Diagnosis in complex system with multiple failure sources

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ABSTRACT: *This paper proposes an approach to accurately localize the origin of product quality drifts, in a flexible manufacturing system (FMS). The failure propagation mechanism in a production process is proposed based on the relationships between failure sources to explain the failure propagation following production flow. The logical diagnosis model is used to reduce the search space of suspected equipment in the production flow; however, it does not help in accurately localizing the faulty equipment. In the proposed approach, we model this reduced search space as a Bayesian network that uses historical data to compute conditional probabilities for each suspected equipment. This approach helps in making accurate decisions on localizing the cause for product quality drifts as either one of the equipment in production flow or product itself.*

KEYWORDS: *Fault diagnosis, complex manufacturing system, Bayesian network.*

1 INTRODUCTION

One of main challenges in manufacturing domain is to improve and optimize the production process quality and equipment effectiveness during production operations. To improve product quality and reduce associated costs, fault isolation, detection and diagnosis techniques have been developed. For the fault diagnosis, many methods are proposed through a diagnosis model such as (Sampath et al., 1998; Deschamps & Zamai, 2007) to localize more quickly and accurately the root causes of a detected failure. Theses methods are appropriate for diagnosis of failures that come from equipment and products. However, these methods do not explain the impact of recipes to product quality. In fact, due to the diversity of customer demands, the production recipes frequently change, and so they may trigger the impacts on product quality.

In addition, the production system comprises of hundreds of equipment, monitored by thousands of sensors. Generally, it is difficult to identify a diagnosis model and corresponding variables. Thus, artificial intelligence methods are well suited techniques to analyze the large amount of production information and describe the behavior of system components as presented in (Weber et al., 2012). These approaches can be performed without understanding the underlying structure of a production system (Bouaziz et al., 2011). Among the probabilistic approaches, the Bayesian network (BN) approach is widely used to identify a graphical structure model that describes relationships between variables in a production system. So, its conditional probabilities will be calculated to provide the risk priorities and support corrective maintenance decisions. Due to the complexity of present-day manufacturing systems, identification of this graphical structure is complex to be performed by a maintenance engineer (Bouaziz et al., 2011). The system elements such as products, recipes, equipment, maintenance schedules and human factors are frequently changed due to the introduction of new production technologies and maintenance management strategies. A change in one element may trigger effect to others. Consequently, we need to retrain the learning phase of the BN model to adapt to newly emerging situations in the production system. The time and work-load for computation are very large, so this result in poor maintenance and additional costs.

Consequently, in this paper, we propose: *(i)* a failure propagation mechanism to explain the relationships between different failure sources and its propagation in the production process, *(ii)* a diagnosis methodology that uses the Logical Diagnosis (LD) model (Deschamps & Zamai, 2007) to reduce the search space for faulty equipment from a given production flow and optimizes the learning phase for the subsequent BN. Thus, joint and conditional probabilities of all faulty candidates are computed to support corrective maintenance decisions.

The characteristics of case study and the diagnosis objective are introduced in the next section. Section 3 presents a review on fault diagnosis methods. In Section 4, we propose the failure model that enables to explain impact and propagation of failure in the product flow. The LD model that results in suspected equipment against a failure drift is explained in Section 5. The proposed diagnosis model is described in Section 6. The conclusion and future perspectives are discussed in Section 7.

2 CASE STUDY AND DIAGNOSIS OBJECTIVE

2.1 Case study

Manufacturing processes evolve to adapt itself to increasing demand diversity. Besides, frequent changes in customer demands, it leads to the changes in corresponding products. This is reason that flexible manufacturing systems (FMS) are widely used in complex and highly competitive manufacturing domains such as (micro-)electronic and automotive industry. The FMS is a complex automated manufacturing system that consists of several production workshops, connected by an appropriate transport system. These production workshops and transport systems are controlled by a control and automation system. It is generally characterized by multiple products, production lines, recipes, and human factors. Generally, a complex system may have many production processes driven by a control law to perform demands of the control system. The structure of a production process describes product type, product lines and corresponding equipment in the operating part of the controlled system. Any change in one of elements (such as product, equipment, recipe and human) through control law leads to changes of the existing processes.

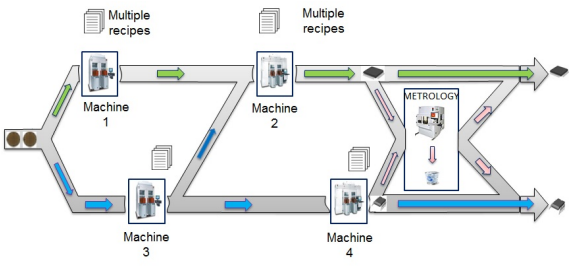

Figure 1: A Flexible Manufacturing System

Consequently, our research in this paper is based on the context of a general complex system under dynamic production environment within the following characteristics: multiple products, production lines, and recipes as shown in Figure 1. In addition, the failure can come from different sources such equipment, products and recipes.

2.2 Diagnosis objective

In complex engineering applications, systems can be composed of many components and subsystems, and the ways in which these elements interact affects the way failures propagate within the subsystems and across subsystem boundaries (Hine, 2005). In this paper, we consider that failure causes may fall among products, equipment and recipes. For monitoring the execution of system components, the hierarchical and modular controls are often used as presented in (Jones & Saleh, 1990). In this context, an automated manufacturing system is organised by Computer Integrated Manufacturing (CIM) architecture that contains: controlled system, product flow and control system, as shown in Figure 2.

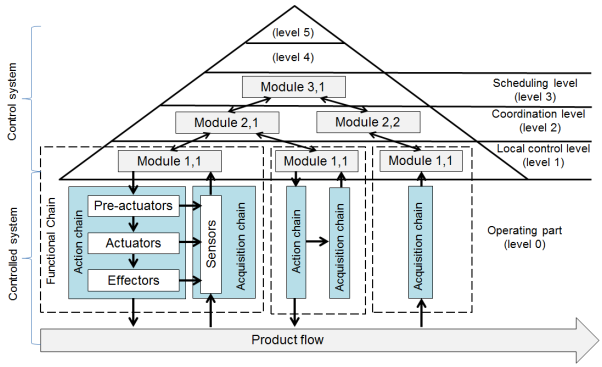

Figure 2: CIM architecture of an automated production system

The controlled system consists of actuators and sensors. The sensors monitor the executions of actuators and product flows. Therefore, actuators and sensors are controlled by a local control module, and the set of these elements are called Functional Chain (FC) (Henry et al., 2005). The FCs receive demands from the coordination level of control system and executes these demands on product flow. When a FC cannot correctly execute a demand, it implies that a fault is produced. In fact, there are many positions of actuators or products which are not observed by the sensors. Hence, when a failure occurs, it is not observed, it may propagate form one FC to another through production lines; and so it called failure propagation. Therefore, this failure propagation not only causes the potential failure on products, but also may have consequences on other system components; and so, the new faults may be created. Consequently, when a fault is detected by the metrology, its root causes may come from one or a part of elements of system. In summary, the diagnosis objective is to precisely and quickly locate the possible origins of failure to support the maintenance operator to save recovery time (for return to a normal status) of the production system.

3 LITERATURE REVIEW OF DIAGNOSIS METHODS

Diagnosis techniques based on failure propagation to analyze component dependencies are propagation graph (Abdelwahed & Karsai, 2006) and temporal chronic (Strasser & Sheppard, 2011). These methods are based on historical production data to locate components that are possible origins of a detected fault. However, these approaches do not analyse the behaviors of the functional chains (FC), so they cannot explain the consequences between elements of a FC and between different FCs. Moreover, these approaches cannot reduce the size of the model. Due to the cyclical operation of the control system, a large amount of information from the production system provokes the problem of combinatory explosion. Consequently, we are especially interested in the Logical Diagnosis model proposed in (Deschamps & Zamai, 2007). In this model, a diagnosis function is proposed to characterize the historical information of a controlled system to search the suspected potential fault origins in real time. Hence, this model provides a set of possible origins under the form of a directed graph, and its size is reduced by the exploitation of the controlled system observations. This is appropriate to diagnose the faults of production equipment and products. However, this method can not explain the impact of recipe to product quality and its correlations to other system elements. In fact, any change of a production recipe may trigger a product quality drift. In addition, this model does not show suspected level of each candidate of possible origins in the diagnosis result. It is difficult to decide the maintenance order in a complex system. Consequently, this approach would be extended to optimize corrective maintenance activities.

Concerning the risk priority of potential failure candidates, the probabilistic approaches are widely used such as Neural network (Khomfoi & Tolbert, 2007) and Bayesian network (Weber et al., 2012). These approaches enable to calculate the probability values from the large database and associated variables from a production system. These probability values allow evaluating the suspected level (high or low) in order to support the decision for a maintenance strategy. In particular, the BN models have the advantages that fit to be applied in manufacturing industry as explained in (Weber et al., 2012). The methods based on BN are introduced in (Bouaziz et al., 2011) to make a diagnosis in a multiple variables system. The Confidence level of feedback information is proposed in (Duong et al., 2013) to provide the probability value that shows the confidence of faulty execution report from equipment. When the database is available, these approaches are practical tools for the corrective maintenance. However, they must be extended due to the following problems. The structure of confidence level model for information feedback (CLFI), as presented in (Duong et al., 2013), is static with seven parameters. In the context of flexible manufacturing system with characteristics such as multiple products, production lines, recipes and human factors, the production situation often change as we presented in section 2. Hence, the set of parameters that can have an impact on the confidence level of equipment is dynamic. In addition, the BN model must be updated based on the information of newly production situations. In practice, when the information of database is available, learning approaches are often used for modelling BN as presented in (Neal & Hinton, 1998). In the learning approaches, a graphical structure and probabilistic rules are estimated from observed data. Many studies in (Bouaziz et al., 2011; Neal & Hinton, 1998) show that these learning approaches are still complex in identifying variables as they depend strongly on expert opinions. The learning workload for computation is still large (Neal & Hinton, 1998). This loses too much time and is not appropriate for real time structural identification as it depends on the exploitation of databases. In fact, production environments are increasingly stressed by strong competition. It shows that the time for locating the root causes of failures and process recovery (return the process to a normal status) is very important. These challenges promote the researches to apply BN model for real time fault diagnosis and corrective maintenance optimization.

This paper proposes a diagnosis model that enables real time localization of the possible failure and root causes that come from equipment, products and recipes, thus dynamically computing conditional probabilities between a failure and its possible causes. This is based on a logical diagnosis model and a BN model. Thus, the diagnosis mechanism is constructed based on four main steps: *(i)* LD model provides a set of possible fault origins. The relationships of members in this set are used to construct the graphical structure, *(ii)* we use this structure for the BN model. The idea is to simplify the variables identification during learning phase in the BN, *(iii)* the historical information of production system is used to estimate probabilistic rules in the learning phase of the BN model, *(iv)* the conditional probabilities of nodes in structural model are computed. These probabilistic values allow to evaluate the risk priority for each possible fault origin. However, the BN model structure depends strongly on cause-consequence relationships between the members in the set of possible origins, while the LD model explains only the propagation of equipment failure and corresponding information (products and recipes), but does not explain their cause-consequence relationships. Consequently, we analyze these relationships and so the failure propagation mechanism in a production process is proposed in the next section.

4 FAILURE PROPAGATION MECHANISM

4.1 Relationships between equipment, recipes and product quality

The diagnosis objective in this paper is to accurately and quickly localize the possible failure origins which may come from equipment, products and recipes. In fact, the relationships between failure sources have impacts on final product quality. Thus, these cause-consequence relationships are analyzed in this section. The product quality depends on equipment state as presented in (Sampath et al., 1998). However, this impact will change when the recipe elements are taken into account. Consequently, we present the definition of recipe and analyze its impacts on equipment and product quality next. The concept of recipe is widely used in the control of Flexible Manufacturing Systems. The representation of the production process is based on the concept of controlled operation with basic and control recipes that are developed through rigorous process R&D used in the automation of batch plants by all major suppliers of process control systems as presented in (Mergen, 1990). The basic recipe is independent of equipment and this describes the production process for a given technology. It is designed to manufacture the product and its quality depends on the basic recipe. Equipment executes demands of basic recipe through the control recipe. The transition to control recipe consists of the basic recipe, the production schedule, the multi-purpose plant description and executable control recipe (Genrich et al., 1994) as illustrated in Figure 3.

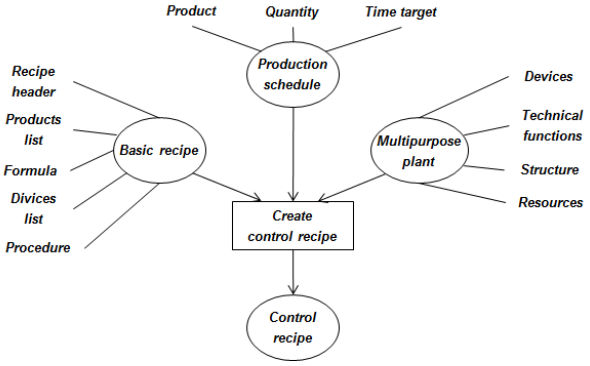

Figure 3: The process to Create a Control Recipe

Generally, the control recipes are created based on the characteristics of system and are tested before applied for the real system (Mergen, 1990). Hence, the control recipes do not trigger a fault on the equipment. However, different equipment execute the same control recipe and give different product quality due to its different physical characteristics. Moreover, an equipment performance may be good for one recipe, but produces bad quality with other recipes. Consequently, there exists the cause-consequence relationships between the equipment, recipe and product quality as shown in Figure 4. It means that product quality drifts may come from one or a part of physical equipment failures and control recipes.

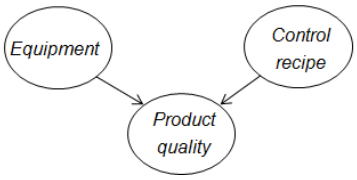

Figure 4: The relationship between different failure sources

In a production process, the failure may propagate from equipment to another through the production flow. Hence, these cause-consequence relationships also propagate following the production flow. This problem is presented in the next section.

4.2 Failure propagation mechanism

The failure occurring on equipment can come from physical failure of itself and/or the input products. Therefore, the failure that occurred on equipment and corresponding control recipe may propagate to the out products. In summary, there is cause-consequence relationship between product quality and the set of equipment and recipe. These relation continues to propagate on the product flow, and so they lead to a failure propagation in a production process as shown in Figure 5.

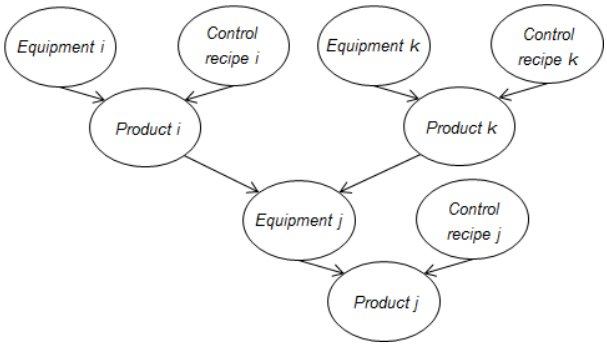

Figure 5: Failure propagation in a production process

Figure 5 illustrates that the failure origin on *Product j* can come from *Equipment j* and *Control recipe j*. Therefore, the failure on *Equipment j* have origins that may be *Equipment i* , *Control recipe i*, *Equipment k* and *Control recipe k* to *Equipment j* through *Product i* and *Product k*. Hence, there is a failure propagation through the products. Consequently, we use the LD model to localize the possible failure origins of a detected fault following the failure propagation on product flow. The principles of the LD model are presented in the next section.

5 LOGICAL DIAGNOSIS MODEL

The Logical Diagnosis model proposed in (Deschamps & Zamai, 2007) is one part in the treatment of failure propagation through products in a complex production process. In this model, a diagnosis function is proposed to characterize the historical information from a controlled system in locating the possible origins of a detected fault. This diagnosis function is presented in three main points:

- First, necessary information is collected from coordination level for fault diagnosis through Operation Models as presented in (Henry et al., 2005). An Operation Model contains information of Functional Chains (equipment, sensors and local control modular), (Pre-)conditions, (Pre-)constraints and effects of operations as shown in Figure 6. The model for diagnosis describes a graphical structure of a production process that consists of system components (as illustrated in Figure 7) and its relationships following product flows (the arrows → in Figure 7).

Operation O_i		
Functional chain ec_i		Service Se_i
During Du_i		
Evolution of function chain ec_i		
Effect	Pre-condition	Pre-contrain
	$Pcd(ec_i)$	$PCt(ec_i)$
⇩ $IC(EfT(ec_i))$	Condition	Contrain
Transient effect EfT (ec_i)	$Cd(ec_i)$	$Ct(ec_i)$
⇩ $IC(EfF(ec_i))$		
Final effect $EfF(ec_i)$		
Premier Evolution of flow of product $ea_{i,1}$		
Effet	Pre-condition	Pre-contrain
	$Pcd(ea_{i,1})$	$PCt(ea_{i,1})$
⇩ $IC(EfT(ea_{i,1}))$	Condition	Contrain
Transient effect EfT ($ea_{i,1}$)	$Cd(ea_{i,1})$	$Ct(ea_{i,1})$
⇩ $IC(EfF(ea_{i,1}))$		
Final effect $EfF(ea_{i,1})$		

Figure 6: Operation Model

- Second, a mechanism to reduce this model is developed by exploiting controlled system observations. Following an operation in this model, if the information provided by these two elements is not coherent, the controlled system sends to the coordination level a faulty execution report. If the coordination level does not receive a faulty execution report from these Functional Chains, it can conclude that the corresponding element is reliable. These reliable elements (the black nodes in Figure 7) will be removed from the model, while the suspected elements (the white nodes in Figure 7) will be retained.

- Finally, a mechanism is defined, based on the failure propagation approach (dash arrows ⇢ in Figure 7), it allows us to search the possible origins and the consequences against a fault when the model receives a faulty execution report from the Functional Chain as described in Figure 7.

Indeed, this logical diagnosis model provides a reduced structural model and a set of suspected operations that have logical relationships with faulty execution. These suspected operations are considered as possible origins $\{O_1, ...O_i, ...O_n\}$ against detected fault. The reduced model describes the logical links between possible fault origins; thus, these logical links are considered as the cause-consequence relationships according to the failure propagation. The form of reduced model is a directed graph in which the nodes represent suspected operations, while the arcs represent the paths of failure propagation through product flows.

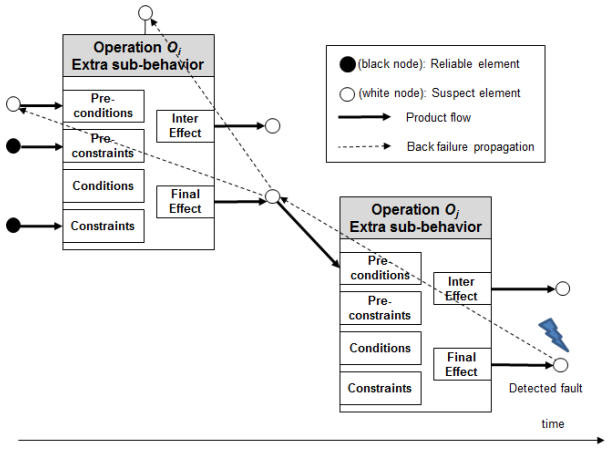

Figure 7: Structural model

For fault diagnosis with equipment failure, products and control recipes, we consider that an Operation O_i contains information of an Equipment E_i, a corresponding control recipe R_i which is a Condition for Operation O_i and a product P_i associated with Equipment E_i which is the final effect of Operation O_i. Consequently, we obtain a set of possible faulty equipment $\{E_1, ...E_i, ...E_n\}$, a set of control recipes $\{R_1, ...R_i, ...R_n\}$ and a set of products $\{P_1, ...P_i, ...P_n\}$. For instance, a failure propagates from Operation O_i to Operation O_{i+1}. The LD model allows to localize the suspected operation and corresponding equipment, product and recipe. However, it does not describe their relationships inside of the operation. For this reason, we have proposed the failure propagation mechanism in a complex process to explain their cause-consequence as presented in section 4. Hence, the directed graph, that describes the failure propagation from Operation O_i to Operation O_{i+1} within the cause-consequence relationships inside these operations, is represented in Figure 8.

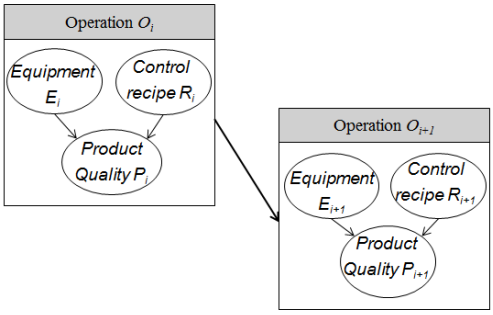

Figure 8: Possible fault origins inside operations

Moreover, to evaluate the risk priority of each candidate, the information given by directed graph and sets of equipment, products and recipes will be used for structural identification of the BN model. Therefore the conditional probabilities are computed by the diagnosis model which is presented in the next section.

6 DIAGNOSIS MODEL

6.1 Model description

The proposed model comprises of logical diagnosis model and BN model as shown in Figure 9. In this model, we use the results given by the logical diagnosis model introduced in Section 5 for dynamic structure identification of a BN. After that, the probability values are computed by the BN model to support the decision-making for corrective maintenance.

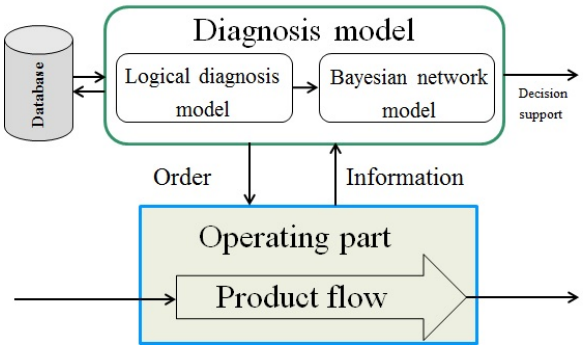

Figure 9: Diagnosis model

The model for diagnosis is based on the control system and dynamic reconfiguration as proposed in (Henry et al., 2005; Deschamps & Zamai, 2007). The reactive loop is characterized by collaboration of several supervision, monitoring and control (SM&C) functions such as detection, diagnosis, prognosis, decision and automatic control (Zamai et al., 1997). The coordination level of control system has capacity to manage a set of Functional Chains and corresponding information. It demands and memorizes the information from the production database. It also provides the information for diagnosis.

Our methodology consists of: *(i)* searching possible root causes against a detected fault in the past evolution of the operating part within controlled system, *(ii)* computing the probability values that show the suspect levels against candidates. The diagnosis model execution is illustrated as following principles:

- This model is generated by the coordination level. Thus, it sends commands and receives reports in real time for and from all system components. This coordination level also provides the necessary information for the logical diagnosis.
- Once a failure is detected by a metrology, a set of possible origins and its correlations are defined by the logical diagnosis model.
- This set of possible origins and corresponding information are sent to BN model. Thus, a graphical structure of failure mode is determined to support the structural identification in the learning phase of BN model.
- After the establishment of graphical structure for BN model, the conditional probabilities associated with all nodes of network are computed based on historical information in the production database. All computed results are stored in the production database to support decision-making for corrective maintenance.

6.2 The execution of diagnosis model

When a fault is detected by a metrology, the diagnosis model manages its execution and will demand the diagnosis results from Logical Diagnosis model and the BN model. The Logical Diagnosis model provides a reduced model of the set of possible faulty equipment $\{E_1, ...E_i, ...E_n\}$, also the set of corresponding Control recipes $\{R_1, ...R_i, ...R_n\}$ and the set of products $\{P_1, ...P_i, ...P_n\}$ as presented in Section 5. These are sent to BN through coordination level, and used to construct the BN model. The conditional probabilities are computed based on the principal theories as presented in (Manfredotti, 2009). The BN model is established and performed as follows:

- First, a graphical structure of BN model is transformed from the sets of possible faulty equipment, control recipes and products that are given by logical diagnosis model. Each member in these sets is considered as a node in the BN model. The equipment $E_{i'}; (i' = 1 \cdots n, i' \neq i)$ is the parent of E_i if it is in front of the node E_i and has direct logical relationship with E_i following a product flow in the directed graph. The product $P_{i'}$ corresponding with $E_{i'}$ is put between $E_{i'}$ and E_i, while the control recipe against $E_{i'}$ is considered a parent of $P_{i'}$.

Consequently, we obtain a graphical structure of the BN model. Each node in this structure may be a parent of child-nodes and may be a child of other parent-nodes. For instance, the parents of a detected fault node are E_i and R_i. Therefore, E_i has a set of parents that are $\left\{P_{i-1}^1, ...P_{i-1}^k, ...O_{i-1}^N\right\}$, with $k_j = 1 \cdots N$. Besides, the parents of each node P_{i-1}^k are E_{i-1}^k and R_{i-1}^k. In this case, the BN model has a hierarchical structure as shown in Figure 10.

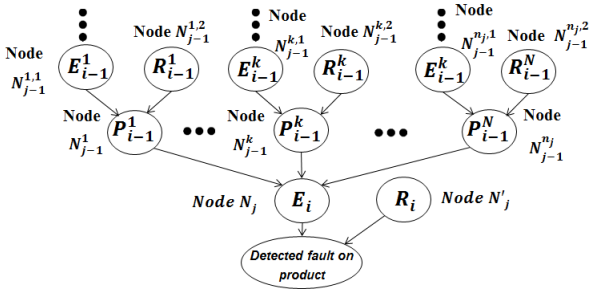

Figure 10: Graphical structure of BN model

- Second, each node in the BN model is assigned with N_j, $j = 1 \cdots n$ to facilitate the computation. Each node N_j has a set of parents as $\left\{N_j^1, ...N_j^{k_j}, ...N_j^{n_j}\right\}$, with $k_j = 1 \cdots n_j$. Hence, the learning phase of BN model is performed to calculate the probabilities $P\left(N_j \mid Product\right)$ for each node N_j following the product, and next the conditional probabilities between the child-nodes and its parents based on the historical information of production database. We consider that each member of the set of fault origins has two states $\{1, 0\}$. Thus, the conditional probabilities over each node N_j with $(j = 1 \cdots n)$ and its parents are defined as a matrix $P\left(N_j \mid N_j^1, ...N_j^{k_j}, ...N_j^{n_j}\right)$ as the next equation:

$$\begin{pmatrix} p\left(N_j = 1 \mid N_j^1 = 1, ...N_j^{k_j} = 1, ...N_j^{n_j} = 1\right) \\ \vdots \\ p\left(N_j = 1 \mid N_j^1 = 0, ...N_j^{k_j} = 0, ...N_j^{n_j} = 0\right) \\ p\left(N_j = 0 \mid N_j^1 = 1, ...N_j^{k_j} = 1, ...Nj^{n_j} = 1\right) \\ \vdots \\ p\left(N_j = 0 \mid N_j^1 = 0, ...N_j^{k_j} = 0, ...N_j^{n_j} = 0\right) \end{pmatrix} \tag{1}$$

- In this paper, in order to compute the conditional probabilities, when we need to extract the distribution over some subset of variables or a single variable, we need to marginalize or sum out the variables other than the variables of interest as explained in (Manfredotti, 2009). The marginalization rule for any sets of variables X and Y is given by :

$$P(X) = \sum_y P(X, y);\ y \in Y \tag{2}$$

The distribution over X can be obtained by summing out all the other variables from any joint distribution containing X. We can use the conditional probabilities instead of joint probabilities to compute the probabilities over X as shown in Equation (3):

$$P(X) = \sum_y P(X|y).P(y);\ y \in Y \tag{3}$$

Finally, the model computes conditional probabilities $P(N_j \mid fault, Product)$ over nodes N_j with $(j = 1 \cdots n)$ given by detected fault according to the Product as illustrated in the next equation:

$$P(N_j \mid fault, Product) = \prod_{i=1}^{n} \sum_{N_i} P(N_j).P(N_i \mid N_j). P(fault \mid N_1, ..., N_i, ..., N_n, Product) \tag{4}$$

with $i = 1 \cdots n,\ i \neq j$. They are used to support the maintenance decision.

The above sections show that the set of possible origins is dynamically determined when a fault is detected. Therefore, when the data is available, the corresponding conditional probabilities are calculated by the diagnosis model. This set of possible failure origins and these probability values are sent and stored in the production database by the coordination level.

6.3 Discussion

The advantages of proposed model are: first to locate the possible fault origin sets in real time, second to reduce the space of this set by the evaluation of suspect levels, and finally less workload for structure identification of the BN model. In the proposed model, the set of possible root causes is significantly reduced by the Logical Diagnosis model. Next, this is used to simplify the structural identification of BN model. Hence, the BN model receives a graphical structure with only elements as possible origins for a detected fault. While other elements not related to the detected fault are removed. Consequently, it does not need to compute all probabilities of all elements in the production system.

In addition, the probability values computed by BN model help to continue reducing the set of possible origins through risk priority to save the recovery time of a production system. This also implies that the combination of a deterministic approach (logical diagnosis) and a probabilistic approach (Bayesian network) help us to locate more accurately and quickly

equipment as the root cause of a detected fault. Consequently, this proposed model is feasible to apply for fault diagnosis in complex automated manufacturing systems with large production information.

7 CONCLUSION

In this paper, the failure propagation mechanism is proposed to describe the impact of recipe on equipment and product quality, and to explain the failure propagation mechanism in a production process. Hence, the proposed diagnosis model dynamically generates the structure of the BN and the associated probabilities. We used a Logical Diagnosis model to significantly reduce the search space for suspected equipment in the given production flow. This reduced set of possible origins which is demonstrated as the directed graph provides the cause-consequent relation to simplify the failure model identification in the learning phase of BN. In addition, the associated probabilities are computed by the BN model to evaluate the suspect level of each member in the set of possible fault origins. Consequently, The proposed model is appropriate in dynamically locating the root causes, in less time and less workload of the computation of conditional probability values in the context of complex manufacturing system that is characterized by multiple products, production lines and recipes. Thus, the diagnosis results support decision-making for corrective maintenance activities.

In future work, we are interested in applying the proposed diagnosis method to production systems to evaluate performances of the proposed method. Therefore, the corresponding algorithms need to be developed in order to adapt to real time manufacturing systems. In addition, we will improve the fault diagnosis in a general manufacturing system with multiple failure sources.

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