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Fault Diagnosis in Multi-station Assembly Systems using an Agent-based Simulation Model (ABSM)

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Abstract: Today's automotive industries require quick ramp-up in order to shorten the time to market and fulfill greater demand for product variety. Since, dimensional tolerance problems are one of the main causes for delay during ramp-up in multi-station assembly systems; hence, rapid diagnosis of faults contributing to dimensional errors is of significant concern. This paper presents an agent-based simulation model (ABSM) which integrates model-based and data-based diagnostics for fault diagnosis and correction in multi-station assembly processes. The fault causing variation sources, their effects on dimensional accuracy, diagnosis from sensors data and corrective actions in multi-station assembly systems are simulated using proposed ABSM. A case study has been considered to illustrate the ABSM methodology for fault diagnosis in multi-station assembly systems.

Keywords: Multi-station manufacturing systems, Agent technology, Fault diagnosis

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1 Introduction

Today's manufacturing is characterized by continuous rise in product variety as well as product quality. With rapid developments in manufacturing technology, the current manufacturing paradigms are shifting from mass production towards product customization. The newly emerging area is characterized by certain key features namely increased customization, product proliferation, shorter production cycles among others. In order to meet these challenges, it is imperative to perform the complete ramp-up in shortest possible time since delayed ramp up may result in significant losses in production during new product launch (Ceglarek, *et al.*, 1994; Ceglarek, *et al.*, 2004).

Common processes involved during the ramp-up phase are related to verification and isolation of faults which occur due to tooling design and installation errors. Further, inefficient diagnosis of faults during launch of a new product also leads to delay in ramp-up which results in depreciation of product quality and extended production bottlenecks. Hence, it is necessary to have an efficient and intelligent diagnostic system for fault diagnosis in assembly processes.

So far, a number of studies have been conducted in the area of dimensional variation of products caused by the failures in assembly processes of rigid parts. Some of them include: fixture failure diagnosis (Ceglarek and Shi 1996); diagnosability analysis (Ding, *et al.*, 2002); and, stream-of-variation methodology (Ceglarek, *et al.,* 2004). The basic requirement of these approaches is complete system design knowledge as represented by CAD/CAM models of product and assembly process. In their work, a set of all possible fault patterns are generated beforehand from off-line CAD information. Then, fault isolation is conducted by mapping the feature patterns of real production data with predetermined fault patterns generated off-line. Specifically, their approach can be recognized as model-based approach for the fault diagnosis in multi-station assembly systems. However, model-based diagnostic methods have limitations due to unmodeled characteristics and environmental noise. On the other hand, data-based diagnostic methods are also not helpful as these are coupled with environmental noise and untraceable system changes/adjustments. Hence, none of the approach *i.e.* neither a model-based nor data-based method is sufficient for diagnosis purposes as both of these are affected by ill-designed assembly systems. Therefore, it is important to develop a methodology which will have capability to (i) integrate both model-based and data-based methods; and (ii) learn about new faults caused by assembly system change/adjustment. Moreover, it is also imperative to have a flexible modeling framework which can be used in launching a new production system.

One of the possible approaches is to employ agent-based simulation models (ABSM) (Jarvis and Jarvis, 2003, Scholz-Reiter, *et al.*, 2004). As agents are individual problem-solvers with some capability of sensing and acting within their environment, for deciding their own course of action in an autonomous way, as well as by communicating with other agents (Monostori, *et al.*, 2006). The proposed ABSM methodology is based on: (1) model-based diagnostics using stream-of-variation (SOV) model (Ceglarek, *et al.,* 2004); (2) data-based diagnostics which utilizes fault region localization based on generalized rough set concept (Mannar, *et al.*, 2006); and, (3) a number of similarly coordinating/communicating agents. ABSM comprises of a group of agents namely: data retrieval agent, fault identification agent, fault localization agent, fault isolation agent, learning agent, process Change agent, and mobile agent. Each of these is assigned for performing specific diagnosis oriented tasks. These agents collectively simulate the process of fault diagnosis and provide necessary feedback to eliminate faults in the assembly system.

2 Agent-based Simulation Model

In an multi-station assembly system, the model-based diagnostics are performed (Ceglarek and Shi, 1996; Ceglarek, *et al.*, 2004) to match the fault symptom with the fault patterns determined off-line from stream-of-variation (SOV) model. Moreover, several new faults due to tooling (*i.e.* welding deformation, cutting deviation, thermal effects) may also occur during this time due to process/system readjustment. Thus, a data-driven fault region localization (FRL) method based on the measurement data is employed to diagnose these new faults. It is necessary to develop an efficient diagnostic system that must be able to discover, diagnose and react to disruptions that are likely to crop up during the launch of a new autobody assembly product.

Therefore, integration of model-based and data-based diagnostics with the help of agent-based simulation model (ABSM) is proposed which performs several complex diagnosis tasks through a group of communicating agents. The specific tasks performed by each of these agents are detailed in Table 1. In addition, Figure 1 illustrates the agent architecture for the proposed ABSM for fault diagnosis.

Table 1. Agents and the tasks performed by them in ABSM

Agent Entity	Assigned Task	Agent Entity	Assigned Task
Data retrieval agent	Data extraction from sensors installed on stations	Fault isolation agent	Identifying root cause by mapping symptom to fault pattern base on the previously determined CSS, candidate component/station and is supported by statistical analysis.
Fault identification agent	Determining candidate set of sensors (CSS)	Learning agent	Employing rough set approach to learn and provide the feedback in the form of correct root cause of a given failure if correct root cause is not isolated
Fault Localization agent	Determining: (i) candidate station; and (ii) candidate component from hierarchical product/process knowledge	Process change agent	Adjustment and changes in the assembly system
		Mobile agents	Human or robots performing the corrective operations

The following subsection describes about various constituent agents of ABS Model for fault diagnosis in automotive assembly operations.

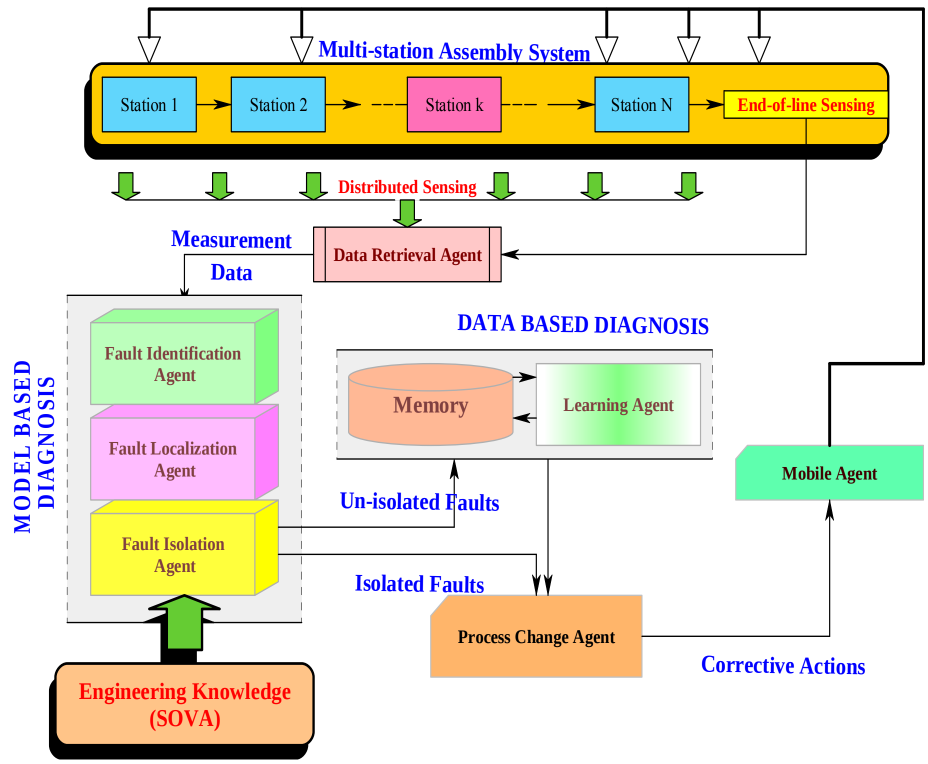

Fig. 1. ABSM architecture for fault diagnosis in Multi-station Assembly Processes.

2.1 Data retrieval agent

A data retrieval agent extracts information regarding current status of the assembly system. Information about the current status is in the form of measurement data from sensors installed on various assembly stations (sensing stations). In order to check the dimensional quality of the assembled product, end-of-line (measurement on last station) and distributed sensing are generally used. Each sensor measures the deviation of a specific point on the part in all the three directions. For example, deviation of measurement points M_1, M_2, and M_3, represented as M_{1x}, M_{1y}…., M_{3y}, M_{3z}, are measured during the assembly of each part. Thus, the deviation of measurement points on a part characterizes its quality. The measurement data collected from each of these sensors are taken up by data retrieval agent and is then is passed on to the fault identification agent.

2.2 Fault identification agent

A fault identification agent performs first step in model based diagnosis. The main function of this particular agent is to select the subset of measurements i.e., candidate set of sensors (CSS) that detect the fault. The selection of CSS is generally based on the data analysis criteria such as standard deviation magnitude and correlation as a contrast function. The measurement data from data retrieval agent is used to compute the variation values (σ^2) for each sensor in X, Y and Z direction. Then, variation percentile chart is generated by plotting the 6-σ values for each sensor (starting from lowest to the highest one). A variation threshold (T_v) is determined such that 70 percent of the inspected points fall below it. Hence, only those points which are above T_v in percentile chart are focused. Further, several simultaneous root causes can lead to larger variation in many measurements; hence, correlation analysis has to be done to classify these measurements based on single root cause. The correlation is calculated for all the sensors with variance exceeding T_v. The correlation threshold, T_c, is selected to be 0.7 for classification purpose. Therefore, the set of all sensors which exceeds T_v and T_c thresholds are defined as CSS.

2.3 Fault localization agent

The fault localization agent simulates the second step of SOVA methodology, whereby, CSS information from fault identification agent and hierarchical knowledge about the product/process is utilized to determine the candidate component and station causing the fault. The output of fault localization agent is candidate station and component. Specifically, candidate part/subassembly is determined by the ratio of the total number of measurement points on a component to the number of measurement points in CSS located on a component. The component having maximum value of this ratio is considered as a candidate component. Further, a candidate station is chosen to be the nearest station between two candidate components in hierarchical representation of product (see figure 2). The information about CSS, candidate station and component is passed on to the fault isolation agent.

2.4 Fault Isolation Agent

The fault isolation agent adopts Principal Component Analysis (PCA) to extract the fault pattern from the CSS. When a process model is available, fault symptom can be mapped to the designated pattern pool (from SOVA and engineering knowledge) to identify the root cause. The candidate station/component information from fault localization agent could facilitate the root cause isolation by reducing the pattern pool. The working of fault isolation agent can be divided into following two steps:

2.4.1 Detection of fault symptom

Fault isolation agent performs fault symptom detection step using Principal Component Analysis (PCA) (Jolliffe, 1986) with an objective to describe the deformation of candidate component. Detection of fault symptom is done by determining the vector of deformation and area of deformation. The vector of deformation is a vector represented by directions and magnitude of variance for each sensor of the CSS. The vector of deformation is estimated using PCA (Ceglarek, *et al.*, 1994). Whereas, the area of deformation of the candidate component is defined in terms of the percentage of sensors located in the candidate component belong to CSS. If this percentage is greater than 75%, then it is assumed to be a global symptom. Otherwise, it is considered as local symptom.

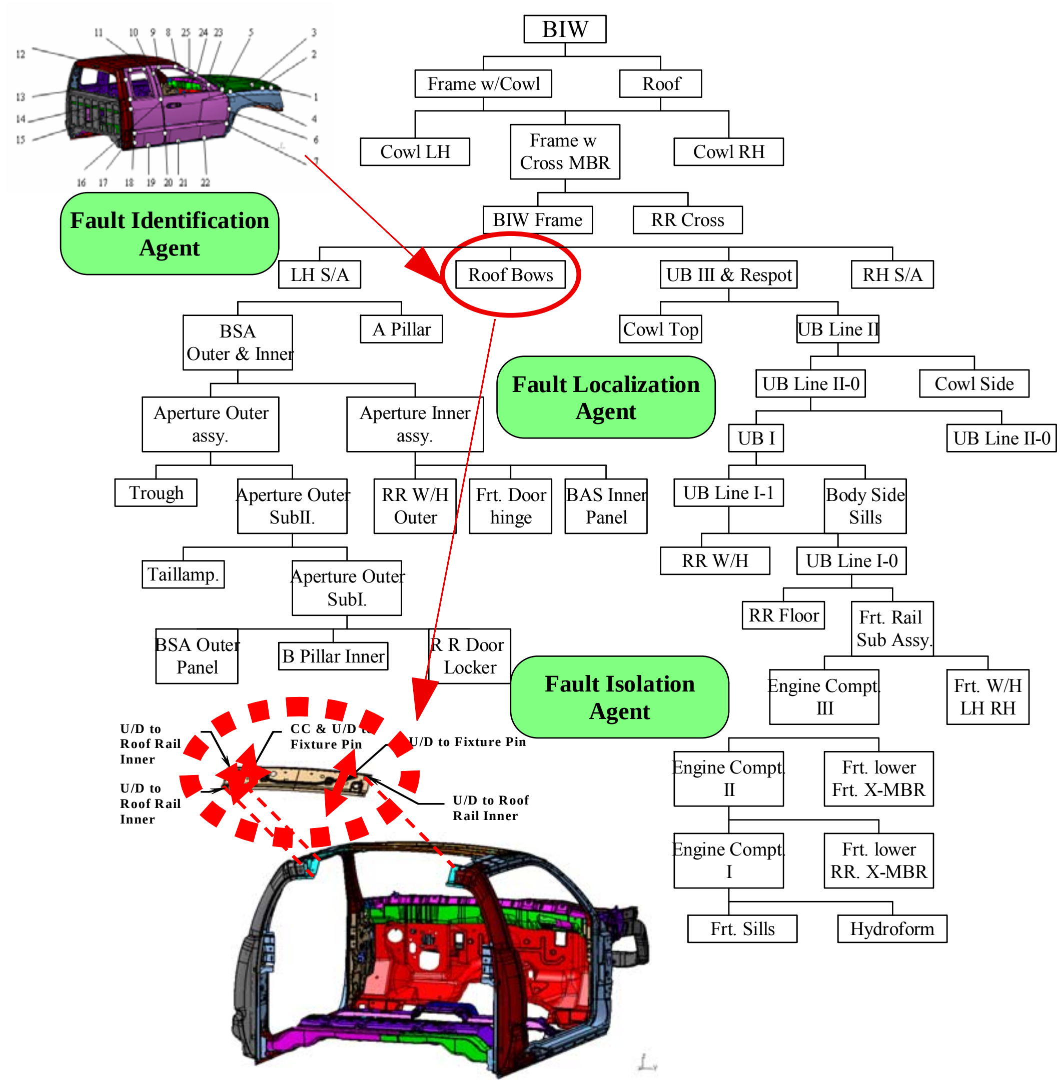

Fig. 2. Model-based diagnosis using Fault identification, localization, and isolation agents on Heirarchical Groups of autobody product

2.4.2 Fault isolation

In this step, fault isolation is carried out on the basis of information about the direction and area of deformation. The relationship between most of the root causes and their corresponding symptoms are summarized in Table 2 and based on this classification faults are isolated. The information about root cause is passed on to the process change agent, if the correct root cause is identified. Otherwise, complete information about the CSS, candidate station and the components is sent to the learning agent.

2.5 Learning Agent

A learning agent works primarily on the principal of fault region localization (FRL) approach (Mannar, *et al.*, 2006) for identifying failure region (FR), boundary region (BND), normal region (NR) in measurement data. FRL methodology employed by learning agent for diagnosis purpose is based on the the method of rough sets (Pawlak, 1982, Mannar, *et al.*, 2006). Generally, rough sets are utilized for analysis and classification of imprecise data. The basic idea behind rough sets is to use the indiscernability relation *i.e.* inability to distinguish between objects based on measured attributes (measurement data) to construct approximation sets. These sets convey significant information about the assembly process in the form of data-driven regions. Following tasks are accomplished by the learning agent in order to perform data-based diagnosis for the faults that were not isolated by previous agent:

Table 2. Relationship between root causes and their symptoms

Root causes		Fault symptom	
Identification	**Description**	**Direction of Deformation**	**Area of deformation**
2-way locator 1-way locator	i. mislocation ii. worn out iii. loose	X and Z Z or X	Global
Clamp	i. missing ii. not functioning iii. missing iv. not closing properly	Y	Global
Welding spots	i. unequalized welding gun ii. worn out tip iii. missing welding spot iv. malfunctioning of tip v. dressing operation	Y	Local

2.5.1 Generation of System information database

In this step, a system information database $T = (\mathrm{O}, \mathrm{A} \cup \{d\})$ is generated as a training data for particular fault failure. An object in **O** consists of a set of measurements **A** for each of the measured part/subassembly (*i.e.* M_{1x}, M_{1y}…., M_{3y}, M_{3z}) and a decision attribute ‘d’ to characterize its status. In our case only two outcomes are possible for ‘d’ *i.e.* either the part is good or faulty. Hence,

$$d = \begin{cases} f, & \text{part failed} \\ p, & \text{part passed} \end{cases} \tag{1}$$

Since, the system is being continuously improved during ramp-up; hence, system can be assumed to be in a state of continuous fault, although, magnitude of the fault may vary with time. Therefore, all the parts obtained from the system are classified as decision attribute '*f*'. This data is then compared with simulated white noise data (to simulate normal process condition), which is generated for each of the attributes, and are given a different decision attribute '*p*'.

2.5.2 Discretization and determination of equivalent classes

In this subtask, the continuous values of measurement data are discretized into sub intervals using the boolean reasoning algorithm (Ohrn, 1999), as rough set method is based on the indiscernability. The discretization procedure is done in such a way that original information inherent in the system information database T for distinguishing parts from each other is maintained. After discretization, equivalent classes present in **O** are determined. An equivalent class can be defined as a set of all product samples which cannot be distinguished from each other based on the discretized measurements **A.**

2.5.3 Determination of the dependency degree and generation of reducts

The dependency degree α determines the ability of measurements **A** to differentiate between the decision classes d = *p*, and d = *f*. It is calculated based on the concept of membership function for each equivalent class. Next, a minimum subset of measurements $\mathbf{B} \subseteq \mathbf{A}$ for which the dependency α_B is approximately the same as the dependency degree α_A for whole measurement set **A**. This procedure employs the genetic algorithm for the generation of reducts by maximizing α_B towards α_A, thereby simultaneously reducing the cardinality of **B**. For more information, see Mannar, *et al.*, 2006.

2.5.4 Generation of fault, boundary, and normal regions

Based on the identified reduct **B**, following regions were determined: (i) fault region (FR) for faulty products; (ii) normal region (NR) for normal products; and (iii) boundary region (BND) representing the impreciseness or noise in the data. The identified regions are in the |**B**| dimensional space.

The FR and BND regions corresponding to a fault is stored into the memory of the learning agent. Therefore, the learning agent incorporates the learning function by storing the values of measurement data corresponding to FR and BND regions. The learning process reduces the time for future diagnosis, as newer measurement data are first matched with the rules stored in the memory of the learning agent. If sensor measurement lies within the ranges of FR and BND of previously identified fault, then the information about fault are sent directly to the process change agent. Otherwise, FRL approach is applied to learn new faults. Hence, this particular agent works as a database manager, whose function is to update the memory of agent after every arrival of new faults.

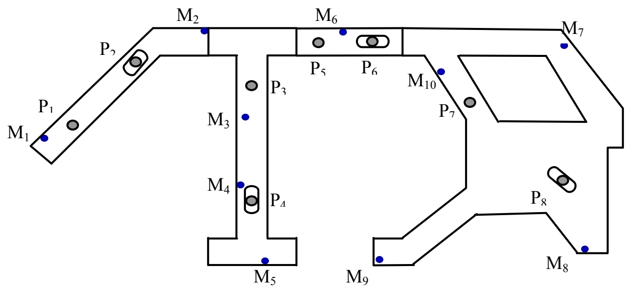

Fig 3. Case study: Side frame of Sports Untility Vehicle with locating pins and measurement points

2.6 Process Change Agent

The process change agent decides required changeovers in the current multi-station assembly systems given the type of faults present. These decision may be provided by the human or machine on the basis of some historical data or from previous engineering knowledge. Decisions are then passed on to next agent known as Mobile Agent.

2.7 Mobile Agent

Here, humans (operators)/ machines (robots) may be called mobile agent, whose function is to perform all the decisions provided by process change agent. Since, some of redesigning operations or improvements may be intricate; hence, human workers instead of mobile robots are to be employed. These agents have direct access to the assembly system.

3. Case Study and Agent Simulation

The case study utilized in this paper to illustrate ABSM based diagnostic methodology include side frame of sports utility vehicle (SUV) (see Figure 3). It comprises of four components namely the A-pillar, the B-pillar, the rail roof side panel, and the rear quarter panel that are assembled on three stations and finally inspected on station IV. Measurement points, marked as M_1 - M_{10} in Figure 3, are key dimensional features and 3-2-1 fixturing mechanism has been employed on every station to hold the workpiece/part. Points P_1-P_8 are principal locating points which are pinholes used to position a part on an assembly station. Two types of pins are generally used to hold each part *i.e.* four way pin to position the part in two directions (X and Z) and two way pin to position part in one direction (Z). Also three blocks of NC are required to restrain part deviation in Y direction.

The major emphasis here is to demonstrate the applicability of ABSM approach during the launch of a new product in multi-station assembly process. The detailed steps of proposed ABSM based diagnostic methodology is outlined below:

Step I: Data retrieval agent: It collects the information about status of the assembly system through sensors. Now, this data is transferred to next agent known as fault identification agent.

Step II: Fault identification agent: The threshold values were defined to be T_v = 3.2mm and T_c=0.70. The level of T_v is such that 70% of all sensor variations remains below variation threshold value. Then CSS is determined to be CSS = [M_{3Z}, M_{4Z}, M_{5Z}, M_{8Z}].

Step III: Fault localization agent: Mapping CSS to the hierarchical knowledge about the product to be assembled. It is identified that all of the elements in CSS are located on B-pillar and rear quarter panel. Further, the candidate station is determined as 2nd station.

Step IV: Fault isolation agent: The vector of deformation and area of deformation is estimated by the method given in section 2.3. It can be inferred from CSS that all the measurements are in only Z-direction. Therefore, the direction of deformation is along Z-axis and it is determined as the percentage of sensors localized in the candidate component B-pillar and rear quarter panel. The area of deformation for B-pillar is global and for rear quarter panel is local. Hence, the symptom is identified as:
B-pillar: global deformation in Z
Rear quarter panel: local deformation in Z
Based on the above symptoms, root cause for of the faults is: (i) due to the malfunctioning of locators P_3/P_4 in Z-direction on B-pillar; and (ii) due to external interference in Z direction. Since, identified fault in B-pillar is isolated; hence, information regarding faulty component, root cause of faults, and candidate station is sent to process change agent. However, the proper root cause for second fault *i.e.* local deformation in Z direction is still not isolated. Therefore, unisolated faults are then passed on to the learning agent.
Step V: Learning agent: The fault region localization (FRL) methodology is used to identify different faults in assembly process, which are not diagnosed by model-based diagnosis approach. The incoming measurement data of CSS is utilized to perform data-driven diagnosis for identifying FR, BND and NR regions. Two rules are generated from the application of FRL methodology (Table 3) to sensor data:

Table 3. Rules Generated from reducts for P_4 failing in Z direction (* denotes maximum/minimum values for each attribute)

Rule I	M_{3Z}[0.625, *] AND M_{8Z} [0.814, *]	FR
Rule II	M_{3Z} [0.491, 0.625] AND M_{8Z} [0.658, 0.814]	BND

These rules are used to form FR, BND regions. Since, fault identified is new, therefore, it is stored into the database of the learning agent. Information regarding FR, BND, and NR is passed on to Process change agent for tolerance revaluation.
Step VI: Process change agent: This agent works in following two ways:

(i) For root causes isolated by model-based diagnosis: Corrective actions are decided for the faulty locators in P_3 and P_4 of B-pillar.

(ii) For faults identified by FRL methodology: Based on the FR and BND regions, tolerance limits are revaluated for the rear quarter panel (see Mannar, *et al.*, 2006)

The corrective actions are then floated towards Mobile agent
Step VII: Mobile agent: These agents make necessary changeovers into the multi-station assembly systems as desired by the process change agent.

4 Conclusion

This paper illustrates the application of agent-based simulation model (ABSM) for fault diagnosis in multi-station assembly systems. ABSM approach integrates model-based and FRL based diagnostic methodology for isolation of complex faults. Further, ABSM provides necessary adjustments in order to restore normal operative conditions. Clear applicability of ABSM approach for diagnosis purposes is illustrated. Moreover, a case study in industrial setting is detailed in a step by step procedure. The ABSM approach provides an effective tool allowing the multi-station personnel benefit from the results of advanced statistics without requiring expertise in advanced statistics. The application of the ABSM requires complete knowledge about the information sharing and flow among the different agents of the system. Moreover, a good computational background (for database management, information retrieval, sharing, and following certain protocol) is required for its implementation in real world application

Future research in this area would be to incorporate communication and monitoring aspects in current ABSM methodology for fault diagnosis.

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