ResourceNet: a collaboration network among decentralised manufacturing resources for autonomous exception-handling in smart manufacturing

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Abstract: The fast-changing market and increasing demand for customised products have imposed manufacturers to improve the flexibility and robustness of their manufacturing execution systems. The ability to recover from exceptional events is fundamental to autonomous manufacturing systems in the era of smart manufacturing. Currently, the various types of manufacturing exceptions remain unclear. This research investigated the typical exceptions and proposed a general framework that supports the autonomous exception-handling and resource discovery in dynamic environments. A multi-layer peer-to-peer network is used to model the resources, services, and events in decentralised manufacturing systems. The exception-handling mechanism is designed that incorporates rule-based reactions, matching of features, recording of behaviour patterns etc. The feasibility of the proposed methods is also discussed, which shows many exceptions that were ignored in previous scheduling models can be timely identified and easily handled. This research explores the complex relations among manufacturing resources and provides an intelligent overall framework for self-organising manufacturing with self-diagnose capabilities.

1 Introduction

In recent years, technologies such as the internet of things [1], big data analytics [2], and edge computing [3] are developing rapidly. They have received much attention in both academia and industries. The continuous application of various new technologies has brought many opportunities for companies to upgrade their manufacturing systems and deal with the increasingly fierce market competition. These companies need to continuously improve their productivity and robustness of their systems to respond quickly to market changes and optimise the resource configuration in the dynamic environment with uncertainties. The complexity of production processes has been significantly improved due to the variety of production tasks and the specific requirements from individual customers. Consequently, there is a higher chance for exceptions to occur during manufacturing, such as the delayed material handling during task switching, the lack of qualified operators for processes that require specific treatment, and the inaccurate feedback information from customers that misleads the quality inspection system [4]. In addition, some exceptions may be invisible and cannot be timely identified by simply monitor the production progress. The influence of such tiny exceptions may accumulate over time and threaten the critical process, leading to some inevitable loss in business value or products’ reputation. Therefore, it is crucial to understand the various exceptions in the era of smart manufacturing and deal with them effectively.

Researchers have discussed a number of manufacturing exceptions and the potential solutions to handling them [5–7]. Generally, the implementation of distributed sensors and communication networks has improved the accessibility of the real-time status of manufacturing resources. Although the production data becomes more transparent, ambiguities still exist in the types of exceptions. It can be difficult to identify an exception without having a comprehensive view of different kinds of exceptions.

Besides, there are lots of different models dealing with the rescheduling problem after exceptions occur [8–10]. Since these models may have different assumptions and effectiveness, it is not easy to compare one from another and choose the best one for implementation. It is necessary to study some general strategies for exception-handling in smart manufacturing systems. The primary research questions are summarised as follows.

(i) It should be considered how to manage the various information (i.e. the states of resources, events etc.) in a unified framework to support the autonomous operation of manufacturing systems.

(ii) It is essential to understand how to identify the typical exceptions in smart manufacturing systems.

This research aims to summarise the typical exceptions in smart manufacturing systems and design a primary mechanism for the exception-handling. By applying a peer-to-peer network structure, a collaboration network among resources and services (i.e. ResourceNet) was established that can support the autonomous resource discovery and service recovery in the execution stage of decentralised manufacturing systems. The typical exceptions were analysed and modelled for timely production control. The interrelations among resources were discussed and the general strategies for exception-handling were designed in this research. Therefore, manufacturing systems will become more robust in a dynamic environment.

The rest of the paper is organised as follows. The overall architecture of ResourceNet is proposed in Section 2. The typical exceptions and disruptions during manufacturing execution and some treatment on them are discussed in Section 3. Detailed models of resource collaboration are explained in Section 4. An illustrative case is provided and analysed in Section 5. Section 6 summarises the paper and proposes some future research directions.

2 Overall architecture of ResourceNet

Modern advanced manufacturing systems require timely management that can effectively track exceptional production events in the workshop, which must have the intelligent-discovery and rapid-response ability to realise the integrated operations of process monitoring, data collecting, information communicating, early warning, disposing and evaluation of exceptional events, thereby improving the robustness and flexibility of manufacturers.
The overall architecture of the resource collaboration network for autonomous exception-handling and resource discovery (ResourceNet) is shown in Fig. 1, which shows the relations between the physical domain and the information domain in decentralised manufacturing workshops.

### 2.1 Physical domain

There are a large number of uncertain factors in manufacturing enterprises that cannot be clearly quantified and controlled. Several types of factors such as personnel, equipment, material, and environment may be the root causes of visible problems such as degradation of production performance, the decline in product quality, increase in energy consumption etc. All these factors need to be monitored in the physical domain to identify any potential exceptional events during manufacturing. Five categories of resources are included in this research, namely machine, material, operator, environment, and order.

- **Machine** refers to all the physical equipment that is used during manufacturing, e.g. a lathe, a milling machine, robotic arms, the material handling system composed of multiple belt conveyors, automated guided vehicles, and forklift trucks. It is necessary to collect their operating parameters for process monitoring and exception identification. The quantity and availability of materials and operators are also required in production management. Environment refers to the working conditions including the data collected from temperature sensors, pressure sensors, radio frequency identification readers etc. The information of orders should be updated timely as well to deal with situations such as a change in delivery time or production priority.

### 2.2 Information domain

The data flow is illustrated in the information domain in Fig. 1, where the dynamic multi-layer peer-to-peer network is applied to model the resource collaboration network (i.e. ResourceNet). In this research, the three-layer network is used to reflect the physical resources, the interrelations among the resources, and production events.

- The network in the mapping layer presents the exact topology of physical entities, where vertexes represent resources and edges represent (direct) communication interfaces. This layer can reflect the physical connections between resources.
- The network in the relation layer shows the maintained relationships between resources. An edge between two vertexes indicates these resources have a close connection and tend to cooperate during manufacturing. These relations are fundamental to resource discovery processes. This layer enables resources to manage their relations proactively within the decentralised network, thereby realise the intelligent and autonomous resource discovery and exception-handling operations.
- The event layer highlights the various events during manufacturing for the convenience of process monitoring. The vertexes indicate events that happen on the resources, e.g. the event chain of ‘(previous) process complete’, ‘material handling’, and ‘(next) process begin’ can mark up the production route on the event layer. Any changes in this layer represent the appearance of new events.

The multi-layer network contains sufficient information about the workshop and can be generally regarded as its digital twin [11]. ResourceNet will update and evolve to represent the real-time characteristics of the decentralised resources. The monitored events are processed through an event sequence to scan for potential exceptions. When the monitored parameters exceed the predefined range or match some failure patterns, an exceptional event is identified and thrown to the application layer.

### 2.3 Application: the autonomous exception-handling

The key features of the exceptional events need to be extracted first (e.g. the types of sensors that detect abnormal values) and analysed by the event classifier to determine the type of exception. An existing solution for resource reconfiguration will be applied if the features match the scenarios stored in the knowledge base. Otherwise, the required operations needed for exception-handling will be used to search for qualified resources. The functional-similarity-based resource discovery mechanism relies on the relationship maintained by resources on the relation layer, viz. resources may connect with each other based on their functionalities for a temporary replacement or joint operations on specific processes.
Exception handling in manufacturing systems

Exceptional events may happen within a workshop (e.g., equipment failure, quality deficiency, and personnel faults) or at the external environment (e.g., material delay caused by the supply chain and the change of orders). For most manufacturing companies, the dynamics, complexity, and unpredictability of the production process may lead to exceptional events. The occurrence of such events often causes production downtime and even long-time production suspension, which affects the execution of production tasks, product quality, and order delivery time. This section discusses some general ways to monitor processes and categorise some typical exceptions during manufacturing.

3.1 Techniques for exception discovery

The exception discovery technology is intended to deal with and avoid possible production disruptions as much as possible, and provide effective early warning methods for production abnormalities.

The use of automatic production equipment such as numerical-controlled machine tools and industrial robots, and the establishment of the data stream from the manufacturing operations to the products make the data fully available and closed-looped, which can improve the overall production efficiency of the enterprise, reducing labour inputs, and managing and optimising the flow and consumption of various resources effectively. In addition, embedded sensors can capture different types of data to guarantee that the manufacturing execution system is fully aware of the processes [12]. More details of detecting changes at sensor levels can be found in [13].

The existing research on early warning models can be used to better detect the production exceptions in the production processes. However, most of them failed to consider the characteristics of exceptional events in the big data environment, and cannot guarantee good early-warning effects for massive, diverse, and unstructured data. The problems of exception handling in the workshop will draw on the data analytics and prediction model to form an intelligent analysis method. For example, using deep learning to realise the cognition and prediction of the contents of physical activities by statistical analysis, feature extraction, association mining, pattern recognition from various activity data related to people, equipment, and materials.

3.2 Processing and mining of big data for exceptional events

The pre-processing of the massive, high-dimensional, and multi-source manufacturing data includes multi-level combinatorial optimisation of filtering rules, unified data modelling based on ontology, and multi-dimensional view construction based on dictionary learning, which can be realised by cleaning and denoising manufacturing data, modelling integration, and multi-scale classification, respectively.

3.2.1 Filtering rules: Multi-level combinatorial optimised data cleaning and the manufacturing data collected by intelligent workshops may have various situations such as data defects, data errors, data conflicts, and data duplication, which reduce the availability and reliability of the data. On this basis, it is necessary to further study the multi-level combinatorial optimisation of filtering rules, and analyse the impact of different combinations of multi-level filters on data quality. Through the multi-stage filter structure optimisation, the workshop manufacturing big data cleaning is realised, and the data credibility is improved.

3.2.2 Ontology-based data modelling integration: Manufacturing data in intelligent workshops are multi-source and heterogeneous. Therefore, it is necessary to propose a global-oriented manufacturing data model and relationship description based on ontology modelling, and define the multi-dimensional context and corresponding metric values of data through ontology construction. In particular, the need to establish a semi-structured and unstructured data structured text description means to achieve the construction of structured, semi-structured, and unstructured manufacturing data unified modelling.

3.2.3 Multi-dimensional view based on dictionary learning: There exist the reuse requirements of manufacturing data for workshop analysis and decision making. Since there are a large number of sparse matrices in the multi-dimensional databases, it is necessary to establish a sparse representation framework for manufacturing big data, as well as an online learning method for dimension member dictionaries, and cluster clustering of data according to the distribution of dimension members at a specified scale, to quickly establish multi-dimensional classification views of manufacturing data and support specific applications for workshop analysis and decision making.

3.3 Typical exceptions in manufacturing systems

The typical exceptional events are classified into seven groups, as listed in Table 1. Exceptions related to machines include component failure (which generally requires much time to repair) or electrical failure (which generally can be recovered soon), degradation of quality, efficiency (i.e. processing speed), functionality etc. Exceptions related to tools are usually caused by resource conflict (i.e. being occupied by another resource) or quality degradation. When the production line changes significantly, some necessary tools may not be ready for the new processes.

Material exceptions can be caused by late delivery and quality issues. Besides, there may be some limitations to the acceptable materials for different machines. Personnel exceptions include improper operations that do not meet the production rules or failed to complete the process within the planned time. The absence or shortage of operators is also possible during manufacturing. Environment exceptions may generally influence the quality and processability of workpieces. Some misleading data or delayed feedback may make it impossible to follow the resource plan, causing further exceptional events. Order exceptions are frequently encountered in a dynamic environment where production priority needs to be adjusted timely.

4 Multi-layer network for resource discovery

Decentralised management and control can guarantee the flexibility and robustness of manufacturing systems. The previous work [14]...
was inspired by the friendship development in social networks and proposed a mechanism of relationship management for resource discovery. A peer-to-peer network with the distributed hash table overlay was applied to model the relations among manufacturing services. The peers (including resources and requirements) were characterised by their (actual and required) capabilities and can seek for optimal matches through the introduction of friends. We extended this network model and introduced a three-layer resource network in this section.

4.1 Three-layer network model

The necessity of having multiple layers is that a lot more information on resources, services, tasks etc. can be included in the model by giving specific values or weights to different vertexes and edges. It also becomes possible to introduce the directions of some relations as some layers may use directed networks to reflect the relations while others use undirected networks. To avoid conflict representations or misunderstandings, vertexes of each layer are duplicated from each other and represent the same entities. The edges at different layers may rewire as required.

The three layers are responsible for recording the physical topology and primary parameters of the resource network, the relations among resources, and the events happen on the resources, respectively.

The mapping layer can illustrate the relations between components and resources, e.g. a turning machine may be connected with a vibration sensor, a turning speed meter, a distance measuring equipment etc. In the network model, vertexes that represent the sensors are commonly connected to the vertex representing the turning machine. The edge between different types of resources may represent some connection such as granted access, operation capability, adequate knowledge, etc. For example, an operator is connected to a numerical-controlled machine, indicating the qualification to operate the machine properly.

The relation layer generally follows the principles mentioned in [14] so that most resources can have enough number of friends that can be the backups when the exception occurs. They will also have enough friends that are different in functionalities, so that tasks can pass on through resources and seek for suitable capabilities. In other words, an edge that connects two resources in this layer can represent the similar or complementary relation of their functionalities. With this layer established, the resource discovery process in a discrete environment will be easier and more flexible. Therefore, the replacement of resources during manufacturing exceptions can be achieved.

The event layer is an additional abstraction of the manufacturing system for the convenience of exception handling. Generally, this layer contains directional graphs that represent the events in the manufacturing system and the states of the resources. The directional edge starts from the event trigger and ends at resources that have been affected by the event. Each vertex contains a parameter set that can describe the states of the resource. All the events and states will update timely to represent the dynamic environment. The events will be filtered and scanned for exceptions.

4.2 Workflow of exception diagnoses

The workflow of exception diagnoses is shown in Fig. 2. Related technologies used in this process are introduced as follows.

4.2.1 Data pre-processing: Data obtained directly from production equipment cannot avoid the interference of system noise. These interferences are easy to cause prediction errors, so the original data must be processed before it can be applied in modelling. Generally, the original sequence is cumulatively calculated to obtain an accumulated sequence, which weakens the influence of noise interference on the data, thus enhancing the regularity of the new sequence. The selection and calculation of characteristic parameters and data classification to ensure that the initial data sent to other modules is accurate and reliable. Technical details of big data pre-processing including data cleaning, the selection of meta model etc. can be found in [15].

4.2.2 Establishment of diagnostic model: The kernel principal component analysis algorithm is used to select the kernel function and a new type of kernel function is constructed. The information fusion method is used to study the feature selection and fault diagnosis method based on mutual information. Aiming at the problem that mutual information is difficult to calculate in high-dimensional space, under the condition that the feature information is not seriously deviated from the uniform distribution, the feature selection algorithm based on second-order mutual information can be used to adaptively estimate the candidate feature and the known feature, about the redundant information of output category, it is not necessary to artificially set parameters related to the degree of feature redundancy. The algorithm can provide accurate feature evaluation criteria and has high model adaptability.

4.2.3 Knowledge base: The knowledge base is used to store the sample fact library (diagnostic case) and interpretation mechanism, provide rule knowledge and training for principal component analysis and neural network models and explain new knowledge and samples. Editing knowledge base diagnostic knowledge can be described either in the system’s programming language or in human–machine dialogue. The three learning results are expanded by knowledge checking and evaluation, and the neural network can be trained. A more accurate neural network model is obtained, which makes the fault diagnosis result of the system more accurate and reliable. In the knowledge base, knowledge is expressed in a certain form. The knowledge base consists of two parts, one is the known data information related to the current, and the other is the general knowledge and domain knowledge used in the reasoning.

There are many ways to represent this knowledge. Commonly used are rules, networks, logic, and processes. Therefore, the amount of data is a key factor in determining whether a knowledge base is superior or not. The ability of a fault diagnosis system depends on the quantity and quality of knowledge contained in its knowledge base, thereby reducing its dependence on expert systems.

5 Case study

For simplicity yet without losing generality, the exception handling processes were tested in an illustrative production scenario. The production data (i.e. the production routes, the processing time of each process etc.) were collected from a factory that produces cutting tools and have been pre-processed to eliminate the commercial sensitivity. The results have been analysed in this section.

We selected four manufacturing resources (specifically speaking, four different machines) and five tasks (denoted as I, II, III, IV, and V) for the case study. The four machines are represented as A, B, C, and D. All the four machines support numerical control and were mutually connected to an event-based middleware. The intercommunication between machines can be realised through information exchange on the middleware. The
was placed. The production route of each task specifies the ResourceNet, listed in Table 2, where the starting time indicates when the order indicate their substitutive resources. In this case, machine A can be (including setup) for the process. The time for material handling IET Collab. Intell. Manuf. This is an open access article published by the IET under the Creative Commons Attribution -NonCommercial License (http://creativecommons.org/licenses/by-nc/3.0/)

Table 2 Detailed information of tasks

| Task | Starting time | Production route | Due time |
|------|--------------|-----------------|---------|
| I    | 0            | (A, 6)–(B, 5)–(D, 3)–(C, 4)–(A, 5)–(C, 3) | 27      |
| II   | 1            | (D, 3)–(C, 6)–(B, 7) | 22      |
| III  | 8            | (A, 5)–(D, 4)    | 20      |
| IV   | 21           | (B, 6)–(D, 6)    | 35      |
| V    | 21           | (C, 3)–(B, 6)    | 37      |

Table 3 Comparison of the exception-handling processes with or without ResourceNet

| Task | Due time | Delivery time with exceptions | Delivery time using ResourceNet | Delivery time without ResourceNet |
|------|----------|------------------------------|-------------------------------|----------------------------------|
| I    | 27       | 26                           | 32                            | 31                               |
| II   | 22       | 21                           | 23                            | 23                               |
| III  | 20       | 18                           | 20                            | 20                               |
| IV   | 35       | 33                           | 35                            | 40                               |
| V    | 37       | 35                           | 35                            | 40                               |

Fig. 3 Gantt chart of the manufacturing tasks
(a) According to the original plan, (b) After the exception handling supported by ResourceNet, (c) After the exception handling without ResourceNet

Table 3 shows the delivery time for different tasks after the occurrence of the exception. After the exception occurred and using the exception-handling method supported by ResourceNet, all tasks except for task I can be completed no later than the schedule provided by the other real-time scheduling strategy. With the help of the proposed multilayer structure and exception diagnosis model, the filtered manufacturing events can provide valuable information, especially for the proactive manufacturing rescheduling. It can be inferred that the impact brought by exceptions can be controlled quickly when the exceptional event is about to be settled. Fewer tasks that were previously assigned to the failed resource will flow to the other parts of the manufacturing system, mitigating the spread of the exception and avoiding the cascading failures in the manufacturing network.

6 Conclusion
The on-site production environment of modern manufacturing enterprises is complex and changeable. There are a lot of uncertain factors, which leads to frequent occurrences of exceptional events in the production workshop. Therefore, the improvement of production management and the manufacturing capacity of modern manufacturing enterprises urgently requires a rapid response.

Central middleware and four connected machines formed the general topology of the mapping layer in ResourceNet. In the relation layer, each machine maintained a list of pointers that can indicate their substitutive resources. In this case, machine A can be replaced by machine B. Despite that, no more substitution was possible among the four machines. The details of the five tasks are listed in Table 2, where the starting time indicates when the order was placed. The production route of each task specifies the predefined sequence of processes. The notation (resource, time) represents the required resource and the corresponding time (including setup) for the process. The time for material handling was ignored in this case. The Gantt chart of the original production plan is shown in Fig. 3a.

During the manufacturing execution processes, various production events happened at the machines and were collected by the middleware. When an exceptional event (such as those listed in Table 1) was detected, the related resources whose production process has been affected can search for alternative resources and change the production route temporarily as required. Through the multilayer structure, the individual resources can have a better view of the real-time production scenario and can possibly adapt to the new environment with more supporting data.

In this case, machine A broke down at time $T = 7$. This exceptional event was captured at the event layer in ResourceNet, triggering the update of the complete multilayer structure. Machine A disconnected with the middleware in the mapping layer and started searching for alternative resources in the relation layer (i.e. the list of pointers aforementioned in this section). The collaborative relations between machine A and other resources also broke down, indicating that other resources cannot send tasks to this machine for now. Meanwhile, the exceptional event was classified and analysed according to the descriptions in Section 4.2. By confirming various sources of data including the real-time current and voltage of the machine, it was concluded that the exception was caused by the unstable power supply that triggered the safety features of machine A. The exception diagnose model reported the average time for electrical recovery was 17. This information is vital for the exception handling during manufacturing. The subsequent tasks preassigned to machine A can receive the precaution in time and seek for alternative resources effectively, e.g. the first process of task III that was to start at $T = 8$ was shifted to the processing queue of machine B. For the fifth process of task I that was planned to start at $T = 18$ on machine A, it was postponed and the new starting time became $T = 24$. The new schedule after the occurrence of the exception is shown in Fig. 3b.

For comparison analysis, the real-time scheduling strategy proposed in [4] was also tested in this particular scenario, whose outcome is shown in Fig. 3c. Without supporting information from ResourceNet, the manufacturing resources were unaware of the possible recovery time of machine A. Although IoT devices have been installed to collect various data, the value-adding of these data was limited due to the lack of a comprehensive structure that deals with the intercommunication between the networked resources. It can be observed that manufacturing processes will not be assigned to a machine that may recover at some time in the future when using the strategy proposed in [4]. Therefore, the remaining resources (i.e. the substitution of the failed resource) that were still available may suffer from too much pressure from the reassignment, causing fundamental delays in the overall manufacturing progress.

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research draws on the innovative ideas of socialised activities between people and proposes a multi-layer peer-to-peer network architecture for the autonomous resource discovery and exception handling. There are two main contributions, i.e. the typical exceptional events during manufacturing have been summarised and the flexible and robust manufacturing network architecture is designed. The research results have accumulated experience in self-organising manufacturing and advanced exception-handling methods, which can reduce the impact of production uncertainty, help the self-adjustment of manufacturing processes, and improve the self-diagnoses ability of the manufacturing system. The proposed multi-layer structure stimulates the information exchange and data sharing among manufacturing resources. Therefore, the autonomous decision-making supported by the precise and value-added data can be achieved. This research considered the scenario where only one exceptional event may occur at a time. When dealing with multiple or interdependent exceptions, some coordination mechanism should be designed to ensure the consistency in the control flow. Future research may further study the complex combinations of multiple exceptions during manufacturing, which is not uncommon in real-life cases.

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