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An intelligent decision support system for production planning based on machine learning

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Abstract
This paper presents a new methodology to solve a Closed-Loop Supply Chain (CLSC) management problem through a decision-making system based on fuzzy logic built on machine learning. The system will provide decisions to operate a production plant integrated in a CLSC to meet the production goals with the presence of uncertainties. One of the main contributions of the proposal is the ability to reject the effects that the imbalances in the rest of the chain have on the inventories of raw materials and finished products. For this, an intelligent algorithm will be in charge of the supervision of the plant operation and task-reprogramming to ensure the achievement of the process goals. Fuzzy logic and machine learning techniques are combined to design the tool. The method was tested on an industrial hospital laundry with satisfactory results, thus highlighting the potential of this proposal for its incorporation into the Industry 4.0 framework.

Keywords Artificial intelligence · Intelligent manufacturing · Machine learning · Operation management · Decision support system

Introduction

The integration of new technologies into existing industrial processes according to the Industry 4.0 roadmap is not an easy task. Limitations in infrastructure financing, and logistical and social constraints prevent an immediate reconversion. A reasonable alternative to reach this goal is a gradual development, starting the path for transformations in areas of operations management (Kang et al. 2016).

Closed Loop Supply Chains (CLSC) are also addressed in the field of Industry 4.0. A supply chain (CS) is a network of activities associated with the flow and transformation of goods and information from the treatment of raw materials to the final customer (Haq and Boddu 2017). In contrast, a CLSC includes the need to recover a value from the customer (Guide et al. 2003). The activities of a CLSC from the point of view of operations management are focused on production and distribution planning, stock control, manufacturing process control, performance evaluation and coordination between organizations of the chain.

CLSCs add, compared to conventional ones, their own uncertainties, related to the quantity and quality of the returned products (Pishvaee et al. 2011). This specific problem requires adequate control of stocks, with the purpose of making decisions that allow the expectations of all the agents in the CSLC to be balanced (Aengchuan and Phruksaphanrat 2018). The operative management levels, those that drive the activities of the production process, must also adopt tactical decisions to meet the objectives pursued by all parties, since the admissible time horizons are usually very short.

In this context, it will be necessary to have decision support systems in the CLSC production operational management centres, to reconcile the satisfaction of the goals with reactions to unforeseen events. This will integrate both tactical and operational decisions. The interest of this work arises because no integral solutions have been proposed to solve the problem of managing the production in a CLSC context in the presence of uncertainties.

Thus, the general objective of this work is to propose a decision support system that allows the management of production operations to control the stocks of a CLSC, balancing the interests of all agents.

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The methodology used to design the computer decision system is based on the application of artificial intelligence techniques that combine fuzzy inference systems with machine learning. More specifically, the machine learning decision support tool used was decision trees. With the combination of these techniques, the inaccuracy and uncertainty of the data can be adequately managed, and, at the same time, the experience and knowledge of the expert can be easily included in the algorithm.

From a wider perspective, the availability of a software system that can act as a production operator would allow the idea of a plant-wide simulation using the concept of the Digital Twin. This technology, integrated in Industry 4.0, includes, in its latest evolutions, capabilities related to software decision-making. Therefore, the system resulting from this study could be integrated as a part of a digital twin in a simulation scenario of the entire CLSC.

As a case study for the implementation of the algorithm, this article considers the real case of designing the decision-making system for the production manager of an industrial hospital laundry (IHL). This system is first trained with data acquired from real situations during production. The data set includes information on the evolution of production and the corresponding decisions made by the production manager. The main objective of this system is to provide a tool capable of making decisions on the scheduling of tasks based on the criteria of the production manager, while minimizing the effect of taking decisions under pressure or potential distractions during the decision taking.

The main contribution of this paper is, then, the proposal of a new methodology to design an intelligent decision-making system for production centres in CLCS with uncertainties. Unlike other proposals (Mehdizadeh et al. 2018; Sherafati and Bashiri 2016), our method allows us to automatically synthesize the decision system from production data and the experience of the decision manager. Despite using artificial intelligent techniques, the self-explanatory structure of the decision trees together with fuzzy logic algorithms turns our proposal into a really useful tool for non-expert profiles in artificial intelligence. The validation has been done on an industrial laundry, but the proposed methodology can be used in any production centre integrated in CLSCs.

This article is structured as follows: after the Introduction, a literature review is presented. Then the general problem and the main concepts are described. In the next section, the Artificial Intelligence methods and the specific intelligent decision support system developed in this research are explained. In the second part of the paper, the application to a real case is presented. Finally, the main results and conclusions reached in this work are summarized.

Literature review

Intelligent manufacturing, considered the fourth industrial revolution (also known as Industry 4.0), is a collection of cutting-edge technologies that support highly efficient and precise engineering methods in real-time decision-making (Kang et al. 2016). Industry 4.0 defines a methodology to generate a transformation to massive digital manufacturing (Oztemel and Gursev 2018) and leads the future direction of automation and information in the manufacturing field (Zhang et al. 2019). Industry 4.0 defines its six design principles as interoperability, virtualization, local talent, real-time capabilities, service orientation and modularity (Oztemel and Gursev 2018).

In the management of operations in a production centre integrated in a Supply Chain (SC), it is essential to have reliable strategies both for the supply of raw materials and for the delivery of finished products (Xu et al. 2011). Thus, decision-makers in the SC are constantly trying to improve the process of meeting customer demand while reducing the associated costs through advanced models and decision-making techniques (Fathian et al. 2018). But CLSC faces a great variability of possible scenarios in the management of stocks, even more than the production process. Recent studies have discussed the limitations of CLSC because of this complex dynamics (Linder and Williander 2017). For example, nonlinear dynamics appears when changes in SC inputs are not, in general, linearly related to production changes (Surana et al. 2005). Therefore, the establishment of a system capable of making intelligent decisions to improve production management is the subject of many research projects (Shi et al. 2017).

The most important operational function in a CLSC is the planning of production and distribution, using inventory policies to make production decisions according to the demands of the product. Therefore, the formulation of effective strategies in this area is essential to reduce operating costs.

The search for optimization when looking for a global optimum is not realistic in industrial practice. Therefore, the best option is to find a sub-optimal solution that offers good results with a relatively low consumption of resources (time and money) (Kuehn 2018). In this sense, many decision-making problems in production planning are solved on the basis of past experiences and the knowledge that the production manager has (Vasant 2006). That is why one of the important challenges in CLSC research is data-based analysis (Hou and Jiao 2019).

Two main difficulties arise in developing the decision-making system: the uncertainty and inaccuracy of the data (quantities and composition of raw material, time for delivery, etc.) In these cases, decision-making can be significantly improved by the use of Artificial Intelligence technologies (Kuehn 2018; Mohammadi et al. 2017; Lee et al. 2009). Fuzzy logic appears to be an adequate tool to deal with these systems (Büyüközkan 2012; Gonzalez-Cava et al. 2018; Zadeh 1965, 2015; Mendez et al. 2018). Some fuzzy logic applications dealing with the representation of uncertainty in CLSCs can be found in (Coenen et al. 2018; Govindan et al. 2015). Machine learning techniques have been also applied for decision-making in industry. They can be seen as an application of Artificial Intelligence in which computers are able to make decisions after a training process. Specifically, these methods are capable of learning patterns automatically from a dataset instead of being programmed explicitly [Kuehn (2018); some applications have been demonstrated by Kumar (2019), Dilli et al. (2018)].

Recently, the Digital Twin concept has emerged as a promising technology for manufacturing companies that are looking for optimal support for decision-making in the digitization of production elements (Kunath and Winkler 2018; Zhang et al. 2019). Digital Twin integrates engineering, operational and behavioural data that connect them through its own architecture (Bricogne et al. 2016).

Similar problems to the one studied in this article use alternative artificial intelligence methodologies. For instance, in Mehdizadeh et al. (2018) genetic algorithms are used to obtain the appropriate levels of production rates, inventory, hiring of workers and quantities of products that are outsourced. Fuzzy logic based solutions can be found in Sherafati and Bashiri (2016) for tactical decisions in CLSC and Zarandi et al. (2011) for designing tasks. Other research lines are focused in the modelling issues of the problem. Thus, in Bai et al. (2019) dimension reduction techniques are proposed as they improve the performance of modelling of decision-making systems in manufacturing. In contrast, the main contribution of our work is the capability of designing a decision-making system automatically based on real data captured from the process.

We conclude this review by pointing out that machine learning and artificial intelligence have revolutionized several disciplines, which are not limited to the recognition of images, dictations, translations, recommendations for content, advertising and autonomous driving (Coley et al. 2018) but are also applied to production planning and management.

The problem of closed loop supply chains (CLSC) with uncertainties

In CLSCs, the final products demanded by the consumers are obtained by processing raw materials and/or components, new or reused in the SC Production Centres. In this context, a Stock (SK) can be defined as a set of components, raw materials and/or manufactured elements, which are required to form, or already form, a determined volume of final products. We can also define the Productive Availability (PA) as the estimated production capacity with the estimated or real available resources in a given production period. Table 1 summarizes the different types of SKs in a CLSC.

The production centres of a traditional SC are all affected by uncertainties. Some of them are inherent to the centre, such as those generated by the unforeseen unavailability of resources, and involve different PA values. Another source of inherent uncertainties comes from suppliers, due to the breach of commitments in the supply. In the CLSCs there are additional uncertainties arising because of the complexity of the different types of stock handling. The difficulty in the management of the production centre in a CLSC framework is related to the presence of these uncertainties affecting the process. The main sources of uncertainties are:

- Uncertainties in the quantities and composition of unsegregated products (SK_{un}).
- Errors in the stock demanded by the consumers (SK_d) defined in the distribution centre.

Table 1 Types of stocks in the production centre of a CLSC

Variable	Definition
Unsegregated stock (SK_{un})	Estimated SK of unsegregated components recovered from consumers
Segregated stock (SK_{se})	Real SK of segregated components recovered from consumers
Demanded stock (SK_d)	SK demanded by consumers through distribution centres
Forecast stock (SK_f)	Predicted production SK according to initial conditions and the productive availability (PA).
Processed stock (SK_r)	Real processed stock
Delivered stock (SK_{dc})	SK delivered to the distribution centres
Regulation stock (SK_{rg})	Available final products that can be used to compensate for the small differences between SK_r and SK_d
Contingency stock (SK_{cg})	Available final products that can be used to compensate for the large differences between SK_r and SK_d

- Nondeterminism in the returned stock due to logistic constraints.

The presence of uncertainties in SK_{un} is one of the main problems when doing the production planning. This uncertainty directly affects the first stage of the process, the segregation stage. At the beginning of the segregation, only an estimation of the stock is available (SK_{un}). When segregation is running, a real segregation value is obtained (SK_{se}). This is one of the great uncertainties for the managers of product recovery processes. Unless the task has started, it is not possible to decide what elements to process according to the raw material inputs. Also, an excess of one type of product will generate problems in the process as the storage capacity of the classified components is limited. In addition, the production needs in a period are much higher than the warehouse limits. Thus, decisions must be recursively made along the productive period to reprogram the tasks according to the information captured from the segregation phase.

The errors in SK_d produce imbalances between stocks. It is frequent that the SK_d is much larger than the SK_{un}. This situation can occur for two reasons: on the one hand, because consumers are not returning the expected quantities of used products according to the demand, and on the other hand because the SK_d forecast made by the Distribution Centres does not correspond to the real need for consumption. In both cases, if the imbalance response is to fully address the SK_d with no other considerations, inefficiencies will be generated by introducing into the chain an excess of of new or transformed components. If this situation persists over time, the process will no longer be profitable. On the other hand, if the chosen path is to process only the SK_{un}, thus avoiding the SK_d, it could eventually cause a shortage of one or more types of products.

It is common that the returned products do not match the desired quantity to satisfy the demand requirements. This usually happens because of logistical constraints or incidents downstream of the Production Centre.

As a result, the existence of these main sources of uncertainties leads to stock imbalances in the production centre (differences between the SK_d and the SK_{un}). A common situation is that these stock imbalances are only significant in one or a few components.

Decision-making in the inventory management of the CLSCs

The Production Centre is the organization in a CLSC in which the most efficient control can be applied. It is able to implement regulatory actions by making decisions to start the circulation of recovered products, cushioning an excessive flow of one or several components, or driving reduced flows.

The organizations that receive recovered products, the Distribution Centres or Consumers, demand that the SCs provide all the necessary quantities of the SKs at the right time. But efficiency is also needed in the Production Centres. Industrial processes lie in human resources and adjusted materials that need to be managed under economic optimization criteria.

The production management of a Production Centre is usually carried out by an expert manager who has command over human and material resources, and takes decisions that pursue the following objectives:

- Establishing a production rhythm according to the current needs, using the efficiency standards established by the Production Centre management. This will allow an SK_f close to the SK_r and, as a result, the values of the SK_{dc} may be similar to SK_d.
- Managing properly the SK_{rg} and SK_{cg} to guarantee the final product stocks that a Production Centre must have.
- Deciding the outsourcing level of the production needed to meet the Demanded Stock.

In general, the basic variables that any manager of a Production Centre has to consider are the remaining production time, pending scheduled production, differences between the quantities of each type of incoming and outgoing product from the storage of classified components, and the segregation pace. All these variables, which depend on the available resources, can be integrated into the Productive Availability (PA). The manager will process the PA information and then a short-term plan will be determined to try to balance the available production time with the scheduled production, using the resources in the most efficient way.

The process manager can usually act on the segregation pace of used products or outsource some tasks to avoid collapses. However, these variables generate very diverse situations due to the specific uncertainties of these processes. This makes it necessary to have an important specific training in that environment, including the capability of dealing with the presence of external disturbances such as admissible production rhythms.

In light of the above, the design of elements involved in the decision-making support for process managers is pursued in this study. This will make it possible to comply with the basic objective of the CLSC, resulting in the efficiency of the Production Centre. In short, the main point is to look for an efficient methodology to control the uncertainties that will be generated in this type of SC.

Artificial intelligence methods

Artificial Intelligence (AI) is an emerging branch of data analysis widely used when trying to obtain intrinsic relationships between data. This methodology has been used in different applications with successful results (Patel et al. 2009; Azizi 2017; Zahraee et al. 2016). Among the diverse methods, there are several techniques to use depending on the features of the data. Sometimes, the complexity behind these techniques makes it harder to understand the intrinsic knowledge from a data set. Specifically, in Closed Loop Supply Chains (CLSC), the presence of ambiguous concepts in the decision-making process due to uncertainties in the management makes it difficult to define crisp values or strict predefined criteria when making decisions. Fuzzy logic deals with this problem in a natural manner through fuzzy limits and the introduction of categories or membership functions that fully regard these specificities. In addition, fuzzy logic is a well-known method, capable of summarizing the heuristic knowledge behind the process in a set of rules that are easily interpretable for production managers without involving a previous study of the algorithm. Moreover, no complex mathematical modelling is needed as the Fuzzy Inference System is based on a linguistic characterization of the quality of the controlled process. On the other hand, regression tree models are algorithms capable of learning automatically from a dataset to build a set of rules that can be easily interpreted. As a result, merging the self-explanatory structure of regression trees by means of rules with the easily interpretable elements of fuzzy logic capable of dealing with uncertainty makes this combination of fuzzy logic and the regression tree model a suitable option for dealing with the CLSC problem. The theoretical basis of decision trees and fuzzy logic is described in Sects. 4.1 and 4.2.

Decision trees

Regression and classification trees methods have been widely used when dealing with complex data in different fields (Babapour Mofrad et al. 2019; Ahmad et al. 2018; De'Ath and Fabricius 2000). Unlike classification trees, which are based on the classification of a certain input inside a category or label, regression trees focus on predicting a numeric or continuous value. Generally, decision trees use a tree structure based on nodes and leaves to make predictions. From the root node, a sequence of questions about different features of the input is asked. Depending on the answer, different branches could be taken to the next question (internal node). Finally, a numeric predicted value straightforwardly related to the features of the input (leaf node) is obtained.

There are different methods to build regression trees. Generally, they can be automatically built after a training step based on a set of input and output data. Data consists of p inputs and a response, for each of N observations. The algorithm needs to decide on the splitting criteria and shape of the tree (Hastie et al. n.d.). In general, a regression tree f can be considered as an additive model according to the expression:

$$f(x) = \sum_{m=1}^{M} c_m \cdot I\left(x \in R_m\right) \tag{1}$$

where R_M are each of the M regions into which the input data are divided according to the output, x is a certain input, c_M are constants and I is a function returning 1 if the argument is true and 0 otherwise. For this purpose, the Bayesian optimization algorithm has been proposed in this study (Xia et al. 2017). This algorithm uses a Gaussian process to fit it to a training dataset. Then, the algorithm can compute the expected improvement during each iteration of the optimization. As a result, the highest expected improvement is tried next. This algorithm aims to minimize the error between the real output of a dataset and the predicted output obtained from the tree. The parameter to optimize is the number of leaf node observations. This means that each leaf has at least n observations per tree leaf. This variable must be an integer, upper and lower constrained as follows:

$$n_{min} = 1 \tag{2}$$

$$n_{max} = maximun\left(2, floor\left(\frac{N}{2}\right)\right) \tag{3}$$

where *floor* is a function that rounds a number to the next smaller integer. To avoid a local objective function minimum, an iterative method to escape overexploiting an area was considered.

Overfitting is one of the main problems when using a machine learning algorithm to obtain a model. To deal with this issue, the cross-validation method is used when training the regression tree (Kohavi 1995). A 10-fold cross-validation is commonly applied, in which the original sample is randomly divided into 10 equal sized subsamples. One subsample is considered for the validation of the model (validation data), while the remaining 9 subsamples are used for training (testing data). The training process is repeated 10 times, combining the subsets and obtaining as a result an average for a single estimation (see Fig. 1).

Fuzzy inference systems

The fuzzy logic term was first introduced in 1964 by Zadeh (1965). Fuzzy Inference Systems (FIS) are based on fuzzy set theory, in which there are not crisp predefined criteria to

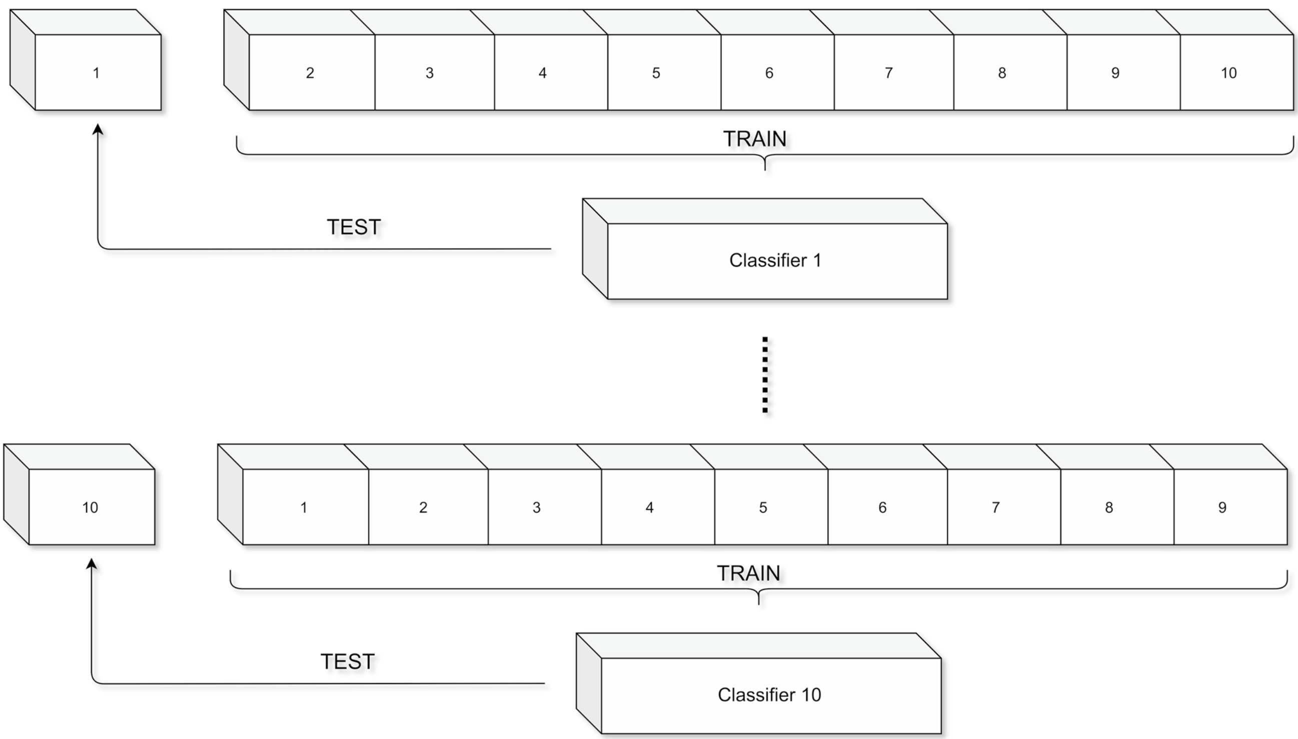

Fig. 1 Scheme of the training process for a 10-fold cross-validation

classify an object in a unique category. As a result, an object may "belong to" several categories according to a degree of membership that could range from 0 to 1, expressed as:

$$n_{min} = 1 \tag{4}$$

$$\mu\left(u_i\right) = X \rightarrow [0, 1] \tag{5}$$

where $\mu\left(u_i\right)$ is a membership function that quantifies the grade of membership of an object in a certain category u_i. This feature allows us to use fuzzy logic as a tool to translate heuristic knowledge into a set of rules in different fields in which the uncertainty is a problem to deal with Bockstaller et al. (2017), Mendez et al. (2018), Méndez et al. (2016). Let us consider an FIS with n inputs and m outputs, where the inputs and outputs are defined, respectively, as:

$$u_i \in U_i, \quad i = 1, 2, \ldots, n \tag{6}$$

$$y_i \in Y_i, \quad i = 1, 2, \ldots, m \tag{7}$$

U_i and Y_i are the *universe of discourse,* that represents all the possible values that the inputs and outputs can reach. When using an FIS, any input and output must be defined as linguistic variables $\tilde{u}_i$ and $\tilde{y}_i$, preferably related to the physical meaning of the variable. Then, the inputs and outputs can reach different j values that are described through linguistic values $\tilde{A}_j^i$. First, the input is matched with the j-th linguistic value $\tilde{A}_j^i$ predefined for each linguistic variable $\tilde{u}_i$. The process that turns a crisp input value into a linguistic value is named *fuzzification*. Once the input is fuzzified, the inference mechanism maps the inputs and outputs through a set of rules. Each rule is defined in a natural manner by means of a set of *if–then* statements:

$$IF\ u_1\ is\ A_j^1,\ AND\ u_1\ is\ A_j^2,\ AND\ \ldots,\ AND\ is\ A_j^n,\ THEN\ b_i = g_j(\cdot), \tag{8}$$

The output $g_i(\cdot)$ can be represented by a constant value or by a linear function that depends on the input terms u_i, according to the Takagi−Sugeno inference (Passino and Yurkovich 1998). Finally, a crisp output value y is obtained by a *defuzzification* method in terms of the equation:

$$y = \frac{\sum_{i=1}^{R} b_i \cdot \mu_i}{\sum_{i=1}^{R} \mu_i} \tag{9}$$

The structure of a fuzzy inference system is depicted in Fig. 2.

Intelligent computer-aided decision system

The main objective of this study is to design an artificial intelligence system that is able to help in the decision-making process in the manufacturing sector. Specifically, this system is expected to work with closed-loop supply chains

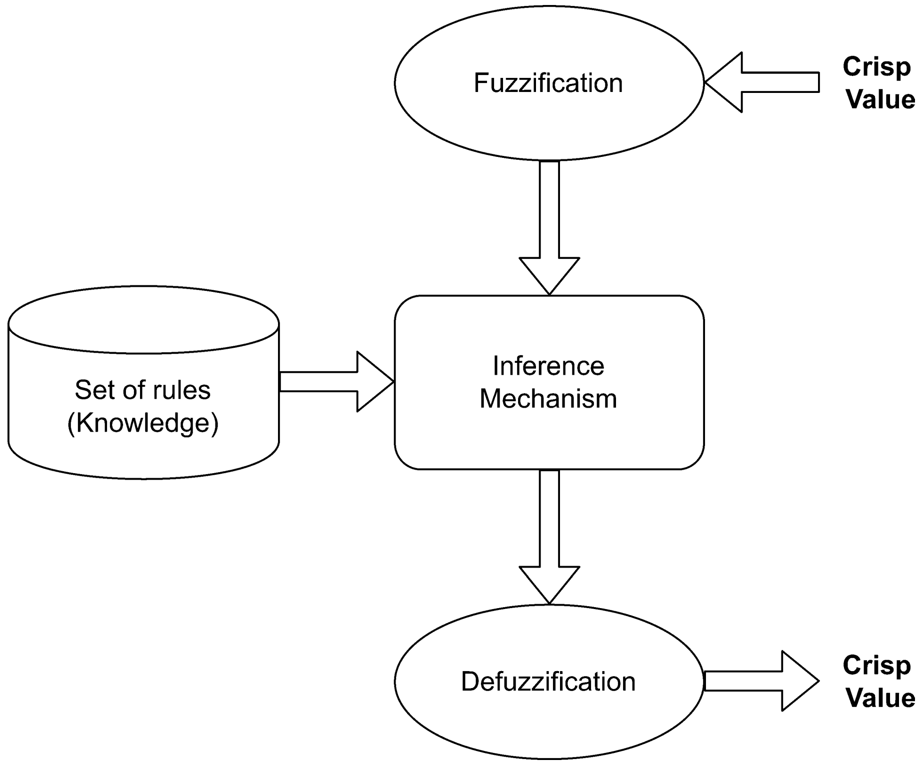

Fig. 2 General structure of a Fuzzy Inference System (FIS)

in an uncertain environment. This implies that the decisions depend on the daily variable behaviour of the plant. In the end, this model will help the production managers to take more efficient decisions based on previous experience and modelled from that experience. To make it easier to be acquainted with the techniques behind the model, a combination of regression trees and a fuzzy inference system is proposed. One of the main problems when defining an FIS structure is to determine the distribution of the membership functions along the universe of discourse together with the rule base. In this kind of process in which decisions are affected by uncertainty, or where there are not crisp predefined criteria for the decision-making process, it is especially hard to build a model. The key idea is to take the information from a regression tree to automatically design an FIS. A regression tree algorithm (RT) is capable of obtaining automatically a model from knowledge behind a dataset. The regression tree model is defined by nodes and leaves that, based on simple yes-or-no conditions, establish a correlation between an input and an output. As a result, it is possible to translate the nodes and leaves from a regression tree to a membership function structure to relate the fuzzy inputs and outputs by means of *if–then* statements. This methodology was first introduced in the medical field (Gonzalez-Cava et al. 2018) due to its several strengths. Some similarities between both problems can be found, such as the presence of uncertainty in the variables involved in the process, or the relevance of heuristic knowledge for decision-making based on expertise. One of the main advantages of using FIS is that no complex mathematical modelling is needed. Consequently, the set of rules can be easily interpreted by non-expert profiles. Finally, the kind of decisions to make, based on the absence of strict predefined criteria due to variability in the conditions, or even a lack of knowledge, makes fuzzy logic a powerful tool to deal with it through the definitions of membership functions.

For the definition of the AI decision-maker in this study, we have considered a general manufacturing system formed by a Main Subsystem (main product) which determines certain constraints that affect the production of several Secondary Subsystems (the rest of the products). The general scheme is depicted in Fig. 3. The decisions of the expert will be focused on the actions that affect each subsystem, such as variations in the production rate, the supply of products from Contingency and Regulation Stocks (SK_{rg} and SK_{cg}) and the outsourced production. During the decision-making process, the expert will take different requirements into account, such us the remaining production, available time or the availability of external sources.

The general methodology described in this research can be divided into two steps. First, a data collection step provides the data for the training process. In this respect, it is important to analyse and identify all possible variables that may be taken into account for the decision-making process. Then, it is necessary to define a protocol to capture the data. In simple systems, in which a few decisions

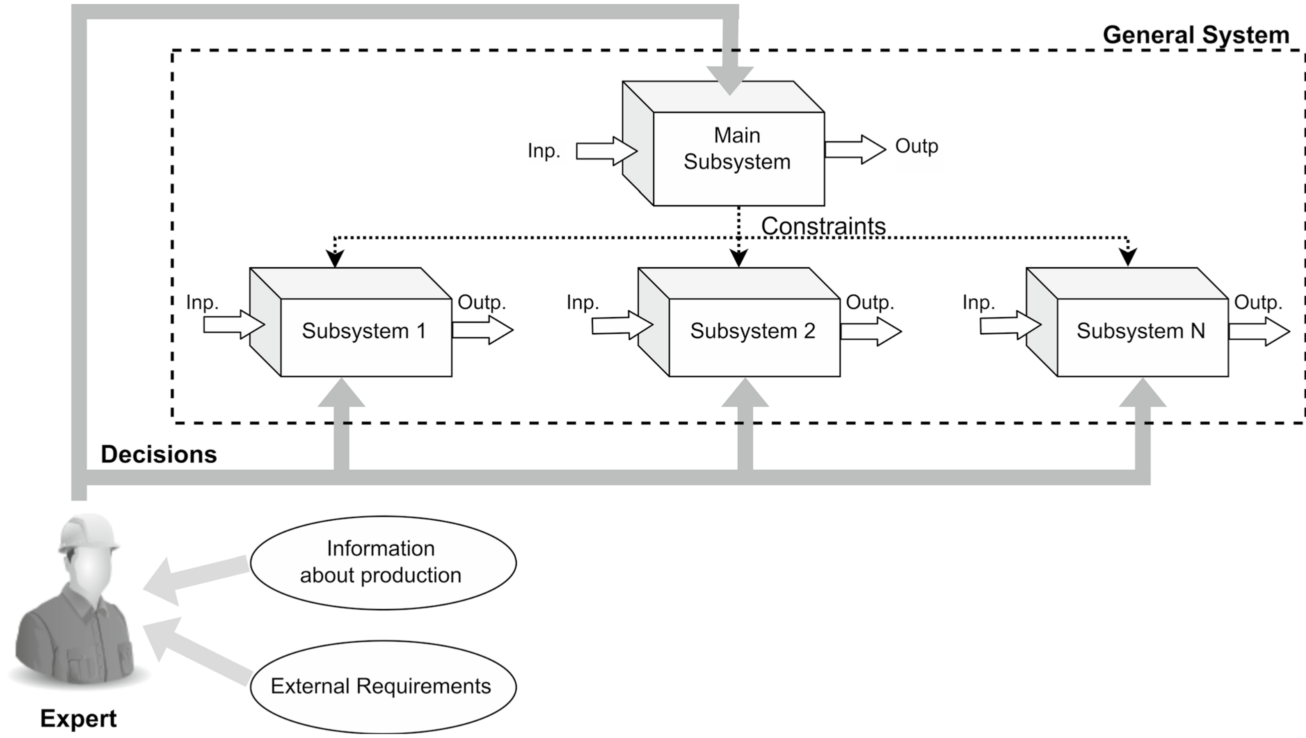

Fig. 3 Schematic view of the decision processes in a general manufacturing system

involving a low number of variables are made per day, data can be written down in a computer by the expert. It will be necessary to record both input variables and the decisions made by the expert. Otherwise, if there is a larger amount of data or the decisions must be made with a higher frequency per day, it will be necessary to obtain data automatically by means of an auxiliary tool such as a SCADA. As a general rule, the greater the number of samples, the better the results that can be achieved.

Secondly, samples must be analysed before the artificial decision system is trained. The preprocessing of the data makes it possible to correct some wrong values in the dataset (typo errors, null data, outliers…) or determine which variables can offer valuable information for each decision. Once the dataset is ready, it is possible to train the algorithm according to the scheme in Fig. 4.

This algorithm has been adapted from the structure proposed in (Gonzalez-Cava et al. 2018) to the manufacturing sector problem presented in this study. On the one hand, the predicted decisions in the original algorithm were categorical variables. As a matter of fact, a decision tree algorithm was used. However, continuous numeric decisions are more common in the industrial manufacturing field. As a result, regression trees applying cross-validation were used in this study. The fuzzification of the regression tree to generate the FIS is depicted in the scheme of Fig. 5.

Triangular and trapezoidal membership functions are proposed for intermediate and edge partitions respectively of the Universe of Discourse. The limit of each membership function will be defined through the conditions in the test nodes of the regression tree. In this sense, it has been established that the test nodes determine the cut-off point between two consecutive membership functions for a degree of membership value of 0.5. Consequently, the limits of each membership function are determined by:

$$Lower\,Edge = a - \frac{b-a}{2} \cdot 0.5 \tag{10}$$

$$Upper\,Edge = a + \frac{b-a}{2} \cdot 0.5 \tag{11}$$

where a and b are two consecutive nodes sorted in ascending order such as $a < b$. The output of the FIS is constant values obtained from the leaves of the tree. The *if–then* rules will be automatically generated from the conditions in the regression tree. With this purpose, N seeds are generated in order to study all the possible relationships among inputs and outputs, N being the total number of membership functions. Each seed is defined so that it only belongs to a single membership function. In this case, we have considered the mean point between two consecutive conditions for defining each seed. Then, all possible combinations among the

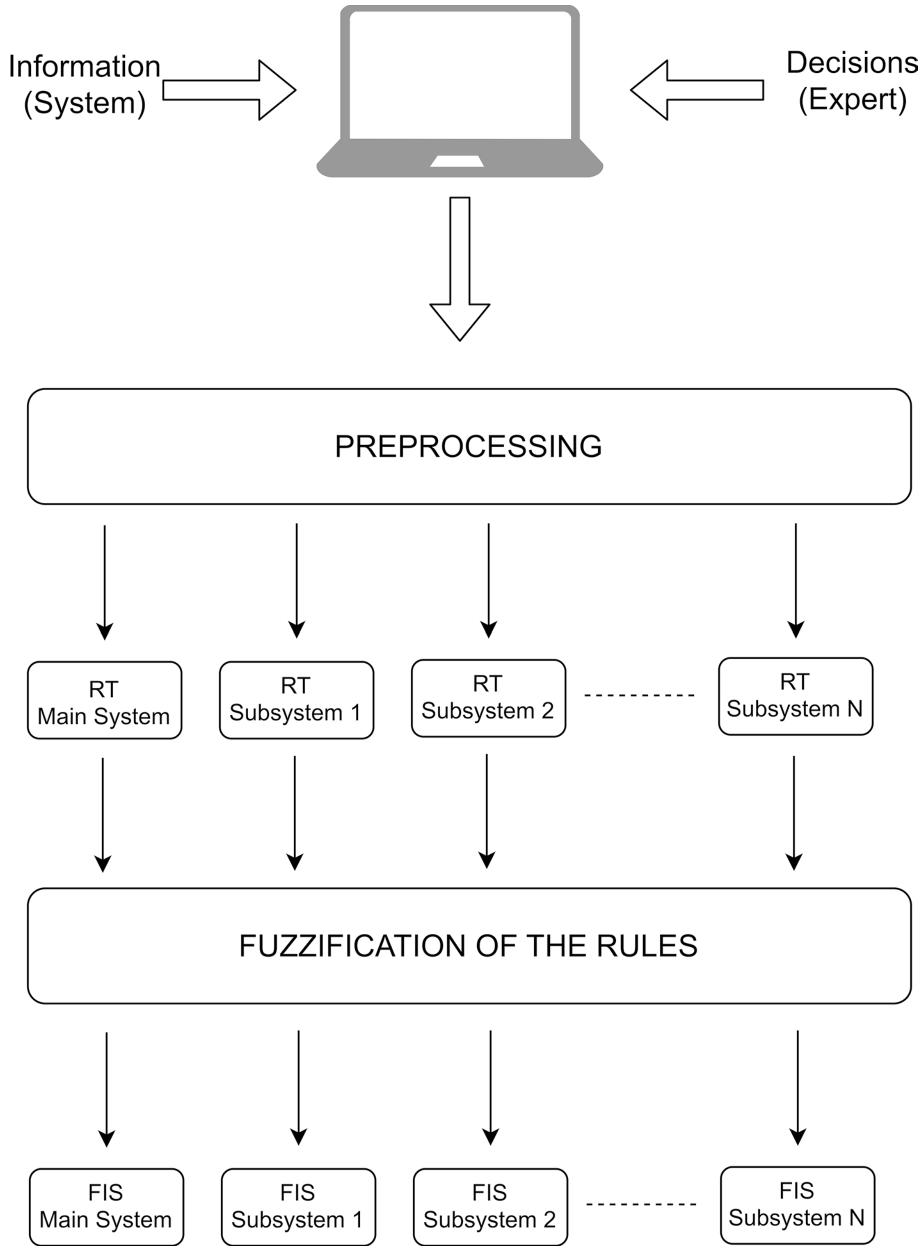

Fig. 4 Structure of the computer-aided decision system proposed. Two main stages are depicted: the preprocessing stage that produces a set of regression trees and the fuzzification stage where this information is used to obtain the FIS systems

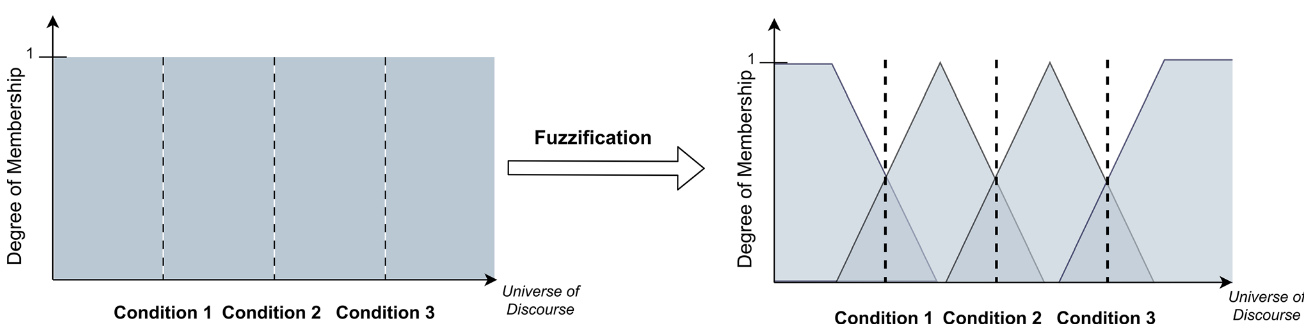

Fig. 5 Graphical representation of the fuzzification process proposed in this study

input membership functions expressed by means of the seeds are defined. The combinations of seeds representing each membership function are applied to the original regression tree. Finally, all the rules relating each of the input membership functions and the outputs are automatically defined as *if–then* statements.

Case study

Process description

The real case of an Industrial Hospital Laundry (IHL) with 16,000 kg of daily production, integrated in a CLSC, which aims to reuse dirty hospital clothing, was considered. This activity has a daily average consumption of 4000 litres of fuel, 280,000 litres of water and about 660 Euros of daily expenditure on detergents. The variability in the amount of dirty clothes received and the demanded clean clothes makes it necessary to make decisions on production classification and outsourcing rhythms. This has a significant influence on the consumption and, consequently, on the operating costs of the production centre.

In an attempt to solve this Hybrid Flow Shop problem, the need to first solve the tactical decisions of stock management planning was identified. Then, the problem considered in this work is to provide a solution for the decision support in the management of operations for the control of stocks at a tactical level.

The circuit of reuse of hospital clothing is based on a network of organizations linked by activities that are developed in both directions. It produces clean clothes with the aim of meeting the demand of a final consumer, from whom the product is obtained after its use.

Phases of the production process

The basic tasks of the process of an IHL can be summarized as:

1. *Classification* Segregation and classification of dirty clothes by garment types according to sequences, procedures, number of cycles and execution times in the post-classification processing phase criteria.
2. *Processing* Washing, drying, ironing and folding of garments.
3. *Expedition* Packaging and definition of destinations. The destinations can be external to the IHL, that is, to the Logistics Centres of the Hospital where clothes are used, or internal, to the Regulation or Contingency Stores.

If the resulting stock of products at the end of the production period is below the target, the remaining products will be outsourced. This option will be undesirable as the operation costs increase considerably.

In the example considered here, two main decision variables that the manager needs to accomplish the objective will be considered: the classification rate (CR) and the externalization index (E), which represents the percentage of clothes obtained by outsourcing.

Production objectives

The decision-making on the stocks of the IHL must provide the correct classification rate in the segregation phase and the externalization index with the aim of reaching a Processed Stock (SK_r) equal at least to the Demanded Stock (SK_d). This objective must be obtained subject to the following constraints:

1. The objective is achieved with the resources that the pre-established strategies of the company consider necessary to achieve the SK_r.
2. Levels of the stocks in the regulation and contingency warehouses are maintained above the established minimums.
3. There will be no collapses during the production period.
4. Appropriate conditions for the start of the production following the scheduled period must be guaranteed.

To reach the objective, the production manager will make decisions at specific time instants of the production period. The decision will be based on the information obtained from the evolution of production since the last decision made. The available data include the remaining production time, pending programmed production, differences between the quantities of each type of incoming and outgoing garment from classified dirty clothes storage, and the segregation pace. This information will be processed and, after that, it will determine a very short-term plan to try to balance the available production time with the scheduled production.

An intelligent solution for laundry operation management

The main objective is to design a tool to help in the decision-making process, that is able to propose solutions aligned with the business strategy in terms of efficiency, and avoiding human mistakes due to the presence of disturbances that may affect the decisions. Consequently, the production manager will be released from the low level interpretation of the information and will assume a supervisor level to evaluate the proposal of the computer-aided decision system. In this way, the efficiency of the management process will be improved.

The intelligent replicator of the operations manager will be a system composed of a Main Subsystem (MS) and several Secondary Subsystems (SSs). The first of the subsystems makes the most important decision for the manager. It establishes the processing rate of the plant according to the real evolution of the garment involved in the process. Simultaneously, it decides on the corresponding task outsourcing. On the other hand, the SSs only make operational decisions concerning the task outsourcing of the rest of the garments involved in the IHL. Each type of the remaining garments will be associated with a specific SS.

The real manager makes the decisions based on the information received from the evolution of the production. For this reason, the digital replica will do the same, analysing the current production situation and providing decisions according to the different subsystems. The information considered for the decision-making process of both MS and SSs is:

- *CR* Classification Rate corresponding to the current period expressed as a percentage of the maximum rate allowed.
- *I–O* Difference in percentage between incoming and outgoing dirty clothing from the classification store corresponding to the garment that governs the subsystem.
- *AT* Available Time for the production expressed as a percentage of the time duration of the work shift.
- *RP* Remaining Production of the specific subsystem in percentage of the whole scheduled production.

In light of the above, one Fuzzy Inference System per decision will be trained. The inputs and outputs involved in the IHL scenario are described in Table 2. The general scheme for the design of the artificial decision-making process is depicted in Fig. 6.

Data including the information for the decision-making process as well as the corresponding decisions made by the expert in real situations are saved manually in an Excel file. One expert is in charge of the data acquisition for the training dataset. Before the training process, wrong data including missing data or abnormal situations must be checked by the expert according to his/her expertise. Finally, data will be saved as csv files. As a result, two different csv files will be generated respectively for each kind of decision. Files are structured in four columns containing the information of the inputs and one column with the decision made by the expert. Once the two regression trees are obtained according to Sect. 4.1, they will be fuzzified following the method described in Sect. 5 to obtain two Fuzzy Inference Systems.

Model validation

The performance of the training step will be analysed by means of two different error-based measurements. For the validation of the regression tree, the cross-validation error will be computed. It will be defined as the mean of the Mean Square Error (MSE) when testing the models over the different subsets into which the original data set was divided for the 10-fold cross-validation. MSE is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \tag{12}$$

where $\hat{Y}_i$ is an array of N predictions and Y_i is a vector of the N original outputs. Consequently, the lower the values of MSE, the better the performance of the regression tree. Then, once the fuzzification of the regression trees is applied, the error when predicting the FIS output over the original output of the dataset is analysed:

$$error = \left(\hat{Y}_i - Y_i\right)^2 \tag{13}$$

Results

A total of 322 situations were registered from the IHL for the training step of the virtual decision-maker based on an FIS structure. The dataset was previously analysed by the expert as part of the preprocessing step in order to check the goodness of the different data acquired. Finally, all 322 situations were considered for the experiment. Information about the original distribution of the different inputs and outputs considered in this study is depicted in Fig. 7.

To obtain the virtual operation manager for the IHL, the process depicted in Fig. 4 was applied. First, the regression tree algorithm was trained based on the dataset. For the training process, Matlab R2017a software was used.

Table 2 Description of the different products involved in the laundry process and the set of the considered inputs and outputs for the decision-making process

Decision/product	Outputs	Inputs
Bed sheet (main subsystem)	New classification rate (FIS 1) Externalization (FIS 2)	Remaining production Differences between input and output Available time Classification rate
Blankets	Externalization (FIS 2)	
Bedcovers		
Towels		
Pyjamas		

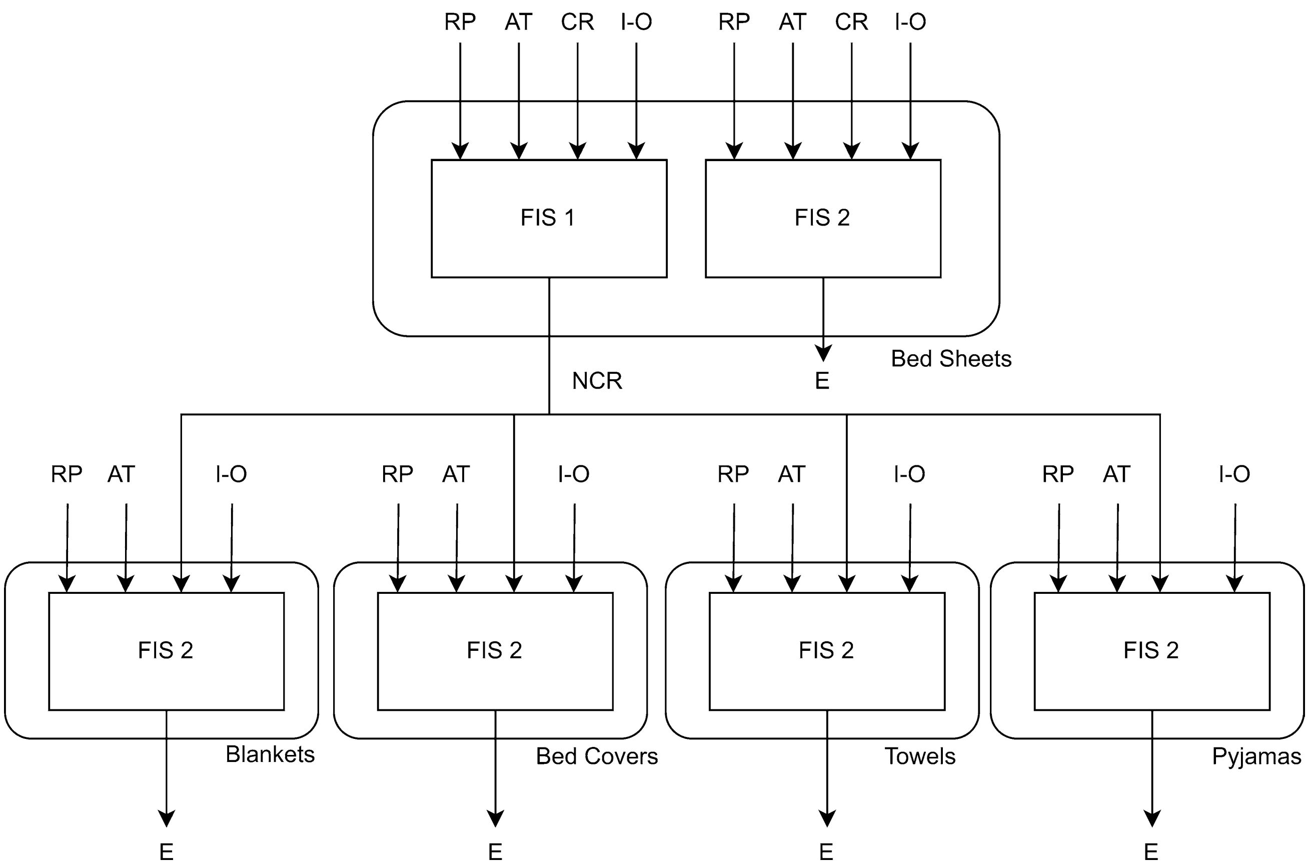

Fig. 6 Structure of the computer-aided decision system proposed for the laundry process. Two different FIS are designed depending on the decision: FIS 1 (New Classification Rate) and FIS 2 (Externalization). Variables refers to Remaining Production (RP), Differences between input and output (I-O), Available Time (AT), Classification Rate (CR), New Classification Rate (NCR) and Externalization (E)

Regression trees were trained using the function *fitrtree* and 10-fold cross-validation including the considerations explained in Sect. 4.1 As a result, two regression tree models for Externalization and New Classification Rate decisions were obtained respectively. To test the performance and generalization capacity of both models, the cross-validation error as described in 6.3 was analysed. A cross-validation error of 43.12 and 208.70 resulted from the prediction of Externalization and the New Classification Rate respectively. The higher cross-validation error obtained from the prediction of the New Classification Rate may not be due to a worse performance of the classifier, but to the difference in the original distributions for both decisions as depicted in Fig. 7. From the business perspective, Externalization is an undesirable decision that is only made when the process is not capable of dealing with the current demand using its own resources. Consequently, unlike the Externalization decision, which mostly ranges between 0−10% for normal situations, decisions regarding the New Classification Rate are mostly balanced and distributed within the 0−100% range. As a matter of fact, the greater set of values that this decision may reach results in higher values of cross-validation error in terms of MSE.

Once the regression trees were obtained, the fuzzification step described in Sect. 5 was applied for each previous model. Definition and distribution of the membership functions along the Universe of Discourse as well as rules were inherited from the regression trees structure. The main features of each FIS are described in Table 3. An example of two surfaces of response from the resulting FIS for the prediction of the Externalization and the Classification Rate is shown in Fig. 8. To validate the final fuzzy system, the error according to Eq. (13) was computed. The error of the Fuzzy Inference system when predicting the Externalization was 5.48 ± 10, while the error after applying the fuzzification for determining the New Classification Rate was 6.92 ± 9.04. The distribution of the error when comparing the real and the predicted output is depicted in Fig. 9. It was observed that the numerical values of the error were normally distributed around a mean value close to zero for both decisions. This evidences that the system is performing the tasks according to the decisions that the expert would make. In addition to the previous results, the general behaviour of

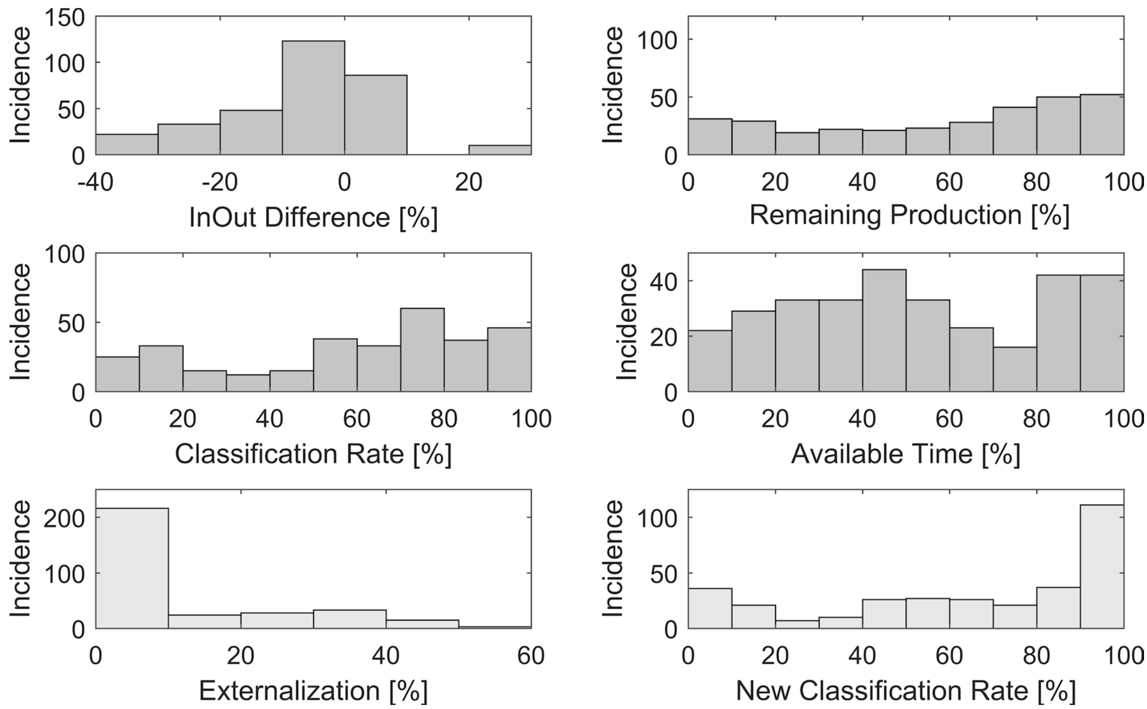

Fig. 7 Histograms for the analysis of the original distribution corresponding to each input (dark grey) and output (light grey) involved in the decision process

Table 3 Description of main features of each Fuzzy inference system developed

	Inputs	Number of input membership functions	Number of output functions
FIS 1	CR	6	42
	I–O	6	
	AT	19	
	RP	15	
FIS 2	CR	11	28
	I–O	10	
	AT	7	
	RP	10	

both resulting FIS was analysed by means of the corresponding surface of response depicted in Fig. 8. In general, when the available time decreases, and the pending production is not accordingly satisfied, the use of external resources is increased. Under the same scenario, it was also observed that the Classification Rate should also be increased. Consequently, considering the surface of response, we could check that the knowledge of the operation manager was correctly implemented by the virtual decision-maker.

Some outliers are observed when analysing the error in Fig. 9. This may be caused by eventual situations registered during the acquisition process that differ from normal situations in the daily production. The AI techniques used in this research tend to minimize the cross-validation error by means of rules based on patterns that model the general behaviour of the system. As a result, the FIS may not have been able to learn from particular situations as being a minority. To deal with this issue, and regarding the incidence and consequence of each abnormal situation, relevant auxiliary decisions could be manually added to the set of rules of the corresponding FIS to minimise the possible negative effects.

Finally, 20 new scenarios were defined to check the validity of the proposed virtual decision manager. These situations, not previously included during the training step, consisted of decisions considering not only normal conditions during production, but also some less common situations in order to check the validity of our AI solution under a wider operational range. Three different human experts familiar with the IHL were asked individually to propose the decisions that they would have made under the same input information. We compared the predictions of each FIS with the decisions of the experts. The results of the analysis are depicted in Fig. 10. On the one hand, it is important to highlight that there were slight differences when comparing the decisions made by the different experts. These divergences could even be magnified when considering disturbances appearing during the workday such as stress or fatigue. In general, regarding the New Classification Rate, very similar

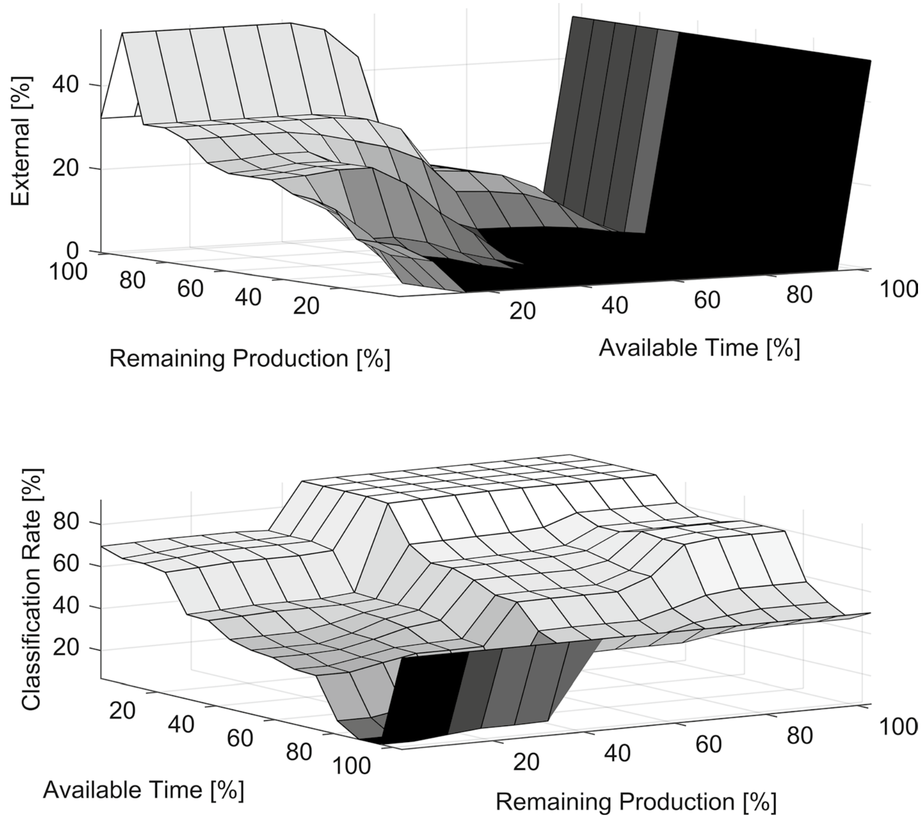

Fig. 8 Surfaces of response of FIS for the prediction of the Externalization and Classification Rate considering different combinations of inputs

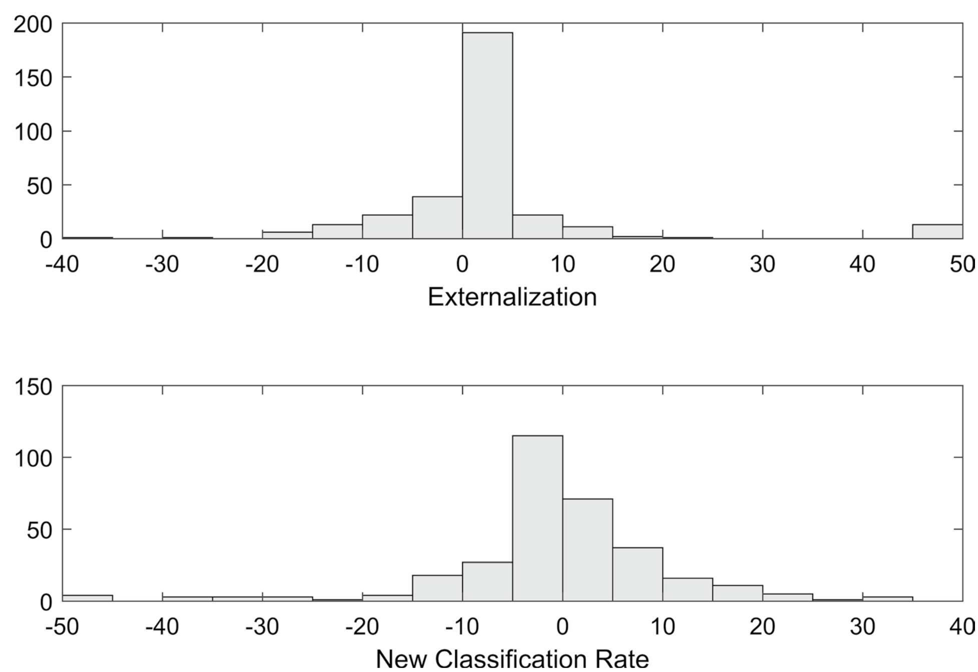

Fig. 9 Histogram describing the distribution of the error when comparing the FIS output with original output in the dataset. Y axis represents the incidence

results were obtained when comparing the human with the virtual decisions. In terms of error, 75% of the virtual predictions differed less than 5% with the human behaviour. Situation number 20 was the worst case as the error reached a value around 25%. This scenario corresponded to a situation in which only 13% of time remains, I-O is close to 0%, remaining production is 11.4% and the classification rate is 35%. Analysing the side-effects of the virtual manager decision, we could conclude that it applied a conservative criterion, as far as increasing the current

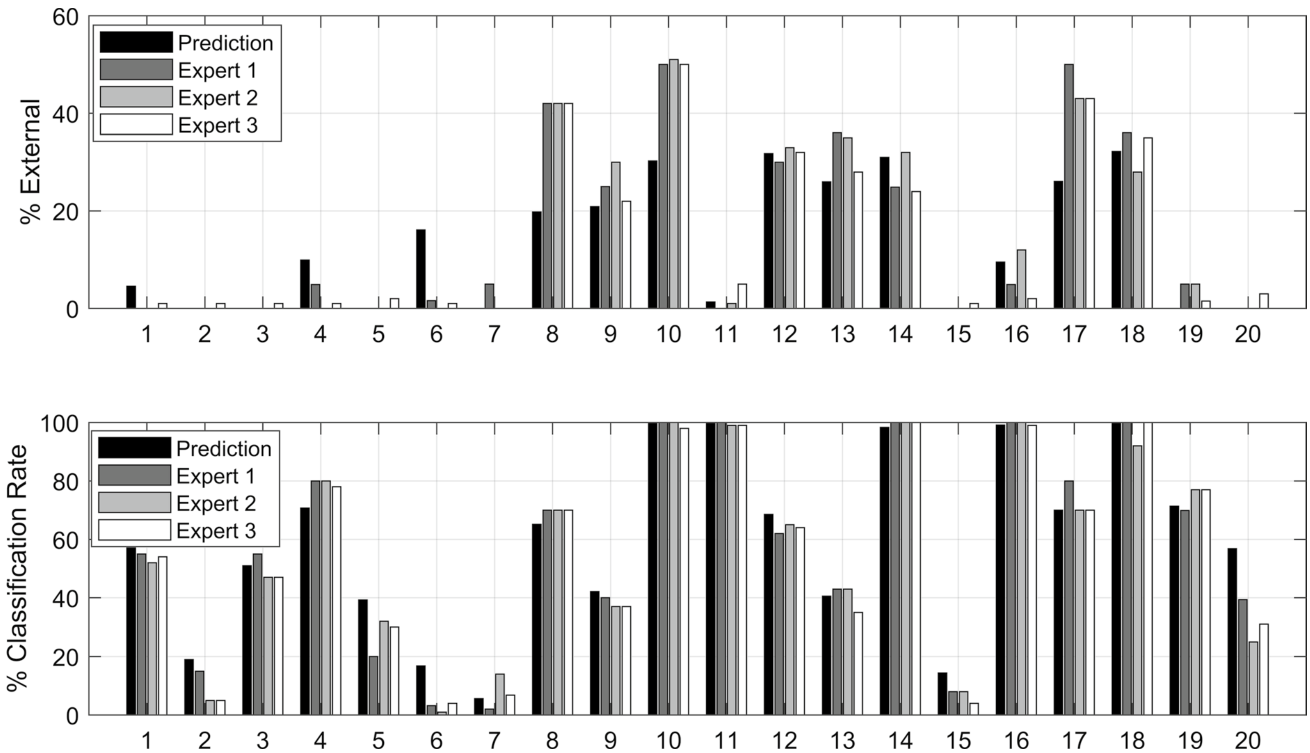

Fig. 10 Prediction of the virtual decision manager vs. decisions made by three human experts under 20 real new situations

classification rate would ensure meeting the objectives of demand in case of any disturbance in the process at the end of the day. As a result, no dangerous consequences for the process are expected. Considering the External predictions, 80% of the decisions made by the virtual manager matched the decisions of the experts, resulting in an error lower than 5%. The worst results were obtained in situations number 8, 10 and 17. All these cases referred to situations in which the Externalization decision made by the experts was greater than 40%. All these three scenarios represent abnormal situations in which the remaining time is very low compared to the pending production (38% vs 71%, 42% vs 93% and 27% vs. 70% respectively). If we observe Fig. 7, only 6% of the decisions included in the training dataset considered Externalization values greater than 40%. As a matter of fact, this shows that these situations hardly occur in the process. In practice, these effects could be minimised by including new rules in the FIS provided by the heuristic knowledge of the experts. Additionally, an alarm system could be set to give warning of an abnormal situation. Then, the expert could evaluate the possible effects and consequences of the proposal of the virtual decision-maker. In the future, including more information about these abnormal situations in the training dataset would improve the virtual manager automatically by means of performing a new training step.

After this analysis, it can be assumed that the proposal described in this study was able to find acceptable decisions to cope with the production management in the hospital laundry. The benefits of this tool are related to the guarantee that decisions will be aligned with the strategy of the company, avoiding uncertainties caused by human errors in the process. In short, the results show the potential of the proposed method to deal with the management of CLSC in productive processes.

Conclusions

A new methodology for the closed loop supply chain management problem through a decision-making system based on artificial intelligence was proposed. The main advantage of our method is that it automatically synthesizes the decision system from production data and the experience of the decision manager. The resulting tool can be directly used in production planning in the context of CLSC to improve the efficiency of the production and avoid collapses. This digital decision making system can also be used to evaluate the effects of the decisions in the process in a simulated scenario.

The system is based on a combination of fuzzy logic and regression trees. This proposal uses machine learning to process the real data and uses this information to generate a decision making system automatically. The methodology was described for a general industry and then applied in a real case study. The problem considered was the production planning in an industrial hospital laundry. Specifically, 75% and 80% of the decisions made by the virtual decision-maker to determine the appropriate classification rate and externalization respectively differed by less than 5% with the human decision based on expertise. These results showed satisfactory performance and promising perspectives for the future.

Thus, this study appears as an efficient tool to start the way towards the total integration of elements and decisions in an intelligent system in the context of the Industry 4.0 paradigm. Future works will be focused on the integration of this tactical-level decision tool with the low-level flow shop problem. The combination of both tools can be regarded as a first step for the development of a digital twin capable of simulating all the process involved in the manufacturing sector.

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Compliance with ethical standards

Conflict of interests The authors declare that they have no conflict of interest.

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