PREDICTION OF ENERGY CONSUMPTION INDICES IN THE AUTOMOTIVE INDUSTRY

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Abstract – **Since the automotive industry is one of the most competitive markets, key players should be capable of evolving their management strategy from a reactive to proactive approach. This way, it is critical for this type of companies to explore a new performance management approach where an effective interaction between the strategic and operational layers should be achieved.**

In line with this vision, a framework is presented that helps stakeholders make decisions based on the ability to anticipate future performance behaviours. Using leading indicators as reference, the key idea is to structure and model the existing knowledge within a mathematical tool, in order to project the manufacturing system's behaviour into the future.

In order to show the reliability and importance of this framework, this paper presents a research performed at an automotive plant. The aim is to model the factors affecting energy consumption and thus estimate the future behaviour in terms of sustainability issues.

Keywords – **Estimation, Performance Management, Automotive Industry, Systems Dynamics, Machine Learning, Sustainability.**

I. INTRODUCTION

Currently, performance analysis in complex manufacturing systems is performed in an ad-hoc way since the main objective is to verify if the strategy designed has been helping companies achieve their targets following a reactive approach. However, companies performing within competitive markets, such as the automotive sector, are strongly required to change their management strategy from a reactive to a more proactive approach. This way, simple methods as described before are no longer suitable for this type of companies and, therefore, it is essential to explore an effective approach that allows them to accelerate the learning process of their complex systems [1].

The performance management concept defines that in order to take the decision that will really improve the manufacturing system and support the organisation in achieving their strategic targets, it is crucial to periodically collect and assess information feedback about the real world. By using this information in a continuous way, it is possible to revise the existing understanding on the system, as well as the strategy adopted, driving the perception of the systems' state closer to reality [2].

However, achieving this organisational maturity level depends on the organisation's capability to understand the system as a whole. Hence, industrial dynamics emerged with the goal of dealing with the information that should be available at a decision point, as well as the consequences of defects and gaps in the information considered. Only this way can organisations provide decision-makers with the right information that will allow them to approximate their vision of the system to reality, and thus develop a proactive management attitude.

In order to meet these challenges, this paper proposes a framework based on the combination of the System Dynamics approach and the concept of Learning Machine. From this combination, the Performance Management Thinking methodology was developed as an extension of the Systems Dynamics approach for the process-based performance management area. Furthermore, if this qualitative approach is extended by a learning machine tool capable of correlating the different feedback loops and its measurements, then this framework should be capable of anticipating how the system will behave in the future based on the leading factors that can be envisioned.

Therefore, this document is divided into five main chapters. After the introduction chapter where the research context is depicted, the second chapter explores the literature review supporting this research, as well as the connection between the different research topics. Next, chapter three will explore the Predictive Performance Management Framework, where both the methodology and the mathematical tool will be presented. Finally, the proof of concept validation scenario developed within an automotive plant will be presented, as well as the results obtained.

II. LITERATURE REVIEW

A. System Dynamics

Aiming to provide an important contribution in the scope of the industrial dynamics, Jay Forrester at the MIT developed the system dynamics approach as a solution to help decision-makers enhance their knowledge on varying (or dynamic), non-linear, closed boundary system behaviours and in converting real-life situations into enhanced simulation models [3]. The system dynamics approach was then created as a standard to represent information flow using a complex system based on the policies that manage those systems.

The fundamental concept of this methodology is that manufacturing systems should be represented by a series of stocks and rate variables, embedded within a feedback structure. Stock variables represent accumulations within a system, or describe the state of the system. Furthermore, rate variables flow from one area of the system to another and control stock changes. In other words, rate variables model the system's policies imposed by endogenous and exogenous factors in order to represent the system dynamics as reliably as possible. While endogenous variables can be easily managed, since they are strictly connected with the decision made by systems stakeholders, exogenous factors cannot be controlled due to the fact that they are mainly linked to the external environment that surrounds the system and, directly or indirectly, affects the normal behaviour of the system. From the knowledge generated by this learning model, it is possible to understand and represent the synergies observed in the real world, and thus understand how the manufacturing system will behave in the future, based on a series of leading factors that can be measured from the operational level, captured from the strategic level or estimated based on an external environment analysis (such as market, economic, social analysis).

B. *Machine Learning*

Complexity is one of the most significant characteristics of today's manufacturing. This fact is more relevant, not only due to the required specifications of manufacturing systems, but also due to the products' features and organisational structures necessary and imposed by the market needs. Moreover, since it has been observed that the life cycles of products and manufacturing systems are decreasing, the methods and tools developed to control and manage current manufacturing systems should be dynamic and flexible enough to operate in a changing environment life with uncertainty.

In line with these constraints, over the past decades, the field of Artificial Intelligence (AI) has been explored toward computerising human reasoning capabilities, in order to handle with specific problems identified within the manufacturing scope, such as scheduling, part routing and order processing [4]. Three specific methods for perception and cognitive processes modelling have been followed:

- Expert knowledge: representing information utilised by recognised experts;
- Heuristic knowledge: representing information that has been proven to work well in prior circumstances. This usually takes the form of correlational links between system conditions and actions to be taken to achieve a specific objective;
- Derived knowledge: representing correlational information about conditions and actions that is inferred from a set of data pertinent to the system at hand.

An important trend within the derived knowledge representation area is machine learning. Machine learning essentially seeks to acquire knowledge from available data and facts and use it to create new theories about the domain in question, in an entirely automated manner, reusing this acquired knowledge in future decision-making situations.

Machine learning techniques employ a small number of extremely general principles for knowledge acquisition and organisation, coupled with some basic knowledge about the domain in question. This knowledge may involve structural descriptions of domain characteristics, procedural explanations of domain operation, or even discoveries of new concepts in the domain, and can be stored in a variety of formats including rules, semantic nets, and others.

A specific approach of machine learning involves the definition of an algorithm that mimics the processing characteristics of the nervous system, called artificial neural networks (ANNs). Investigations confirmed that adaptive ANN techniques are a viable solution for the lower level of intelligent, hierarchical control and monitoring systems where real-time operation, uncertainty handling, sensor integration, and learning are essential features.

Most research on Machine Learning has dealt with methods that employ a single learning strategy (monostrategy methods). However, aiming to develop systems capable of being applied to a wider range of problems, algorithms that integrate multiple inference types and learning mechanism should be explored (multistrategy approach).

III. PREDICTIVE PERFORMANCE MANAGEMENT APPROACH

The Performance Management Framework was developed with the main purpose of helping decision-makers structure their knowledge concerning their manufacturing systems behaviour, based on a causal loop approach, taking as reference the respective KPIs that are directly linked to their strategic goals. The causal loop approach is mainly related to the ability to identify and understand intricate processes and root causes. In other words, this methodology is expected to inspire decision-makers to think on their process performance, instead of simply using performance measurements as numerical variables, and thus achieve the objectives described in the introduction section

Two distinctive perspectives compose the predictive performance management framework [2]: a qualitative perspective called Performance Thinking Methodology, and a quantitative perspective called Predictive Performance Engine. The Performance Thinking Methodology is mainly responsible for structuring and formalising the empirical knowledge of the experts concerning a specific KPI, while the predictive performance engine is responsible for the mathematical representation and modelling of the system's behaviour.

A. Performance Proactive Methodology

The methodology developed, and named Performance Thinking Methodology (PTM), is an extension of the system dynamics approach to manage performance. The PTM is composed of seven main steps: industrial process description, hypotheses generation, key variables identification, boundary chart modelling, reference modes design, subsystem diagram design, causal loop diagram design, predictive model setups and running mode.

Initially, 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. Next, after the process is understood, testimonies from stakeholders involved in the process should be collected and analysed in order to create an initial knowledge base. From the different hypotheses provided in the previous stage, 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, exogenous or excluded. Afterwards, the reference mode step should be performed. This means that it is necessary to design and understand the behaviour of each variable represented by the 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 behaviour of each variable (trends, periodicity and fluctuations) will be deeply analysed for a specific time horizon. Since with this step the aim is to think in terms of graphs over time, looking for long-term dynamic behaviours, a proper selection of the time horizon will affect the overall result of the framework application.

If well performed, previous steps will support the design of the subsystem diagram. The main goal of this step is to represent, in a graphical way, the overall architecture of the system's model, where the key variables are presented, as well as its influence on the system behaviour. Finally, a causal loop diagram (CLD) should be designed. This is a causal diagram that helps visualise how interrelated variables affect one another. The diagram consists of a set of nodes representing the connected variables.

After concluding the application of the methodology, it is important to go from a qualitative to a quantitative perspective, using the knowledge gathered from this methodology to setup the learning machine.

B. Predictive Performance Engine

The Predictive Performance Engine (PPE), which is a mathematical tool composed of Neural Network (NN) and Kalman Filter approaches, was developed to enhance the performance management discipline envisioning proactivity. The main goal of this tool is to provide decision-makers with performance estimation values, as well as help decision-makers stipulate ambitious and yet achievable targets, taking into account the normal behaviour of the system, captured by the PTM, previously presented. By combining the NN and the Kalman Filter approaches, it is possible to model a complex system, in a simple and intuitive manner for the final user, and to guarantee that this model is capable of following the natural evolution of the manufacturing system. Figure 2 shows the architecture of the PPE tool.

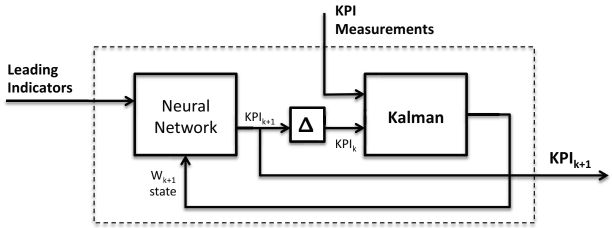

Figure 1 - Predictive Performance Engine Architecture

A neural network critically depends on the set of weights that emulate the system's behaviour curve. Nevertheless, if a batch-training algorithm is used, then it is not possible to assure that this network is capable of adjusting itself or even following the continuous evolution of the system, maintaining or increasing the estimation reliability of future KPI values (KPI_{t+1}). Therefore, a combination of batch and incremental training algorithms is proposed which is composed of both backpropagation and Kalman approaches [5]. 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.

IV. PILOT CASE

Aiming to evaluate and demonstrate the real importance of this innovative approach, a pilot case was performed at an important automotive plant, located in Portugal. In this pilot case, a critical issue strictly related to the sustainable production was explored, the energy consumption. In fact, more and more, world class companies are understanding the importance of improving environmental and social performances in order to save money, enhance product quality, improve corporate image, as well as stimulate optimised operational performances, in order to build a competitive advantage.

For this pilot case, two important organisational 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 organisational units have the most complex manufacturing behaviour 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 shop presents a job shop layout where the knotty flow of information, materials and products substantially increases the level of complexity of this organisational area.

Next, a detailed analysis of each area will be presented, respecting the privacy rules imposed by the company where the study was conducted, as well as the results obtained.

A. Painting Shop

Approximately 60% of the energy required by the entire plant is consumed at the Paint Shop, and the emphasis is on gas consumption. Thus, due to its impact on the overall plant performance, for sustainability issues, this area was selected for the initial test case implementation.

Externally, the boundary of this manufacturing system is the output of the body area and the input of the trim area, as well as the external suppliers that provide the materials, being owners and responsible for some internal industrial processes. Internally, this organisational area is divided into four main operational areas: Sealer, Primer, Enamel and Final Line.

In order to assess the sustainable production index in terms of energy consumption, the KPIs selected were gas and electricity consumptions. Despite the similarities between these two indicators, these were handled separately in order to enhance the results obtained for each of them.

According to the methodology described before, the first objective proposed for this research was identifying the main factors that could influence gas and energy consumptions. From this stage, it was possible to understand that the painting area is strongly influenced by the external environment (temperature and humidity), by the decisions made at the administrative layer, such as DownDays and shutdown scheduling, as well as by the tactical decisions made within the painting area boundaries, such as preventive maintenance scheduling. Figures 2 and 3 present the causal loop diagrams showing how each variable affects the gas and electrical energy consumption rate, respectively.

In order to assess the reliability of the predictive performance engine, the KPIs Gas consumption and Electrical Energy Consumption were estimated for the first semester of the year 2012, based on the data acquired between 2008 and 2011. Figures 4 and 5 present the results obtained, not only taking into account the actual data (Real) but also in comparison with other techniques, such as: Exponential Smoothing (ES), Linear Regression (LR) and Holt Winters (HW).

As it is possible to see, the PPE performs much better when compared to the other technics. In fact, even during the estimation of electrical energy consumption, where consumption fluctuates substantially, the PPE was capable of anticipating the system's behaviour. Moreover, during the estimation of gas consumption, the PPE was also capable of following the usual trends of this indicator.

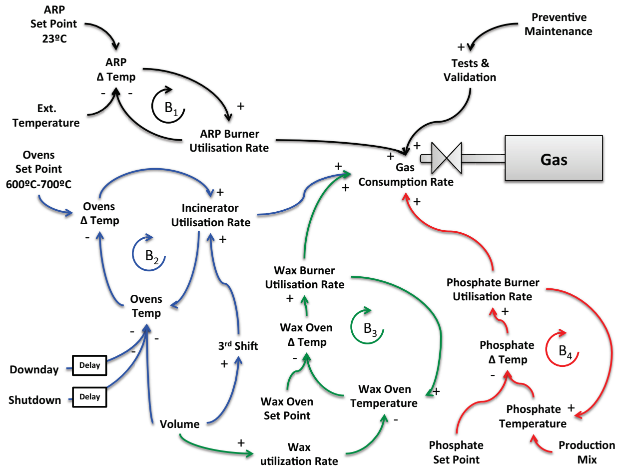

Figure 2 - Causal Loop Diagram for Gas Consumption at the Paint Shop

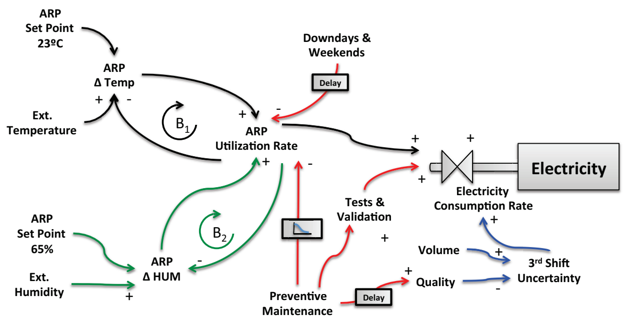

Figure 3 - Causal Loop Diagram for Electrical Energy Consumption at the Paint Shop

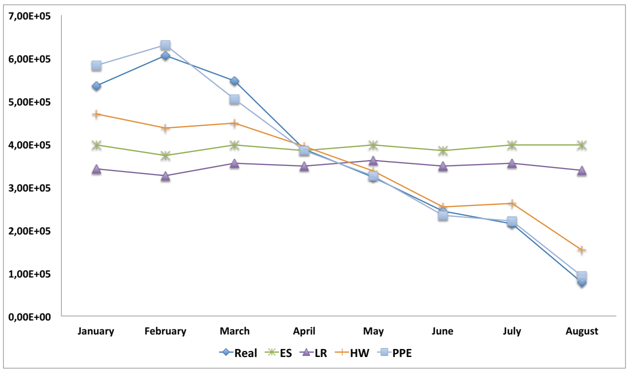

Figure 4 - Estimation of Gas Consumption at the Paint Shop

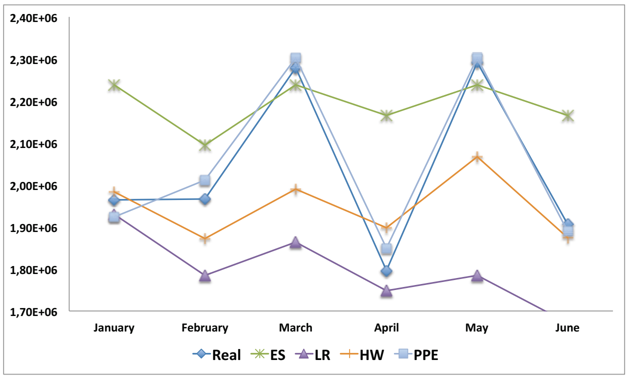

Figure 5 - Estimation of Electricity Consumption at the Paint Shop

B. Body Shop

Contrarily to the paint shop, the body area is responsible for most of the electricity consumed by the entire plant. Externally, the boundary of this area is the output of the press area and the input of the paint line. Internally, this organisational area is divided into six main operational areas, scattered along the facility: Underbody Subparts, Bodysites, Underbody, Framing, Doors to Body, and Metal Finish. Despite the complexity already imposed by the operational structure of this area, each operational area is also divided by family or groups of product families. Due to this intricate structure, the level of complexity of this manufacturing system increases substantially, affecting the modelling efforts necessary to approximate the structured knowledge about the system's synergies as much as possible to reality. In order to assess the sustainable production index at this complex production area, the indicator selected was the electricity consumption.

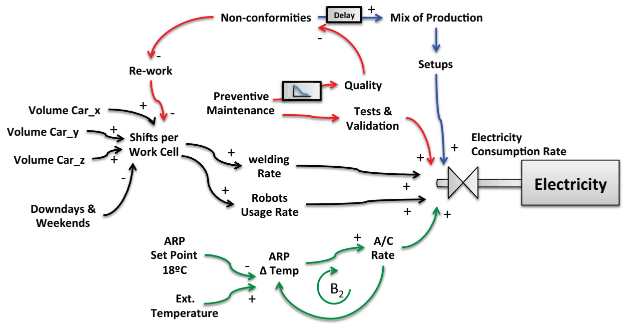

Figure 6 - Causal Loop Diagram for Electrical Energy Consumption at the Body Shop

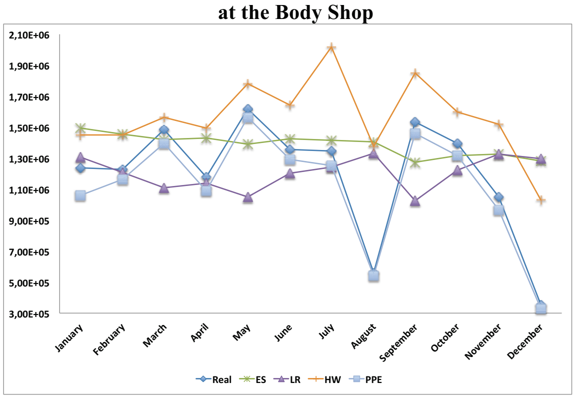

Figure 7 - Estimation of Electricity Consumption at the Body Shop

Based on the PTM, it was possible to understand that the variation of the production mix, imposed by the press area, can be seen as the main feedback loop responsible for the disturbances in energy consumption. In fact, due to the flexible structure of the body shop, this is the factor that directly affects the rate of utilisation of each work cell. However, similarly to the paint area, the body area is also influenced by the decisions made at the administrative layer, as well as by the tactical decisions made within the body area boundaries. Figure 6 and 7 present the causal loop diagram, as well as the chart showing the estimation of electricity consumption for the entire year of 2012.

In order to rank the different estimation approaches, a geometrical mean of relative absolute errors (GMRAE) algorithm was used (Table 1). The GMRAE compares each of the estimation methods used using a naïve approach as benchmark. If the comparison result for a certain estimation method is smaller than 1 means that the method is better than the benchmark while a value greater than one means the opposite.

Table 1 – Energy Consumption Estimation Accuracy Comparison

	ES	LR	HW	PVE
GMRAE	1,03	0,84	1,30	0,29

V. CONCLUSION

Contrarily to a discrete event analysis where manufacturing systems can be analysed as a causal chain of events, in the proposed approach the system behaviour analysis emerges from the synergies between the existing feedback loops within the manufacturing system. This means that route causes are not the events that start the cause and effect chains, but instead they are the synergies between different endogenous and exogenous factors. As shown in previous charts, one of the main advantage of the framework presented here is that contrarily to linear regression methods, the estimation of performance behaviour is not only dependent on the knowledge extracted from past measurements, but also depends on the organisation's capability to foresee future leading factors, increasing its reliability. Thus, it was possible to gather, structure and use the knowledge around the issues of energy consumption, aiming at estimating the future system's performance with a high level of confidence.

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