A DECISION THEORY APPROACH TO SUPPORT ACTION PLANS IN COOKER HOODS MANUFACTURING

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UN ENFOQUE TEÓRICO DE LA TOMA DE DECISIONES PARA APOYAR LOS PLANES DE ACCIÓN EN LA FABRICACIÓN DE CAMPANAS DE COCINA

ABSTRACT:
Nowadays, Knowledge-Based systems are widespread decision-making tools applied in product design and manufacturing planning. The series production requires agile and rapid decision-making methods to support actions in manufacturing lines. Therefore, agent-based tools are necessary to support the detection, diagnosis, and correction of accidental production faults. The context of Industry 4.0 has been enhancing the integration of sensors in manufacturing lines to monitor production and analyze failures. The motivation of the proposed research is to study and validate decision theory methods to be applied in smart manufacturing. This paper shows a Knowledge-Based approach to support action decision-making processes by a Bayesian network model. The proposed method aims at solving production problems detected in the manufacturing process. In particular, the focus is on the automatic production of cooker hoods. A case study describes how the approach can be applied in the real-time control actions, after a problem in quality is detected.

Keywords: Knowledge Base, Bayesian Network, Industry 4.0, Cooker Hoods.

1. INTRODUCTION

Nowadays, with the development of Industry 4.0, knowledge-based systems (KBSs) have become more and more necessary in the industrial world [1]. During the 90s, KBSs have been considered as a solution to improve design phases [2] with enhancements concerning time and quality. Since then, several tools and methods have been developed in the field of knowledge-based systems to support designers during their decision-making and product configuration phases [3, 4]. The product configuration phase has also been extended to complex systems [5] such as manufacturing production and power production systems [6]. In the recent years, the context of smart factories has been enhancing the implementation of knowledge-based solutions, to perform the manufacturing control [7] and to improve quality and efficiency [8]. Generally, the recent improvements in Information and Communication Technologies have allowed enterprises to move from highly data-driven solutions to knowledge-driven environments [9]. Therefore, the actual research is mainly focused on tools and methods to monitor and support decision-making processes. Cloud-based solutions [10] have also been studied, in order to perform computing and provide feasible real-time solutions. However, at the time of this study, a lack of commercial platform tools has been observed in the market. In particular, a lack of tools that can efficiently implement the production knowledge for supporting the solving of quality alerts and problems. Moreover, smart factories require Artificial Intelligent solutions [11] to perform a machine learning approach and enlarge the implemented knowledge base. In fact, a production system is a dynamic process [12] where events and actions change over time; thus, the related knowledge base has to be continuously updated and revised. A machine learning approach might be the right solution to overcome this limit and provide constant performance improvement in automatic decision-making processes.

The proposed paper aims at developing a knowledge-based method to support the action planning, after a problem is detected in the manufacturing process (Fig. 1). This paper describes the methodological approach and introduces an application case, focused on the production of kitchen hoods. The studied case shows how to support the real-time control action after a problem in quality is detected. In this context, an approach based on a Bayesian Network has been proposed, in order to deal with the uncertainty and incompleteness of the analyzed knowledge base. This method is based on inference procedures, e.g., belief propagation or junction tree [13]. A Bayesian Network is a graph that links variables by conditional probabilities, where model outputs are probabilities calculated using Bayes' Theorem [14]. This approach is useful for data mining. The relationship among variables represents the expert knowledge able to identify key uncertainties [15].

The application context is focused on a manufacturing plant of an Italian company which is a worldwide leader of cooker hoods. In particular, the application case concerns the development of a knowledge base into a KBS tool, to support the control actions of an automatic assembling line for sheet-metal parts. This production line consists of robots and forming presses to produce kitchen-hood frames from sheet-metal foils.

2. APPROACH

The methodological approach, described in Fig. 1, proposes a Bayesian network for the formalizing and the management of the acquired knowledge. Bayesian Network method has been selected and applied due to its intrinsic modelling characteristics. It is indeed a consolidated method able to model causal and probabilistic systems efficiently and with a high flexibility [14], and it fits for working with KBSs.
The Bayesian network concerns the graphical representation of cause and effect relations [16, 17]. A weighted edge, converted into conditional probability table, describes each cause-effect relationship. The use of a Bayesian approach, empowered with reinforcement learning, gives the possibility to include a machine learning process into the problem-solving workflow. Interviewers and technical briefings have been done with experts, to acquire the knowledge related to cause-effect Bayesian Network model for fault diagnosis aim.

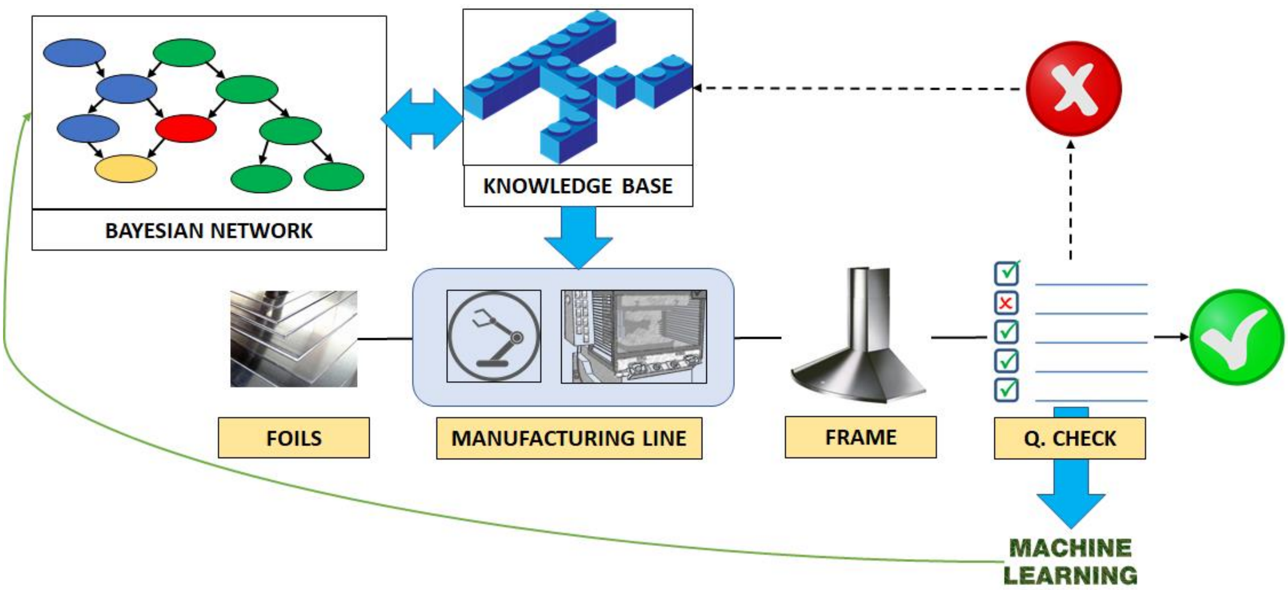

Fig. 1. A schematic representation of the Knowledge Base System applied to the manufacturing line.

Generally, automatic production lines, for household appliances, present robots and different types of machinery, such as stamping presses for cutting and shaping. The system complexity is directly related to the manufacturing of the different versions of the product, within the same production line. Some product families might be configured in different ways, with changes in dimensions and shape; therefore, a manufacturing line must provide smart solutions to support the production of every family model. In addition to this, in the context of small batch production, frequent changes in the manufacturing lines are required. The small batch production is a typical characteristic of the household appliances manufacturing [18]. In particular, the production of medium-high level cooker hoods concerns many product versions and a high variation in production volumes, due to non-constant production demand. Therefore, flexibility is a mandatory characteristic in this context; however, frequent changes in manufacturing settings can cause some quality problems. Quality checks are always applied to control the manufacturing state. Each quality alert or problem-detection can stop production and run a manual workflow, for searching causes and solving the related issue. This workflow requires expert operators that can solve the detected problem, using their know-how and trial-and-error procedures. Therefore, frequent stops in production can cause time-delays and inefficiencies. The development of a KBS platform might be a solution to support rapid problem-solving actions.

3. SYSTEM MODELLING

This section describes the modelling phases, used to analyze the workflow in the proposed decision theory approach. Fig. 2 highlights the four phases which constitute the modelling process, from the setting of the quality control detection to the definition of each action plan.

As cited in the previous section, the Knowledge Base has been represented using a Bayesian Network and assigning a weight factor to each link between parent nodes and each child. The modelling approach, described in Fig. 2, has been used to develop a KBS tool to support the detection and solution of problems related to production activities.

Fig. 2. The system modelling.

3.1. QUALITY CONTROL SETTING

Each Statistical Process Control provides a variable setting. Generally, each numerical variable is defined by a Control Limits (CL) range. This range consists of an Upper Control Limit (UCL) and a Lower Control Limit (LCL). During a Quality Control (QC) process, the values of each sample must be lower than the UCL and greater than the LCL, in order to pass the samples check. In the proposed research, the sampling concerns a production process. In this application context, sample values can be manually measured or automatically acquired by sensors. The proposed approach provides a software tool to compare each value of a sample point with the relative CL range. The definition of the variables and their CL range is a phase named QC Setting. Fig. 3 describes a report related to a QC Setting with some CL ranges, as implemented in the proposed KBS tool.

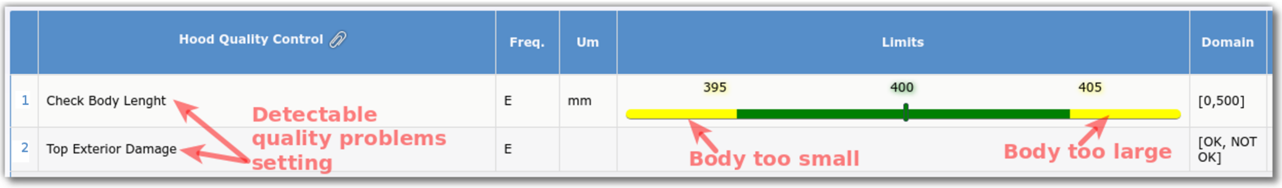

Fig. 3. Report of a Quality Control (QC) Setting.

During a QC phase, an “out of control” (OOC) signal is generated when a sample value is out of range. A detected OOC is an effect of one or more possible quality problems, related to the manufacturing process. As described in the following section, a Bayesian Network has been defined to represent each possible cause-effect relationship, using a probabilistic model.

3.2. KB TOPOLOGY DEFINITION

The second step of the process modelling (Fig. 2) concerns the definition of a topology, to represent the Knowledge Base (KB) related to a cause-effect relationship in the detection of production problems. The approach provides the implementation of a Bayesian network to represent the proposed KB using a causal-based model (Fig. 4). The Bayesian Network is described using nodes and edges that connect each node with a cause-effect logic. Each node can be a cause or an effect; however, leaves are usually considered as effects and their relative parent nodes as their causes. A probabilistic approach regulates the relationship between two consecutive nodes. Each node can assume one of three values such as True, False, and Unknown, during a QC process.

The implementation of a such network requires the employment of experts for the knowledge formalization into a cause-effect model. Therefore, the Bayesian network, described in the proposed test case, has been implemented after an analysis phase, which involved the experts of manufacturing processes for cooker hoods.

Regarding the Bayesian Network modelling, the construction process starts with the identification of every node, considering both causes and effects. Then each node-cause is connected to its effects using directed edges with the connection direction from cause to effect. Two optimization strategies have been applied for increasing the network efficiency. Firstly, if a node has too many parents, some intermediate nodes are defined for grouping parents with a similar cause. Secondly, if some causes are missing in the nodes tree, leak nodes are added to represent the other causes (as highlighted in Fig. 4).

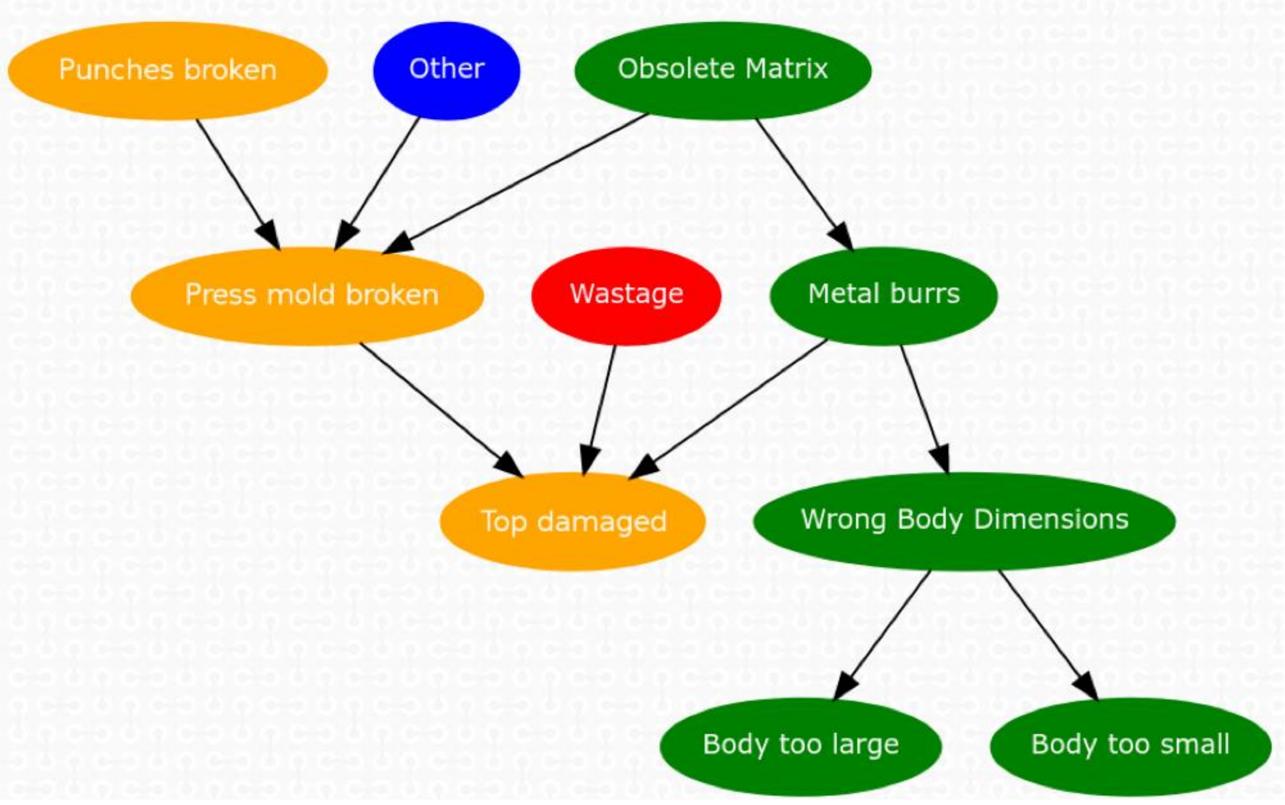

Fig. 4. An example of a Bayesian Network

The proposed Bayesian Network has been developed using *Improve* by NeXT (www.mynext.it). This software platform implements tools and methods for the definition of a generic Bayesian Network. As previously mentioned, the construction of the network started with the definition of each cause. After that, the second step was the definition of the list of all the possible effects, which represents the information from the production plant. The third step was the definition of the relationship between causes and effects. The last step was the assignment of the probabilistic weight to each cause-effect relationship. The *Improve* tool provides a graphical-user-interface to design the network and to visualize the resulting graph. The list of effects represents the variables that have to be elaborated into a probabilistic inference by a Bayesian Network. While the effects are the input variables of an inference process, the causes are the output of this process. Considering a quality control case, the variables are related to different production states. In order to be used into an inference model, based on a Bayesian Network, these variables have to be discretized, with the exception of the variables related to sensors from robots or machineries, which have already a discrete form. On the other hand, variables related to visual quality check are not a discretized information. This kind of variables were discretized using Boolean variables or feedback levels.

Regarding the interaction between the proposed Bayesian Network and QC, when an OOC event occurs, the methodological approach provides the searching of the OOC effect within all Bayesian Network leaves (Fig. 4). The node, related to the effect highlighted with the OOC event, changes its state in True. The diagnosis for the detected problem is analyzed through the study of each cause-effect connections, with a probabilistic approach, based on defined weights for each connection.

3.3 KB WEIGHT DEFINITION

A weight factor has been assigned to each cause-effect relationship, to avoid the developing of a Conditional Probability Table relate to each Bayesian Network node. In fact, the definition of such table is a time expensive process, since the number of independent entries grows exponentially along with the number of parents. A way of overcoming this worst-case scenario is the use of the Noisy-OR model [17] (Fig. 5).

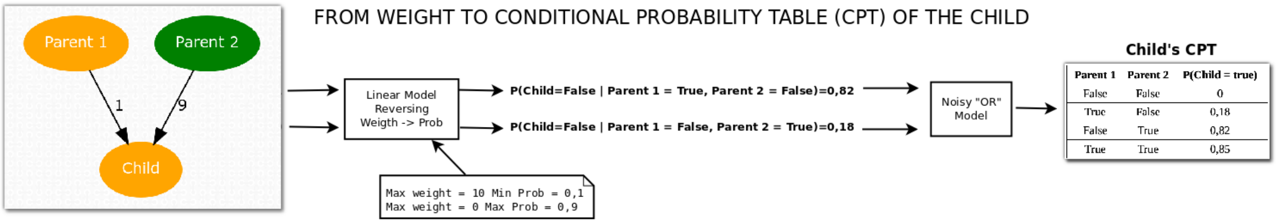

Fig. 5. The description of the Noisy-Or model.

This solution requires one value for each edge. The assumptions related to the use of a Noisy-Or model are three:

1. all the possible causes for each event are listed (if not, a "leak" node can be added);
2. negated causes do not have any influence on the event;
3. the probability of an independent failure is alone for each cause.

The weight of each edge represents how much each parent affects the child.

3.4 ACTION PLANS DEFINITION

The definition of each Action Plan (AP) is the last phase of the proposed system modelling (Fig. 2). An AP is a sequence of automatic/manual actions for solving process issues after a detected problem. The proposed KBS tool can associate an AP solution to each state of the system. In particular, when an event occurs, the KBS tool identifies the leaf nodes with True values and computes the related probability values using a Markov inference and considering the KB weights. A sub-set of these nodes is related to the belief state of the system. Therefore, different AP plans are possible for a system state.

Using a Maximum Expected Utility method, the proposed KBS tool can select the more suitable AP plan for each situation. This method provides a utility value for each proposed AP. This value is weighted by the probability of each node in that output state. The system suggests a collection of possible APs to the users. The resulting list of APs is ordered by the utility value. If the selected AP is successful, the positive feedback is registered and learned by the system, storing it in the database related to the Utility Table

4. TEST CASE

The described KBS tool has been developed and tested in the context of an automatic assembling line for the manufacturing of cooker hoods. In particular, the manufacturing line regards the fabrication of some external sheet-metal parts, such as the appliance shape and frame. This production line includes five robots, three forming presses, and a rotary machine (Fig. 6). Each manufacturing station is synchronized with the production takt time. Table I describes each station related to the proposed manufacturing line.

Fig. 6 describes the automatic line analyzed in this paper. The process is divided into three phases: the manufacturing of the frontal shape, the manufacturing of the rear frame; and the riveting of all the parts. This automatic line is the first part of an assembly line. The second part concerns the assembly of motor, impeller, filter, etc.

Table I: List of the main components of the highlighted manufacturing line.

Station	Description	Nominal Power
1	Robot-1	2 kW
2	Forming Press (first frame bending: frontal shape)	40 kW
3	Forming Process (second frame bending: frontal shape)	15 kW
4	Robot-2	2 kW
5	Forming Process (third frame bending: rear frame)	22 kW
6	Robot-3	2 kW
7	Rotary machine	5 kW
8	Robot-4	2 kW
9	Riveting machine	3 kW
10	Robot-5	2 kW

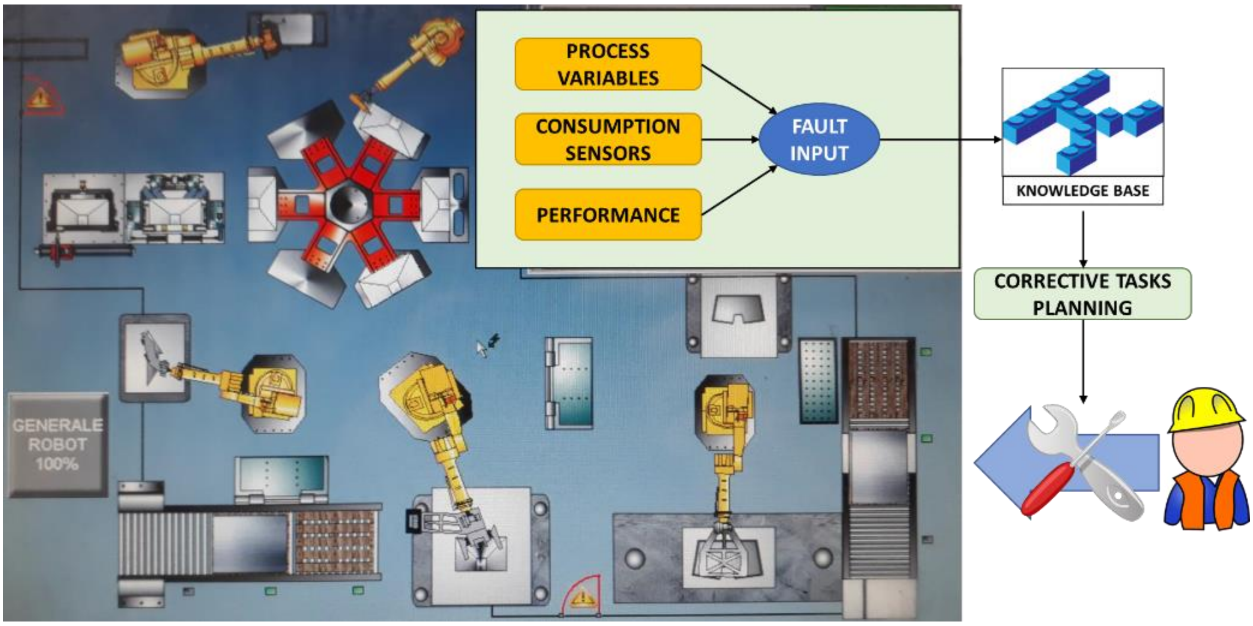

Fig. 6. The described manufacturing line and the proposed fault diagnostic flow.

As an example, this paper shows how the KBS tool works for a problem detection such as the presence of burrs, which are dented by molding press. The detection of this quality issue is done by the quality operator during the sample inspection process. When the operator registers a burrs issue, the system sends a signal of detection related to the kind of highlighted issue (e.g. the presence of burrs).

The KBS system reads the Bayesian Network and sets each True value on each leaf node which is interested by the belief state of the system. Then, this tool calculates all the probability values and the utility values for each AP, in order to return the plan with the higher value of utility. If the operator selects the proposed Action Plan and adds a positive feedback, the system increases the utility value of that plan for that belief state. Otherwise, if the operator selects another plan, the system decreases the utility of the first plan and increases the utility of the selected plan.

Regarding the proposed test case, the KBS tool suggests the cleaning and lubrification of the shearing press for the burrs issue. Fig. 7 describes the action plan for the solution of burrs detection, related to a shearing press.

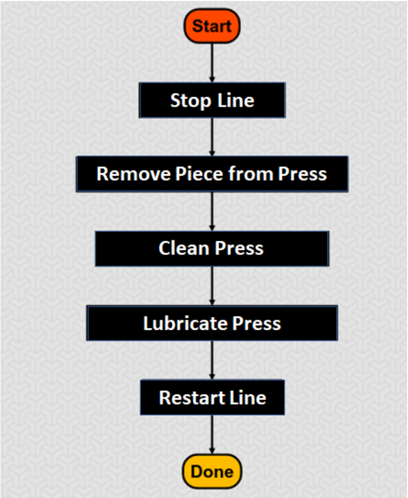

Fig. 7. The action plan for the solution of burrs detection, related to a shearing press.

Fig. 8 describes the percentage of success for the burrs solution, using the action plans proposed by the developed KBS tool. In particular, this report concerns the daily success percentage, evaluated during a period of 4 weeks. The use of a machine learning approach shows an increase in the percentage of success after each sampling period. In comparison with a traditional approach, without the use of a KBS tool, a time reduction of approximately 50% was achieved for solving the mentioned quality problems.

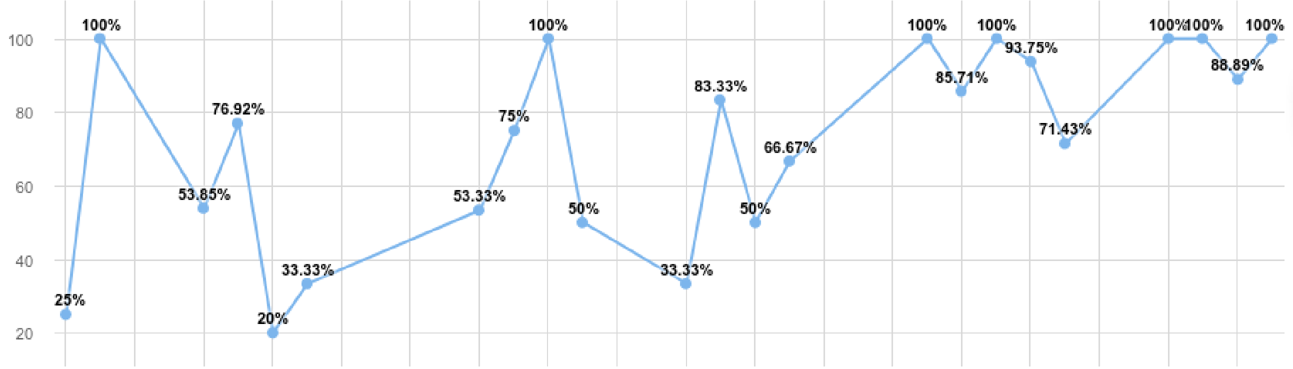

Fig. 8. The daily percentage of success for the burrs solution, using the Action Plans proposed by the KBS tool, for a 4-week production.

5. CONCLUSIONS

A Knowledge Base approach has been described to support the decisions of action plans for solving problems in automatic production lines. In particular, the proposed Knowledge Base has been represented using a Bayesian network which reproduces every cause-effect relationship related to the faults detection. This approach has been performed within a KBS tool. This tool receives events for any detected issue, and it queries KB to elaborate the possible action plans list with their probability of utility. A machine learning approach allows the corrective action plans to be proposed as first solution to the user. Even if the proposed platform is a prototypical tool, the results show a reduction in time of approximately 50% for solving quality problems and restart the production. The reinforced learning increases the reliability of the fault diagnosis in less than four production weeks, as highlighted during the testing demo.

As a future development, the Bayesian network and the proposed KBS tool can be implemented in a Cloud Computing, in order to develop a Cyber Physical System for the control of many manufacturing lines which operate in different production plants.

NOMENCLATURE

AP: Action Plan

CL: Control Limits

KBS: Knowledge-Based System

KB: Knowledge Base

QC: Quality Control

LCL: Lower Control Limit

OOC: Out of Control

UCL: Upper Control Limit

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