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Article

A Modified FMEA Approach to Predict Job Shop Disturbance

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Abstract: Failure modes and effects analysis (FMEA) is a systematic approach that focuses on evaluating critical disturbances in a system. However, traditional FMEA has its own drawbacks, such as invalid computations and ambiguous priority definitions, which lead to many constraints in the application of complex production processes, especially in job shops with various resources. Therefore, this paper proposes an analytic disturbance prediction method for job shop with multiple resources and multiple evaluation indexes, which combines the vector computing techniques, FMEA, and fuzzy analytic hierarchy process (FAHP). In contrast to other work, this paper focuses on the establishment of FMEA mathematical model to improve the readability of multi-resource disturbance risk results. To this end, the projection of the disturbance vector is visualized to reduce repeated calculation results, triangles and trapezoids are used as membership functions to improve the accuracy of weight, and the differentiation index is used to reduce the ambiguity of priorities. The proposed method can effectively discover the critical disturbances and enable managers to undertake more assertive decisions.

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1. Introduction

A primary goal of any job shop is to increase its throughput. Little's law [1] states that throughput can be enhanced by reducing cycle time, increasing the level of inventory (or resources in general), or any combination of cycle time and resources. Job shops are generally characterized by a high level of cycle time variation. The additional job shop-related variation is due to the highly customized product mix and the system's capacity and capability to adjust and produce such a diversified product mix. The absence of proper capacity and capability significantly impacts the job shop's customer service level, product quality, and manufacturing cost. The ability of a job shop to be competitive in these three performance outcomes determines the reputation and growth of a manufacturing company [2]. In other words, improving throughput through the mitigation of disturbances could enhance a company's position in the market [3].

Job shops consist of a varied set of machines (e.g., lathes, milling machines, drills) that are grouped to perform specific operations in a particular sequence that may vary according to each product [4]. This diversity and complexity introduce greater variation and disruption to production as compared to more repetitive production processes, such as continuous flow. Hence, an enhanced throughput for an existing job shop flow is achieved when process variation and disruption are mitigated. Disruption increases cycle time and lowers throughput, reducing capacity and negatively impacting customer service level, product cost, and company's competitiveness in the market [5]. Therefore, a systemic understanding of disturbances and the introduction of process reliability as a prudent approach for mitigating them is one of the most important considerations in designing and operating job shops.

The disturbance is defined as the temporary production stoppage at any operation within the product routing [6]. There are numerous root causes for a production stoppage, but the industry norm is to explicitly consider only a fraction of the root causes. The

most popular disturbances are usually equipment-related stoppages, such as maintenance and setups. However, other kinds of disturbances may also entail significant impacts on job shop performance, such as the ones related to materials, personnel, or scheduling/information [6]. In this sense, Ahmad et al. [7] proposed four critical dimensions for stability (personnel, materials, equipment, and schedules) of a productive system. Similarly, Smalley [8] adapted these and considered manpower, machines, materials, and methods as basic modules of manufacturing. Finally, Sawhney and Subburaman [9] connected these four dimensions (personnel, equipment, material, and schedule/information) to reliability.

However, few studies have verified how these disturbances should be prioritized in a job shop environment. The prioritization of these disturbances is usually performed based on failure mode and effect analysis (FMEA) and lacks linkage with the desired operational outcomes (e.g., service, quality, and cost) [10,11]. Moreover, there are still some deficiencies in visual analysis, effective calculation, and explicit priority of job shop disturbances. Thus, although FMEA is a widely used method, its application still deserves further development to fulfill such gaps. Based on these arguments, a research question can be raised: “how to prioritize disturbances in a job shop environment so that their mitigation positively impacts cost, quality, and service”.

To answer this question, this study proposed an FMEA-based risk vector approach to prioritize disturbances in order to minimize their impact on service, quality, and cost in job shop environments. The proposed approach also categorizes disturbances based on personnel, equipment, scheduling, and material, as suggested by Sawhney et al. [9]. The application of this method is illustrated through the utilization of an existing dataset from a secondary source, which comprises 111 different organizations whose manufacturing is job shop-based. Finally, disturbances’ evaluation of the entire job shop is composed of the risk vectors obtained from service, quality, and cost through linear mathematics. Results of the proposed method are then compared to traditional FMEA to check for divergences and similarities in the final disturbances ranking.

In addition to its theoretical contribution, this research also implies practical outcomes. Based on our approach, job shop production managers can undertake more assertive decisions with regard to which disturbance to address first. Such an aspect is fundamental since companies usually look for operational performance maximization with minimum efforts. As job shop contexts add a significant amount of complexity to daily decisions, the availability of a method that facilitates prioritizing existing disturbances contributes to a more effective managerial approach. The rest of the paper is structured as follows. Section 2 presents a literature review on the main topics approached in this study, such as FMEA and disturbances sources. Section 3 describes the proposed method, whose results are illustrated and discussed in Section 4. Finally, Section 5 concludes the study and indicates future research opportunities.

2. Literature Review

2.1. Dimensions for Process Stability

First, in terms of personnel, they are directly or indirectly responsible for a variety of disturbances in a job shop. Among the main personnel-related disturbances, employee absenteeism stands out as a key cause of disruptions for production since it impacts not only the productive capacity but also reduces the skill set availability. In fact, Hausknecht et al. [12] demonstrate that productivity losses due to employee absenteeism cost organizations millions of dollars each year. Furthermore, other reasons originated by personnel issues can also impact production, such as employees’ generational changes, cultural differences, and employee turnover [13,14]. A specific personnel issue regards the discipline in following standard operating procedures (SOPs). In job shops, SOPs are usually difficult to develop and implement, which jeopardizes their adherence. Finally, the lack of employees’ engagement and alignment to organizational objectives has been highlighted by Kang et al. [15] as a threat to an enhanced productive flow, since it undermines communication and collaborative behaviors on a daily basis.

Second, equipment disturbances can certainly cause loss of capacity and throughput. Equipment failures cannot be underestimated since they are a common issue in most productive environments [16]. The pursuit of maximizing production benefits has led to machine overloading, accelerating equipment damages. Additionally, improper usage of equipment operated by an unskilled employee might cause speed losses, which waste time and capacity [17–19]. It is noteworthy that qualified tooling, required auxiliary equipment, and utilities in general are all closely associated with equipment. Any of them can affect the efficiency of the equipment, which affects the production process of the entire job shop.

With regard to scheduling, it refers to the allocation of resources to perform a set of tasks over a period of time [20]. In a job shop, scheduling is of great concern to scholars, whose most usual methods comprise algorithms to optimize single or multi-object production [21,22]. Under the environment of the industrial revolution, job shops are facing a big challenge of automation which requires stable scheduling. Proactive scheduling or knowledge-based scheduling all need the ability to recognize unplanned disruptions [23]. As part of job shop management, scheduling has its complex characteristics due to different disturbances. Product diversities and order requirement variability lead to several task inputs, which further result in more complex scheduling [24,25]. Therefore, developing the ability to recognize disturbances originating from the scheduling is critical for operations and production managers.

Finally, regarding materials, which include raw material, work-in-process (WIP), and finished goods [9], a usual management issue is to protect supply chains from serious and costly disruptions and at the same time reduce inventory [26]. At the same time, production and delivery of non-conformity parts can be a serious issue, and it is considered one of the main failures in terms of material [27,28]. Furthermore, material accumulation can generate losses in material, either due to inventory accuracy or deterioration [29,30].

2.2. Performance Outcomes

Yin et al. pointed out the importance of the relationship between product and customer during the revolution of industry [31]. The criteria for a customer to judge a company are service, cost, and the product's quality. The absence of any one factor will lead to the loss of customers [32]. Moreover, the above disturbance will produce three outcomes of service, quality, and cost corresponding to delivery on time, reject, or rework, and any cost-related factors, respectively. The three evaluation criteria will be used as the primary elements of the evaluation function of job shop disturbances.

Service is a potential evaluation standard of a customer for a company. This standard is an accumulating effect that affects whether customers will continue to order products from the company (whose production department belongs to job shop). This customer-to-business relationship will map to the impact on job shop. Therefore, a job shop disturbance affecting the service will cause a serious loss to the company. Learning what disturbances have an impact on the service and the extent of disturbances influencing the service is necessary for this paper. To simplify the difficulty of classification and quantify the service, the term tardiness will replace the service, which is widely quoted in many literature works and could be represented by time and reflects the service in a measurable method [33,34]. Thus, the service below is also tardiness.

Quality is the lifeline of a manufacturing company. It determines whether a company could operate for a long time. Health prognosis [35] and quality-based fault diagnosis [36] are all current topics in academic research today. Good quality products tend to win customer trust which will occupy more market shares, while unqualified products will make customers lose confidence in the product and brand. Therefore, the quality could be a dominant criterion to evaluate a disturbance for job shop. Moreover, the weight of quality could be changed according to the demand of different companies. In this part of the classification, the division of disturbances is based on whether they cause parts, semi-finished, and finished products to be scrapped.

Cost can best reflect the expenditure of a company, and it is also one of the biggest concerns by shareholders. In the past, Rohleder pointed out the importance of cost in the performance measurement of shop [37]. Even now, manufacturing organizations are still faced with pressure on cost [38]. It includes direct material cost, direct labor cost, other direct cost, and indirect cost [39]. Similarly, this paper considers the cost as labor cost [40], equipment cost, scheduling cost [41], and other material cost from the perspective of resources which will explain disturbances more simply.

2.3. Failure Mode and Effects Analysis

FMEA is a design tool that mitigates risks during the design phase before they occur [10]. In evaluating the risk, a risk priority number (*RPN*) represented by severity (*S*), occurrence (*O*), and detection (*D*) is widely accepted by practitioners and researchers, given by:

$$RPN = S \times O \times D \quad (1)$$

where:

S = the severity of a failure;

O = likelihood of occurrence of the failure; and

D = probability of failure being detected before it happens.

Each parameter takes a number from 1 to 10. Higher values of *S* and *O* mean higher effects of a failure and higher probability of a failure happening, respectively. Higher values of *D* mean that it is more difficult to find and prevent a failure before it happens. Therefore, high *RPN* indicates a high risk of priority of failures and managers should focus on these failures to keep the system, process, or the whole workshop reliable. Although FMEA has been proven to be a vital early preventative action, the traditional *RPN* method suffers from many drawbacks when conducted in practical situations [42]. For example, the same *RPN* value could be acquired by different sets of *S*, *O*, and *D*; the weights of three factors are not considered. The following Table 1 is the representative list of research efforts that attempt to overcome the FMEA drawbacks and the prioritization of the corresponding model [9,43–52].

Table 1. Relevant studies on FMEA improvements and prioritization.

Author	Main Contribution
Franceschini and Galetto (2001)	introduced a new method to calculate the risk priority level for the failure model in FMEA in which data is given on qualitative scales and provided by the design team [43]
Xu et al. (2002)	presented a fuzzy-logic-based method integrated with expert assessment for FMEA to overcome the potential difficulty in sharing information among experts from various disciplines [44]
Sharma et al. (2005)	used Occurrence (<i>O</i>), Severity (<i>S</i>), and Detectability (<i>D</i>) as members of a fuzzy set to determine the riskiness level of the failure [45]
Yang et al. (2008)	developed a novel fuzzy rule-based Bayesian reasoning (FuRBaR) approach for prioritizing failures in FMEA [46]
Sawhney and Subburamam (2010)	presented an index of Risk Assessment Value (RAV) to replace the traditional risk level of <i>RPN</i> to assess the failure better in Lean systems [9]
Xiao et al. (2011)	extended the definition of <i>RPN</i> by multiplying it with a weight parameter to address which failures need to be considered and how to combine them appropriately [47]

Table 1. *Cont.*

Author	Main Contribution
Liu et al. (2015)	combined interval two-tuple linguistic variables and gray relational analysis to overcome the shortcomings of low efficiency caused by inconsistent views [48]
Sun et al. (2017)	set up a novel FMEA system that integrated database, self-maintenance, and auto-link with other related production systems [49]
Yazdi (2019)	utilized fuzzy set theory to deal with possible uncertainties during evaluation in FMEA. Analytical hierarchy process and entropy technique were to solve the problem of objective weight [50]
Filz (2021)	used deep learning models on historical and operational data to overcome the subjectivity of fault probabilities [51]
Jin et al. (2022)	integrated the fuzzy into the FMEA algorithm, and used analytic hierarchy process (AHP) to determine the weights of risk indicators [52]

Although the above has many improvements for FMEA, none of them construct an FMEA that addresses job shop issues. Other priority methods are mostly based on other new methods (e.g., fuzzy theory) to study the prioritization, but they are also based on the study of traditional RPN values. Section 3.3 will introduce a modified FMEA using a new concept (risk vector) to assess risks which will provide managers and researchers with a new perspective to understand and evaluate the job shop disturbances.

3. Methodology

In this section, we first introduce the definition of job shop disturbances from three basic requirements. The framework of disturbances division will be described in the form of tree in the second part. The third part presents an analytic disturbance prediction method for job shop with multiple resources and multiple evaluation indexes, which combines the vector computing techniques, FMEA, and FAHP. The last part is to find the critical disturbances through the differentiation index and achieve the prioritization of the disturbances.

3.1. Job Shop Disturbances Definition

There is no universal agreement on a definition for the term disturbance in job shop. Through the search of the literature and other materials [53], we define disturbance as a temporary change in average environmental conditions that causes a pronounced or inconspicuous change in job shop. As highlighted above, temporary change, average environmental conditions, and pronounced or inconspicuous change are the basic requirements in defining disturbance.

- Temporary change: Personnel unavailability or fluctuations in capability. Equipment failure or unplanned events causing performance not up to standard. Scheduling rules and optimization object parameters will vary for the causes of the complexity of job shop. Materials availability and quality will vary due to a volatile market and government behavior.
- Average environmental conditions: Personnel is available and capable of operating machines to get qualified products or conduct other processes. Equipment can work normally without unexpected downtime. Scheduling is appropriate without any disruptions or variance. Materials are available, qualified, and delivered on time.
- Pronounced or inconspicuous change: Production delay, even unable to meet customer needs. Production scrapped resulting in rework or rejection. Company revenue and expenditure changes.

3.2. Framework of Disturbances Division

A framework is developed that consists of two basic phases divided into four levels as outlined in Figure 1:

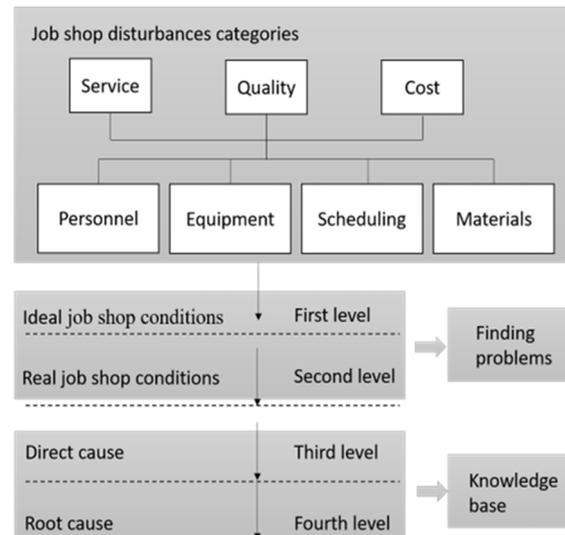


Figure 1. Framework of disturbances division.

- Finding problems: after defining job shop disturbance, finding problems or symptoms in real job shop conditions that differ from ideal job shop conditions becomes the first phase which contains two levels. At the first level, ideal job shop conditions are listed according to the definition to build an ideal job shop that no disturbances will happen, and all activities will remain in their course. Then, at the second level, the actual job shop conditions are established accordingly to reflect the phenomenon that disturbances may happen anywhere at any time. Any actual job shop conditions that are not under the ideal job shop conditions will be considered the so-called disturbance trigger conditions affecting the job shop.
- Knowledge base: it is the second phase of the framework which develops a knowledge base of disturbance causes in the form of a tree. As shown in the figure, the third and fourth level as a knowledge base consists of the core part of the disturbances division and lay the foundation for the following prioritizing disturbances. The knowledge base of this disturbance source comes from the above literature review and experience of Sawhney's research team with over 100 manufacturing organizations, many of which are part of the job shop. Figures 2–5 illustrate the knowledge base in the form of detailed hierarchical trees developed for the personnel, equipment, scheduling, and materials from the perspective of service. Appendix A shows the knowledge base from the perspective of quality and cost.

It can be seen from Figure 2 that based on the criteria of service, personnel in ideal job shop state are shown as available, capable, trained, error free operation, and effective communication. However, in the actual environment, what is opposite to error-free operation is the phenomenon of product defects, customer complaints, incomplete maintenance, insufficient production, and machine halt. Among them, taking the insufficient production as an example, the direct causes include lack of standard process guidance, failure to follow SOP, and lack of training. The root causes of exceeding personal capability include work overload, poor capability, lack of motivation, etc.

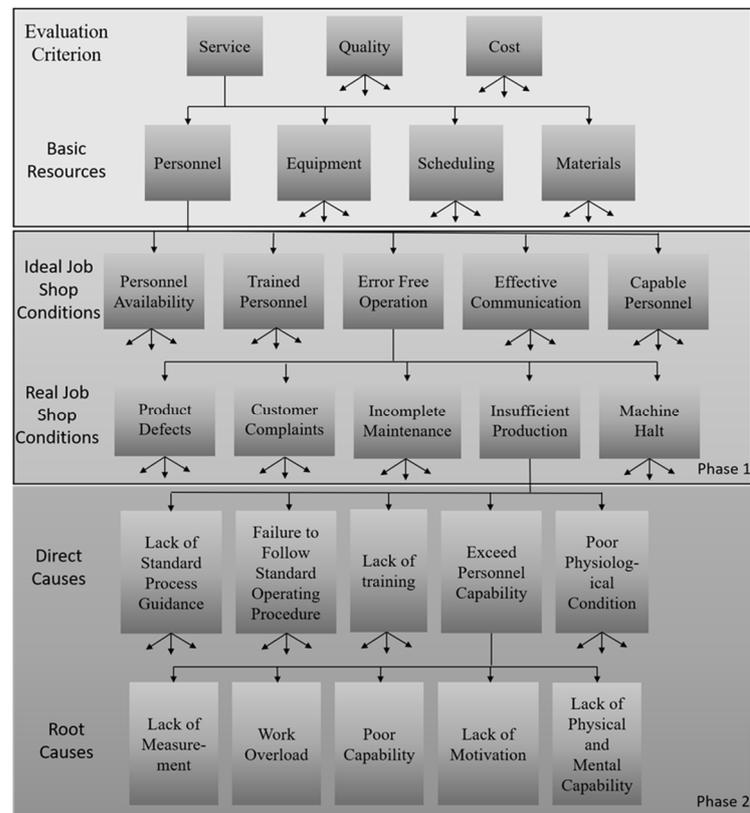


Figure 2. Sample of detailed hierarchical tree for personnel on service.

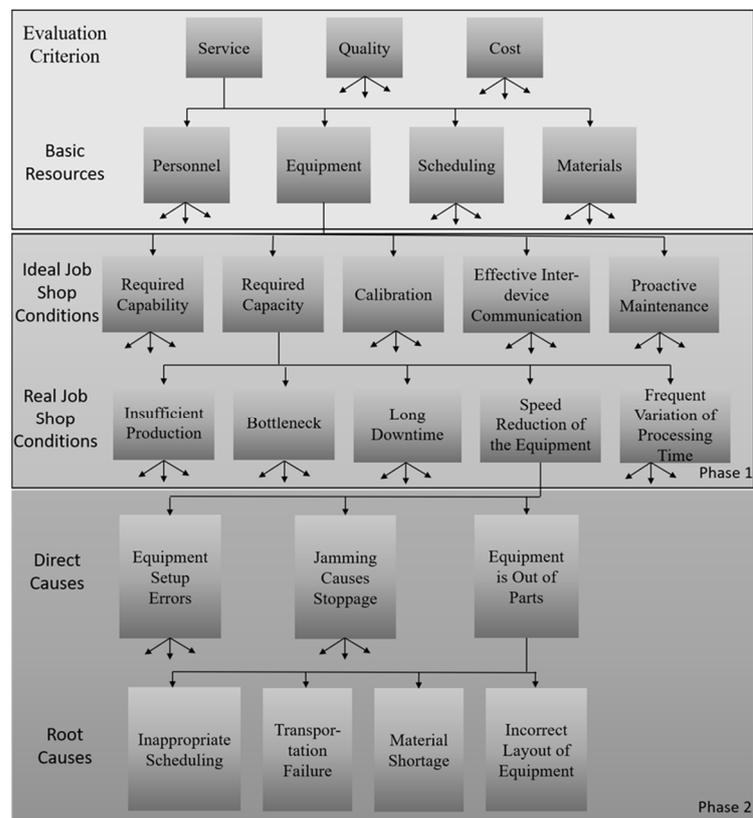


Figure 3. Sample of detailed hierarchical tree for equipment on service.

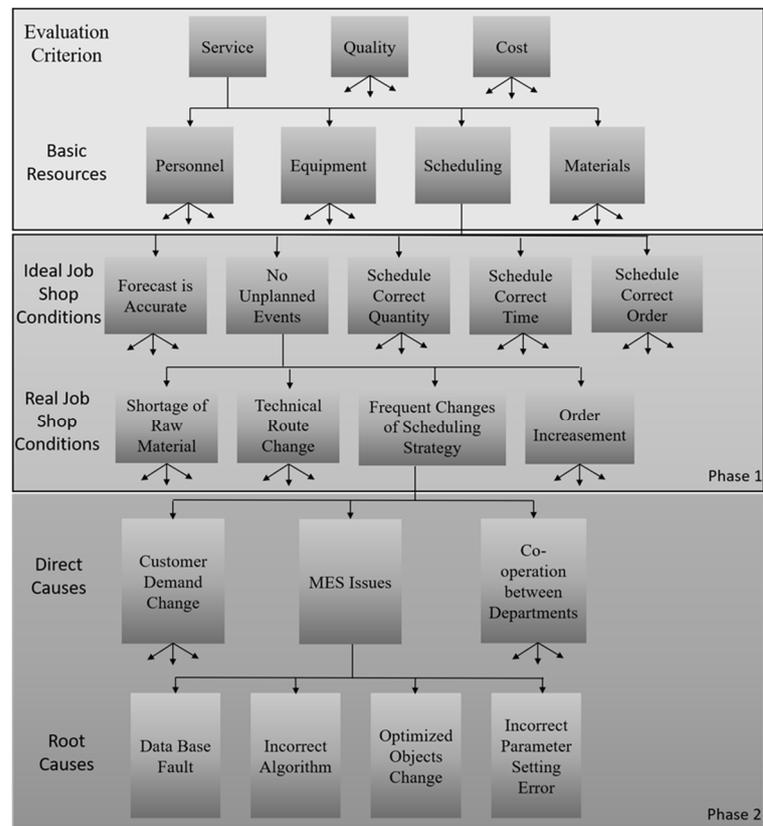


Figure 4. Sample of detailed hierarchical tree for scheduling on service.

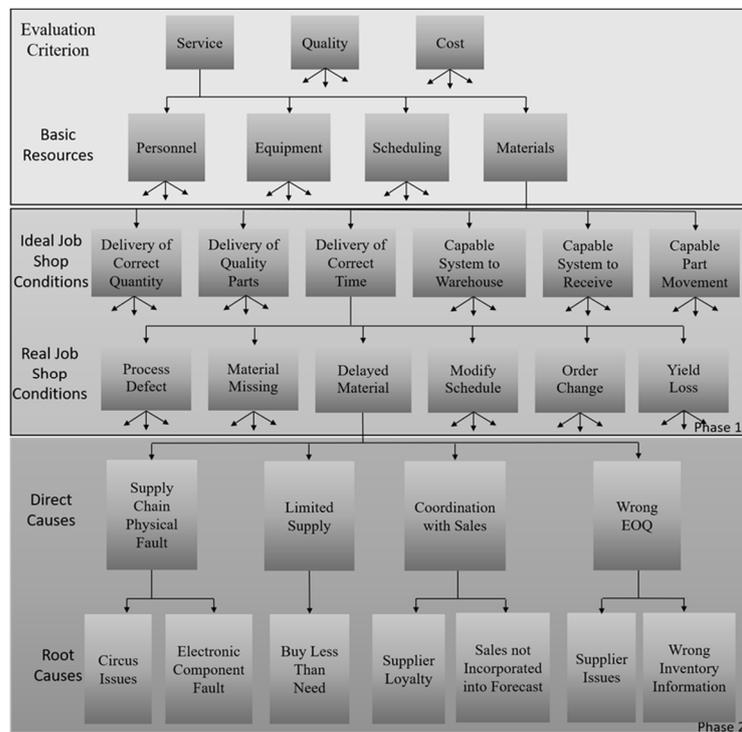


Figure 5. Sample of detailed hierarchical tree for materials on service.

As shown in Figure 3, equipment in ideal job shop conditions based on service are required capability and capacity, calibrated, effective inter-device communication, and proactive maintenance. However, in the actual environment, the opposite of having the

required capacity is the resulting problems such as insufficient production, bottleneck, long downtime, speed reduction of equipment, and frequent variation of processing time. Among them, taking the speed reduction of the equipment as an example, the direct causes include equipment setup errors, jamming causes stoppage, being out of parts, etc. The root causes of being out of parts include inappropriate scheduling, transportation failure, material shortage, and incorrect layout of equipment.

It can be seen from Figure 4 that based on the criteria of service, scheduling in an ideal job shop condition is manifested as accurate forecast, correct quantity and time, etc. However, in the actual environment, what is opposite to no unplanned events is the phenomenon of shortage of raw material, technical route change, frequent changes of scheduling strategy, and order increasement. Among them, taking the frequent changes of scheduling strategy as an example, the direct causes include customer demand change, MES issues, cooperation between departments, etc. The root causes of manufacturing execution system (MES) issues include data base fault, incorrect algorithm, changes of optimized objects, parameter setting error, etc.

As shown in Figure 5, the material in ideal job shop conditions based on service is the delivery of correct quantity, delivery of quality parts, delivery of correct time, etc. However, in the actual environment, the opposite of delivery of correct time is the resulting problems such as process defect, material missing, delayed material, etc. Among them, taking the delayed material as an example, the direct causes include supply chain physical fault, limited supply, coordination with sales, and wrong economic order quantity (EOQ). The root causes of the wrong EOQ include supplier issues and wrong inventory information, etc.

3.3. Disturbance Model

- Risk vector

To evaluate the risk associated with job shop, first, the risk vector of a disturbance is proposed which is defined as follows:

$$\vec{rv}_n = |S_n| \times \vec{i} + |O_n| \times \vec{j} + |D_n| \times \vec{k} \quad (2)$$

where n is a natural number, \vec{rv}_n is the n th disturbance risk vector. $|S_n|$, $|O_n|$, and $|D_n|$ are the severity, likelihood of occurrence, and probability of detection of the disturbance risk vector, respectively, and \vec{i} , \vec{j} , and \vec{k} correspond to the unit direction vectors of x , y , and z axes of three-dimensional coordinates, respectively.

Formula (2) represents the risk assessment of individual disturbance, which includes two characteristic attributes of disturbance direction and magnitude, reflecting the degree of deviation of disturbance to parameters (S , O , and D) and the magnitude of disturbance risk vector, respectively. The disturbance risk vector number (RVN) is recorded as the square of the vector module, that is:

$$RVN = |\vec{rv}|_2 = |S|^2 + |O|^2 + |D|^2 \quad (3)$$

Define the priority of the risk vector of the bias vector \vec{r} on the plane A as:

$$RVN_{A \rightarrow \vec{r}} = |\vec{rv}|^2 \times \cos(\langle \vec{rv}, \vec{r} \rangle) = (|S|^2 + |O|^2 + |D|^2) \times \cos(\langle \vec{rv}, \vec{r} \rangle) \quad (4)$$

where $\cos(\langle \vec{rv}, \vec{r} \rangle)$ the cosine value of the angle between the projection vector of \vec{rv} on the plane A (the plane of the intended projection) and the vector \vec{r} . Since the value of S , O , and D of the disturbance vector parameters are positive numbers, the disturbance vectors are all distributed in the first quadrant. If the plane with normal vector $\vec{i} \times \vec{j}$ is taken as the projection plane, and vector \vec{r} is the unit positive vector of vector \vec{i} , the priority of the risk vector biased to vector \vec{i} on the plane SO can be obtained as follows:

$$RVN_{SO \rightarrow i} = \frac{|S| \times (|S|^2 + |O|^2 + |D|^2)}{\sqrt{|S|^2 + |O|^2}} \tag{5}$$

The risk vector explains the risk of disturbance from the vector mathematical model, converts a single numerical value that is difficult to analyze into a three-dimensional vector, which can reflect the different degree of deviation of the disturbance, and more intuitively expresses the distribution of different disturbance. *RVN* directly reflects the value of disturbance vector and provides a standard for quantitative analysis of disturbance. $RVN_{A \rightarrow \vec{r}}$ defines the priority of the risk vector of the bias vector \vec{r} on the plane *A*, reflects the different degree of bias of the priority of the disturbance risk vector and provides a reference for further analysis of the priority research.

In addition, by traversing the values of parameters *S*, *O*, and *D*, different disturbance risk assessment values can be calculated by the mathematical expression. The specific comparison is shown in Table 2.

Table 2. Comparison of repeatability of disturbance risk number.

Disturbance Risk Assessment	Ndv	RNdv	NNdv	Rr
<i>RPN</i>	120	12%	114	95%
<i>RVN</i>	157	15.7%	150	96%
$RVN_{SO \rightarrow i}$	965	96.5%	34	3.5%

Where Ndv is the number of different values that can be generated by the disturbance risk model. RNdv refers to the ratio of the Ndv generated by the model to the total of 1000 (10 × 10 × 10) combinations. NNdv is the number of elements in Ndv, whose value is not unique in the total 1000 results. Rr is the ratio of NNdv to Ndv. The results show that the new mathematical model can get more different solutions in the numerical results, realize the differentiation of different disturbances, and provide a more continuous solution set for explaining different disturbances.

- Job shop disturbance risk vector

After defining a single disturbance, the overall job shop disturbance risk assessment model can be obtained. The disturbance risk vectors and logical relations of each layer are as follows:

$$\overrightarrow{RVJS} = \{ \overrightarrow{RV}_s, \overrightarrow{RV}_q, \overrightarrow{RV}_c \} \tag{6}$$

$$\overrightarrow{RV}_s = \{ \overrightarrow{rv}_{sp}, \overrightarrow{rv}_{se}, \overrightarrow{rv}_{sd}, \overrightarrow{rv}_{sm} \} \tag{7}$$

$$\overrightarrow{RV}_q = \{ \overrightarrow{rv}_{qp}, \overrightarrow{rv}_{qe}, \overrightarrow{rv}_{qd}, \overrightarrow{rv}_{qm} \} \tag{8}$$

$$\overrightarrow{RV}_c = \{ \overrightarrow{rv}_{cp}, \overrightarrow{rv}_{ce}, \overrightarrow{rv}_{cd}, \overrightarrow{rv}_{cm} \} \tag{9}$$

where \overrightarrow{RVJS} represents job shop disturbance risk vector. \overrightarrow{RV}_s , \overrightarrow{RV}_q , and \overrightarrow{RV}_c represent service disturbance vector, quality disturbance vector, and cost disturbance vector, respectively. \overrightarrow{rv}_{sp} , \overrightarrow{rv}_{se} , \overrightarrow{rv}_{sd} , and \overrightarrow{rv}_{sm} are the personnel, equipment, scheduling, and material disturbance vector related to the service. Similarly, \overrightarrow{rv}_{qp} , \overrightarrow{rv}_{qe} , \overrightarrow{rv}_{qd} , and \overrightarrow{rv}_{qm} are the personnel, equipment, scheduling, and material disturbance vector related to the quality. \overrightarrow{rv}_{cp} , \overrightarrow{rv}_{ce} , \overrightarrow{rv}_{cd} , and \overrightarrow{rv}_{cm} correspond to the resource disturbance vectors related to the cost. Service-, quality-, and price-related disturbance vectors (Equations (7)–(9)) are the set of individual disturbance vectors, while job shop disturbance vector (Equation (6)) is the set of service-, quality-, and cost-related disturbance vectors. The logical relationship is shown in Figure 6.

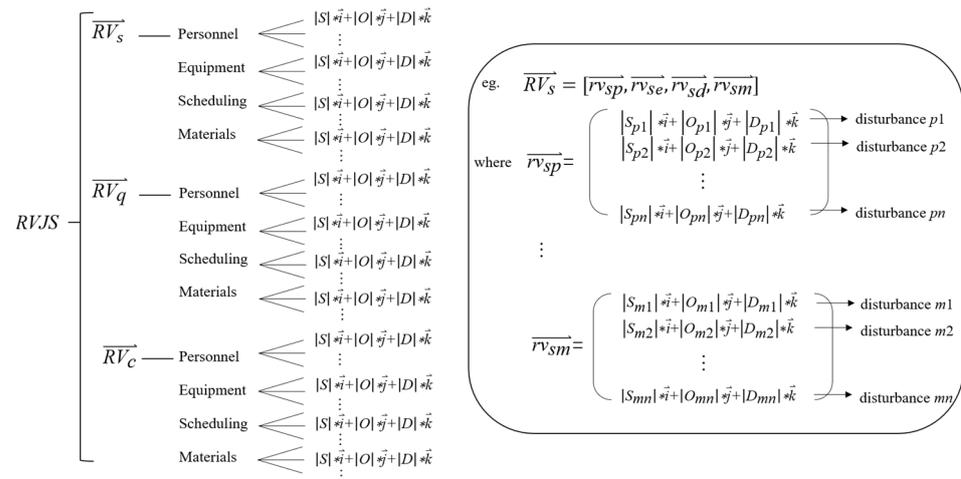


Figure 6. Disturbance risk vector of job shop.

In order to express the magnitude relationship between $RVJS$ and risk vector, Equations (6)–(9) can be written as following expression:

$$\overrightarrow{RVJS} = \omega_s \overrightarrow{RV_s} + \omega_q \overrightarrow{RV_q} + \omega_c \overrightarrow{RV_c} \tag{10}$$

$$\overrightarrow{RV_s} = \omega_{sp} \overrightarrow{rv_{sp}} + \omega_{se} \overrightarrow{rv_{se}} + \omega_{sd} \overrightarrow{rv_{sd}} + \omega_{sm} \overrightarrow{rv_{sm}} \tag{11}$$

$$\overrightarrow{RV_q} = \omega_{qp} \overrightarrow{rv_{qp}} + \omega_{qe} \overrightarrow{rv_{qe}} + \omega_{qd} \overrightarrow{rv_{qd}} + \omega_{qm} \overrightarrow{rv_{qm}} \tag{12}$$

$$\overrightarrow{RV_c} = \omega_{cp} \overrightarrow{rv_{cp}} + \omega_{ce} \overrightarrow{rv_{ce}} + \omega_{cd} \overrightarrow{rv_{cd}} + \omega_{cm} \overrightarrow{rv_{cm}} \tag{13}$$

where ω is the weight, and the FAHP with the trigonometric function and the trapezoidal function as the membership function [50] is used to obtain a more reliable weight value. The steps are as follow:

Step 1: Obtain the fuzzy judgement matrix $[a_{ij}^e]$ ($i = 1, 2, \dots, n; j = 1, 2, \dots, n; e = 1, 2, \dots, E$)

$$[a_{ij}^e] = \begin{bmatrix} 1 & \tilde{a}_{12}^e & \cdots & \tilde{a}_{1n}^e \\ 1/\tilde{a}_{12}^e & 1 & \cdots & \tilde{a}_{2n}^e \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n}^e & 1/\tilde{a}_{2n}^e & \cdots & 1 \end{bmatrix} \tag{14}$$

where \tilde{a}_{ij}^e is the fuzzy relative importance by comparing index i with index j provided by eth expert. The fuzzy corresponding number for relative importance and membership function are shown in Table 3 and Figure 7.

Table 3. The fuzzy corresponding number for relative importance.

Fuzzy Numbers	Qualitative Terms	Fuzzy Numbers
$\tilde{9}$	Absolutely important (AI)	(8,9,9,9)
$\tilde{7}$	Very strongly important (SI)	(5,6,7,8)
$\tilde{5}$	Strongly important (OI)	(4,5,6)
$\tilde{3}$	Weakly important (WI)	(2,3,4,5)
$\tilde{1}$	Equally important (EI)	(1,1,1,2)
$\tilde{2}, \tilde{4}, \tilde{6}, \tilde{8}$	Intermediate value of adjacent positions	(1,2,3), (2,3,4,5), (5,6,7,8), (7,8,9)
The reciprocal of the above numbers	Reciprocal of corresponding position	\tilde{a}_{ij}^{e-1}

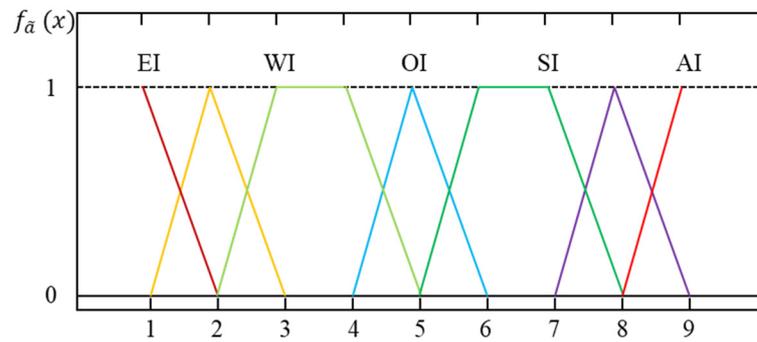


Figure 7. Fuzzy membership functions.

Step 2: The aggregated fuzzy judgement matrix $[\tilde{a}_{ij}] = \sum_{e=1}^E \omega_e \times \tilde{a}_{ij}^e$ is obtained, which is the accumulation of fuzzy judgement matrix of all experts. ω_e is the weight of expert e and could be obtained by the method of AHP by comparing the position, length of service, and education.

Step 3: Examine the consistency of fuzzy judgement matrix. In case $[a_{ij}]$ is consistent, $[\tilde{a}_{ij}]$ is also consistent [54].

Step 4: Using the asymptotic normalization coefficient method, the fuzzy weights of fuzzy comparison values between index is calculated by Equation (15) as follows.

$$\tilde{R}_I = \tilde{a}_{i1} \oplus \tilde{a}_{i2} \oplus \dots \oplus \tilde{a}_{in} \tag{15}$$

where \tilde{a}_{in} is a fuzzy comparison values of index i to index n .

Step 5: For each criterion, the initial fuzzy weights are defined as follows.

$$\tilde{I} = \tilde{I}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} \tag{16}$$

where \tilde{I} is defined as the initial fuzzy weight of index i .

Step 6: Defuzzification procedure. Using center of area to calculate the best non-fuzzy performance value of the fuzzy weights.

$$\omega^* = \frac{\int f(x)xdx}{\int f(x)dx} \tag{17}$$

where ω^* is the weight with a single value obtained from the defuzzification procedure by the center of area method, $f(x)$ is membership function, and x is the variable.

Step 7: Normalize weights.

$$\omega_i^* = \omega_i^* / \sum_{i=1}^k \omega_i^* \tag{18}$$

where ω_i^* is the final weight of each index, and k is the number of different comparison indexes under the same comparison layer.

3.4. Prioritization

After obtaining a series of disturbance vectors, how to prioritize the disturbances that need to be resolved or predict the disturbances that may occur is a problem that job shop managers need to pay attention to. This paper uses the difference index to divide the priority of disturbances and provides the reference for managers to find key disturbances in the first time. Table 4 lists the different indicators and parameters required for priority determination. The key meanings are as follows:

- Disturbance: this refers to the disturbance judgment condition in an ideal job shop environment.
- Parameter: this column contains three parameters: severity, occurrence, and detectability, which are manually entered by the user.

- Risk vector: this is a vector with direction and size acquired by the values of probability of occurrence, severity, and effectiveness of detection. The direction means different degrees of inclination towards the three assessments and modulus (value of risk vector) represents the risk level of a disturbance on different classifications. The square of modulus can range from 3 representing the lowest risk to 300 which represents the highest risk.
- Differentiation index (Diff.index): risk vector practices presenting high risk vector values are critical for the company and should be viewed as improvement opportunities. To best level the disturbances, we use the differentiation index described as follows:

$$\text{Diff.index} = \frac{|\mathbf{RV}|^2 - \overline{|\mathbf{RV}|^2}}{Std} \tag{19}$$

where $|\mathbf{RV}|^2$ represents square of the modulus of each disturbance, $\overline{|\mathbf{RV}|^2}$ and Std represent the average and the standard deviation of risk vector practices respectively. The values which are larger than 1.0 will be considered as the most critical ones [55], and, thus, prioritized to make managers learn these disturbances in their job shops are more important.

Table 4. Prioritization matrix.

Criterion		Parameter		Tradition			Improvement			
Resource	Disturbance	<i>S</i>	<i>O</i>	<i>D</i>	<i>RPN</i>	\vec{rv}	3D	<i>RVN</i>	<i>Diff.index</i>	$RVN_{SO \rightarrow \vec{i}}$
<i>R</i>	<i>c1</i>	<i>S_{c1}</i>	<i>O_{c1}</i>	<i>D_{c1}</i>	<i>RPN_{c1}</i>	\vec{rv}_{c1}	Fig.c1	$ \vec{rv}_{c1} ^2$	<i>Diff.index_{c1}</i>	$RVN_{c1SO \rightarrow \vec{i}}$

	<i>cn</i>	<i>S_{cn}</i>	<i>O_{cn}</i>	<i>D_{cn}</i>	<i>RPN_{cn}</i>	\vec{rv}_{cn}	Fig.cn	$ \vec{rv}_{cn} ^2$	<i>Diff.index_{cn}</i>	$RVN_{cnSO \rightarrow \vec{i}}$

4. Results and Discussion

4.1. Risk Vector

Based on the utilization of previous data, we now illustrate the application of the proposed methodology. The results for service are shown in Tables 5–8 and the remaining are shown in Appendix B.

In total, 63 failure modes were related to either service, quality, or cost, which correspond to different disturbance classifications and prioritization under different criteria. Using the proposed method, 8 critical disturbance sources were obtained, which are shown in bold. As their differentiation indexes were larger than 1.0, such disturbance sources were deemed as critical or special causes, seriously affecting service, quality, or cost of the organization. The remaining failure modes were considered as common causes [56] in all data results analysis. Managers should focus on the above-mentioned critical disturbance causes and clarify the representative ones in their job shops. Compared with the previous method, this method can detect critical disturbance sources from a series of disturbances and achieve efficient job shop disturbance prevention and management. For example, from the results of personnel on service shown in Table 5, the risk vector value of effective communication is 189, and the differentiation index is greater than 1. Therefore, we can conclude that effective communication of personnel on service is the critical cause that managers should pay more attention to.

Table 5. Disturbance priority matrix of personnel on service.

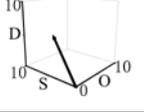
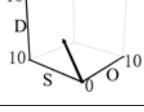
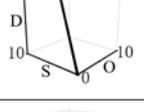
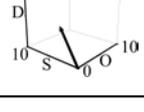
Service		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Personnel	Trained personnel	5	2	5	50	$5\vec{i} + 2\vec{j} + 5\vec{k}$		54	-1.09	50.14
	Personnel availability	7	3	5	105	$7\vec{i} + 3\vec{j} + 5\vec{k}$		83	-0.37	76.29
	Error free operation	7	4	3	84	$7\vec{i} + 4\vec{j} + 3\vec{k}$		74	-0.59	64.25
	Effective communication	8	5	10	400	$8\vec{i} + 5\vec{j} + 10\vec{k}$		189	2.26	160.27
	Capable personnel	5	2	4	40	$5\vec{i} + 2\vec{j} + 4\vec{k}$		45	-1.31	41.78

Table 6. Disturbance priority matrix of equipment on service.

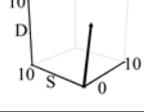
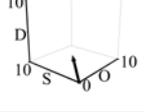
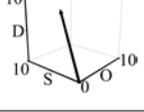
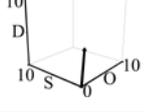
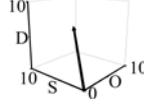
Service		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Equipment	Required capability	5	8	6	240	$5\vec{i} + 8\vec{j} + 6\vec{k}$		125	0.67	66.25
	Required capacity	2	1	3	6	$2\vec{i} + 1\vec{j} + 3\vec{k}$		14	-2.08	12.52
	Calibration	7	4	8	224	$7\vec{i} + 4\vec{j} + 8\vec{k}$		129	0.77	112
	Effective inter-device communication	5	7	2	70	$5\vec{i} + 7\vec{j} + 2\vec{k}$		78	-0.49	45.34
	Proactive maintenance	7	6	6	252	$7\vec{i} + 6\vec{j} + 6\vec{k}$		121	0.58	91.87

Table 7. Disturbance priority matrix of scheduling on service.

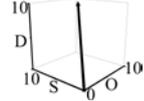
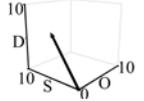
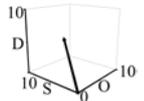
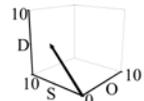
Service		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Scheduling	Predictive is accurate	6	4	8	192	$6\vec{i} + 4\vec{j} + 8\vec{k}$		116	0.45	96.52
	No unplanned events	7	7	10	490	$7\vec{i} + 7\vec{j} + 10\vec{k}$		198	2.49	140.01
	Schedule correct quantity	7	2	6	84	$7\vec{i} + 2\vec{j} + 6\vec{k}$		89	-0.22	85.58
	Schedule correct time	8	6	5	240	$8\vec{i} + 6\vec{j} + 5\vec{k}$		125	0.67	100
	Schedule correct order	8	2	5	80	$8\vec{i} + 2\vec{j} + 5\vec{k}$		93	-0.12	90.22

Table 8. Disturbance priority matrix of material on service.

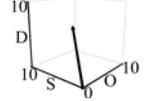
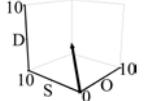
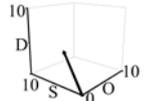
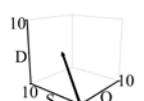
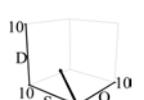
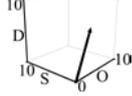
Service		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Material	Delivery of correct quantity	7	6	6	252	$7\vec{i} + 6\vec{j} + 6\vec{k}$		121	0.58	91.87
	Delivery of quality parts	4	3	5	60	$4\vec{i} + 3\vec{j} + 5\vec{k}$		50	-1.19	40
	Delivery of correct time	8	5	3	120	$8\vec{i} + 5\vec{j} + 3\vec{k}$		98	0	83.1
	Capable system to receive	7	4	5	140	$7\vec{i} + 4\vec{j} + 5\vec{k}$		90	-0.19	78.14
	Capable system to warehouse	8	5	2	80	$8\vec{i} + 5\vec{j} + 2\vec{k}$		93	-0.12	78.86

Table 8. Cont.

Service		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
	Capable part movement	2	6	6	72	$2\vec{i} + 6\vec{j} + 6\vec{k}$		76	-0.54	24.03

Moreover, we obtained 26 sequences changed by comparing the disturbances ranking of the traditional method and the new method. The new order is usually determined by the set which has one of the largest values in S, O, and D. It means that in a series of disturbance ordering, the group with the largest influencing factor (S, O, D) usually has the highest sequence number. For example, there are four sequence changes in the fifth group (the first table in Appendix B). In the traditional method, the order from large to small is [8,4,3]-[9,3,3]-[3,2,4]-[7,1,3], while in the new method, the order changes to [9,3,3]-[8,4,3]-[7,1,3]-[3,2,4], which stresses the importance of the higher influencing factor.

While in the case where the magnitude of the influence factor is equal or the difference is small, the group with a large number of large influence factors has the highest serial number. For example, there are two sequence changes in the sixth group (the second table in Appendix B). The traditional order from large to small is [8,6,6]-[8,4,8], while the order of the new method is reversed. From the results, the maximum impact value of both groups is 8, and the two largest influence values of the latter group are 8, while the former group is 8 and 6, which is smaller than the latter. Therefore, the latter has a higher comprehensive risk value, which is the result of the new method. This also illustrates that the new method is more capable of highlighting high-risk disturbances than the traditional methods.

4.2. Job Shop Disturbance Risk Vector

Three experts are selected, and the weight values are 0.27, 0.51, and 0.22 by using the analytic hierarchy process according to the position, length of service, and education. Using the above-mentioned fuzzy analytical hierarchy process, the values of ω_s , ω_q , and ω_c are 0.36, 0.47, and 0.17, respectively; the values of ω_{sp} , ω_{se} , ω_{sd} , and ω_{sm} are 0.475, 0.124, 0.12, and 0.281, respectively; the values of ω_{qp} , ω_{qe} , ω_{qd} , and ω_{qm} are 0.204, 0.393, 0.264, and 0.139, respectively; and the values of ω_{cp} , ω_{ce} , ω_{cd} , and ω_{cm} are 0.23, 0.36, 0.29, and 0.12, respectively. The fuzzy judgment matrix can be seen in Appendix C. From Equations (11)–(13), it can be seen that the service-related disturbance vector, quality-related disturbance vector, and price-related disturbance vector are: $\vec{RV}_s \equiv 32.86\vec{i} + 21.49\vec{j} + 27.6\vec{k}$, $\vec{RV}_q = 32\vec{i} + 20.15\vec{j} + 28.95\vec{k}$, $\vec{RV}_c = 33.78\vec{i} + 24.71\vec{j} + 25.07\vec{k}$. Finally, from Equation (10), it can be obtained that the comprehensive job shop disturbance risk vector is $\vec{RV}_{JS} = 32.61\vec{i} + 21.41\vec{j} + 27.8\vec{k}$.

According to (6)–(13), the weighted service-, quality-, and cost-related disturbance vectors can be moved to the same coordinate, and the end points of the obtained disturbance vectors can be used as the scatter points to further analyze the job shop disturbance vector. In this paper, the relationship between the magnitude of the disturbance risk vector (RPN), the severity (S), and the frequency of occurrence (D) is taken as an example. As shown in Figure 8a, wxs , wyo , and $wz-rv$ are the coordinates of S, O, and RVN after weighting. Service-, quality-, and cost-related disturbances have also been marked in the figure, and the vector addition can be used to obtain \vec{RV}_s , \vec{RV}_q , \vec{RV}_c , and \vec{RV}_{JS} . In Figure 8b, polynomial plane fitting is then carried out and the equations are: $wz = -3.905 + 7.113wxs + 15.93wyo$; $wz = -3.31 + 11.84wxs + 10.84wyo$; $wz = -2.844 + 10.52wxs + 8.709wyo$, where R-square is 0.7729, 0.8297, and 0.8604. The disturbance vector is mainly located on the right side of the plane $wyo = 0.929wxs + 0.117$. It can be seen from the result that after considering the weights, the risk of quality-related disturbances is on average higher than that of the service

and cost disturbance vectors, which is consistent with reality. The analysis and fitting of the three-dimensional vector provide a comprehensive judgment method for the analysis of job shop disturbance, which is convenient for analyzing the distribution of disturbances of different indicators and also provides the possibility to distinguish different risks.

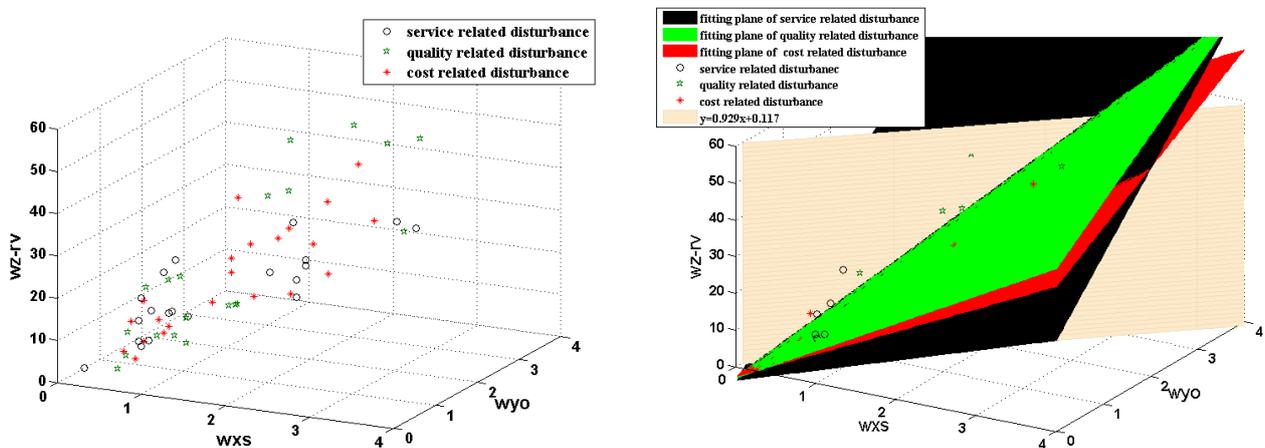


Figure 8. The scatter and fitting diagram of job shop disturbance vector.

5. Conclusions

In this paper, we presented a method for classifying job shop disturbances and provided a detailed explanation of how to evaluate and prioritize these disturbances. The proposed method clearly defined the concept of job shop disturbance and developed the knowledge base of three evaluation criteria and four basic resources in the form of a hierarchical tree to classify the whole job shop disturbances. Risk vector and *RVJS* were developed to realize the visual analysis of the macro disturbance of the whole job shop and improve the ability to analyze different disturbances, while the FAHP with triangle function and trapezoidal function as membership function was integrated into the model to improve the accuracy of the weight. Subsequently, those critical disturbances that should be prioritized were extracted through the differentiation index, which provided a targeted job shop disturbances management method for enterprise managers. Similarly, it is also applicable to other types of workshops. The difference is that the severity, occurrence, and detectability may be different, and the problem with the job shop is that there are more possibilities for its disturbances. The results of repeatability show that the new mathematical model can distinguish more different disturbances. Compared with the traditional FMEA method, the proposed method is more capable of highlighting high-risk disturbances. Moreover, the risk vector and fitting analysis provide a more intuitive visualization method to study the distribution and differences of different disturbances.

The method proposed in this paper still has certain limitations: disturbance correlation and knowledge accuracy still need to be improved. The future work is to further improve the mathematical model and investigate more manufacturing enterprises and factories to enrich the disturbance knowledge base.

Author Contributions: The conceptualization, methodology, writing, and validation were completed by Y.Q.; writing-review and editing, H.Z. All authors have read and agreed to the published version of the manuscript.

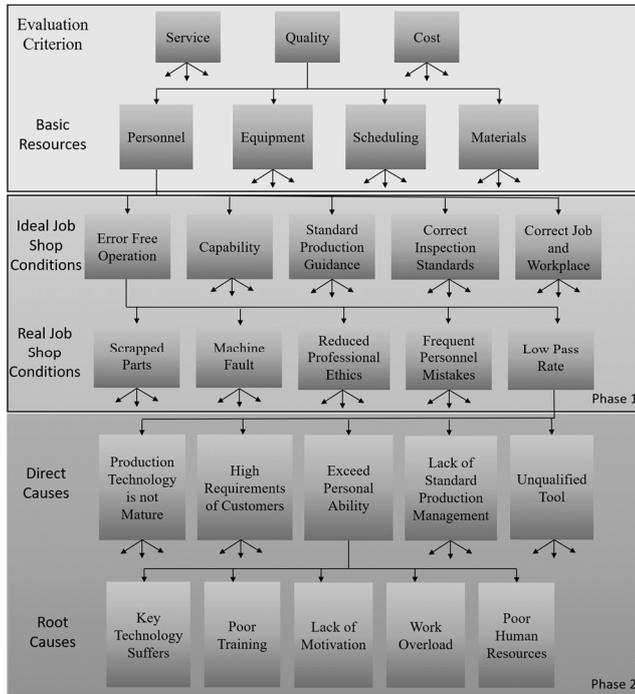
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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

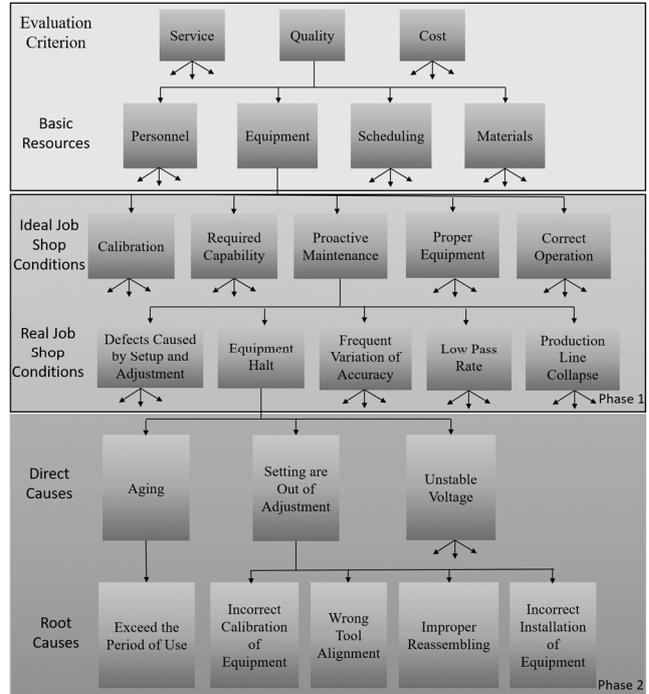
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Conflicts of Interest: The authors declare no conflict of interest.

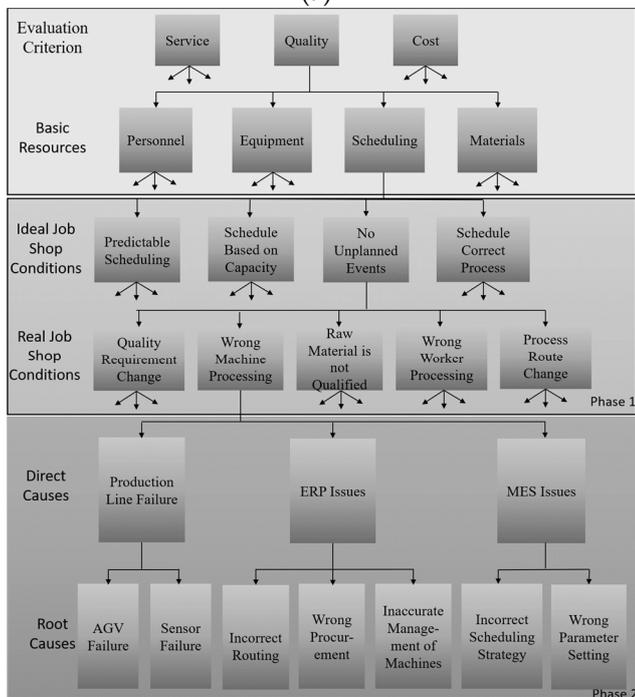
Appendix A



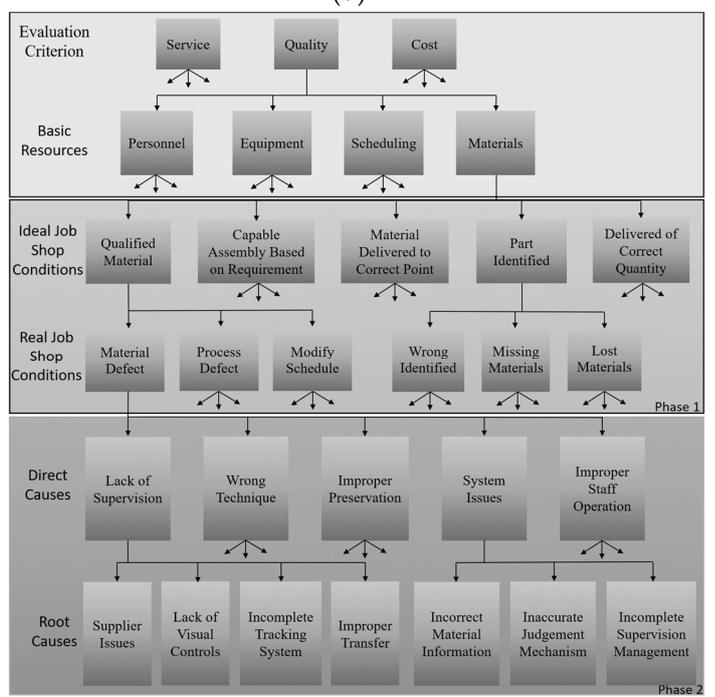
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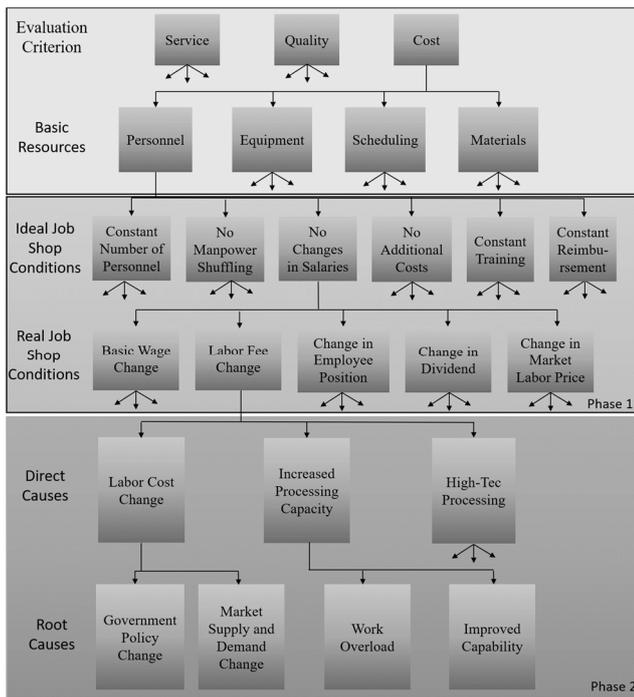


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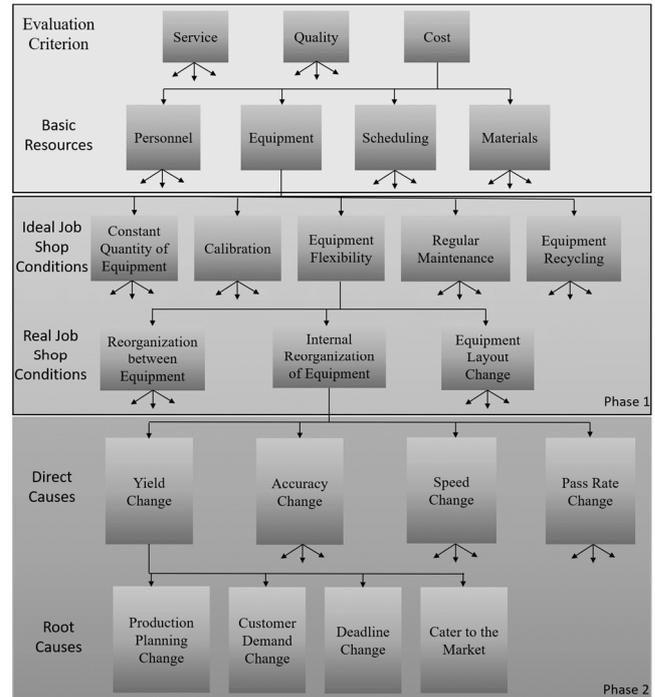


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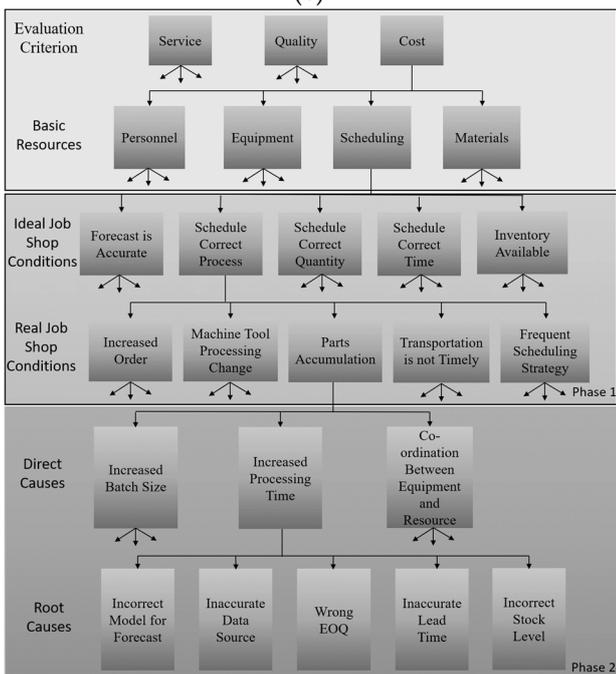
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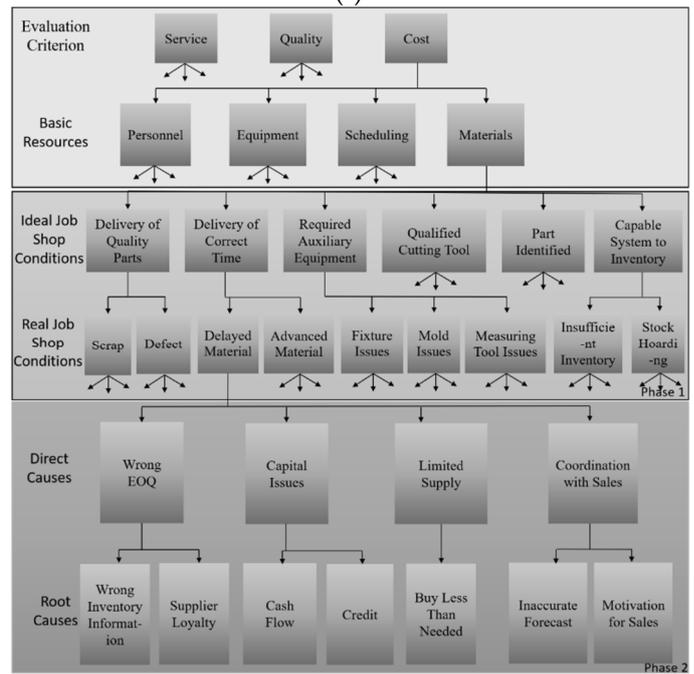
(e)



(f)



(g)



(h)

Figure A1. (a) Diagram of disturbance division for personnel on quality. (b) Diagram of disturbance division for equipment on quality. (c) Diagram of disturbance division for scheduling on quality. (d) Diagram of disturbance division for material on quality. (e) Diagram of disturbance division for personnel on cost. (f) Diagram of disturbance division for equipment on cost. (g) Diagram of disturbance division for scheduling on cost. (h) Diagram of disturbance division for material on cost.

Appendix B

Table A1. Disturbance priority matrix of personnel on quality.

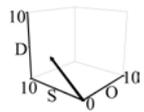
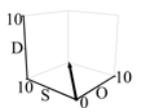
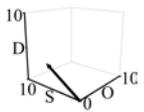
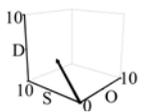
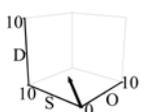
Quality		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Personnel	Error free operation	9	3	3	81	$9\vec{i} + 3\vec{j} + 3\vec{k}$		99	0.03	93.92
	Capability	3	2	4	24	$3\vec{i} + 2\vec{j} + 4\vec{k}$		29	-1.71	23.25
	Standard production guidance	7	1	3	21	$7\vec{i} + 1\vec{j} + 3\vec{k}$		59	-0.96	58.41
	Correct inspection standards	8	4	3	96	$8\vec{i} + 4\vec{j} + 3\vec{k}$		89	-0.22	79.6
	Correct job and workplace	3	1	3	9	$3\vec{i} + 1\vec{j} + 3\vec{k}$		19	-1.96	18.02

Table A2. Disturbance priority matrix of equipment on quality.

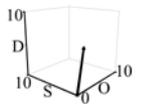
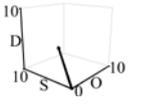
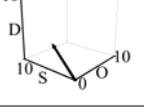
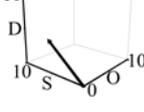
Quality		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Equipment	Calibration	8	4	8	81	$8\vec{i} + 4\vec{j} + 8\vec{k}$		144	1.15	128.8
	Required capability	5	8	6	24	$5\vec{i} + 8\vec{j} + 6\vec{k}$		125	0.67	66.25
	Proactive maintenance	8	6	6	21	$8\vec{i} + 6\vec{j} + 6\vec{k}$		136	0.95	108.8
	Proper equipment	6	2	9	96	$6\vec{i} + 2\vec{j} + 9\vec{k}$		121	0.58	114.79
	Correct operation	9	3	3	9	$9\vec{i} + 3\vec{j} + 3\vec{k}$		99	0.03	93.92

Table A3. Disturbance priority matrix of scheduling on quality.

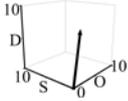
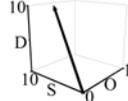
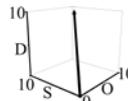
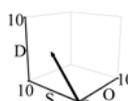
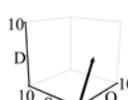
Quality		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Scheduling	Predictable scheduling	2	4	7	56	$2\vec{i} + 4\vec{j} + 7\vec{k}$		69	-0.72	30.86
	Schedule based on capacity	8	3	10	240	$8\vec{i} + 3\vec{j} + 10\vec{k}$		173	1.87	161.98
	No unplanned events	7	7	10	490	$7\vec{i} + 7\vec{j} + 10\vec{k}$		198	2.49	140
	Schedule correct process	7	2	5	70	$7\vec{i} + 2\vec{j} + 5\vec{k}$		78	-0.49	75
	ERP system is capable	2	6	5	60	$2\vec{i} + 6\vec{j} + 5\vec{k}$		65	-0.81	20.55

Table A4. Disturbance priority matrix of material on quality.

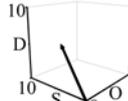
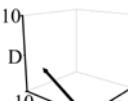
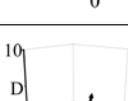
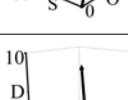
Quality		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Material	Qualified material	7	3	5	105	$7\vec{i} + 3\vec{j} + 5\vec{k}$		83	-0.37	76.29
	Capable assembly based on requirement	9	2	3	54	$9\vec{i} + 2\vec{j} + 3\vec{k}$		94	-0.09	91.76
	Material delivered to correct point	9	4	4	144	$9\vec{i} + 4\vec{j} + 4\vec{k}$		113	0.38	103.26
	Delivered of correct quantity	3	6	4	72	$3\vec{i} + 6\vec{j} + 4\vec{k}$		61	-0.91	27.28
	Part identified	7	7	8	392	$7\vec{i} + 7\vec{j} + 8\vec{k}$		162	1.59	114.55

Table A5. Disturbance priority matrix of personnel on cost.

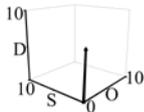
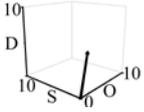
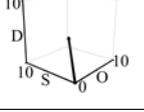
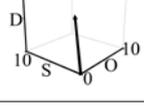
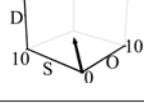
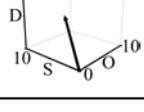
Cost		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Personnel	Correct number of personnel	6	8	4	192	$6\vec{i} + 8\vec{j} + 4\vec{k}$		116	0.45	69.6
	No manpower shuffling	5	8	3	120	$5\vec{i} + 8\vec{j} + 3\vec{k}$		98	0	51.94
	No changes in salaries	8	8	3	192	$8\vec{i} + 8\vec{j} + 3\vec{k}$		137	0.97	96.87
	No additional costs	6	6	5	180	$6\vec{i} + 6\vec{j} + 5\vec{k}$		97	-0.02	68.59
	Constant training	3	2	3	18	$3\vec{i} + 2\vec{j} + 3\vec{k}$		22	-1.89	18.31
	Constant reimbursement	6	4	5	120	$6\vec{i} + 4\vec{j} + 5\vec{k}$		77	-0.52	64.07

Table A6. Disturbance priority matrix of equipment on cost.

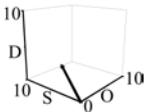
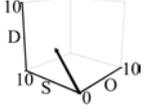
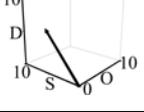
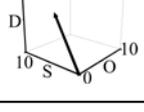
Cost		Parameter			Tradition		Improvement			
Resource	Disturbance	S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
Equipment	Constant quantity	7	4	2	56	$7\vec{i} + 4\vec{j} + 2\vec{k}$		69	-0.72	59.91
	Calibration	8	4	8	256	$8\vec{i} + 4\vec{j} + 8\vec{k}$		144	1.15	128.8
	Equipment flexibility	9	3	5	135	$9\vec{i} + 3\vec{j} + 5\vec{k}$		115	0.43	109.1
	Regular maintenance	7	3	6	126	$7\vec{i} + 3\vec{j} + 6\vec{k}$		94	-0.09	86.4

Table A6. Cont.

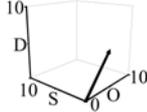
Resource	Cost	Disturbance	Parameter			Tradition		Improvement			
			S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow \vec{i}}$
		Equipment recycling	2	8	4	64	$2\vec{i} + 8\vec{j} + 4\vec{k}$		84	-0.34	20.37

Table A7. Disturbance priority matrix of scheduling on cost.

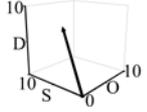
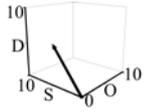
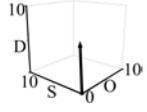
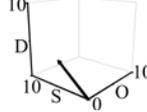
Resource	Cost	Disturbance	Parameter			Tradition		Improvement			
			S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow \vec{i}}$
Scheduling		Forecast is accurate	7	4	7	196	$7\vec{i} + 4\vec{j} + 7\vec{k}$		114	0.4	98.98
		Schedule correct process	7	2	5	70	$7\vec{i} + 2\vec{j} + 5\vec{k}$		78	-0.49	75
		Schedule correct quantity	2	2	6	24	$2\vec{i} + 2\vec{j} + 6\vec{k}$		44	-1.34	31.11
		Schedule correct time	8	6	6	288	$8\vec{i} + 6\vec{j} + 6\vec{k}$		136	0.95	108.8
		Inventory available	8	3	2	48	$8\vec{i} + 3\vec{j} + 2\vec{k}$		77	-0.52	72.1

Table A8. Disturbance priority matrix of material on cost.

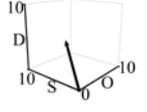
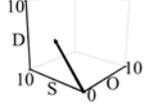
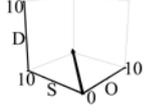
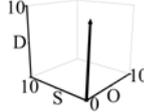
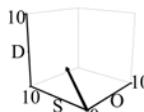
Resource	Cost	Disturbance	Parameter			Tradition		Improvement			
			S	O	D	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow \vec{i}}$
Material		Delivery of correct quantity	5	3	5	75	$5\vec{i} + 3\vec{j} + 5\vec{k}$		59	-0.96	50.59
		Delivery of correct time	7	6	5	210	$7\vec{i} + 6\vec{j} + 5\vec{k}$		110	0.3	83.52
		Material delivered to point of use	9	4	4	144	$9\vec{i} + 4\vec{j} + 4\vec{k}$		113	0.38	103.26

Table A8. *Cont.*

Cost		Parameter			Tradition		Improvement			
Resource	Disturbance	<i>S</i>	<i>O</i>	<i>D</i>	RPN	\vec{rv}	3D	RVN	Diff.index	$RVN_{SO \rightarrow i}$
	Delivery as per schedule	6	5	3	90	$6\vec{i} + 5\vec{j} + 3\vec{k}$		70	-0.69	53.78
	Part identified	5	7	8	280	$5\vec{i} + 7\vec{j} + 8\vec{k}$		138	1	80.21
	Capable system to inventory	8	5	2	80	$8\vec{i} + 5\vec{j} + 2\vec{k}$		93	-0.12	78.86

Appendix C

Table A9. Fuzzy judgement matrix of service-quality-cost.

	Service	Quality	Cost
Service	(1,1,1,2)	(1/5,1/4,1/3,1/2) (1,2,3) (1/6,1/5,1/4)	(2,3,4,5) (2,3,4,5) (1,1,1,2)
Quality	(2,3,4,5) (1/3,1/2,1) (4,5,6)	(1,1,1,2)	(4,5,6) (1,1,1,2) (4,5,6)
Cost	(1/5,1/4,1/3,1/2) (1/5,1/4,1/3,1/2) (1,1,1,2)	(1/6,1/5,1/4) (1,1,1,2) (1/6,1/5,1/4)	(1,1,1,2)

Table A10. Cumulative fuzzy judgement matrix and weight of service-quality-cost.

	Service	Quality	Cost	$\tilde{\omega}_i$	ω_i^*
Service	(1,1,1,2)	(0.6,1.13,1.15,1.71)	(1.73,2.46,3.19,4.19)	(0.32,0.36,0.38,0.37)	0.36
Quality	(1.69,2.27,2.49,3.23)	(1,1,1,2)	(2.47,2.96,2.96,3.96)	(0.49,0.48,0.46,0.43)	0.47
Cost	(0.42,0.45,0.51,0.91)	(0.59,0.61,0.61,1.43)	(1,1,1,2)	(0.19,0.16,0.15,0.19)	0.17

Table A11. Cumulative fuzzy judgement matrix and weight of service-quality-cost on service.

	Personnel	Equipment	Scheduling	Material	$\tilde{\omega}_i$	ω_i^*
Personnel	(1,1,1,2)	(3.02,4.02, 4.51,5.51)	(2.54,3.54, 4.27,5.27)	(1,1,22, 1.22,2.22)	(0.41,0.44, 0.46,0.4)	0.475
Equipment	(0.18,0.23, 0.27,0.37)	(1,1,1,2)	(1,1,27, 1.27,2.27)	(0.61,0.63, 0.67,1.27)	(0.15,0.14, 0.13,0.16)	0.124
Scheduling	(0.19,0.24, 0.3,0.43)	(0.82,0.87, 0.87,1.73)	(1,1,1,2)	(0.6,0.62, 0.64,1.2)	(0.14,0.12, 0.12,0.14)	0.12
Material	(0.85,0.89, 0.89,1.78)	(1.49,1.98, 2.47,3.47)	(2.03,2.52, 2.74,3.74)	(1,1,1,2)	(0.29,0.29, 0.3,0.3)	0.281

Table A12. Cumulative fuzzy judgement matrix and weight of service-quality-cost on quality.

	Personnel	Equipment	Scheduling	Material	$\tilde{\omega}_i$	ω_i^*
Personnel	(1,1,1,2)	(0.61,0.63, 0.67,1.27)	(0.82,0.87, 0.87,1.73)	(1.49,1.98, 2.47,3.47)	(0.216,0.2, 0.196,0.195)	0.204
Equipment	(1.49,1.98, 2.47,3.47)	(1,1,1,2)	(1.51,2.29, 2.8,3.8)	(3.35,4.35, 5.08,6.08)	(0.405,0.429, 0.444,0.354)	0.393
Scheduling	(1,1,2.7, 1.27,2.27)	(0.37,0.43, 0.44,0.81)	(1,1,1,2)	(2.54,3.54, 4.27,5.27)	(0.271,0.278, 0.273,0.239)	0.264
Material	(0.61,0.63, 0.67,6.37)	(0.18,0.22, 0.28,0.4)	(0.19,0.24, 0.3,0.43)	(1,1,1,2)	(0.109,0.093, 0.088,0.212)	0.139

Table A13. Cumulative fuzzy judgement matrix and weight of service-quality-cost on cost.

	Personnel	Equipment	Scheduling	Material	$\tilde{\omega}_i$	ω_i^*
Personnel	(1,1,1,2)	(0.64,0.7, 0.72,1.4)	(1.44,1.66, 1.66,2.41)	(1.22,1.44, 1.66,2.66)	(0.25,0.221, 0.21,0.23)	0.23
Equipment	(1.22,1.71, 1.93,2.93)	(1,1,1,2)	(1.55,2.33, 3.06,3.92)	(1.73,2.73, 3.46,4.46)	(0.32,0.357, 0.393,0.361)	0.36
Scheduling	(1.63,1.9, 1.9,2.7)	(0.42,0.72, 0.78,1.18)	(1,1,1,2)	(2.03,3.03, 3.25,4.25)	(0.295,0.306, 0.289,0.274)	0.29
Material	(0.82,0.84, 0.85,1.67)	(0.24,0.32, 0.38,0.64)	(0.26,0.36, 0.38,0.69)	(1,1,1,2)	(0.135,0.116, 0.109,0.135)	0.12

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