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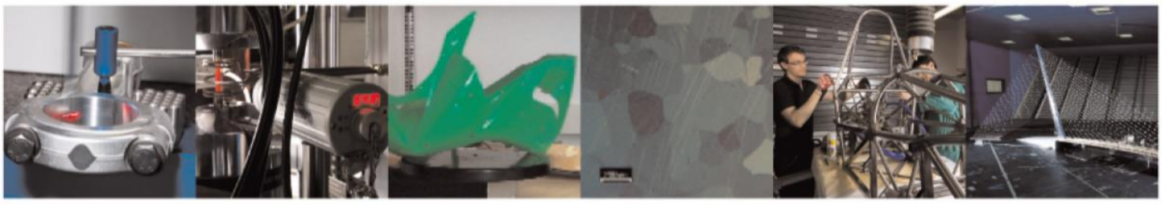

Human factors' complexity measurement of human-based station of assembly line

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Abstract

Human’s cognitive heterogeneity to the operations’ complexity causes large fluctuation in operation time and high human error rate in the human-based station on the assembly line. To quantitatively characterize the degree of cognition, considering the influence of cognition on the operation of operator, this study is concerned with measuring the human factors’ complexity of human-based station based on the information entropy. Firstly, the influence of the operators' cognition on the operation time is analyzed. The operation time is modified by the correction method in the human cognitive reliability model afterwards. Finally, the human factors’ complexity measurement model is built. In a case study, the human factors’ complexity in terms of the qualified rate of operation is used to verify the validation of the proposed method. The Pearson correlation coefficient shows that the human factors’ complexity in terms of qualified rate is highly related to the complexity in the aspect of operation time.

KEYWORDS

assembly line; human-based station; human factors; complexity measurement; human cognition

1 INTRODUCTION

With the intensification of market competition and the changing needs of the market, the current manufacturing industry faces serious challenge in low cost, high quality and personalization requirements (Wang, and Hu, 2010). The assembly line, while meeting these challenges with greater flexibility and adaptability, requires extremely complex production process (Papakostas, Efthymiou, Mourtzis, et al., 2009) and simultaneously puts a higher demand on the operational complexity of the operators in the production process. Operators strive to learn and be familiar with new operations in order to achieve the desired agility. As a result of such demand, high human error rate and time-consuming proficiency leads to unstable production process, low production efficiency and poor product quality. So, one possible way to cope with these problems is to quantify the performance and try to understand the behavior of operators when they face the high product variety and short lead times.

Human is one of the key factors in the research, development and application of modern manufacturing systems and technologies. The quantification of human factors is the research focus of the manufacturing system. With modern manufacturing systems and other high-risk industries to gradually improve the safety and stability requirements, higher requirements for related research are put forward. Related research methods are Human reliability, Human factors' complexity, Questionnaire or rating scale, Simulation method and so on.

Pasquale, Franciosi, Lambiase, et al. (2017) propose a beginning taxonomy of human error consequences which may support data collection in manufacturing systems and to identify the probability of human error. The data collection and availability is a meaningful dataset to quantify human reliability. Petruni, Giagloglou, Douglas, et al. (2017) introduce a method to support the evaluation and the choice of a suitable Human Reliability Analysis technique for the automotive sector. It can be provided beneficial to the industry allowing the provision of the right balance between complexity and accuracy for the level of analysis and output required. Aalipour, Ayele and Barabadi (2016) employ Human Error Assessment and Reduction Technique, Standardized Plant Analysis Risk-Human Reliability, and Bayesian Network to estimate the probabilities of human error. The study results demonstrated that time pressure, lack of experience, and poor procedure are the main causes of human error during maintenance activities. Givi, Jaber, and Neumann (2015) study the human error rate and reliability with time and propose a model to estimate the human error rate while performing an assembly job under the influence of learning–forgetting and fatigue–recovery.

ElMaraghy and Urbanic (2004) focused on operational complexity, considering human characteristics to gain insight into system performance and agility, and established a framework to use human performance models to measure operational complexity. Wang and Hu (2010) study manufacturing complexity based on the choices of assembly activities that operators make in serial in manual mixed-model assembly lines. They also consider the assembly system configuration including the parallel and hybrid configurations and operator choices to measure the complexity of manufacturing system. Zhu, Hu and Koren (2008) propose a complexity measure called “operator choice complexity” to quantify human performance in making choices for a series of assembly activities. And then they study the sequence planning of assembly line based on the “operator choice complexity”. The complexity can quantify the human performance in making choices, such as selecting parts, tools and so on (Zhu, Hu, Koren, et al. 2012). Fan, Li, Moroni, et al. (2017) propose an operation-based approach to measure the configuration complexity of manufacturing system. The purpose of the operation-based configuration complexity model is to measure the configuration complexity of a manufacturing system and to quantitatively describe the relationship of the complexity between operations and stations.

In order to maximize the comfort of operators in mixed-model assembly lines, Bautista, Alfaropozo and Batallagarcía (2016) evaluate the maximum ergonomic risk and the average absolute deviations of ergonomic risk to research assembly line balancing models. Barathwaj, Raja and Gokulraj (2015) focus on mixed model assembly line balancing and take ergonomics as an additional objective function. They use accumulated risk posture to evaluate the ergonomic risk level of a workstation. Then the assembly line balancing is optimized with the objectives of reducing the number of workstations, work load index between stations and within each station. Akyol and Baykasoğlu (2016) consider ergonomic risks to propose a new type of assembly line worker assignment and balancing problem (ALWABP). In this type, ALWABP occurs when task times vary along with the assigned worker. The operation time of a task is assumed to be fixed in classical assembly lines, it depends on the operator who executes the task. Battini, Faccio, Persona, et al. (2011) analyze the relationship of ergonomics and assembly system design techniques. They also propose a new theoretical framework to analysis the technological variables related to work times and methods, environmental variables and ergonomics evaluations in purpose of assessing a concurrent engineering approach to assembly systems design problems with ergonomics optimization.

Wang, Wang, Wu, et al. (2013) use Jack (Siemens PLM Software) to build the required human body model, and use the OVAKO Working posture Analyzing System (OWAS) and Rapid Limb Assessment (RULP) analysis tools to simulate the manual work in the production line. And they study the staff's human factors' defects in the production line operation based on the simulation analysis, combining with the principles of human factors to improve the design of the corresponding improvement program to improve the operation of staff operations. Chen, Wu, Zhao, et al. (2009) use CATIA software to build a virtual simulation environment based on the analysis of human physiological characteristics, anthropometric measurement and working space design. In order to improve operating efficiency, reduce labor intensity, and reduce movement fatigue, access to the best standards of personnel operations, the approach is used to carry out accurate simulation of on-site personnel, human factors' analysis of personnel operation, and optimize the operation of personnel. Papakostas, Efthymiou, Mourtzis and Chryssolouris (2009) study the complexity of manufacturing system based on discrete event simulation and nonlinear dynamics theory. A set of manufacturing models is simulated and evaluated through a series of experiments, employing diverse workload patterns. The approach is used for determining the sensitivity of a manufacturing system to workload changes, measuring and controlling the complexity of manufacturing system.

Michalos, Makris and Chryssolouris (2013) analyze the effect of high fatigue accumulation and high task repetitiveness for the final product's quality. They use human error probability quantification techniques to predict the performance of the assembly line based on the analysis. Myszewski (2010) consider the probability distribution of human error and demonstrate a probabilistic model of human error. The model can represent substantial phenomena of various types (continuous and discrete). Baykasoglu, Tasan, Tasan, et al. (2017) propose a systematic approach in order to handle assembly system design, while considering ergonomic risk factors. It considers interrelations between technological variables, such as workers' physical attributes and ergonomics evaluations. ElMaraghy, Nada and ElMaraghy (2008) develop a model to assess the probability of human errors in reconfigurable manufacturing systems, based on tasks characteristics, work environment, as well as workers capabilities using the multi-attribute utility analysis. It can predict the probability of errors caused by human involvement.

In summary, there are still some limitations in the exist study. The traditional methods such as Human reliability analysis (HRA) method cannot get the complexity index to evaluate the complexity of human factors, but only reflects the operational error rate, volatility. However, Human Reliability Analysis (HRA) is the basis of human problem, and its rationality is of great significance to the follow-up study.

At present, the researches on the complexity of manufacturing systems mainly focus on describing the complexity caused by the diversity characteristics of the system, and the few researches focus on the complexity caused by human factors. The human factor’s complexity is an important index to measure the degree of influence of operating uncertainty on manufacturing process. Mostly, researchers consider operator choices to quantify human performance. However, operator choices and other factors will affect the operation time. Moreover, the measurement of human factors’ complexity based on operation time has the type of manufacturing big data generated in the entire assembly process. The accurate measurement can be achieved by utilizing the useful information from such huge and dynamic databases. So, it provides a significant research route in aspect of operation time to describe the human factors’ complexity.

This study demonstrates an approach of measuring the human factors’ complexity of human-based stations from the point of view of operation time, and describes the trend of human factors' complexity along with the changing cognition of operators. The rest of this article is organized as follows. The methods of human factors’ complexity measurement model are given in Section 2 while analyzing the influence of the operators' cognition on the operation time of the human-based station. Simultaneously, the operation time model of human-based station is modified by the correction method. Then the volatility of operation time is used to describe the human factors’ complexity and the heterogeneity of cognition. After that, a case study of engine assembly line from China SAIC Motor Corporation is used to verify the validation of the human factors’ complexity measurement model in Section 3. Finally, the result analysis and conclusions are proposed, respectively, in Section 4 and 5.

2 HUMAN FACTORS' COMPLEXITY MEASUREMENT METHOD WITH HUMAN COGNITION

2.1 Human cognition on human factors' complexity problem

There are dynamic changes in the modern manufacturing industry in both technical and organizational aspects. The development of industry puts forward higher requirements for the production system of human and machine. The performance of the man-machine system largely depends on the performance of the human. There is an urgent need to take full account of human factors in the production and manufacturing systems during the design phase (Liu, Sheng, and Yang, 2002).

The performance and response of operator in manufacturing system are complex and difficult to quantify. It is unstable and shows the fluctuation of the operation time. It results in operating error rate increase and product passing rate decrease. The instability and randomness of the operator are the key points of the study, which are not only related to the economic loss of production, but also to the safety of the operators. Figure 1 shows the propagation of operators' performance in production process.

FIGURE 1 Propagation of operators' performance in production process

It's meaningful to understand how the operator works as a manufacturing process participatory element and affects the complexity of manufacturing process, and then quantify the extent of its impact. In order to improve the production process by balancing the performance of operators and machines, information and knowledge from the process are valuable to analyze the operators' behavior in the process on assembly line. Information and knowledge are characterized by quantity of information, diversity of information and information content (ElMaraghy, ElMaraghy, Tomiyama, et al., 2012). Moreover, complexity theory, especially information entropy, provides effective methods to describe the performance tendency within the normal operating range (Fan, Li, Liu, and Xu, 2017).

The aim of this present approach is to solve the complexity uncertainty caused by the cognitive factors of human in the assembly line based on information entropy. Workers in the human-based station will select the components and fixtures for assembly operations in the given order. This selection process is susceptible to the workers' misunderstanding of the content of the assembly operation, which directly results in the fluctuation of the operation time and the decline of the passing rate, then seriously effects on the quality and efficiency of the whole assembly line. Considering the human cognition, quantifying the human factors' complexity of the human-based stations can provide the basis for the performance evaluation of the assemble line. In complex assembly environment, the optimization of human factors' complexity can effectively reduce the human error rate and raise the assembly qualified rate and product quality.

2.2 Operation time model considering cognitive

Cognitive model can improve the performance model of the human-machine system in the manufacturing process, which applies many theories like human-computer interaction theory, ergonomics, human theory, cognitive psychology, sociology and so on. Cognitive psychology studies how humans perceive the surrounding environment, and how they react, think and plan, and can predict and measure human performance through cognitive psychology. Data collection methods, human training and mental state lead to the lack of human reliability data which hinders the human cognition evaluation. Operation time has a greater data source than the reliability data of error rate. Moreover, knowledge management and information technologies give innovative methods to solve this problem based on big data from the process of the assembly line. The modified operation time represents the real operating time under the influence of the training and psychological factors. These data have great significance for the quantitative prediction of human behavior in complex systems.

According to cognitive psychology, human's understanding of the human factors' complexity will gradually deepen over time, which mainly shows in the decrease of operation time and promotion of operation pass rate.

Learning Curves can be used to estimate the time to complete a selected number of units on an assembly line (Thomopoulos, 2014). The theory states that the assembly time per unit declines by some constant percentage with the number of assemblies' doubles. This is represented mathematically by a two-parameter function. Meanwhile, the operation time in a human-based station can be estimated based on Learning Curves.

$$t(x) = ax^b \tag{1}$$

where, t is the operation time in seconds; a represents the first operation time for a period of time; b is a negative constant the absolute value of which represents the learning index; x is the operating time in the order.

2.3 Modification of operation time model considering behavior correction factor

Manual operation time t is monitored by the Manufacturing Execution System. Considering that the operation time may vary with different operators and situation, it needs to be corrected. The human cognitive process is a complex psychological activity that reflects the characteristics and connections of objective things and reveals the meaning and function of things to human beings. HCR model (Human Cognitive Reliability Model) (Hirschberg, 2005) is based on the cognitive psychology in the analysis of human reliability, focusing on human emergency dynamic cognitive process, including exploration, diagnosis, decision-making and other intentional behavior, to explore human error mechanism and the establishment of models.

Human cognitive reliability (HCR) model is based on the allowable time and execution time of an operation to derive the error rate of operation. It is mainly based on two basic assumptions, in which the basic assumption 2 (Wang, Gao, 2006): the probability of failure for each category of behavior is only related to the ratio of the allowable time and the execution time, and it complies with 3 parameters Weibull distribution.

Since the execution time of each running team may vary depending on the situation, it is necessary to correct the equation before using Learning Curve. The key behavior modification factors considered in the HCR model are training ($K1$), psychological stress ($K2$) and man-machine interface ($K3$). HCR model is the first-generation method of human reliability research. It is comparatively mature and has been proved to be practical in related research. Therefore, the modified method of HCR in execution time is used to correct manual work time. The correction formula is as follows (Wang and Ma, 2010).

$$\boldsymbol{T} = \boldsymbol{t}(1+\boldsymbol{K}1)(1+\boldsymbol{K}2)(1+\boldsymbol{K}3) \qquad (2)$$

where, T represents the corrected operation time, it is for the execution time of general situations (such as simulator training); t is the operation time; $K1$, $K2$, $K3$ are selected as shown in Table 1.

TABLE 1 Behavior formation factor and correlation coefficient of the HCR model

2.4 Modeling of human factors' complexity based on operation time

Entropy has its own meaning in physics and information theory. It can be used to represent the degree of disorder of the system in physics, and it can reflect the uncertainty and amount of information contained in the system in information theory. Information entropy is regarded as a measure of the degree of disorder in the system. With the randomness increases, it's more difficult to understand the system state. With the uncertainty of message elimination goes up, the amount of information involved increases. A small probability event contains a large amount of information, so the information entropy can be used to describe the complexity of the system states. When there are m events with individually occurring possibilities p_1, p_2,⋯, p_i,⋯, p_m, then entropy is I (Efthymiou, Mourtzis, Pagoropoulos, Papakostas, and Chryssolouris, 2015).

$$\boldsymbol{I} = -\sum_{i=1}^{m} \boldsymbol{p}_i \log_2 \boldsymbol{p}_i \tag{3}$$

In the performance of human choice-making activities, Hyman (1953) holds that it is approximately a linear function of information entropy conveyed by the stimulus. The information entropy in assembly station k conveyed by stimulus is equal to the complexity of the station, H^k. Therefore, the average reaction time related to station k is equal to $TS^k = \alpha + \beta \cdot H^k$, where α and β are constants if all operators are assumed to be homogeneous (Wang, and Hu, 2010).

Obviously, the operation time increases linearly with the complexity, so its changes can describe the changes of the complexity. The concrete complexity measure of human-based station is given as follows:

$$\boldsymbol{H} = \frac{\boldsymbol{T}}{\boldsymbol{C}_T}\{\boldsymbol{p}_0 \log_2 \frac{1}{\boldsymbol{p}_0} + (1-\boldsymbol{p}_0)\log_2(\frac{1}{1-\boldsymbol{p}_0})\} \tag{4}$$

Where, H is complexity of human factors' complexity considering the cognition and operation time; T is the modified operation time; C_T is the cycle time of the assembly line of which the units are seconds; P_0 is the initial qualification. P_0 calculation method: In the first day of a statistical time, an operation time and the production cycle are used to determine whether the operation is eligible. The operation is considered qualified if the operation time is less than the production cycle. The number of times of reliable operation and the total number of operations are counted in the first day, and P_0 is the ratio.

In this study, the human factors' complexity measurement method from the point of operation time can modify the operation time data of the operator in the assembly line, then use the modified time data to fit a polynomial and finally built the complexity measure model, at last derive the specific numerical complexity, which quantitatively characterized the human factors' complexity considering the cognition.

3 CASE STUDY

There are a number of human-based stations for tightening operations on an engine assembly line of China SAIC Motor Corporation. All the tightening guns are equipped with the sensors monitoring the real-time to measure all the process data (Torque, angle, etc.) and upload to the data center. A tightening station is selected to continuously collect the start time point and the end time point of each within the long total sample time. Figure 2 shows the schema of a human-based station.

FIGURE 2 The schema of the human-based station

3.1 Curve fitting for operation time

In the actual assembly environment, with the deepening of cognition, workers for the manual operation are more skilled, and operating time shows a significant reduction trend. The shortest operation time in the day is counted as a measure of the complexity of the data for the current time of operation. The fastest operation time can characterize the worker's proficiency in the operation. Table 2 shows the fastest operation time of the operator in the human-based station for a long period of time. Figure 3 shows the data fitting diagram of the fastest operation time from the operator in human-based station.

TABLE 2 Fastest operation time at human-based stations

FIGURE 3 Fitting graph of fastest operation time at human-based station

The red curve in Figure 3 is the fitting results as equation (1) and the specific parameters of the fitting curve model are as follows.

$$\boldsymbol{a} = 89\,\mathrm{s}$$

$$\boldsymbol{b} = -0.1633$$

The parameter of t is the fastest operation time of the human-based station, the unit is second, a represents the first assembly time for a period of time, so a equals 89s. And the absolute value of b represents the learning index.

3.2 Operating time correction

According to the formula (2), on the basis of the comprehensive quality level of the assembly line operator, $K1$ is set to -0.22, $K2$ is set to 0.28, $K3$ is set to 0.00.

From the results of the fitting curve, the operation time shows an overall trend of tending to stable.

3.3 Calculation of the human factors' complexity

The modified polynomials which have been corrected are substituted into the complexity measure model. If the operation time is less than the production cycle time, the operation will be considered qualified. The qualified rate of a day is expressed as the ratio of the number of reliable operations to the total number of operations in that day. C_T equals 75s, so P_0 is calculated by the method and equals 0.5497. The complexity is calculated with equation (4) which is shown in Table 3. The curve is plotted to quantitatively characterize the complexity of human factors in the human-based station with considering the cognition. The curve is shown in Figure 4.

TABLE 3 The human factors' complexity based on the operation time

FIGURE 4 The human factors' complexity based on the operation time

From the plotted curve, it can be seen that the complexity of human factor in terms of the operation time presents a decay trend and gradually stabilizes.

4 ANALYSIS OF METHOD VALIDITY

4.1 Qualified rate fitting and the human factors' complexity measurement

With the increase in the number of operations and the increase in operating time, the operation proficiency and accuracy of workers increases in human-based stations, and operating qualified rate shows a significant upward trend. The operation time and production cycle time is used to determine the eligibility of the operation or not. If the operation time is less than the production cycle time, the operation will be considered qualified. The qualified rate of a day is expressed as the ratio of the number of reliable operations to the total number of operations of that day. Production cycle time is 75s, Table 4 shows operating qualified rate statistics of the operator at human-based station in a long period of time. Figure 5 shows operating qualified rate curve of the operator at human-based station.

TABLE 4 Operating qualified rate at human-based station

FIGURE 5 Curve of operating qualified rate at human-based station

As for the complexity of operation in the assembly process, the information entropy theory is used to measure the complexity based on operating qualified rate, and the measurement method of operation complexity of the station is given (Fan, Li, Moroni, et al., 2017):

$$\boldsymbol{h} = \sum_{j=1}^{n} \{\boldsymbol{p}_j \log_2 \frac{1}{\boldsymbol{p}_j} + (1 - \boldsymbol{p}_j) \log_2 (\frac{1}{1 - \boldsymbol{p}_j})\} \tag{5}$$

Where P_j is the operating qualified rate， h is the corresponding complexity. The corresponding operation complexity h is calculated for each P_j, the result list is as

Table 5. The curve is plotted in Figure 6.

TABLE 5 Complexity based on operating qualified rate

FIGURE 6 Curve of human factors' complexity based on qualified rate

4.2 Result analysis and discussion

The human factors' complexity of operator at human-based station is modeled separately from both the operation time and the operating qualified rate, both of which reflected a decrease in human factors' complexity over time and a great increase in operator proficiency at human-based stations. There is also a similarity between the two models and both models are similar to the attenuation type. The model based on operation time was validated by the human factors' complexity model based on operating qualified rate. Figure 7 shows curves of two models in the same coordinate system.

FIGURE 7 Curves of the two models

As Figure 7 shows，the black curve is the curve of complexity model based on operating qualified rate, the red one is the fitting curve of complexity model based on operation time(the production cycle time is 75s). The two curves were analyzed by correlation analysis.

The correlation coefficient of two random variables is an indicator of its linear dependence. If each variable has N scalar observations, the Pearson correlation coefficient is defined as (Benesty, Chen, Huang, et al. 2009):

$$\rho(\boldsymbol{A},\boldsymbol{B})=\frac{1}{\boldsymbol{N}-1}\sum_{l=1}^{N}(\frac{\overline{\boldsymbol{A}_l}-\overline{\mu_{\boldsymbol{A}}}}{\sigma_{\boldsymbol{A}}})(\frac{\overline{\boldsymbol{B}_l}-\overline{\mu_{\boldsymbol{B}}}}{\sigma_{\boldsymbol{B}}}) \tag{6}$$

where μ and σ denote the mean and standard deviation, respectively. The Pearson correlation coefficient describes the degree of linear correlation between the two variables. The greater the absolute value, the greater the correlation is.

Using the formula, the correlation coefficient of the two models is 0.8341 and the correlation coefficient is over 0.8, which shows the strong linear correlation between the two models, which verifies the reliability of the complexity measure model based on operation time, then the square root of the sum of residual squares is divided by the number of sample points, and the result is 0.0733. It shows that the model can effectively predict the trend of the complexity of human factor affected by cognition, which is of great significance.

With the cognition enhancing of operator to assembly tasks, the operation time gradually decreases and operating qualified rate gradually improves. The information and knowledge in the manufacturing process is positively correlated with information entropy and its complexity. Therefore, the human factors' complexity measure model based on operation time can be validated by the method based on qualified rate. However, in comparison, the operation time has a greater data drive. It is more beneficial to depict the relationship of the human factors and system performance.

5 CONCLUSION

A human factors' complexity measurement model is built considering human cognition based on the information entropy. The model is proposed to measure the human factors' complexity and quantitatively describe the influence of the operators' cognition on the operation time of the human-based station on the assembly line. A practical case of an engine assembly line from China SAIC Motor Corporation is studied for the validity verification. The operation complexity measure model based on operating qualified rate is used to verify the validity of human factors' complexity measure model based on operation time. The results show that the proposed human factors' complexity measure model can describe the human factors' complexity of the human-based stations and effectively predict the trend how human factors' complexity changes.

Comparing to the human reliability method using the human error rate to feed the data collection, the proposed complexity method is based on operation time which makes full use of the data in the production process. Furthermore, the behavior correction factors are fully considered, because the operation time may vary with different operators' situation. Therefore, the measurement of human factors' complexity is more accurate and is more in line with the actual conditions.

In continuative research activities, the proposed approach can be combined with the evaluation to machine's performance degradation to optimize the configuration of manufacturing system. In addition, the performance evaluation of manufacturing system should be taken into account.

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