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IMPROVING BUSINESS PROCESS IN SEMICONDUCTOR MANUFACTURING BY DISCOVERING BUSINESS RULES

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ABSTRACT

Process and data are equally important for business process management. Data is especially relevant in the context of automated business processes, and process controlling. In the context of knowledge-intensive domain, data modified by engineers and used by a fully automatic manufacturing system can lead to unpredictable errors. In this paper, a method permitting the discovery of truly enforced business rules used by the process is proposed. These rules will be highlighted using data from the model of the studied process. The proposed methodology is mainly based on a data mining approach. The proposed method has been tested on data from semiconductor industry, in which processes are known to be complex, and the number of business rules is known to be important. The results show that the method is efficient in assisting engineers in process errors detection and practical process improvement.

1 INTRODUCTION AND MOTIVATION

Business Process Management (BPM) is the discipline that combines knowledge from both information technology and management sciences, then applying this to operational business processes (Van Der Aalst 2003). One of the primary focus of BPM was the design, and documentation of processes. Nevertheless, following its adoption in industries, BPM received more attention as *a systematic and structured approach to analyze, improve, control, and manage business processes* (Elzinga et al. 1995). A business process model *"generally describes a set of activities that an organization should perform to fulfill a specific business goal"* (Lindsay et al. 2003). It has been showed that there are different perspectives in a business process model (Van Der Aalst et al. 2011). The control-flow perspective (modeling the ordering of activities), is the one who received the more attention, and many approaches use formal methods to mathematically formalize the business process models to check whether the control-flow perspective is conform to the specifications or some desirable properties (Maruta et al. 1998; Bi and Zhao 2004; Van Der Aalst 1997). Another aspect of a business process is the data perspective (modeling decisions, data creation, etc.). However, even if a number of authors stated that data is important for business process management, the data perspective received less attention. In (Meyer et al. 2011) the authors point out the relevance of data within process controlling, and especially in the context of automated business processes. In fact, data highly impacts the behavior of process execution. For instance, many decisions in processes are data driven. Thereby, data used by these processes have to be controlled because they may be at the origin of many unpredictable errors in processes. Furthermore, manufacturing industries have to adapt to external constraints such as rapid changes in the market, regulations, etc. In addition, they also need to face internal constraints like continuous improvement of the production performance indicators, and the challenges imposed by the different certifications relating to the various services of the company. Moreover, engineers can face managerial constraints such as the adoption of a certain way of working, which can be more or less restrictive from one service to another within the same company. As a result, business rules are enforced to reflect decisions in data used by processes, and consequently act on them. Many authors have proposed a number of definitions for business rules. In (Hay et al. 2000) the Object Management Group (OMG) defines a business rule as a statement that defines or constrains some aspect of the business. It is intended to assert business structure, or to control or influence the behavior of the business. A distinction is made between structural rules and behavioral rules. Structural rules define the business information model. and the latter is about how the business reacts to business events.

Von Halle says in (Halle et al. 2006) that *"business rules are the ultimate levers with which business management is able to guide and control the business. In fact, the businesss rules are the means by which an organization implements competitive strategy, promotes policy, and complies with legal obligations"*. Traditionally, useful information for an organization is essentially owned by members of that organization. Knowledge management has always existed to allow the organization to survive all the hazards it may encounter (e.g. departures, resignations, or other causes of unavailability of information). However, because this management is often not formalized, there are many examples of organizations that did not know precisely the rules under which they were operating, and consequently, operated under different and often conflicting sets of rules. Hence, there is one major challenge : organizations need to know which business rules they are using, and whether they are using them consistently or not. Moreover, when trying to express the rules, a well known problem arises: knowledge acquisition bottleneck (Feigenbaum 1977; Wagner 2000). Since the verification of compliance rules are often specified using formal logic, incorrect or too general rules may return too many false errors.

We address here the problem of the discovery of business rules, which goal is 1) to allow decision makers to have a view of the current operative rules and therefore to have a better understanding of the model 2) to detect possible errors in the model and 3) to serve as a basis for the capitalization of knowledge within a company.

2 RELATED WORKS

Classical data mining techniques have been studied in order to improve existing processes. However, they are mostly data-centric and thus cannot provide a complete description of the end-to-end process (Van Der Aalst 2012; Van Der Aalst et al. 2016). Process mining is a research field related to data mining, that supports process understanding and improvements. Process mining is said to be process-centric and therefore allows organizations to look inside end-to-end processes by providing an important bridge between data mining and business process modeling and analysis. The starting point for all process mining techniques is an event log. These techniques assume that it is possible to sequentially record events in a way that each event refers to an activity (i.e. a well-defined step in a process) and is related to a particular process instance. From there, three types of applications exists : Process Discovery, Conformance Checking and Model Enhancement. Process Discovery allows to automatically construct models based on observed events. Where process discovery constructs a model without any a priori information (other than the event log), conformance checking uses a model and an event log as input. The modeled behavior and the observed behavior (i.e. event log) are then compared to detect possible deviations. Model Enhancement aims to extend or improve an existing process model using information about the actual process recorded in event logs (Van Der Aalst, Wil 2011). In (Rozinat and van der Aalst 2006), authors use the events log produced by an information system in order to apply process mining techniques and discover the process model. Then, they identify decision points in the generated model and finally run a data mining algorithm (i.e. decision tree) to extract decisions rules. Learning classifiers to predict decisions in the case of choices is a different type of process model enhancement (Van Der Aalst, Wil 2011). It is related to our approach given that a decision tree can be represented as a set of business rules that explain the behavior of variables used by others tasks. In (Es-Soufi et al. 2016), authors propose a generic method that couples mining and learning techniques in order to assist engineers in their decision making processes. First a process mining analysis is performed to identify the most suitable design activities to be executed. Then, for each activity, the most convenient design choices are identified with machine learning techniques. In (Es-Soufi et al. 2017), authors propose a method that extends the decision point analysis (Rozinat and van der Aalst 2006) which allows only single values to be analyzed. The proposed method takes into account time series data (i.e. sequence of data points listed in time order) and allows one to generate complex decision rules with more than one variable. Improving business process decision making based on past experience is described in (Ghattas et al. 2014). Most of the studies support only control-flow related decisions(Van Der Aalst 2000; Ouyang et al. 2007) or provide recommendations for activity selection and performance predictions based on a partial trace of the execution up to a certain moment. Several studies were done for mining the business rules. Among them, three approaches to solve the rules classification problem are prominent. The methods based on the construction of a neural network gives very accurate classifications results. However, the output rules might be quite complex which makes it then harder to translate into a self-explanatory decision model. Another approach uses support vector machines, in order to build a model providing also very accurate classifications rate. Even though there are existing solutions for translating the model built by support vector machines into a set of rules (Barakat and Bradley 2010), the applications suffer from drawbacks (Shin et al. 2005). With that, the application of another approach solves the rule classification problem with the help of the decision trees, allowing easy creation of business rules from the output decision trees.

3 APPROACH

In a classification problem, data is represented by a collection of records (called instances). Each of them is described by a n-dimensional attribute vector $X = (X_1, X_2, \ldots, X_n)$, where $n \in \mathbb{N}$ and a target attribute Y, called the class (or label). The goal is to build a classification model that associates each instance X with one of the predefined class labels Y. One of the main classification approaches is a decision tree-based classification. This method is widely used in the industry sector as it has several advantages. Indeed, tree based methods are exploratory as opposed to inferential. They are non-parametric, meaning that only a few assumptions are made about the model and the data distribution. Thus, trees methods can model a wide range of data distributions. Moreover, they perform classification by a sequence of simple and easy-to-understand tests with clear semantics for domain experts. The decision tree formalism itself is intuitively appealing due to the fact that it is directly interpretable, as it can be analyzed by an expert of the field. In addition, their efficiencies have been compared to other data mining methods and experts. Decision tree-based classification methods have demonstrated several benefits including knowledge acquisition from classified data to tackle the problem of acquiring knowledge from experts. Several works highlight the robustness of the decision trees when learning on noisy data. For all these reasons, tree based methods have been used in this work. Decision tree is a flowchart like tree structure that includes a root node, internals nodes, branches, and leaf nodes. The highest element is the root node, leaf nodes are the terminal elements of the structure and the nodes in between are called internal nodes. Each internal node denotes test on an attribute. Arcs coming from a node represents possible values of the attribute test and leaf nodes hold a class label. A splitting criterion is used to select the tested variable in a node. The C4.5 Decision (Quinlan 1993) tree that we used in this paper, uses Gain Ratio as splitting criterion to construct the tree. The element with the highest gain ratio is taken as the root node and the dataset is split based on the root element values. Again, the information gain is calculated for all the sub-nodes individually and the process is repeated until the prediction is completed. To avoid unnecessary complexity, pruning procedures are applied in order to facilitate the interpretation of the tree by removing parts of the tree that are not meaningful . First, pre-pruning is applied to stop the tree's growing when the number of instances within a node is below a given threshold. In a second step, after the tree's growth, we use the reduced error pruning : starting at the leaves, each node is replaced with its most popular class. If the prediction accuracy is not affected then the change is kept. While appearing somewhat simple, reduced error pruning has the advantage of simplicity and speed.

In the next paragraph, we will use the detailed method to build the set of rules. After that, the obtained rules will be analyzed and discussed.

3.1 RULES SET CONSTRUCTION

The purpose of the procedure is to produce a set of rules of the form: if *LHS* then *RHS* where, *LHS* and *RHS* stand respectively for Left and Right Hand Side. Note that, *LHS* is conjunction of attribute value called condition and *RHS* is a class assignment. The initial set of rules is constructed in the following way, each path from the root of the tree to a leaf corresponds to a rule. Each of the internal nodes of a path corresponds to a condition in the LHS. At the end of this procedure, we obtain a set of rules R of size l, equal to the number of leaves in the tree. The proportion of instances that satisfy the rule condition over the total number of instances, $Cov(r_i)$ is defined as follows

$$Cov(r_i) = \frac{|\sigma_{LHS}(r_i)|}{n} \tag{1}$$

Where n is the total number of instances, and $\sigma_{LHS}(r_i)$, the set of instances which satisfies the condition (LHS) of the rule r_i, with $i \in \{0 \dots k\}$, $k \in \mathbb{N}$. The rule accuracy ($Acc(r_i)$) which corresponds to the number of instances that satisfy both *RHS* and *LHS* divided by the number of instances that only satisfy the rule condition, is given by

$$Acc(r_i) = \frac{|\sigma_{LHS}(r_i) \cap \sigma_{RHS}(r_i)|}{|\sigma_{LHS}(r_i)|} \tag{2}$$

Where $\sigma_{RHS}(r_i)$, is the set of instances which satisfies the consequence (RHS) of the rule r_i. Note that, $|Z|$ stands for the cardinality of the set Z.

From there, rules with low coverage (*Cov*) can capture abnormal instances or special cases, therefore these rules and the corresponding instances are communicated to the expert for further analysis. Furthermore, rules that have a high coverage are more robust, so instances that do not respect high coverage rules (i.e.abnormal instances), are send to experts. Regarding the accuracy (*Acc*) of a rule, if it is weak, it is communicated to the experts so that they can give us -if necessary- a new variable to add in the data, that will be useful to build the model .If the accuracy of a rule is greater than a threshold s, the instances not respecting the rule are also declared as abnormal. It is important to notice that all the instances that are not concerned with low $Cov(r_i)$ rules are considered to be normal. This is also the case of instances that satisfy a rule (r_i) of high $Acc(r_i)$.

4 INDUSTRIAL USE CASE

In the semiconductor industry, a product is obtained following a sequence of more than 200 steps of production . The succession of production and measurement steps defines a manufacturing route. Given that the needs of our industrial partner concern the measurement steps, the focus of this application will be on these steps. Moreover, measurement steps have a significant impact not only on the quality but also on the productivity of the production line. A measurement step is defined by a physical property such as thickness, Critical Dimension (CD), etc. In this case, these physical properties are called parameters. A measurement step is also characterized by the type of the Statistical Process Control (SPC) chart related to it (MacGregor and Kourti 1995). We will note that the same step can be in different stages of the same manufacturing route. Besides the fact that the steps are distinguished by the subset parameters that define them and the charts related to them, they also have actions that experts choose to assign to each step. For example HOLD LOT, DOWN EQUIPMENT in case of Out Of Specifications (OOS) or Out Of Control (OOC) that follow SPC methods. The measurement steps are managed by a Manufacturing Execution System (MES) which means that the system is fully automatic. This automatic execution can lead to a significant number of problems. In addition to this, one can face an other problem concerning the introduction of new measurement steps or the modification of the old ones. Since these changes are ordered by metrology experts and executed by SPC engineers, problems may occur in the execution phase because of the lack of specific and accurate knowledge of SPC engineers in the each metrology area. The aim here is to use model metrology data in order to discover expert rules so that the SPC engineers can gain insight on metrology steps which would permit the detection of possible model errors. To achieve this purpose, data from the previously cited components of the metrology steps are extracted from the MES of a High Mix Low Volume production line with more that two hundred products that can be concurrently run in semiconductor plants. In addition, we can note there are different types of machines (serial and parallel single-wafer machines, batch machines, furnaces, and wet bench machines). The set of data is composed by 122984 instances with all their corresponding components (step, parameter, type of SPC chart, OOS action, OOC action). We will note that all the variables are nominal values. Also, actions variables (OOS and OOC) are boolean. It is important to notice that these variables have been selected by the SPC engineers during the procedure. The implementation of the algorithm C4.5 in KNIME (Berthold et al. 2008) has been used for the application. Kindly note that due to confidentiality reasons, the true values used in the studied semiconductor company are not disclosed in this paper. However, the approach and the results of this method are not impacted.

5 RESULTS

Usually, classifiers are evaluated by their prediction capacity. In our case, not much interest is given to the prediction capacity of the model . Our focus is on the relevance of the obtained results. In this context, experts have been asked for validation of the relevance of the obtained model. The proposed model has been validated and the extracted rules have allowed experts to rapidly gain insight, and correct suspicious or erroneous OOS or OOC actions for several measurement steps. Moreover, this result permits a better understanding of the global behavior of the process and the discovery of previously unknown rules.

Table 1: Example of 20 extracted rules.

id	rule	σ_{LHS}	σ_{RHS}
R_1	PARAM = ”P1” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4860	4822
R_2	PARAM = ”P2” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	4620	4620
R_3	PARAM = ”P3” & EQT TYPE = ”THM” & EQT CLASS = ”CHAMBER” $\rightarrow H1$	7586	7484
R_4	PARAM = ”P4” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4679	4641
R_5	PARAM = ”P5” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4679	4641
R_6	PARAM = ”P6” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	4679	4634
R_7	PARAM = ”P7” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4679	4641
R_8	PARAM = ”P8” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4679	4641
R_9	PARAM = ”P9” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	4679	4604
R_{10}	PARAM = ”P10” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	4679	4659
R_{11}	PARAM = ”P11” & EQT TYPE = ”THM” & EQT CLASS = ”CHAMBER” $\rightarrow H1$	4600	4496
R_{12}	PARAM = ”P12” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	4457	4457
R_{13}	PARAM = ”P13” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	4457	4457
R_{14}	PARAM = ”P14” & EQT TYPE = ”THM” & EQT CLASS = ”CHAMBER” $\rightarrow H1$	3192	3192
R_{15}	PARAM = ”P15” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	2128	2128
R_{16}	PARAM = ”P16” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	2128	2128
R_{17}	PARAM = ”P17” & EQT TYPE = ”THM” & EQT CLASS = ”CHAMBER” $\rightarrow H1$	1273	1263
R_{18}	PARAM = ”P18” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	1257	1257
R_{19}	PARAM = ”P19” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H0$	1161	1161
R_{20}	PARAM = ”P20” & EQT CLASS = ”ONE CHAMBER MAINFRAME” $\rightarrow H1$	8400	8397

Remark 1 In Table 1, PARAM stands for PARAMETER and EQT for EQUIPMENT. $H0$ and $H1$ stand respectively for PUT LOT ON HOLD and DO NOT PUT LOT ON HOLD

20 rules were extracted and tested with the proposed approach, these rules are presented in Table 1. Obtained results show that, for some rules such as Rule 1, $\sigma_{LHS} \neq \sigma_{RHS}$. This means that a number of instances equal to $\sigma_{LHS} - \sigma_{RHS}$ are considered to be abnormal or special cases. However, when $\sigma_{LHS} = \sigma_{RHS}$ it means that we are not in presence of any abnormal or special case. This is the case of Rule 2 and 12. For the case where we have abnormal or special cases, further analysis have to be done by SPC engineers in order to determine the causes of the observed differences between normal and abnormal instances. For the rest of this example, we will focus on Rule 20. First, let us remark that $\sigma_{LHS} - \sigma_{RHS} = 3$ which means that we have 3 instances that do not satisfy the Rule 20. This rule has an important coverage with $Cov(R_{20}) = \frac{8400}{122984} = 6.83\%$. Also, Rule 20 has an accuracy of $Acc(R_{20}) = 99.9\%$. Hence, the 3 instances that do not satisfy R_{20} are sent to experts for further analysis. See for instance Table 2 where the 3 instances are summarized.

Table 2: Instances that do not satisfies the rule R_{20}.

Step	Parameter	Procedure	Equipment
EVENT-12	P20	SCP-P-X-BAR1	EQPT-A-CH-01
EVENT-12	P20	SCP-P-X-BAR1	EQPT-A-CH-02
EVENT-12	P20	SCP-P-X-BAR1	EQPT-A-CH-03

For information, the experts analysis has lead to the deletion of these 3 control charts. Another result of the method was to switch the HOLD LOT decision related to several control charts (e.g. rule R_{10}), from DO NOT HOLD to HOLD. This type of correction was critical as the decision to DO NOT HOLD a product may lead to a non-conform product.

Building on these examples, we can say that thanks to this method, experts have effectively improved the production system. Indeed, there were fourteen engineering change notices (ECN). Each ECN corresponds to a correction made to the production model by modifying one or several SPC charts definitions.

6 CONCLUSION AND FUTURE WORK

In this paper, a method permitting the improvement of business processes by learning business rules is proposed. This method uses an algorithm based on data mining algorithm. The proposed approach permits the discovery of previously known rules as well as new rules. The method has been tested using industrial data used by MES for process control. The application of the method on an industrial process permitted to: gain knowledge about the existing rules, serve as a base to knowledge capitalization and assist experts to detect problems in measurement steps.

In future work, we plan to extend the method by automatically discovering relevant attributes in order to discover rules related to human based activity. We also plan to take into account structural rules of the overall process to gain knowledge regarding the impact of a data modification.

It would also be interesting to take these rules into a simulation system and see if its fidelity and the quality of the associated decison-making could be enhanced.

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