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Adama Arama, Eric Villeneuve, Christophe Merlo, Laura Laguna Salvadó

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An approach of decision support system for drift diagnosis in cyber-physical production systems

Adama Arama
Univ. Bordeaux

ESTIA INSTITUTE OF TECHNOLOGY
Bidart, France
a.arama@estia.fr

Christophe Merlo
Univ. Bordeaux

ESTIA INSTITUTE OF TECHNOLOGY
Bidart, France
c.merlo@estia.fr

Eric Villeneuve
Univ. Bordeaux

ESTIA INSTITUTE OF TECHNOLOGY
Bidart, France
e.villeneuve@estia.fr

Laura Laguna Salvado
Univ. Bordeaux

ESTIA INSTITUTE OF TECHNOLOGY
Bidart, France
l.lagunasalvado@estia.fr

Abstract—Despite the development and application of new digital solutions in the production industry, the human operator is still essential in the production chain monitoring and control processes. In this context, some activities can be crucial for the human operator like, for example, drift diagnosis in production control process. It requires attention and experience and can be assisted by Decision Support System (DSS) to guide operators in decision-making in industrial production process control. Drift diagnosis process is a challenging problem in this context and artificial intelligence technologies are promising to tackle this issue. In this paper, we propose a new approach of DSS for drift diagnosis. The proposed approach is built upon a literature review on drift concept, drift detection methods and failure diagnosis approaches. This multi-model approach is designed to address all the diagnostics tasks of production systems and is based on Machine Learning (ML) algorithms to model the behavior of production systems, a knowledge-based model to integrate human experiences and a data-driven model to combine historical data from sensors. When the drift occurs, the proposed DSS can help human operator to determine drift causes and to suggest corrective actions. This article also provides guidelines about the design of a decision support system to support human operators in complex decision activities.

Index Terms—Industry 4.0, cyber-physical production systems, drift concept, decision support system.

I. INTRODUCTION

The introduction of digital solutions to the industrial production processes have led to new needs like safety, re-organization and re-adaptation. These new technologies development has been a key factor for the migration toward the smart production industry. This evolution is commonly known as Industry 4.0 [1] and attracts much attention of the researchers these last few years. There are several definitions, see e.g. [2], [3], [4] related to Industry 4.0 in the literature. However, in [5], the authors defined Industry 4.0 as a complex technological system that is being shaped fundamentally by connectivity, integration and production digitization, emphasizing the opportunities of integrating all elements in a value-adding system. The production system part of Industry

4.0 consists in a cyber-physical production system (CPPS) combined with cloud computing and Internet of Things (IoT) [6]. In this context, CPPS are used to monitor and control industrial processes, including continuous production (cement, steel, chemicals, etc.).

This monitoring and controlling activity is highly critical for the production industry. It allows for timely mitigating actions such as fault checking, drift diagnosis, predictive maintenance and system shutdown to be taken such that potential loss caused by system failures can be avoided [7]. On the other hand, despite the technological evolution in the context of Industry 4.0 represented by increasing automation and autonomy of machines, human operators yet represent an important and vital factor in Industry 4.0 [8]. Nowadays, it is not possible to automate everything. Indeed, the technologies of Artificial intelligence (AI) are often not properly trained in some situations/contexts to perform efficient, effective, flexible or creative decision-making. In this case, human operators can play an important role in the production industry process, because they have all these characteristics [9]. However, human operators will need a Decision Support System (DSS) due to the difficulty of understanding of such a complex system of production. Thus, in this context, DSS will help human operators to understand system behavior and to make decision accordingly. Usually, decision-making process is done collectively and it involves human operators who use their knowledge to manage a given problem.

This paper is focused on drift diagnosis in continuous production process. Drift diagnosis process is a daily activity of collective decision-making for human operators, see e.g. [10], [11]. In this scenario, using a DSS can help human operators to make the “best” decision in production control process and, thus to perform the “best” operation of the production industry. Eventually, the primary objective of this study is to provide a new approach of DSS for the drift

diagnosis process.

The remainder of this paper is therefore organized as follows. We briefly introduce the background of study in the next section. Our proposition is presented in Section 3. Section 4 is focused on discussion and limitations of the proposed methodology. Lastly, Section 5 presents final conclusions and futures works.

II. BACKGROUND

Thanks to the advance of digital technology, production industry is becoming a global interconnected system in which machine, sensors, information systems, monitoring and other professional softwares, and products are constantly communicating. The work on which is based the presented study is conducted in the chemical field, in this context of digitalisation. The studied production industry is involved in a process of liquid-liquid extraction or rare earths separation. This process is composed of three main sub-processes: ore treatment; separation process through batteries; and final preparation for customers.

The ore comes in solid form to the ore workshop. It is attacked with nitric acid which makes it liquid and forms a solid pulp which is a waste. The liquid part is recovered by the battery shop for separation or extraction. And then the final product is sent to customers. Basically, the activities of the studied production industry are focused on two mains functions (**Figure 1**).

- Transform raw material (RM) to liquid
- Split liquid which consists to recover liquid from the first workshop in order to split in group or sub-group.

After processing, rare earths are stored in tanks that the customers can use. So, this study is focused on the battery part and aims to improve the control of the batteries in the production process by the DSS for drift diagnosis.

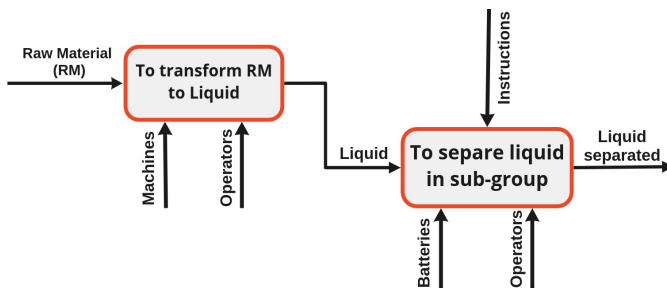


Fig. 1. Main function

A. Cyber-physical production system concept

A cyber-physical production system (CPPS) is a concept, which consist in an integrated system with computer system, control system and physical system [12]. Therefore, CPPS is key technology of the production industry sector digitalisation and modernization. The production system would control the progress and quality of the product being manufactured.

In [13], authors present CPPS like a set of cyber-physical systems. This conducted CPPS to be considered as a system of systems (SoS) and one of the pillars of Industry 4.0. The use case studied here (rare earths extraction) is considered to be a CPPS. According to the definitions in [14] and [15], the studied system is, indeed, a complex system made of autonomous and cooperative elements. On the other aspect, the digitization of the production industry allows access to both the variety and availability of data. Thus, there are new opportunities for innovative uses of data which allows to led towards the Industry 4.0. Among these opportunity, it enable the ability to detect and correct the drifts that appear sometimes in the production control process.

Drift concept is a phenomenon in which the statistical properties of a target domain change over time in an arbitrary way [16]. Drifts cause a lot of problems to the human operators and can lead to plant shutdown. In addition, the drift management involves the (i) drift detection, the (ii) diagnosis of causes and, the (iii) proposal of a corrective action, in a quick way. It represents one of the most challenging tasks in continuous production processes.

In this context, the focus of this study is on the diagnosis of drift causes which is a complex process for human operators. It requires a good understanding of the industrial process and of the available data, which are potentially very numerous and heterogeneous. Thus, a decision support system makes sense to assist human operators in their work.

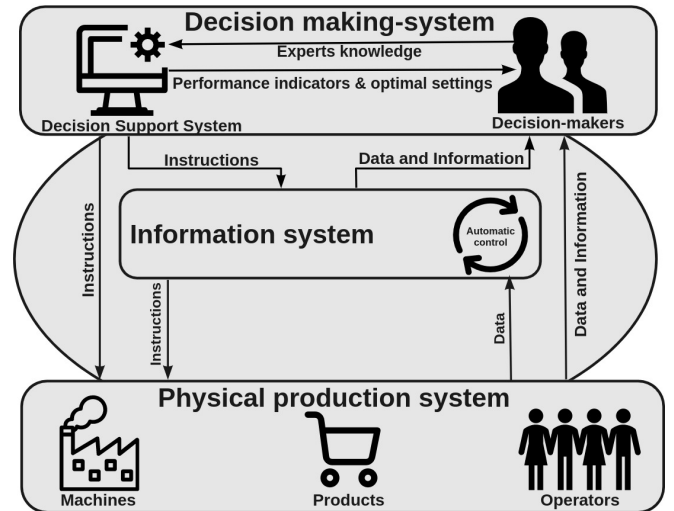


Fig. 2. Proposed generic CPPS model [17]

When studying the literature about CPPS, the observation was made that the human operator role in CPPS is often absent of the proposed models, or the models that consider human in the loop are difficult to apply in other contexts, see e.g. [18], [19] and [20]. As mentioned above, human operator represents an important factor to the good functioning of CPPS. It is important to model CPPS with human in the loop to get a better understanding about both its behavior and operating

way. Thus, on a previous research work in the field of complex systems modeling, we proposed a generic model of CPPS (**Figure 2**). This model is designed to get a better understanding of any CPS-based production system. It allows to consider human operator as part of both physical production and decision-making systems. The main contributions of this model are the :

- consideration of human operator as a physical part of CPPS
- definition of all human roles in the CPPS
- definition of DSS role to help human operator in its decision-making to control industrial production process.

Human operator takes an important place in this model and, thus, allows to correct the perceived shortcomings of the main competing models from the literature.

B. Drift concept

Drift management is a topic which attracts a lot of attention both in industrial and academic researches due to its potential benefits in terms of reliability, safety and maintenance costs [21]. Beyond drift detection, it is more necessary for a human operator to know the causes of the observed phenomenon in the production control process in order to act accordingly and to avoid the problem in the future. Consequently, in recent years, drift concept has been widely studied in the literature. The research involves the development of methodologies and techniques for drift detection, understanding and adaptation. In [22], authors describe drift concept as an unforeseeable changes in the underlying distribution of streaming data over time. Also, the changing of the production system behavior, called drifts, may be considered as an indication of malfunction beginning, see e.g. [23], [24].

In this work, we define a drift as a discrepancy in relation to parameter values. Regarding the case study, it is a gap between the value wanted by the human operators and the measured value. The drift is an usual problem encountered in production control process of batteries. When it occurs, it must be corrected as quickly as possible so that it does not spread to other floors. To do this, the batteries have to be slow down, which has an impact on production or worse, can stop it. The human operators are sometimes able to detect that problem visually.

Drift can have various natures. According to [25], there are two kinds of concept drift that may occur in the real world. They are normally distinguished in the literature by (1) sudden (abrupt, instantaneous), and (2) gradual drift. Drift management can represent a challenging issue in industrial environment that can impact several application domains, see e.g. [21], [26]. The downtime of tools, equipment, pump failures, or any other machines can cause a direct loss of revenue to production process. Forecasting such failures using sensor data can prevent or reduce the downtime [27]. Drift management in CPPS presents several challenges for human operators. We translate those into three main challenges for a DSS such as the (i) drift detection, (ii) drift diagnosis, i.e to determine its causes and (iii) proposed a corrective action.

Drift detection methods allow to detect drift quickly using sensor data and are based on strategies to identify suspicious behavior in data streams, emerging from condition monitoring. Detection methods can be divided in two categories [24]:

- Classifying data streams as normal, drifting or defective based on a comparison with a large instance pool of formally under supervision categorized data sets.
- Predicting the next values in a data stream with a regression method and comparing these estimations with actually sensed values; an increasing prediction error might indicate an underlying drift. Regression models are used both to detect and predict drifts.

There are many detection methods in literature and only the significant proposals, chosen to illustrate the diversity of existing detection methods, are detailed above:

- Generic Model for Detecting Drifts (GMDD) [27]. Here, the authors explored three drift detection techniques that identifies drift, notifies the early warnings of the drift and helps operators to act proactively to fix the issues.
- Drift Detection Method (DDM) [28]. This drift detection method is based on statistics (using binomial distribution) to estimate the probability of errors in process and predict if a drift occurs.
- Early Drift Detection Method (EDDM) [29]. The method EDDM has been developed to improve the detection in presence of gradual drift. At the same time, it keeps a good performance with sudden concept drift. The basic idea is to consider the distance between two errors classification instead of considering only the number of errors.

As mentioned above, there are a lot of detection methods for drift situation but, in the best of our knowledge, very few methods for drift diagnosis [22]. Thus, the focus of next sections is on DSS to assist drift diagnosis process.

C. Decision support for drift diagnosis

Making decision in drift diagnosis process presents several challenges for a human operator. For better understanding the decision process in the production industry, a literature review has been made. Moreover, a field study has been made to identify actors involved and to characterize and model decision processes used by these actors.

To be fully operational and have a good performance, production systems need to be controlled [30]. For that, decision support systems remain essential in the production industry control process. According to the objectives and context, the decision support approaches can be different, see e.g. [11], [31]. While performing the field study, the main actors involved in drift diagnosis decision process have been identified (**Figure 4**). There are four decision actors in this process. At the strategic level, Day Foremen (DF), are top decision hierarchical level which interacts with all actors of production process. They are like a general manager of all production parts. The Shift Foremen (SF) constitute an intermediary between DF and the others actors of production.

At the operational level, Shopfloor Operators (SO), can act directly on the batteries. Then, there is the Control Room operators (CRO), which also interact with the batteries but mainly with the support of software.

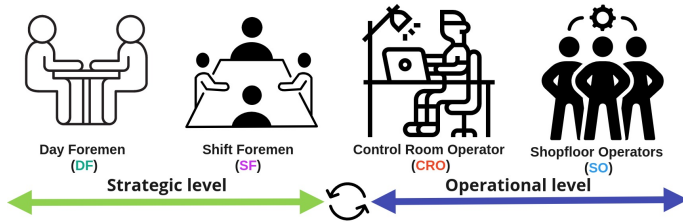


Fig. 4. Decision actors of the case study

In the decision process, actors can have different roles :

(a) **Day Foremen’s tasks (DF)**

- Provide instructions to SF (about product quality for example)
- Comment results of Laboratory (via a software or voice)
- Meet every afternoon with customers
- Meet every week with SF

(b) **Shift Foreman’s tasks (SF)**

- Transmit DF’s instructions to its team
- Receive team requests
- Transmit to DF the requests of others
- Visit shopfloor

(c) **Control room operator’s tasks (CRO)**

- Monitor and control the production process using a software
- Detect drift on the production line
- Act on the batteries using a software
- Communicate and send instructions to the shopfloor via walkie-talkie (or phone).

(d) **Shopfloor operator’s tasks (SO)**

- Apply SF’s instructions
- Inspect the batteries room
- Collect samples and send them to laboratory

All these roles above are essentials to the operating of the studied production system. The SO plays an important role in the production control process, as he is the main operator that physically interacts with production process. All of these people are responsible for the daily control of the batteries. CRO and SO are keys actors of the drift diagnosis, because the drift is usually detected by them.

When a drift occurs, it must be corrected as quickly as possible so that it does not spread to other floors. For more understanding, **Figure 3** shows the actual drift diagnosis mechanism and decision process. It shows also the interaction between the four actors involved in drift management. It allows to understand production decision process. To manage a drift the four actors can interact.

This actual mechanism (**Figure 3**) of drift diagnosis can be summarized in four main steps which are as following:

• **Analyze drift**

This step comes once the drift is detected and confirmed by the human operators (CRO or SO). It consists in analyzing drift causes by the actors of operational level and including actors of the strategic level if necessary.

• **Define action**

There are several actions to be defined after analyzing process. These possible actions range from ignoring the drift to stopping completely the production system. Usually, the CRO refers to a document which contains predefined actions regarding some drifts. If the corrective action of a drift is not in this document, the CRO will consult SF or DF.

• **Execute action**

Defined actions are executed automatically by the CRO or manually by SO. Sometimes, in order to execute action automatically, the CRO collaborates with the help.

• **Experience feedback**

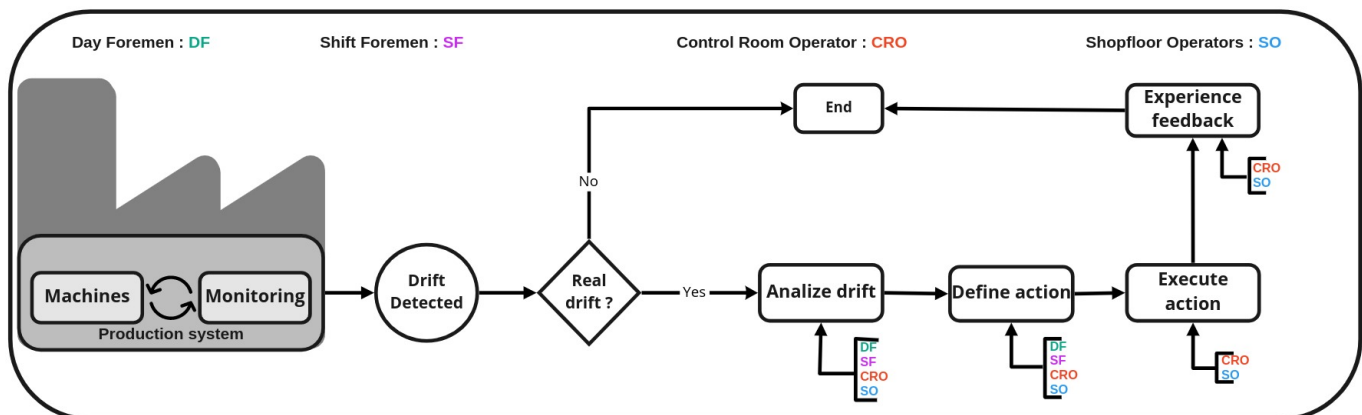


Fig. 3. Present Drift Diagnosis Mechanism

Following action execution, experience feedback is done by SO. Thus, these different feedback are send to the actors of strategic level in order to improve the referred document.

Nowadays, we noticed that this process is very collaborative and iterative. Knowledge required for making decisions depends mostly on the experience of human operators. Existing software tools only give basic information and experts knowledge is available inside a huge support document in paper format. Our aim is to propose a proactive environment (DSS) for helping human operators, and improve their decisions, workloads and mental load.

III. PROPOSITION

Proposal in this paper is based on an inductive research approach. Inductive, because both the problem and the solutions are based on field research, with the goal of creating a common general hypothesis. In this section we propose a methodology to drift diagnosis with a DSS.

A. Overall methodology

As a reminder, this study is interested in drift diagnosis process in the production industry control. In the case study, the roles of cyber-physical software consists to extract data about the physical state in order to inform some decision-making process in the production control process. This data is used to diagnosis processes, such as dashboards displaying the current status of a system or alarms which detect drift or errors within the system. In this context, DSS is needed to

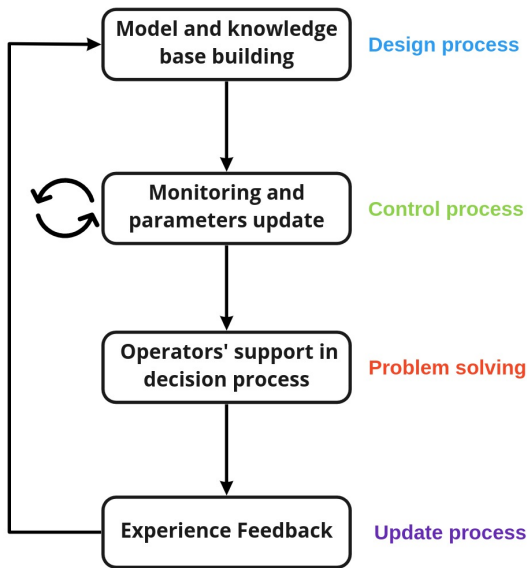


Fig. 5. Global view of DSS process

assist human operators in their decision-making process for the drift diagnosis. Decision support in the production control process has been summarized into four main steps (Figure 5). The different steps are described as following:

- **Design process**

This first step consists to build both production industry model and knowledge base. Key parameters are extracted from data collected though IoT technologies installed on the physical components of CPPS. This is stored and constitute the historical Data Base (DB) to be used by Machine Learning (ML) technologies. Knowledge Base (KB) building is done by interviewing actors. All actors (DF, SF, SO and CRO) will be interviewed in order to extract the business rules. The KB includes also relevant pieces of information (e.g.: rules, object descriptions) in an application domain (case study here). Technically, relevant pieces of information will be done using formalism, like logical representation or semantic network representation for example. Thus, the proposed DSS designed using a multi-model approach, combining data-driven model (based on DB) and knowledge based model (based on KB).

- **Control process**

Based on AI technologies, the DSS records and processes data from production. This second step consists in continuous monitoring of production system. The human operator (CRO here) makes the monitoring of the keys parameters and constantly update parameters until drift occurrence.

- **Problem solving**

When a drift is detected in the monitoring process, the CRO use DSS to solve the problem. The DSS suggest different solutions and the CRO makes the best choice in collaboration wither others human operators (DF, SO and SF).

- **Update process**

The last step is based on the experience feedback. After the application of each corrective action for a drift, experience feedback is made to improve both the KB and DSS globally.

B. Decision support system for drift diagnosis

As studied above, few drift diagnosis method are present in literature [22]. Thus, our proposal consists in a new DSS approach to address this issue. Once drift detected, DSS allows to diagnose the drift, i.e to determine its causes and propose corrective action. Figure 6 shows drift diagnosis process using the proposed DSS. When the drift is detected, human operator (CRO) use DSS. Some blocks of this process are not linked by arrow because actions are not sequential. Human operators often need to iterate some actions until the best action and until all actors have reached a consensus. The proposed decision support process for drift diagnosis allows, once drift detected, to suggest (i) probable causes, to propose (ii) corrective actions and to capitalize the problem solving process though experience feedback to improve DSS. Nowadays, ML is efficient mechanism to model the behavior of such complex systems for design and optimization. The DSS for drift diagnosis is based both on the ML technologies and on a multi-model approaches which allows to combine of data-driven model and

knowledge-based model. We assume that the drift is already detected. The DSS will proceed directly to determine its causes in the first block (Determine causes). In DSS, the drift will be directly categorized using AI algorithms, K-Nearest Neighbors or Decision Tree for example. Depending on the category of the drift, the DSS uses relevant algorithms of AI to suggest drift causes with probability rate to inform human operators. The final decision is made by human operators using these suggestions.

Once the cause of drift is known, the second block of DSS (Corrective action) consists to propose a corrective actions to the human operator, which will choose the set of action. For that, DSS will proceed in the same manner as previously. The last step consists to capitalize experience feedback done by human operators (CRO and SO).

IV. DISCUSSION AND LIMITATIONS

In this paper, the crucial importance of the human operators in the CPPS and especially in the drift diagnosis process, is highlighted. Drift diagnosis process, i.e to determine drift's causes and to propose corrective actions, is a challenging problem for human operators and AI technologies in production industry scenarios. During studying the literature related to drift diagnosis methods, there are not enough methods able to identify drift causes. In addition, the research gaps that need to be addressed exclusively in the area of ML-based drift diagnosis (multi-approach) has not yet been covered in the existing literature.

The proposed approach of DSS for drift diagnosis allows to determine the causes of a drift and propose to corrective actions. Sensor data collected from monitored CPPS allows to model the data base. The presence of humans operators in the loop allows us also to interact with them in order to extract knowledge to build knowledge base. The multi-model approach (DB and KB) ML-based algorithms will be used to develop the DSS. This proposed study and methods are original on several aspects. Indeed, the study was fully

conducted in the field, but considering very carefully the state-of-the-art from literature. The CPPS model proposed takes into account the shortcoming like human absence in CPPS's physical part. The originality of this new approach is also about the complementarity between human operator and DSS in the control process of production industry. Other particularity is also based on integrating the human operator at the heart of the drift diagnosis, and taking into account the human knowledge in DSS design process. The proposed methodology is a step forward in the drift diagnosis process, but it suppose that drift is detected before diagnosis process. As there are many existing drift detection methods in the literature, we plan to integrate into the proposed approach a drift detection methods in data streams scenario.

However, once drift is detected, DSS can assist human operator for the drift diagnosis. A prototype of this approach will be developed in the near future, after having designed knowledge base, which contains a proper formalization of human operators' experience and their behavior when interacting with the CPPS.

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we propose and discuss an approach of DSS for drift diagnosis in CPPS context. It allows a human operator to determine the drift causes and to suggest him corrective actions in production control process. The main contributions of this work can be summarized as follows:

- modelling CPPS as a complex socio-technical system
- definition of all human roles in the production system
- description of the importance of human operator in CPPS
- proposal of a DSS methodology for drift diagnosis.

We have provided a state-of-the-art on drift diagnosis research developments and guidelines about how to develop a decision support system, to support human operators in various decision activities, for drift diagnosis in production industry process.

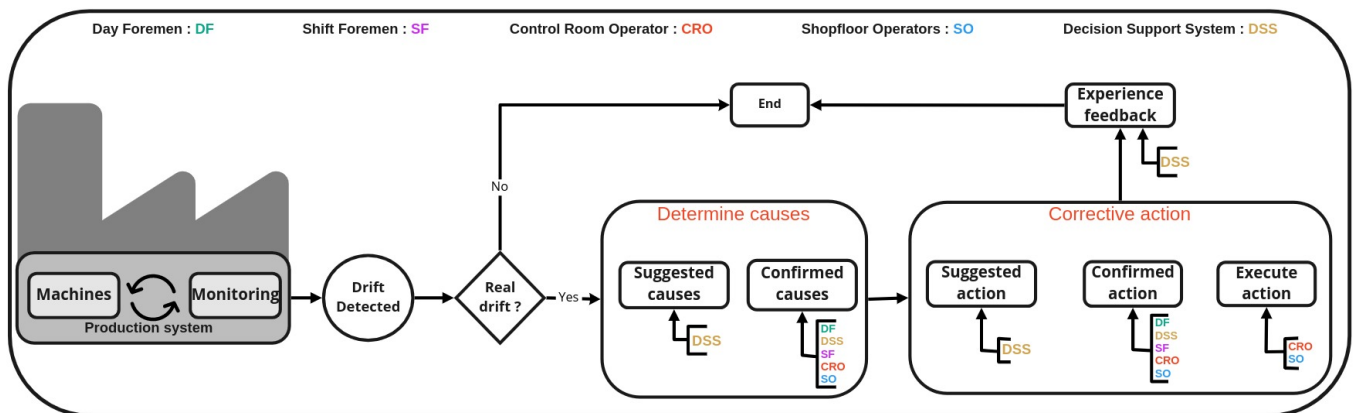


Fig. 6. Drift diagnosis process using proposed DSS

ACKNOWLEDGMENT

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