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Machines Tool Operation Optimization Considering the Effective Criteria for Reliability in Industry 4.0

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Abstract
Industry 4.0 includes an important regeneration of production and management systems within manufacturing, where the majority of the procedures will be entirely or partially automated. However, there are insufficient research studies related to machines tool operation optimization considering the effective criteria for reliability in industry 4.0 to enable plants to measure their own conditions and to make future strategies for their activities in this field. Thus, this article proposes a decision-making model using a combination of DEMATEL, ANP and Shannon Entropy, and VIKOR methods with fuzzy features in cellular production systems, considering the effective criteria for reliability in Industry 4.0. Use of fuzzy features aims to bring the problem closer to the real world in this study. The efficiency of proposed model has been validated in a large automotive parts manufacturing plant as a case study. Based on the results, the most critical machine in the category of automatic lathe machines is Machine3, and the ordinary lathe machines is Machine31. Sensitivity analysis shows that changing the weights of criteria affects the individual prioritization of machines but does not have any impact on their overall prioritization. This prioritization has a high level of alignment in terms of priority and accuracy with the perspectives of experts and decision-making teams. The selected critical machine is a sensitive machine in plant and cannot be replaced throughout its equipment lifetime. Finally, practical recommendations for Machines Tool Operation Optimization have been provided in Industry 4.0.

Keywords: *Machine Tool, Operation, Optimization, Reliability, Industry 4.0.*

Introduction

The term reliability was first used in the 1800s to calculate human life insurance, while later this term was used mostly for machine products (mechanical, electrical, electronic, and structural) and not for humans themselves. Applying the term reliability to humans is usually more complicated due to the complexity of biological organisms compared to machine products, but it cannot be said that it is not measurable. Reliability is a quantitative measure of the correct functioning of parts, devices, and systems in general. These systems can be machine, human-machine, or human. Although they are usually used for mechanical systems or engineering or man-made products and artifacts. In the past decades, reliability has been discussed in industries such as military, communications, oil, and gas production. With the accelerating globalization of the economy, competition among manufacturing industries has increasingly intensified. Automotive manufacturing has always been an important investment and development industry in various countries (Yue et al., 2021).

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An automotive company provides quality assurance services to customers based on two criteria, including time and distance traveled to ensure the quality of its products for them and to remind customers of their credibility (Lee et al., 2021). The factors of time and distance driven are referred to as two-dimensional quality assurance areas, and if a minor error or accident occurs during this time, the automotive company offers a parts warranty that incurs quality assurance costs. For this reason, countless automotive manufacturers are increasing their scope of quality assurance in specific markets (Rajaguru & Matanda, 2013).

Meanwhile, sales are continuously increasing rapidly, with companies subsequently paying tens of billions of dollars in after-sales parts warranties (Schumacher et al., 2016). As a result, identifying the durability of automotive parts and systems, along with determining the appropriate level of quality assurance and quality management, significantly affects the competitiveness of an automotive company (Lee et al., 2021).

Hence, if the possibility of failure in terms of quality assurance can be determined by identifying poor machining processes, it will be easy to manage each part and reduce the cost of quality assurance. To support the reliability of automotive parts, machines are prioritized based on the reliability and manufacturing of intact and defective parts in various ways that can determine the reliability of using equipment. Therefore, one of the most challenging tasks in today's automotive industry is product quality control across the automotive supply chain (Chehade et al., 2022). The automotive industry is becoming customer-oriented and needs faster response times to cope with automotive accidents (Lee et al., 2021).

Paying attention to the reliability of complex products is a serious challenge for most manufacturers. Numerous factors affect reliability and increase complexity [9]. Challenges that may jeopardize the reliability of automotive parts generally fall into two categories: First, the lifespan of the parts is different from each other because drivers act differently from each other and high-risk drivers can always cause unexpected accidents. Second, automobiles have a huge volume of parts and a relatively long warranty period compared to other products, which is a more difficult problem because many parts require prediction and the prediction of parts also takes a long time (Zhan & Xiao, 2022).

The Fourth Industrial Revolution is a general concept that refers to a period of technological advancements in industry and production systems. This revolution is based on the integration of devices and systems into internet networks, artificial intelligence, cloud computing, and data analytics to improve performance and optimize production processes (Schumacher et al., 2016).

In the automotive industry, the Fourth Industrial Revolution plays a crucial role. These innovative technologies and concepts enhance production efficiency and quality, reduce production time and costs, increase flexibility and reliability in the production line, and improve the customer experience. For example, the use of smart systems and connecting production devices to the internet network can lead to the collection and analysis of big data to improve the performance of production lines, predict market needs, enhance quality supervision and control, and monitor system maintenance and repairs (Butollo et al., 2019).

Additionally, the implementation of technologies such as artificial intelligence, robotics, the Internet of Things, and augmented reality in the automotive industry can result in increased automation of production processes, improved accuracy and speed of production, reduced errors and work-related accidents, enhanced security and productivity, and the creation of innovation and development opportunities in this industry. Therefore, the Fourth Industrial Revolution in the automotive industry, by harnessing advanced technologies, improves efficiency, optimizes processes, reduces costs, and brings about significant transformations in this industry (Jafari-Asl et al., 2022).

To address these challenges, a machine prioritization approach based on reliability factors to realize the goals of the fourth industrial revolution in the field of operation optimization seems essential. In this case, changes need to be managed to identify failures. In other words, the main goal of prioritizing auto parts manufacturing machines based on reliability enables us to obtain the probability of failures among machines and to decide on the process of using the future type of auto parts machining. Data related to the machining process, including Machine operation time, The total number of manufacturing parts, Number of non-defective parts, Planned manufacturing quantity, Machine availability, Efficiency, Overall Equipment Effectiveness(OEE), and Percentage of non-defective parts, index are required to identify the probability of failures(Butollo et al., 2019).

In this research, the information recorded from the archived documents of a large automotive spare parts plant is used, which is known as a field claim to determine the parts manufactured by each machine, the operation time of machines, etc. The reason for using this data is that it gives us feedback on the expected life of the product. Because providing appropriate manufacturing products with optimal reliability for customers of auto parts manufacturing units to ensure proper operation of the product during its lifetime is considered by logistics, supply, and supply chain experts.

Based on the above, the most important objectives of this research are as follows:

1- Providing a decision-making model that, in addition to identifying the effect of criteria on reliability to realize the goals of the fourth industrial revolution in the field of operation optimization can determine the prioritization of machines using it.

2- Applying the fuzzy property to bring the problem closer to the real world.

3- Determining Cause-and-effect relationships between criteria affecting the reliability of machines, as well as determining the importance of criteria and prioritizing machines in groups.

The rest of the paper is organized as below. The second section provides a literature review of past studies on the main research topic. In the third section, the proposed research method is provided. In the fourth section, the computational results are implemented in a real case study. Finally, in the fifth section, a general conclusion is provided along with suggestions for future research.

Literature Review

Jafari-Asl et al, in their paper, proposed a new framework for accurate reliability analysis based on the improvement of directional simulation using meta-heuristic algorithms. To apply the proposed framework is first tested on five highly nonlinear criterion functions and then applied to solve four engineering problems with high dimensions. The performance of the six simulation-based reliability analysis methods and the first-order reliability method are compared with the proposed method. Furthermore, the feasibility of other meta-heuristic algorithms is investigated. The results show the high-performance capabilities of the improved version of the directional simulation to solve highly nonlinear engineering problems.

Manouchehrinia et al, proposed an evaluation of reliability based on failure to measure random vibration loads due to unexpected loads in different road conditions. Because random loads have been identified as the main cause of failure in reliability analysis. Acceleration signals were measured during road tests conducted on rural and highway road surfaces. The signals were taken from an accelerometer mounted on the suspension system of an urban sedan automobile. The results of this study showed that failure prediction is not affected by cases of dynamic behavior in components in the time domain.

Huang et al, considered warranties for electronics with failure processes. In this study, the failures include minor failure, excessive failure, and catastrophic failure. Also, a dynamic planning approach is designed to provide reliability to obtain optimal solutions for periodic planning. Mi et al, conducted a comprehensive evidence-based network study to analyse the reliability of complex systems with continuously caused failures and complex uncertainties. In addition, two layers, namely a decomposed event layer and a paired layer, are embedded in the system evidence network, resulting in a hierarchical structure of system reliability. As a result, the importance and sensitivity of different components and their effect on system reliability are identified.

Xiao et al. proposed a new learning function with a parallel processing strategy for selecting new training samples for complex systems using Surrogate models. Using the proposed parallel learning strategy for system reliability problems performed through the Cracking surrogate model, one or more new instructional samples can be selected in each iteration to modify the built surrogate models. Three numerical examples were examined to show the validity of the proposed method. The results show that this method has high applicability and accuracy for complex reliability problems. Wang et al. proposed a new reliability analysis method that is a combination of the improved Cracking method for the possibility of small failures. For this purpose, a new strategy for parallel learning is proposed to enable parallel computing and further reduce overall computational time. The proposed method can be applied to a system with low failure probability, multiple failure regions, high nonlinearity, and implicit functions. Finally, the efficiency and accuracy of the proposed method were demonstrated using four numerical examples and compared with the five competing methods reported.

Lee et al. developed a failure and reliability prediction model for auto parts using the initial 6-month field claim. This paper proposes different deep learning methods and compares the work with different methods such as the parametric method, time series method, and machine learning. By conducting experiments, they confirmed that the proposed deep learning model is superior to the existing relevant study, therefore, it is suggested that the deep learning method can maximize performance compared to other existing methods. Soares et al. developed a method to support maintenance management to identify and analyse equipment reliability in a manufacturing factory. This method involves using Laplace test to identify equipment whose reliability decreases over a given period. Then, they carried out an analysis to identify the critical components and related failure factors.

Abolghasemian et al, presented a new framework for prioritizing time in the construction process using an analytical method based on a mathematical model and simulation. For this purpose, the rework parameter and the variables of frequency, duration, and time of call-back have been considered. Also, the effects of these parameters on tangible performance criteria have been investigated.

Ghazi and Pourghader, using fuzzy logic, tried to predict the reliability of passenger automotive tires using machine learning. Thus, they first identified the key criteria affecting the tire reliability, and then, using the opinions of experts, designed and considered rules for training the network. Finally, to validate the model in the best and worst conditions, the validity of the model was measured to investigate the effect of input variables on the output of the model. Hey et al, developed a two-stage supply chain for automotive logistics services. The computational results of the research show that if reliability increases, the optimal order quantity of logistics capability, purchase price, and all expected profits will decrease. Teymouri and Farahani , proposed a model that in addition to the reliability of the part, well investigates the environmental factors affecting the failure rate. Furthermore, since the consumption of many parts is due to their relationship with other parts and the existence of a concept called part failure interaction, these factors are also included in the model as another group of factors affecting demand. The model proposed in this paper, using reliability models and the renewal process, predicts the consumption of spare parts by considering the reliability, factors in the operational environment, and failure interaction.

Tortorella and Fettermann, assessed the development of Industry 4.0 in Brazilian manufacturing companies. They utilized a multivariate analysis to analyze the lean production (LP) practices of 110 companies which were collected by means of a questionnaire form. They found the implementation of the LP and Industry 4.0 technologies has led to larger performance improvements in Brazilian companies. Skrzeszewska et al, assessed the effectiveness of Manufacturing Execution Systems (MES) for production management in Industry 4.0. They analyzed the readiness level of two companies in three levels of management: operational, tactical and strategic. Sadeghi-Niaraki, developed a comprehensive framework to assess the countries' readiness level in Industry4.0 development. The research conducted in several steps. First, the main required clusters and their criteria of Industry 4.0 development assessment such as technological, social, economic, political and environmental clusters determined. Second, the importance of the clusters and their criteria specified using the Fuzzy DEMATLE and Fuzzy ANP techniques. Third, the countries ranked using the VIKOR technique.

According to literature review, machine learning, parametric, and deep learning methods have been considered in the studies to ensure reliability. However, a decision-based model has not been investigated in Industry 4.0. Therefore, the proposed model in this research enables manufacturing companies to decrease huge costs by prioritizing the machines in Cellular Manufacturing Systems in Industry 4.0, with ensuring reliability, taking into account the exact number of future failures of each automotive part. Table 1, shows the literature review.

Table 1.
Literature review

Author	**Year**	**Goal**	**Tools**	**Solution approach**
Sadeghi-Niaraki	2020	Evaluation countries' readiness level in Industry 4.0 development	Decision making	Fuzzy DEMATLE - Fuzzy ANP and VIKOR
Soares et al	(2021)	Support maintenance management to identify and analyse equipment reliability	Experimental	Laplace test
Lee et al	(2021)	Predicting the failure and reliability of automotive parts	Statistical	Time series
Jafari- Asl, et al	(2022)	Calculate reliability analysis based on the improvement of directional simulation	Simulation	Meta-Heuristic
Manouchehrinia, et al	(2022)	Calculate an evaluation of reliability based on failure	Experimental	-
Huang et al	(2022)	Evaluation warranties reliability for electronics with failure processes	Experimental	-
Mi et al	(2022)	Conducted a comprehensive evidence-based network study to analyse the reliability of complex systems	Experimental	-
Xiao et al	(2022)	Studied reliability using a surrogate model	Surrogate model	Cracking

Author	**Year**	**Goal**	**Tools**	**Solution approach**
Wang et al	(2022)	Analysis reliability using a surrogate model	Surrogate model	Machine learning
This research	(2024)	To prioritize and select the most critical machine in cellular manufacturing systems using effective criteria for reliability in Industry 4.0	Decision making	A Fuzzy Hybrid Method of DEMATEL-ANP- Shannon Entropy/VIKOR

Methodology

The proposed framework of this research includes four basic pillars as follows: 1- Determining the complete relationship between criteria, 2- Determining the importance of criteria, 3- Prioritizing the critical machines to determine the most critical machine in manufacturing halls, and 4- Sensitivity Analysis.To carry out this research, a hybrid decision-making framework using DEMATEL (Decision-Making Trial and Evaluation) method is used to determine the complete relationships between criteria and ANP-Shannon Entropy method is used to calculate weight of criteria. Because, the most significant constraint in using decision-making methods is considering the mental importance of criteria, which may lead to different results by changing its value compared to what has been calculated. To overcome this limitation, this article uses combined weights obtained from Shannon Entropy and ANP methods. Finally, using VIKOR (Vlse Kriterijumsk Optimizacija Kompromisno Resenje) method, the prioritization of machines is determined according to the importance determined for the criteria and their criticality. Figure 1 shows the research implementation framework.

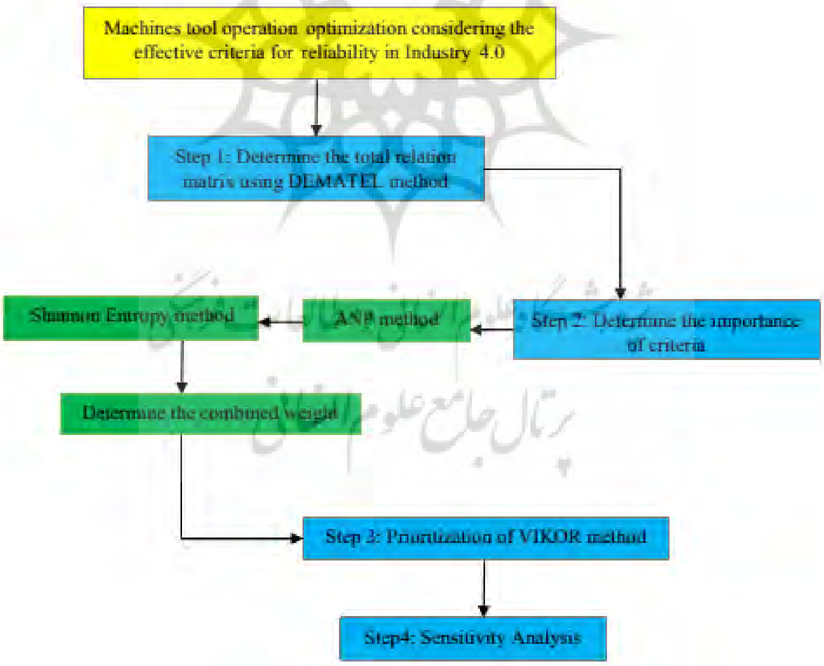

Figure 1. Research method framework

DEMATEL Method

Using DEMATEL method, the effect of criteria on each other is addressed. The steps of this method are:

Step 1: Forming the initial relation matrix

The values of each column and row represent the opinion of experts for the criteria. This matrix shows how each factor affects the other factors of the study. Any criterion that does not affect the similar criterion, its value is considered zero.

$$(1) A = \begin{bmatrix} 0 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 0 \end{bmatrix}$$

Step 2: Normalizing the initial relation matrix

The normal matrix for the initial relations based on Equation 2 can be calculated as follows:

$$(2) \qquad X = {}^{1}\!/_{\max \sum_{j=1}^{n} a_{ij}}$$

$$(3) \qquad N = X.A$$

Where X is the normalized value of each factor and A is the initial relation matrix.

Step 3: Total relation matrix

The total relation matrix Y can be calculated using the normalized matrix N as follows.

$$Y = N(I-N)^{-1}$$

$$(5) \qquad I_n = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$$

Step 4: Calculating sum of the rows and columns in the total relation matrix

In this step, the column matrix $R_{n\times 1}$ is calculated using sum of the rows of the total relation matrix, and the row matrix $C_{1\times n}$ is calculated using sum of columns of the total relation matrix as follows:

$$(6) \qquad R = [\sum_{j-1}^{n} m_{ij}]$$

$$(7) \qquad C = [\sum_{i-1}^{n} m_{ij}]$$

Step 5: Drawing the degree of influence cause and effect criteria diagram

In this step, by calculating $(R_i + C_i)$ and $(R_i - C_i)$ the degree of influence cause and effect criteria diagram is drawn to show the effect of factors on each other.

ANP Method

The steps of ANP method are follows:

Step 1: Building a model and turning the problem into a network structure

In this stage, the problem needs to be turned into a logical system like a network. The network structure can be obtained by brainstorming, nominal group, or any other suitable method. In this research, the relationship between the criteria is obtained using DEMATEL method.

Step 2: Forming a pairwise comparison matrix and determining relative weights vector

The decision elements in each cluster should be compared two by two based on their importance in the equation to the control criteria. Clusters are also compared two by two according to their role and influence in achieving the goal. Also, due to the interdependencies between the elements of a cluster, pairwise comparisons should be made between them.

Step 3: Forming a super matrix and converting it to a limit super matrix

To achieve the final weights in the network, the relative weight vectors are inserted into the appropriate columns of a matrix. The result is a super matrix, each part of which represents the relationship between two clusters in a system.

Step 4: Selecting the top option

The overall priority of the options is obtained from the options column in the normalized limit super matrix.

Shannon Entropy Method

In this step, using Shannon Entropy method, the importance of each of considered criteria for critical equipment prioritizing is determined. To determine the weight, it is necessary to calculate the entropy uncertainty criterion by a certain probability distribution such as p_i in Equation 8:

$$(8) \qquad E_j = -k \sum_{i=1}^{m} p_j \ln(p_j)$$

Therefore, value of d_j or the degree of deviation is calculated, which shows how much useful information the relevant j index provides to the decision maker. The closer measured values are to each other, it shows that the other options are not much different from each other in terms of the index.

$$(9) \qquad d_j = 1 - E_j$$

Finally, the weight of W_j is calculated as follow:

$$(10) \qquad W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

In this research, it is suggested that the weight of criteria be determined using the combined ANP-Entropy method. If the calculated weight of ANP method for considered factors is assumed to be equal to δ_j and the calculated weight of criteria using Shannon

Entropy method is assumed to be equal to γ_j, then the combined weight will be equal to:

(11) $$W_j = \frac{\delta_j \gamma_j}{\sum_{j=1}^{n} \delta_j \gamma_j}$$

VIKOR Prioritization Method

The steps of VIKOR method are:

Step 1: Calculating f_j^* and f_j^- of criteria: for each of criteria $j = 1, \dots, n$, the best f_{ij} is specified as f_j^*, and the worst f_{ij} is specified as f_j^-. The values of f_j^* and f_j^- for positive criteria, are determined from Equation 12.

(12) $$f_j^* = \max f_{ij}\,;\ f_j^- = \min f_{ij}$$

Also, values f_j^* and f_j^- for negative criteria are determined from Equation 13.

(13) $$f_j^* = \min f_{ij}\,;\ f_j^- = \max f_{ij}$$

Step 2: Calculating S_i and R_i according to Equations 14 and 15:

(14) $$S_i = \sum_{j=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}$$

(15) $$R_i = \max[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}]$$

Therefore, $S^* = \min S_i\,;\ S^- = \max S_i\,;\ R^* = \min R_i\,;\ R^- = \max R_i$.

Step 3: Calculating value of VIKOR index for each option according to Equation 16:

(16) $$Q_i = v \times \left[\frac{S_i - S^*}{S^- - S^*}\right] + (1 - v) \times \left[\frac{R_i - R^*}{R^- - R^*}\right]$$

It is assumed that v is a strategic weight and often consider equal to 0.5.

Results

The results of this research have been implemented in alarge automotive spare parts plant. This plant produces aluminum automotive parts, which is considered the main engine parts manufacturer for automotive manufacturers. In the following, the applied results are shown step by step until the results are obtained to determine the critical machines.

The Effect of criteria on each other

By collecting information from the designed questionnaire based on DEMATEL method, considering the scale in Table 2, the decision matrix shown in Table 3 is completed. Table 3 shows direct relation matrix, which is based on the arithmetic mean of the opinions of the experts participating in the research based on DEMATEL scale.

Table 2.
DEMATEL method scale

Verbal phrase	Corresponding value
Much more important	500
Important	400
Intermediate	300
Less important	200
Much less important	100

The triangular fuzzy numbers corresponding to the 5-point Likert spectrum are shown in Table 3. In this table, the certain value corresponding to each verbal value, fuzzy value, and triangular number is written. Fuzzy numbers are converted to crisp numbers using Minkowski formula according to $x = m + {}^{u-l}/_{4}$. In this relation, m is the center of the interval, u is the upper bound, and l is the lower bound of the interval.

Table 3.
Fuzzy numbers of 5-degree Likert spectrum

Verbal variable	Fuzzy value	Triangular fuzzy numbers	Crisp value
Much more Important	$\tilde{1}$	(0,0,0.25)	0.0625
Important	$\tilde{2}$	(0,0.25,0.25)	0.3125
Intermediate	$\tilde{3}$	(0.25,0.5,0.25)	0.625
Less important	$\tilde{4}$	(0.5,0.75,1)	0.875
Much less important	$\tilde{5}$	(0.75,1,1)	1.0625

Table 4.
Direct relation matrix of DEMATEL method

Direct relation matrix	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.000	0.763	0.786	0.768	0.603	0.705	0.714	0.781
C_2	0.777	0.000	0.781	0.741	0.585	0.723	0.737	0.719
C_3	0.723	0.759	0.000	0.696	0.473	0.763	0.830	0.777
C_4	0.808	0.643	0.540	0.000	0.576	0.705	0.799	0.862
C_5	0.625	0.692	0.464	0.496	0.000	0.364	0.531	0.879
C_6	0.790	0.571	0.786	0.670	0.371	0.000	0.763	0.781
C_7	0.808	0.826	0.737	0.741	0.509	0.835	0.000	0.821
C_8	0.692	0.710	0.656	0.817	0.817	0.728	0.786	0.000

To normalize Table 4, it is necessary to specify the sum of rows and columns in the table of the total relation matrix and to divide each of the numbers in this table by the maximum value of these sums. Table 5 shows the sum of the rows and columns of the total relation matrix to determine the maximum value.

Table 5.
Sum of rows and columns

Sum of rows	**Sum of columns**
5.120	5.223
5.062	4.964
5.022	4.75
4.933	4.928
4.051	3.933
4.731	4.823
5.276	5.160
5.205	5.620

According to table 5, maximum value for rows is 5.276 and maximum value for columns is 5.620. Therefore, maximum value is set to 5.620, which is calculated by dividing values of total relation matrix by this value of normal matrix according to Table 6.

Table 6.
Normal matrix

Normal matrix	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.000	0.136	0.140	0.137	0.107	0.125	0.127	0.139
C_2	0.138	0.000	0.139	0.132	0.104	0.129	0.131	0.128
C_3	0.129	0.135	0.000	0.124	0.084	0.136	0.148	0.138
C_4	0.144	0.114	0.096	0.000	0.102	0.125	0.142	0.153
C_5	0.111	0.123	0.083	0.088	0.000	0.065	0.095	0.156
C_6	0.141	0.102	0.140	0.119	0.066	0.000	0.136	0.139
C_7	0.144	0.147	0.131	0.132	0.091	0.149	0.000	0.146
C_8	0.123	0.126	0.117	0.145	0.145	0.129	0.140	0.000

According to tables 7 and 8, using normal matrix and performing necessary operations the total relation matrix $N \times (I-N)^{-1}$ is calculated. For this purpose, first, the inverse matrix obtained by subtracting the identity matrix from the normalized matrix. Then, product of normal matrix in the inverse matrix is obtained as the total relation matrix. In Table 7, the matrix $(I-N)^{-1}$ is calculated.

Table 7.
Matrix $(I-N)^{-1}$

$\boldsymbol{(I-N)^{-1}}$	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**
C_1	1.849	0.928	0.907	0.932	0.701	0.91	0.956	1.019
C_2	0.918	1.758	0.859	0.879	0.608	0.866	0.908	0.954
C_3	0.953	0.917	1.776	0.912	0.674	0.91	0.962	1.007
C_4	0.948	0.885	0.848	1.786	0.679	0.885	0.941	1.002
C_5	0.786	0.765	0.712	0.739	1.492	0.709	0.769	0.862
C_6	0.923	0.854	0.862	0.871	0.633	1.754	0.914	0.966
C_7	1.001	0.961	0.952	0.954	0.706	0.954	1.87	1.052
C_8	0.965	0.927	0.895	0.944	0.737	0.918	0.972	1.905

Table 8.
Total relation matrix

$N \times (I-N)^{-1}$	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.849	0.928	0.911	0.932	0.701	0.91	0.965	1.019
C_2	0.968	0.807	0.908	0.926	0.704	0.911	0.957	1.009
C_3	0.953	0.917	0.78	0.912	0.674	0.91	0.962	1.007
C_4	0.948	0.885	0.852	0.786	0.679	0.885	0.94	1.002
C_5	0.786	0.765	0.714	0.739	0.491	0.709	0.769	0.862
C_6	0.923	0.854	0.866	0.871	0.633	0.753	0.914	0.966
C_7	1.001	0.961	0.925	0.953	0.706	0.954	0.869	1.052
C_8	0.965	0.927	0.898	0.944	0.737	0.918	0.972	0.906

According to table 9, by calculating sum of each row and column, value of D and R are obtained, respectively.

Table 9.
Values of R, D, (D+R) and (D-R)

Criteria	D	R	D-R	D+R
C_1	7.215	7.393	-0.178	14.608
C_2	7.19	7.044	0.146	14.234
C_3	7.115	6.854	0.261	13.962
C_4	6.977	7.063	-0.086	14.04
C_5	5.835	5.325	0.51	11.16
C_6	6.78	6.95	-0.17	13.73
C_7	7.421	7.348	0.073	14.769
C_8	7.267	7.823	-0.556	15.09

By calculating value of D+R and D-R, it is possible to show the degree of influence cause and effect criteria on each other. In this way, the position of each criterion is determined by a point with coordinates (D+R, D-R) in system. Diagram 1 shows the degree of influence cause and effect criteria based on value of D+R and D-R.

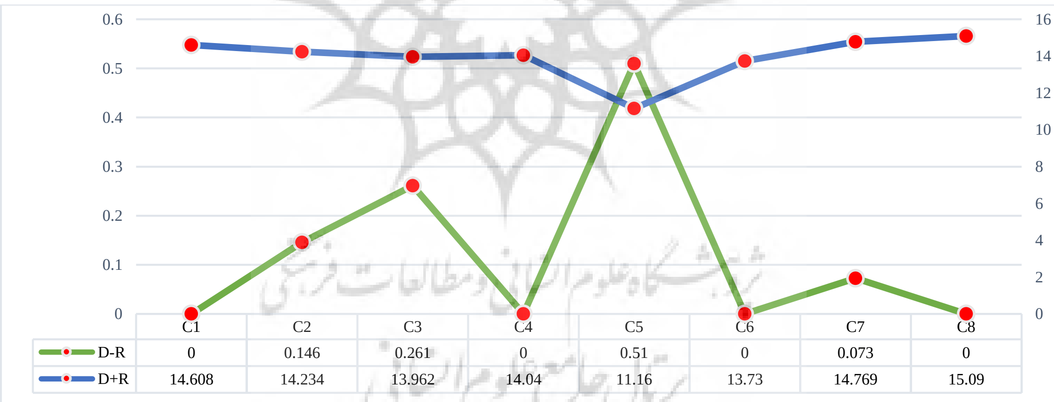

Diagram 1. *The degree of influence cause and effect criteria*

Cause-and-effect variables are also determined using DEMATEL method. Accordingly, Machine operation time, Planned manufacturing quantity, Percentage of non-defective parts, and OEE are causal factors, while Total number of manufactured parts, Number of non-defective parts, Machine availability, and Efficiency are effect factors in this research.

In general, sum of the elements of each row (D) for each factor indicates the degree of influence of that factor on other factors of system. If amount of this variable is more, it means that the factor has more influence. Therefore, Efficiency has the most influence and Machine availability has the least influence on machinery reliability planning. On the other hand, sum of the column elements(R) for each factor indicates the degree of influence of that factor on other factors of system. If value of this variable is higher, it means that the factor is more effective. Based on the results, OEE has the most impact and Machine availability is the least impact.

Based on the above, the horizontal vector (D+R) is how much the intended factor affect in system. In other words, the higher D+R factor, the more it interacts with other system factors. Based on the results, OEE has the most interaction with other criteria and Machine availability has the least interaction. In contrast, the vertical vector (D-R) indicates the effect of each factor. If D-R is positive, factor is a cause variable, and if it is negative, it is an effect.

Accordingly, Machine operation time, Planned manufacturing quantity, Percentage of non-defective parts, and OEE are the criteria of cause, and Total number of manufactured parts, Number of non-defective parts, Machine availability, and Efficiency are the criteria of effect in this research.

Calculation of initial weight using ANP method

To get the initial weight for eight considered criteria, first a network is drawn. The main points of this network as figure 3 are:

Objective: To determine the importance of criteria

Criteria: The eight main criteria are:

Machine operation time (C1).

Total number of manufactured parts (C2),

Number of non-defective parts (C_3),

Planned manufacturing quantity (C4),

Machine availability (C5),

Percentage of non-defective parts (C6),

Efficiency (C7),

OEE (C8).

Options: 33 machines are considered as options.

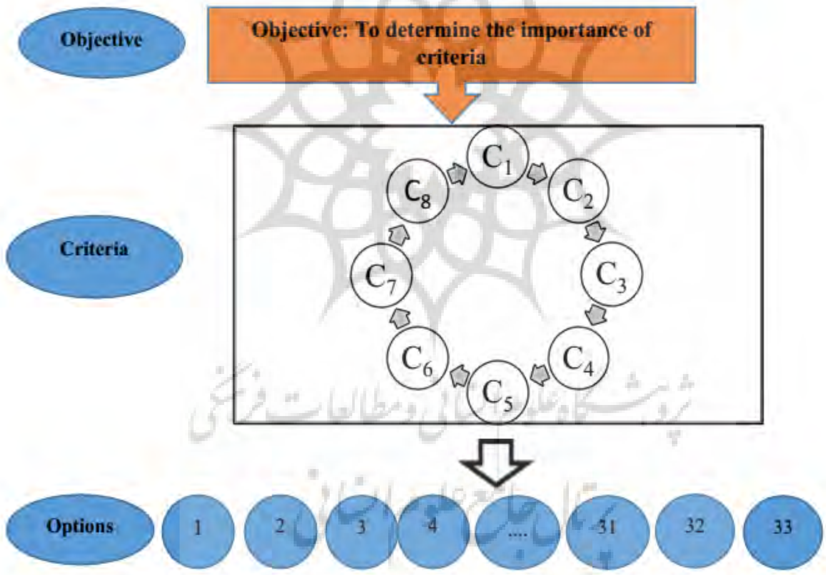

Figure 2. Relationship network of objective, criteria and options

In this stage using ANP method, initial importance of the considered criteria is determined using Super Decision software. For this purpose, the total relation matrix of DEMATEL method is considered as input to pairwise comparison matrix of criteria in ANP method. For the intended pairwise comparison, the incompatibility rate and the importance of criteria are collected.

It is noteworthy that the software has been designed to perform network calculations that focus on ANP method. Therefore, after establishing connections between nodes, it automatically considers the desired network and performs its calculations based on criteria dependencies. Then, by specifying the network relationships in Super Decision software, the pairwise comparison matrix in ANP is obtained that shows in table 10.

Table 10.
ANP pairwise comparison matrix

$N \times (I - N)^{-1}$	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.849	0.928	0.911	0.932	0.701	0.91	0.965	1.019
C2	0.968	0.807	0.908	0.926	0.704	0.911	0.957	1.009
C3			0.78	0.912	0.674	0.91	0.962	1.007
C4				0.786	0.679	0.885	0.94	1.002
C5					0.491	0.709	0.769	0.862
C6						0.753	0.914	0.966
C7							0.869	1.052
C8								0.906

By determining the matrix of pairwise comparisons, the importance of each criteria and the incompatibility rate of pairwise comparison of criteria are calculated. Table 11 shows the importance of all criteria. Given that the incompatibility rate for calculated pairwise comparison is 0.004 and it is less than 0.1, the results of pairwise comparison are acceptable.

Table 11.
Incompatibility rate of criteria

Criteria Number	Value	Criteria Number	Value
C1	0.109	C5	0.119
C2	0.126	C6	0.117
C3	0.135	C7	0.101
C4	0.139	C8	0.151

Calculating combined weight

According to table 12, combined weight of criteria is determined using Shannon Entropy method and weights of ANP method.

Table 12.
Calculations of Shannon Entropy method

Machine Number	C1	C2	C3	C4	C5	C6	C7	C8
Machine1	0.0278	0.0350	0.0351	0.0352	0.0032	0.0031	0.0029	0.0309
Machine2	0.0190	0.0321	0.0323	0.0328	0.0022	0.0031	0.0029	0.0209
Machine3	0.0278	0.0633	0.0637	0.0642	0.0032	0.0031	0.0029	0.0307
Machine4	0.0243	0.0058	0.0058	0.0059	0.0028	0.0031	0.0029	0.0268
Machine5	0.0379	0.0449	0.0451	0.0456	0.0029	0.0031	0.0029	0.0279
Machine6	0.0422	0.0383	0.0376	0.0380	0.0032	0.0030	0.0030	0.0310
Machine7	0.0358	0.0366	0.0368	0.0373	0.0027	0.0031	0.0029	0.0263
Machine8	0.0379	0.0261	0.0262	0.0266	0.0029	0.0031	0.0029	0.0277
Machine9	0.0278	0.0592	0.0596	0.0604	0.0032	0.0031	0.0029	0.0306
Machine10	0.0293	0.0310	0.0312	0.0314	0.0033	0.0031	0.0029	0.0324
Machine11	0.0376	0.0184	0.0183	0.0069	0.0029	0.0018	0.0133	0.0739
Machine12	0.0379	0.0218	0.0209	0.0214	0.0029	0.0030	0.0030	0.0275
Machine13	0.0385	0.0375	0.0377	0.0380	0.0029	0.0031	0.0029	0.0284
Machine14	0.0464	0.0413	0.0413	0.0421	0.0035	0.0031	0.0029	0.0339
Machine15	0.0271	0.0279	0.0281	0.0283	0.0031	0.0031	0.0029	0.0299
Machine16	0.0248	0.0738	0.0742	0.0749	0.0028	0.0031	0.0029	0.0273
Machine17	0.0403	0.0321	0.0323	0.0328	0.0031	0.0031	0.0029	0.0295
Machine18	0.0263	0.0343	0.0345	0.0345	0.0030	0.0031	0.0029	0.0294
Machine19	0.0225	0.0259	0.0260	0.0262	0.0026	0.0031	0.0029	0.0249
Machine20	0.0190	0.0364	0.0366	0.0369	0.0022	0.0031	0.0029	0.0210
Machine16	0.0248	0.0738	0.0742	0.0749	0.0028	0.0031	0.0029	0.0273

Machine Number	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Machine17	0.0403	0.0321	0.0323	0.0328	0.0031	0.0031	0.0029	0.0295
Machine18	0.0263	0.0343	0.0345	0.0345	0.0030	0.0031	0.0029	0.0294
Machine19	0.0225	0.0259	0.0260	0.0262	0.0026	0.0031	0.0029	0.0249
Machine20	0.0190	0.0364	0.0366	0.0369	0.0022	0.0031	0.0029	0.0210
Machine21	0.0420	0.0415	0.0408	0.0414	0.0032	0.0030	0.0030	0.0307
Machine22	0.0286	0.0345	0.0347	0.0352	0.0033	0.0031	0.0029	0.0314
Machine23	0.0278	0.0319	0.0321	0.0325	0.0032	0.0031	0.0029	0.0307
Machine24	0.0278	0.0308	0.0310	0.0311	0.0032	0.0031	0.0029	0.0309
Machine25	0.0293	0.0348	0.0350	0.0356	0.0033	0.0031	0.0029	0.0321
Machine26	0.0247	0.0087	0.0087	0.0086	0.0028	0.0031	0.0030	0.0278
Machine27	0.0278	0.0064	0.0064	0.0069	0.0032	0.0031	0.0027	0.0287
Machine28	0.0266	0.0096	0.0097	0.0097	0.0030	0.0031	0.0029	0.0297
Machine29	0.0231	0.0113	0.0114	0.0114	0.0026	0.0031	0.0029	0.0257
Machine30	0.0299	0.0034	0.0033	0.0033	0.0034	0.0031	0.0030	0.0336
Machine31	0.0285	0.0273	0.0260	0.0263	0.3117	0.2928	0.3111	0.0301
Machine32	0.0266	0.0226	0.0223	0.0226	0.2935	0.3080	0.2955	0.0284
Machine33	0.0269	0.0157	0.0152	0.0158	0.3051	0.3072	0.2954	0.0294
E_j	0.1052	0.1016	0.1015	0.1012	0.0487	0.0490	0.0496	0.1051
d_j	0.8948	0.8984	0.8985	0.8988	0.9513	0.9510	0.9504	0.8949
w_j	0.1219	0.1224	0.1224	0.1225	0.1296	0.1296	0.1295	0.1220
λ_j	0.1090	0.1260	0.1350	0.1390	0.1190	0.1170	0.1010	0.1510
$w_j * \lambda_j$	0.0133	0.0154	0.0165	0.0170	0.0154	0.0152	0.0131	0.0184
W_j	0.1069	0.1240	0.1329	0.1369	0.1241	0.1219	0.1052	0.1481

VIKOR ranking

Table 13 shows the decision matrix in VIKOR method. This table has been compiled based on the classified information contained in the archived documents of a large automotive spare parts plant in the period from April 2020 to April 2022. In this table, Machine operation time is a negative criteria and other criteria are positive.

Table 13.
Decision matrix in VIKOR method

Machine Number	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Machine1	18960	10308	10289	10200	73.15	99.80	101.10	73.79
Machine2	12960	9461	9461	9500	50.00	100.00	99.60	49.79
Machine3	18920	18658	18651	18600	72.99	100.00	100.30	73.19
Machine4	16560	1704	1704	1700	63.89	100.00	100.20	64.04
Machine5	25860	13225	13197	13200	66.51	99.80	100.20	66.5
Machine6	28746	11294	11007	11000	73.94	97.50	102.70	73.98
Machine7	24425	10781	10773	10800	62.82	99.90	99.82	62.66
Machine8	25800	7682	7669	7700	66.36	99.80	99.80	66.09
Machine9	18960	17464	17464	17500	73.15	100.00	99.80	73
Machine10	19960	9129	9129	9100	77.01	100.00	100.30	77.25
Machine11	25620	5424	5357	2000	65.90	58.70	456.50	176.5
Machine12	25860	6414	6124	6200	66.51	95.50	103.50	65.7
Machine13	26215	11055	11041	11000	67.43	99.90	100.50	67.68
Machine14	31650	12175	12111	12200	81.40	99.50	99.80	80.81
Machine15	18480	8217	8217	8200	71.30	100.00	100.20	71.44
Machine16	16880	21759	21736	21700	65.12	99.90	100.30	65.23
Machine17	27500	9470	9470	9500	70.73	100.00	99.70	70.51
Machine18	17960	10117	10117	10000	69.29	100.00	101.20	70.1
Machine19	15360	7630	7630	7600	59.26	100.00	100.40	59.49
Machine20	12960	10729	10729	10700	50.00	100.00	100.30	50.14
Machine21	28620	12247	11949	12000	73.61	97.60	102.10	73.3
Machine22	19480	10167	10162	10200	75.15	100.00	99.70	74.87

Machine Number	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Machine23	18960	9413	9413	9400	73.15	100.00	100.10	73.25
Machine24	18960	9087	9081	9000	73.15	99.90	101.00	73.81
Machine25	19960	10260	10260	10300	77.01	100.00	99.60	76.71
Machine26	16840	2554	2553	2500	64.97	100.00	102.20	66.35
Machine27	18960	1875	1875	2000	73.15	100.00	93.80	68.58
Machine28	18160	2832	2829	2800	70.06	99.90	101.10	70.79
Machine29	15760	3329	3329	3300	60.80	100.00	100.90	61.34
Machine30	20400	989	969	950	78.70	98.00	104.10	80.28
Machine31	19422.00	8054.33	7613.00	7616.67	71.80	93.73	107.00	71.77
Machine32	18109.17	6652.00	6541.17	6533.33	67.62	98.57	101.63	67.71
Machine33	18344.17	4630.33	4461.33	4583.33	70.27	98.32	101.60	70.12

According to table 14, S_i and R_i criteria are calculated using VIKOR method.

Table 14.
Values of S_i and R_i

Machine Number	S_i	R_i	Machine Number	S_i	R_i
Machine1	0.7603	0.1237	Machine18	0.7740	0.1243
Machine2	0.8381	0.1481	Machine19	0.8480	0.1367
Machine3	0.6024	0.1237	Machine20	0.8140	0.1477
Machine4	0.9480	0.1320	Machine21	0.6716	0.1236
Machine5	0.6737	0.1285	Machine22	0.7577	0.1236
Machine6	0.6884	0.1236	Machine23	0.7772	0.1237
Machine7	0.7324	0.1330	Machine24	0.7832	0.1237
Machine8	0.7793	0.1290	Machine25	0.7509	0.1236
Machine9	0.6244	0.1237	Machine26	0.9279	0.1287
Machine10	0.7722	0.1236	Machine27	0.9248	0.1300
Machine11	0.7142	0.1300	Machine28	0.9097	0.1247
Machine12	0.8068	0.1295	Machine29	0.9251	0.1346
Machine13	0.7115	0.1272	Machine30	0.9207	0.1369
Machine14	0.6434	0.1235	Machine31	0.4635	0.1224
Machine15	0.8048	0.1237	Machine32	0.5047	0.1271
Machine16	0.5648	0.1300	Machine33	0.5345	0.1243
Machine17	0.7302	0.1239			

According to Table 15 and consider value of $S^* = 0.463$, $S^- = 0.948$, $R^* = 0.122$, and $R^- = 0.1$, VIKOR index Q_i is calculated.

Table 15.
VIKOR index Q_i

Machine Number	$\boldsymbol{Q_i}$	**Machine Number**	$\boldsymbol{Q_i}$
Machine1	0.3308	Machine18	0.3584
Machine2	0.8865	Machine19	0.6762
Machine3	0.1680	Machine20	0.8538
Machine4	0.6863	Machine21	0.2391
Machine5	0.3368	Machine22	0.3275
Machine6	0.2563	Machine23	0.3482
Machine7	0.4847	Machine24	0.3545
Machine8	0.4551	Machine25	0.3199
Machine9	0.1906	Machine26	0.6025
Machine10	0.3418	Machine27	0.6238
Machine11	0.4064	Machine28	0.5054
Machine12	0.4923	Machine29	0.7136
Machine13	0.3490	Machine30	0.7544
Machine14	0.2074	Machine31	0.0000
Machine15	0.3774	Machine32	0.1349
Machine16	0.2533	Machine33	0.1108
Machine17	0.3039		

According to table 16 and VIKOR index, general and separate prioritization is determined for each of machines.

Table 16.
Prioritization of machines

Machine Number	Q_i	General priority	Separate Priority	Machine Number	Q_i	General priority	Separate Priority
Machine1	0.3308	13	10	Machine18	0.3584	19	16
Machine2	0.8865	33	30	Machine19	0.6762	28	25
Machine3	0.1680	4	1	Machine20	0.8538	32	29
Machine4	0.6863	29	26	Machine21	0.2391	7	4
Machine5	0.3368	14	11	Machine22	0.3275	12	9
Machine6	0.2563	9	6	Machine23	0.3482	17	14
Machine7	0.4847	23	20	Machine24	0.3545	18	15
Machine8	0.4551	22	19	Machine25	0.3199	11	8
Machine9	0.1906	5	2	Machine26	0.6025	26	23
Machine10	0.3418	15	12	Machine27	0.6238	27	24
Machine11	0.4064	21	18	Machine28	0.5054	25	22
Machine12	0.4923	24	21	Machine29	0.7136	30	27
Machine13	0.3490	16	13	Machine30	0.7544	31	28
Machine14	0.2074	6	3	Machine31	0.0000	1	1
Machine15	0.3774	20	17	Machine32	0.1349	3	3
Machine16	0.2533	8	5	Machine33	0.1108	2	2
Machine17	0.3039	10	7				

According to prioritization, the most critical machine in the category of automatic lathe machines is Machine3, and the ordinary lathe machines is Machine31. Based on the results obtained, this prioritization has a high level of conformity with the views of experts and the decision-making team because, in practice, the selected critical machine is one of the sensitive and expensive machines in the plant, and replacing it is impossible to sustain the production process. This underscores the importance of selecting optimal maintenance and repair strategies for the equipment of this plant.

Sensitivity Analysis

By changing value of weight parameter of criteria the alternatives are re-prioritized. For this purpose, the obtained combined weight is replaced by calculated weights of ANP and Shannon Entropy method. Therefore, by using each of the weights for criteria, a separate prioritization has been determined using VIKOR method. Finally, the overall ranking is calculated using the average ranks. It should be noted that the alternative that has the lowest average in the ranks is given higher priority. Based on this, Machine31, Machine33, and Machine32 are placed in the first, second, and third priorities respectively. According to table 17 and diagram 2, the change in the weight of criteria affects the individual prioritization of machines and does not affect the overall prioritization.

Table 17.
Changing the criteria weights and re-prioritization of machines

Machine Number	Q_i Hybrid	Q_i ANP	Q_i Shannon Entropy	Rank Hybrid	Rank ANP	Rank Shannon Entropy	Rank average	Final Ranking
Machine1	0.330838	0.358668	0.82506	13	13	17	14.33333	14
Machine2	0.886533	0.882092	0.902838	33	33	26	30.66667	33
Machine3	0.167972	0.200148	0.682204	4	3	5	4	4
Machine4	0.686265	0.738937	0.996903	29	29	33	30.33333	30
Machine5	0.33677	0.399044	0.737927	14	17	9	13.33333	12
Machine6	0.256325	0.27768	0.748194	9	8	10	9	9
Machine7	0.484705	0.532482	0.792393	23	23	14	20	21
Machine8	0.455076	0.519949	0.833708	22	22	18	20.66667	22
Machine9	0.190602	0.227232	0.702177	5	6	6	5.666667	6
Machine10	0.341812	0.312218	0.835296	15	11	19	15	15

Machine Number	Q_i Hybrid	ANP	Shannon Entropy	Rank Hybrid	ANP	Shannon Entropy	Rank average	Final Ranking
Machine11	0.406396	0.455636	0.78975	21	21	13	18.33333	19
Machine12	0.492311	0.556606	0.857623	24	24	23	23.66667	24
Machine13	0.348982	0.418048	0.771873	17	18	11	15.33333	16
Machine14	0.207403	0.17247	0.705653	6	2	7	5	5
Machine15	0.377362	0.449498	0.865835	20	20	24	21.33333	23
Machine16	0.253334	0.305677	0.64952	8	10	4	7.333333	7
Machine17	0.303916	0.386249	0.787875	10	15	12	12.33333	11
Machine18	0.358379	0.440973	0.838116	19	19	20	19.33333	20
Machine19	0.676158	0.714979	0.907322	28	28	27	27.66667	26
Machine20	0.853781	0.849885	0.881102	32	32	25	29.66667	29
Machine21	0.239107	0.272113	0.733184	7	7	8	7.333333	7
Machine22	0.327474	0.336069	0.822566	12	12	16	13.33333	12
Machine23	0.348246	0.386676	0.840514	16	16	21	17.66667	17
Machine24	0.354489	0.382909	0.845851	18	14	22	18	18
Machine25	0.319858	0.295071	0.816126	11	9	15	11.66667	10
Machine26	0.602522	0.674987	0.978187	26	26	32	28	27
Machine27	0.623771	0.682375	0.975043	27	27	30	28	27
Machine28	0.505416	0.583759	0.960936	25	25	28	26	25
Machine29	0.713644	0.76386	0.976613	30	30	31	30.33333	30
Machine30	0.754432	0.786056	0.968877	31	31	29	30.33333	30
Machine31	0	0.097321	0	1	1	1	1	1
Machine32	0.134885	0.215618	0.107977	3	5	3	3.666667	3
Machine33	0.110838	0.203723	0.09424	2	4	2	2.666667	2

The results of sensitivity analysis implementation is shown in diagram 2.

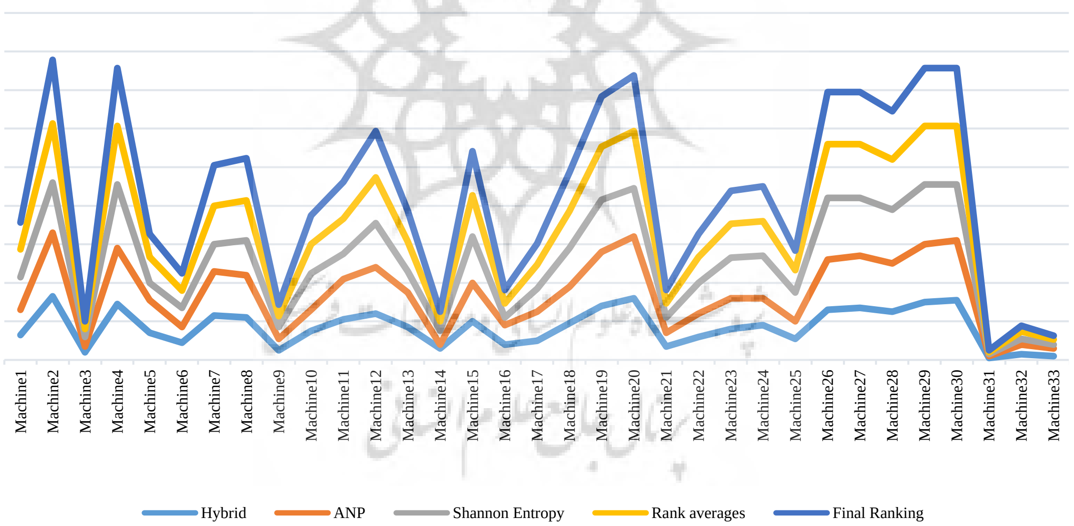

Diagram 2. *The results of sensitivity analysis*

Conclusion

The Industry 4.0 refers to a new concept of industrial and technological advancements in the modern world. Ensuring system safety and reliability is increasingly becoming a fundamental issue in the digital transformation paradigm, also known as Industry 4.0, with the introduction of new technologies and the growth of system complexity. In fact, the concern about reliability and safety is developing in various industries, which plays an important role in meeting demand and increasing productivity and availability at the lowest possible cost and with the least unexpected breakdowns. In order to identify and mitigate process bottlenecks, proactive approaches to reliability and safety analysis are critical in high-risk sectors. As part of the efforts to development of operational strategies in the fourth industrial revolution is prioritization of machinery based on comprehensive analysis of maintenance risks and operational repairs. Based on this, in this paper, a combination of DEMATEL, ANP and Shannon entropy and VIKOR methods with fuzzy features in cellular production systems is presented, considering effective criteria for reliability in Industry 4.0. Based on the results, the implementation of this method can contain valuable knowledge for continuous improvement of maintenance, productivity, increasing the level of equipment availability and increasing efficiency by monitoring equipment performance for maintenance managers. The presented method provides additional information for decision-making, enabling the most critical machine selection in Cellular Manufacturing Systems. As suggestions for future research to optimize machine performance in Industry 4.0, determining critical machine failures, prioritizing critical machine failures, identifying the most critical failures, and investigating the causes of these failures can be considered. Also, solutions can be explored to reduce or eliminate identified critical machine failures.

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