavior. In sum, following such reactive approach, decision makers simply react to effect, instead of managing their causes [4].

Aiming to provide an important contribution for the performance management domain, envisioning a more proactive management approach, this research paper aims to propose a shifting of paradigm regarding the way how decision makers see and use their key performance indicators. If normally stakeholders use KPIs to evaluate and assess system's behaviors occurred in the past, it is also true that this same information can be used to estimate with high levels of reliability how the system is expected to behave in the future. Nevertheless, in order to achieve this level of maturity, it is essential to provide decision makers with both technological and conceptual tools that will allow them to enhance their knowledge and expertise about their system's behavior. Consequently, this paper will propose an innovative framework, focused on the necessity to model and analyze complex manufacturing systems synergies envisioning the prediction of future performance behaviors.

In order to achieve the objectives defined, this paper is structured as following. Initially, a reflection about complexity and its implication on manufacturing systems will be performed. Following, an analysis concerning the importance of properly managing performance information, envisioning manufacturing systems complexity dematerialization, will be accomplished. Based on this conceptual research, the vision for a more proactive performance management approach will be explored, as well as the framework developed. Finally, a simple pilot case demonstrating the application and accuracy of the framework developed will be explored. The paper will finalize with some considerations about the results achieved.

2. Towards a Proactive Performance Management

In 1958, Forrester stated that management was on the verge of a major breakthrough in understanding how industrial company success depends on the interaction between the flows of information, materials, money, manpower, and capital equipment [5]. At his point of view, the capability to understand how these five elements interact with each other as well as understand how these variables are susceptible to external factors would be an important competitive advantage since it would form a basis for anticipating the effects of decisions, polities, organizational forms and investments choices. In line with this, the roots of the Performance Management concept have been defining that, in order to take the decision that will really improve the manufacturing system and support the organization to achieve their strategic targets, it is crucial to periodically gather information feedback about the real world. By using this new information, in a continuously way, decision makers can revise the existing understanding about the system as well as the strategy that should be taken to drive the perception of the state of the system closer to the strategic goals. For instance, the Plan-Do-Check-Act (PDCA) cycle, conceived by Shewhart and later developed by Deming, is a good example of that. This approach stimulates the system learning through an explicit feedback process, facilitating the effective implementation of goal seeking behaviors aiming to achieve the plant's goals.

Nevertheless, the increasing complexity imposed by the current market demands has been hindering the achievement of the objectives previously identified. Thus, it is becoming clear that, in order to setup the right measures and the correct analyzing methods aiming to study the manufacturing complexity, it is no longer feasible to simply rely only on the existing traditional approaches. Therefore, during the last years, the complexity theory, including approaches such as the information and chaos theories, system dynamics as well as the non-linear theory have been explored aiming to provide methods that seem to be useful for the analysis of a manufacturing system's complexity [6]. Therefore, one of the main goals of complex systems management is to make the outputs behavior more deterministic. This, however, is countered by the nature of the inputs and possible internal and external disturbances, as well as by the control and manufacturing processes themselves. The more complex these influences, the harder it is to predict the output.

Presently, there are several opinions about the factors responsible by increasing the level of complexity within manufacturing systems. Some authors propose that manufacturing complexity is a system characteristic that integrates several key dimensions of the manufacturing environment including size, variety, concurrency, objectives, information, variability, uncertainty, control, cost and value. Others understand the necessity to structure this information. For instance, Suh [7] states that dependent upon the domain, complexity can be divided into two types, namely the functional and the physical domains. In the functional domain, complexity is defined as a measure of uncertainty in achieving the functional requirements defined. In the physical domain, manufacturing complexity is also further classified into two types [8]:

- *Static Complexity*, is concerned with the system's structure and configuration, the number and the variety of the products, the system's variety of components (e.g. labours, machines, buffers, transportation mechanisms), as well as their interconnections and interdependencies.
- *Dynamic complexity* is related to the uncertainty of the system's behavior for a specific time period and deals with the probability of the system to be in control. In opposition to the static complexity, the dynamic complexity of a manufacturing system is time-dependent and relates to its real-time operation, material flow patterns, modules reliability and failures. The drivers of dynamic complexity may be internal (e.g., machines reliability, breakdown and maintenance and scheduling policies) or external (e.g., suppliers reliability causing variation in the quantity and timing of materials and tools).

Identify and track the right drivers for the most accurate estimations should then be seen as the key driver to support decision makers estimating system's performance with the highest confidence possible. In fact, the selection of variables and business drivers with greater propensity to have a greatest impact on the strategic goals defined, as well as understand how these variables are able to hinder the system's behavior, is of extreme importance [6]. Nevertheless, the methods developed until now are still very limited, presenting low levels of confidence. This implies that situations and decisions have to go wrong so that decision makers can realize what should be done in the future in order to avoid them. However, due to the competitive environment where almost all organizations need to perform, there is no space for the selection of these inefficient strategies, strictly based on a reactive paradigm [9]. Contrarily, organizations should be capable to analyze, rethink and store data about their performance, so that decision makers become able to identify patterns of behavior, define trends and thus anticipate problems. Moreover, since each manufacturing system is always affected by external factors, not only imposed by the market but also by the environment that surrounds the system in analysis, events such as political decisions, global economic situation, terrorism practices, climatic conditions, and others factors, can critically affect the normal system behavior. Consequently, if it is expected to achieve reliable performance estimation then, it is necessary to take into account not only the endogenous but also the exogenous variables of a manufacturing system.

In sum, there is a need to evolve from a pure feedback control strategy to a combined approach where both feedback and feed-forward strategies should be applied, such as depicted in figure 1. While the leading variables stimulate the estimation model with information that can be foresee for a specific time horizon, on the other hand the lagging indicators will make it possible to continuously updated this mathematical model, based on feedback information about the system behavior.

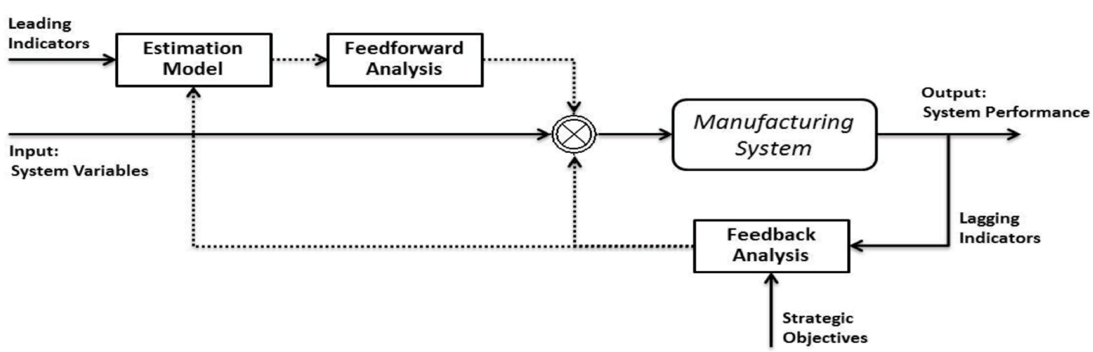

Figure 1. Feedback Control Vs. Feed-forward Control.

3. Proposed Framework

Revisiting Shewhart proposal [10] it is possible to understand that performance measurement, system's behavior prediction and control are three areas of research that should be combined if it is expected to manage industrial processes in a more efficient way. Based on this premise, Shewhart showed that in order to predict future behaviors, decision makers must interpret the present using as driver the performance information extracted from the past. Moreover, according to Shewhart's research, if the historical data collection process is performed under statistical control, i.e. the production system has already achieved a suitable level of stability in which only common and known causes of variation remain, then it becomes possible to make reasonably accurate predictions based on this historical information. In order to meet these challenges, this research work proposes that a framework based on the combination of the System Dynamics approach and the concept of Learning Machine, capable of correlating the different feedback loops and its measurements, should be explored aiming to anticipate how the system will behave in the future, based on the leading factors that can be envisioned.

Consequently, at a first stage, a Performance Thinking Methodology (PTM) was developed aiming to follow decision makers to better understand their manufacturing system behavior, by approximating as much as possible their mental model about the system to the reality. In fact, as important as the confidence and frequency that a KPI is calculated, is the quality and relevance of the information selected. Moreover, identifying the endogenous and exogenous factors capable to hinder and affect the normal system's behavior, it is possible to increase the level of confidence regarding the performance estimation. In concrete, seven main steps compose the PTM, as it is depicted in figure 2.

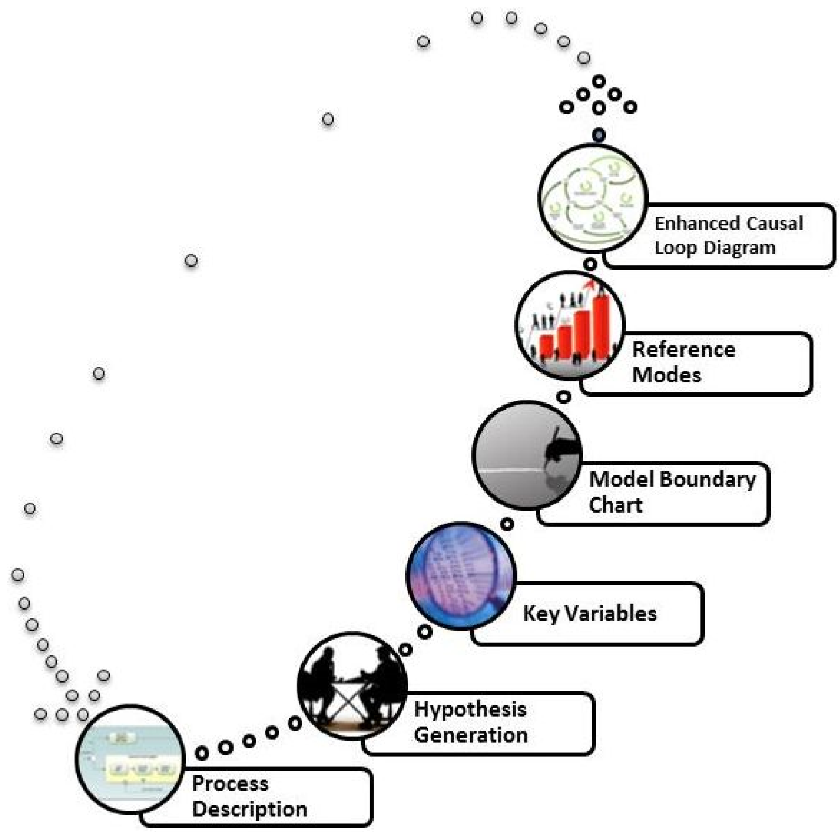

Figure 2. Performance Thinking Methodology.

At the basis of this methodology there is the necessity to clearly model and specify the core processes of the manufacturing system in analysis. Therefore, at a first stage, a detailed description of the process in analysis should be performed. Here, a BPMN approach is used in order to show the real workflow of the process, people involved and events/triggers. Following, after clearly understanding the core processes execution, testimonies from stakeholders involved in these processes should be collected and analyzed in order to create an initial knowledge base. At this stage it is important to guarantee that the interview is mainly focused on the strategic objective, and respective KPI(s) that triggered the implementation of this methodology. Envisioning the knowledge capture and enhancement, this stage of the methodology is one of the most delicate, but critical for the successful implementation of a proactive performance management approach, since it is expected to combine different points of view and mind-sets. If well performed, an important step will be taken towards the achievement of the proactive performance management vision here proposed.

However, only capturing this knowledge is not enough. Consequently, from the set of hypotheses and points of view provided by the different interviews, which should be strategically planned in order to include all the essential perspectives (e.g. product perspective, maintenance perspective, planning perspective, among others), all key variables that can affect the system and hinder the achievement of the expected objectives should be identified, enumerated, classified and described. After selecting the key variables, these should be classified as endogenous (controlled from inside the system), exogenous (affecting the system from outside of the boundary; they cannot be controlled) or excluded (if the variable is very unstable and cannot be modeled). From this study, it is possible to execute the fourth stage of the performance thinking methodology. Indeed, this step of the methodology, called model boundary chart, is strictly related with the necessity to graphically represent the sources of the system's instability and variability, which are the main causes of the manufacturing system's complexity. Thus, the main goals of this step is to represent, in a graphical way, the overall architecture of the system and its surroundings, where the internal and external variables are represented, as well as its influence on the system behavior.

Afterwards, the step called reference mode should be performed. This means that it is necessary to design and understand the behavior of each variable, expressed and represented by its evolution curve. Thus, at this step of the methodology it is essential to guarantee that the data is properly extracted from the different databases in order to assure that the behavior of each variable (trends, periodicity and fluctuations) will be deeply analyzed for a specific time horizon. The final step of this methodology is strictly related with the design of an enhanced causal loop diagram (CLD). By definition, a causal diagram supports decision makers visualizing how distinct but interrelated variables affect one another. In following chapter a practical example of a CLD application will be depicted.

Supported by the knowledge developed with the PTM implementation, then the Performance Estimation Engine (PEE) can be configured. The PEE was developed to enhance the performance management discipline, envisioning its proactivity. This is a hybrid-learning machine algorithm for discrete time stochastic systems, composed by both Neural Network (NN) and Kalman Filter approaches. From this combination, it is possible to model a complex system, in a simple and intuitive manner for the final user, as well as guarantee that this model is capable of following the natural evolution of the system. Figure 3 shows the architecture of the performance estimation engine.

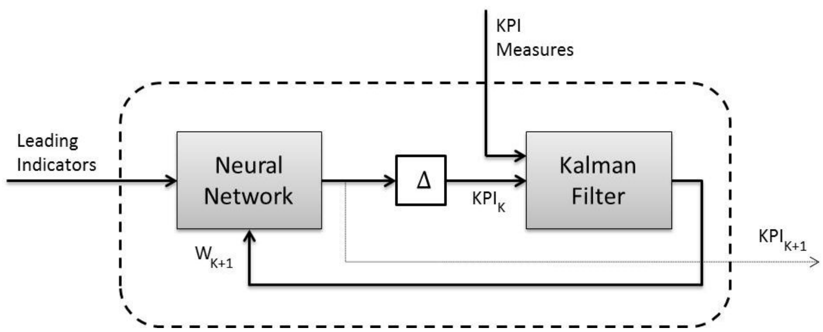

Figure 3. Performance Estimation Engine Architecture.

By definition, a neural network critically depends on the set of weights (w_k) that emulates the system behavior curve. Nevertheless, if a pure batch-training algorithm is used, then it is not feasible to assure that this network is capable of adjusting itself or even following the continuous evolution of the system, maintaining or even increasing the estimation reliability of future KPI values (KPI_{k+1}). Therefore, a combination of a batch and incremental training algorithms is proposed, composed of both backpropagation and Kalman approaches. While the first one will provide a first approximation of the weights of the network, the Kalman filter is responsible for continuously estimating the correct weights of each node of the network, comparing the real KPI measurements with the estimations provided by the NN. Next, a detailed description is provided.

Initially, the network goes through a learning process where a backpropagation algorithm is used to adjust the weight of each neuron in order to guarantee that the behavior curve, represented by this graph, generates a good approximation of the real output for each set of inputs. Since the main objective of this step is to capture the behavior shown by the manufacturing systems in the past, at the end of this stage the network should be capable of estimating the future performance of the system (Eq. 1.1) with some measurement error (e_k). For instance, one of the reasons why the set of weights defined by the training algorithm is not as reliable as expected, directly affecting the process error (r_k), is due to the fact that during the learning stage it was not possible to gather a complete and rich training data set. Therefore, the estimation results depend mainly from a weak generalization capability of the network, which should be enhanced in future iterations.

$$w_{k+1} = w_k + r_k \qquad \text{Eq. 1.0}$$

$$KPI_k = NN(x_k, w_k) + e_k \qquad \text{Eq. 1.1}$$

Hence, at this stage it was not yet possible to achieve the expected level of reliability and the algorithm is still not capable of dynamically following the evolution of the manufacturing system. Thus, aiming to decrease the variable error (e_k) as much as possible and to guarantee that the estimation model is capable of continuously reducing the error index, even over time, the following step is coupling the Kalman filter at the output of the network. With this add-on, the algorithm is capable of continuously monitoring the error e_k and adjusting the weights of each neuron. This way, it is possible to achieve a dynamic learning machine that is continuously changing its parameters in order to approximate the estimation model to reality. The Kalman filter used in this algorithm is the Unscented Kalman Filter (UKF). This special variant of the Kalman concept is very similar to the Extended Kalman Filter (EKF), presenting some details that make it more efficient. Since the EKF algorithm only provides an approximation to the optimal nonlinear estimation, the Unscented Kalman Filter (UKF) can be seen as an important alternative to increase the estimation reliability in more complex systems analysis [11-13].

The UKF is a straightforward extension of the unscented transformation (UT). This is a method for calculating the statistics of a random variable that undergoes a nonlinear transformation. Consider propagating a variable w with dimension L using a nonlinear function, $KPI = NN(w, f_{leading})$. In this specific case, the function NN is related with the structure of the neural network specified to emulate the system under analysis. Thus, as previously explained one of the key inputs of this function is the variable w that is strictly connected to the set of weights of the neural network that better models the system behavior. Now, assuming that w has mean $\bar{w}$ and covariance P_w, in order to calculate the statistics of KPI, it is possible to form a matrix χ of 2L + 1 sigma vectors χ_i according to the following equation (Eq. 1.2):

$$\chi_{k-1} = \left[\bar{w}, \bar{w} + \left(\sqrt{(L+\lambda)P_x}\right), \bar{w} - \left(\sqrt{(L+\lambda)P_x}\right)\right] \qquad \text{Eq. 1.2}$$

where $\lambda = \alpha^2(L+k) - L$ is a scaling parameter, the constant α determines the spread of the sigma points around $\bar{w}$, and the constant k is a secondary scaling parameter, which is used to incorporate prior knowledge on the distribution of w. The mean of these sigma points is calculated using a weighted sample (W_i) of the posterior sigma points (Eq. 1.3),

$$\hat{w}_k \approx \sum_{i=0}^{2L} W_i^{(m)} \chi_{i,k-1} \qquad \text{Eq. 1.3}$$

$$P_w \approx \sum_{i=0}^{2L} W_i^{(c)} (\chi_{i,k-1} - \hat{w}_k)(\chi_{i,k-1} - \hat{w}_k)^T \qquad \text{Eq. 1.4}$$

Finally, the weights set of the network should be updated as presented in equation 1.5,

$$w_k = \hat{w}_k + \mathcal{K}_k(kpi_k - \hat{KPI}_k) \qquad \text{Eq. 1.5}$$

$$KPI_{k+1} = NN(\hat{w}_k, f_{leading}) \qquad \text{Eq. 1.6}$$

where $\mathcal{K}_k$ is the Kalman gain, kpi_k is the measured KPI value and $\hat{KPI}_k$ represents the estimated KPI in the previous time slot. The estimated KPI value for the following time period is calculated by a nonlinear function defined by the estimated weights for each neuron of the graph and the expected leading factors (Eq. 1.6).

4. Application Case

Aiming to test and validate the predictive performance management framework developed, an important pilot case was designed within a real automotive plant, taking as inspiration issues related with the sustainable development of a manufacturing system, more concretely with the energy consumption. Consequently, two important organizational units were selected: the body area and the painting line. If it is true that these two areas are the ones responsible for the highest energy consumption, of both gas and electrical energy, it is also true that these organizational units have the most complex manufacturing behavior in the entire plant. For instance, while the painting shop is defined by a single production line where multifamily products, with different and specific characteristics, share complex industrial processes and resources, the body area presents a job shop layout where the knotty flow of information, materials and products, substantially increases the level of complexity of this organizational area. For each of these organizational areas, two important KPIs for budgeting purposes were defined as object of analysis: *Gas per Vehicle* (GPV) and *Electrical Energy per Vehicle* (EPV).

Therefore, initially a qualitative analysis was performed aiming at understanding the normal behavior of the gas and electricity consumption. From this analysis, it was not only possible to enumerate which variables are responsible for imposing variability in the energy and gas consumption, but also design the causal loops diagram where the feedback loops and respective internal and external synergies can be depicted. Following figure shows the CLD representing the gas consumption at the painting line.

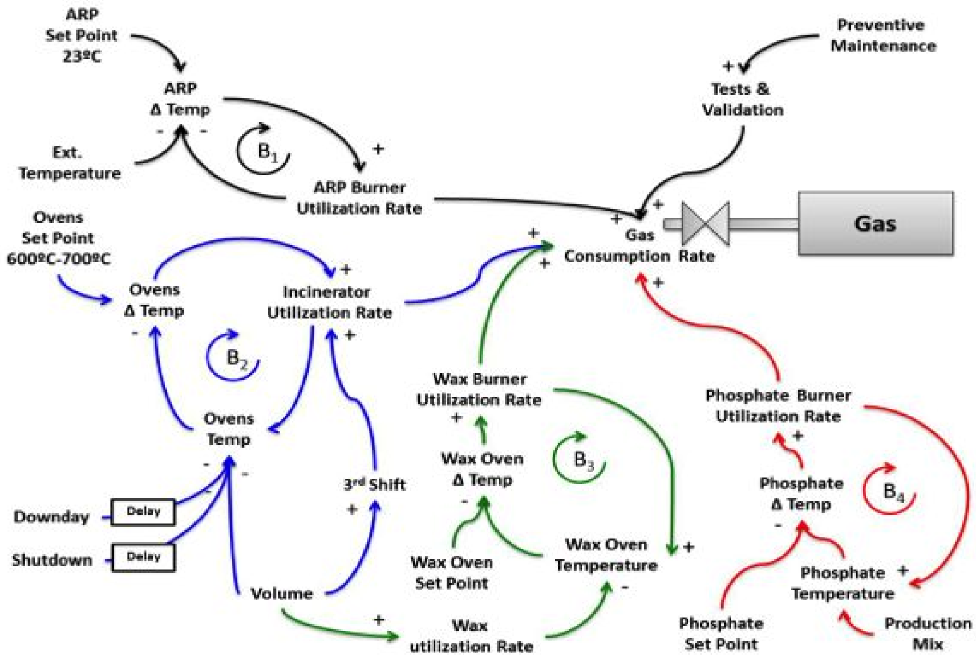

Figure 4. Gas Consumption Causal Loop Diagram (CLD).

After finishing the qualitative analysis, it was possible to transpose the knowledge generated into a mathematical model, envisioning the manufacturing system behavior modeling. In order to achieve this, a neural network constituted by one input, one hidden and one output layers was designed. During this design stage, a training algorithm was performed aiming to calculate the correct weights capable to capture the normal behavior of the manufacturing system, concerning both KPIs GPV and EPV. Aiming to accomplish this objective, during the training process, a dataset obeying to the meta-data identified during the CLD design, and containing real information of the painting line behavior from 2008 to 2011 was used. After capturing the system's behavior, the next step was to prepare an excel file with the expected leading factors from the 1st of January of 2012 to 17th of September of 2012, in order to deploy the estimation model and thus estimate the gas consumption.

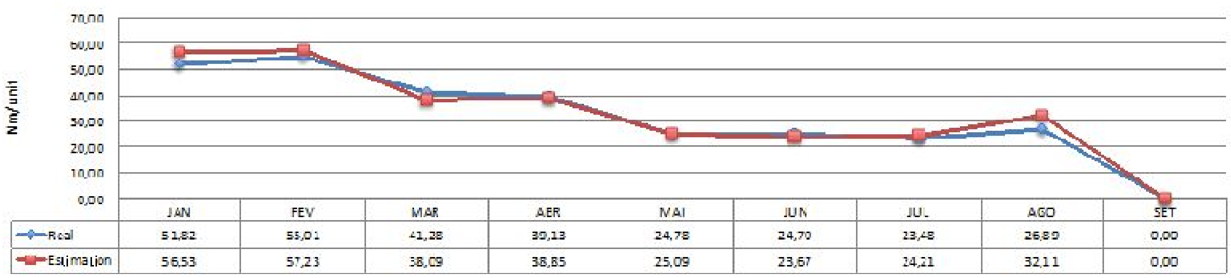

Figure 5. Estimated vs. Real Gas Consumption Per Unit.

From the analysis of the results obtained (figure 6), we can state that the output of the framework is promising, presenting a high level of reliability. For the delta time defined, the medium error of estimation was 1,62 Nm3 per vehicle and the maximum error of 5,22Nm3 (August). It is important to highlight the fact that, the estimation was done based on the leading factors extracted from the fieldwork done, and not based on a simple regression analysis. However, concerning the estimation model, there are still some improvement actions to be performed, since this should be seen as an iterative approach. An example of that is the gas consumption during the shutdown periods and weekends. It is expected that, with the inclusion of the variable "scheduled preventive maintenance" it would be possible to increase the reliability of the mathematical model, significantly decreasing the error.

5. Conclusions and Further Work

In conclusion, using this estimation model, stakeholders responsible for the painting process became capable to define annually the expected budget necessary for the gas consumption per vehicle. Moreover, in cases that the difference between the real and estimated GPV measures are higher than expected (more than 10%), there are only two possibilities: the system changed, requiring a new learning process, or there is some kind of malfunction that is affecting the performance of the system. Thus, this approach not only supports decision makers decreasing manufacturing systems uncertainty, but also enhances their decision-making effectiveness.

In this context, our research demonstrated that combining a robust and competent performance measurement system with an enhanced methodology for complex manufacturing systems design, it is possible to not only identify which variables are able to hinder the system's stability but also analyze and understand its natural evolution along the time. Obviously, if to this logic we add the leading indicators concept, then we have the rational that will lead us to estimate future manufacturing systems behaviors with a high level of confidence. Thus, the main outcome of this research work pursued is a performance management framework, comprising two main elements: the performance-thinking methodology and the performance estimation engine, that helps to systematically and comprehensively estimate performance in complex manufacturing systems, envisioning a more proactive approach.

Acknowledgements

This work is co-financed by the North Portugal Regional Operational Programme (ON.2 – O Novo Norte), under the National Strategic Reference Framework (NSRF), through the European Regional Development Fund (ERDF) and by the Portuguese Government through FCT - Foundation for Science and Technology.

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