IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 25, 2018, accepted June 25, 2018, date of publication July 4, 2018, date of current version July 25, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2852791

Big Data Analysis and Scheduling Optimization System Oriented Assembly Process for Complex Equipment

XINYE WU[1], JIANBO ZHAO[2], AND YIFEI TONG[1]
[1]School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210000, China
[2]713 Research Institute, China Shipbuilding Industry Corporation, Zhengzhou 450000, China

Corresponding author: Yifei Tong (tyf1776@njust.edu.cn)

This work was supported in part by the National Defense Science and Technology Project Foundation under Grant 0106142, in part by the Project of Humanities and Social Sciences, Ministry of Education, China, under Grant 17YJC630139, and in part by the National Key Technology Support Program under Grant 2015BAF18B01.

ABSTRACT Traditionally, the data generated in the manufacturing process is not under full use for management decisions, so it is difficult to achieve the decision optimization in a manufacturing system level. The analysis of the big data with uncertain information that influences the assembly objectives can be helpful to improve the capacity of resisting the disturbance of the scheduling system and realize the optimal production. This paper focuses on the analysis and utilization of assembly big data in the manufacturing process and studies the key technologies of big data analysis and assembly scheduling optimization for complex equipment. A big data analysis and scheduling optimization system is proposed to solve the assembly service execution decision for complex equipment. It proposes to analyze the assembly big data and make decisions with uncertain information by locally linear embedding, adaptive boosting, support vector machine, and D-S evidence theory. In order to explore the influence pattern of assembly task and environment on assembly efficiency, the neural industrial engineering is proposed to be introduced into human error prediction based on physiological big data. Finally, the variable metric clustering of assembly tasks can be provided to ensure the maximization of assembly efficiency and the production balance. The proposed system can effectively handle the dynamic and uncertain information in the assembly, and get better overall scheduling optimization of the assembly system. The support technologies presented in this paper can provide a good theoretical foundation and application reference for big data decision to be used in manufacturing optimization.

INDEX TERMS Big data, multi-objective decision-making, neural industrial engineering, scheduling optimization, uncertain information.

I. INTRODUCTION

The complex equipment in aviation, aerospace, high-speed rail transit and other fields presents the characteristics of complex structure, strict working conditions and high reliability requirements. With the improvement in the comprehensive performance of new generation equipment, the assembly quality and efficiency are of more and more needs. Digital and flexible assembly has become the focus of manufacturing industry in recent years.

Complex equipment manufacturing enterprises are facing the challenges of multi-product manufacturing and shorter production cycle, which result in obvious inadequacies in production scheduling ability. It is also difficult to change assembly orders in time for disturbances. Especially, the heterogeneous data generated during assembly process makes the assembly scheduling optimization problem more complicated. Many common methods and models have limitations on dealing with assembly big data. The assembly scheduling based on big data is essentially a multi-objective NP problem, which refers to multi-objective optimization with constraints of assembly resource capabilities. However, influence of diverse factors is hard to be described by a clear mathematical model.

In fact, assembly scheduling involves a series of problems, such as assembly data acquisition and processing, assembly quality factor analysis, quality evaluation, multi-objective job scheduling optimization, line balancing, etc. On the other hand, the development of data mining makes the optimal scheduling based on assembly big data feasible.

II. LITERATURE REVIEW

A. COMPLEX EQUIPMENT ASSEMBLY MODELING

The Assembly Process Complexity (APC) depends on assembly process attributes such as assembly parts and technologies. The assembly complexity fundamentally determines the rate of human error, and also has an important impact on the quality of products [1]. In addition to the static assembly information of various manufacturing resource and coordination between departments, the large amount of dynamic and real-time resource information generated during the operation of the assembly system will also cause the complexity of the assembly system [2]. How to digitize the information to support scheduling optimization is particularly critical.

The most basic problem is the assembly line/system modeling. Wang *et al.* [3] established a timed places Petri net (TPPN) simulation model which can describe the complex relationship between the technological processes of the aircraft pulsation assembly line. Liu *et al.* [4] proposed a modeling method for assembly process based on matrix operation. This method takes the multiplication process of matrix to describe the production process. Wang *et al.* [5] proposed the concept of assembly tree for product assembly process, which is constructed on the design drawing of assembly and product structure tree. The model is helpful to solve the problem of function extension and description completeness of product structure tree. Moreover, there are some modeling researches on wheeled mobile robots or pull type manufacturing system [6] to [7].

Most of the existing modeling methods of manufacturing system tend to consider the problem from a specific perspective — function model, information model or dynamic model, and do not make full use of the big data of manufacturing process. Furthermore, the common method of Petri net is suitable for modeling asynchronous simultaneously systems, but there is a Curse of Dimensionality. This problem will be more prominent in the manufacturing process modeling of information environment.

B. THE ASSEMBLY RESOURCE SCHEDULING MANAGEMENT

The manufacturing of complex equipment mostly belongs to one-of-a-kind or small-batch production, and its assembly line is often in multi-product, multi-state, multi-batch and mixed production, that the assembly scheduling is extremely complicated. The scheduling of a multi-product mixed model assembly line includes two closely related aspects: the best effective job assignment and the optimal production sequence.

With the aim at minimizing the number of assembly stations, the minimum takt time and the most balanced load between stations, Miltenburg [8], Pereira and Vilà [9] transformed the multi-product mixed model assembly line into a single variety assembly line to realize the job assignment. Jiao *et al.* [10] proposed the objective function of minimizing the assembly time and established a job assignment model for complex weapon equipment assembly line. Hwang and Katayama [11] took a Japanese boiler factory as the object to study the mixed model assembly line based on similarity of operational characteristics, and used the genetic algorithm to obtain an assembly balance in system level. Besides, some researchers used bounded dynamic programming or predefined job sequence to solve the scheduling model [12] to [13].

The previous scheduling studies are mostly based on static scheduling environment, which assume that the execution of tasks is not disturbed. However, in the actual production process, there are often a lot of uncertainties, which lead to the lack of robustness of deterministic model scheduling. In order to solve the problem, there is some research on scheduling with uncertain information [14] to [15]. However, the existing uncertain scheduling research does not take full account of the big data generated in manufacturing. In fact, the analysis and decision-making based on assembling big data can reduce the interference of uncertain factors to manufacturing scheduling to some extent. On the other hand, the past scheduling research also seldom considers the human factors, or they simply dealt with the quantification of human factors and failed to explore the causes and law of human error based on physiological signals [16]. The above research proves the necessity and feasibility of the assembly scheduling optimization oriented assembly process of complex equipment system based on assembling big data.

III. THE ARCHITECTURE OF THE BIG DATA ANALYSIS AND SCHEDULING OPTIMIZATION SYSTEM ORIENTED ASSEMBLY PROCESS OF COMPLEX EQUIPMENT

This study proposes a big data analysis and scheduling optimization system, which aims to integrate the manufacturing and human factor data related to the assembly quality to realize the quality evaluation and job scheduling optimization of complex equipment assembly. Therefore, it is more effective in predicting production status and dealing with production perturbation. The system consists of several sub modules (Fig. 1):

The data operation module: the module collects manufacturing information through the bottom data acquisition system, including the automatic measuring instruments and other manufacturing process and resources database. At the same time, the module needs to process the data preliminarily and encode all the manufacturing resources with a unique identification.

The evaluation and scheduling modules: these core modules provide service of multi-objective assembly quality evaluation, human error prediction of assembly workers and job scheduling optimization.

Visual output module: It timely releases the scheduling scheme to the job site and early warning of stations with abnormal progress or resource shortages.

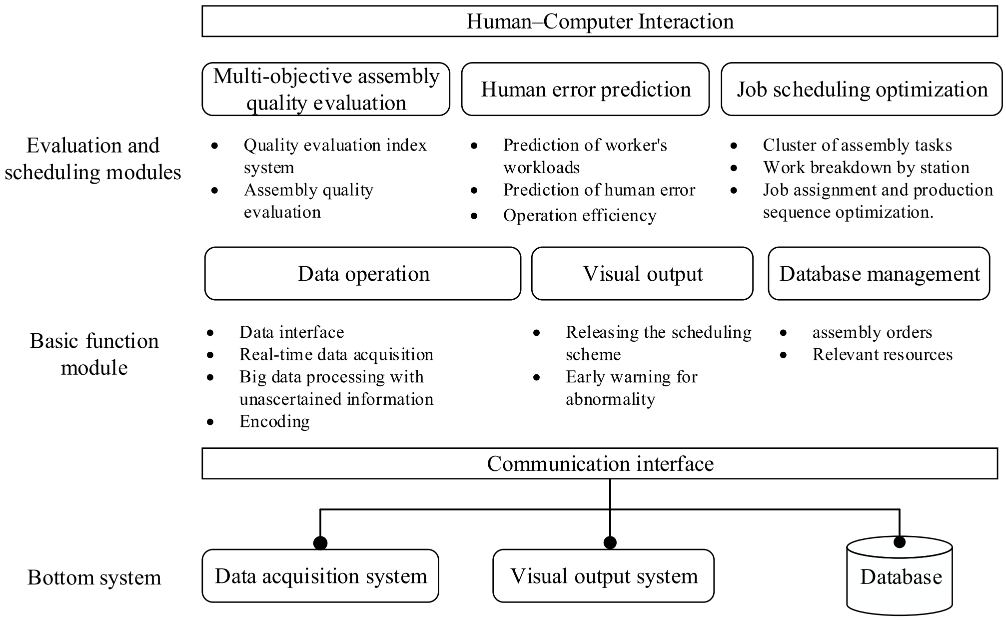


FIGURE 1. Design of big data analysis and assembly scheduling modules.

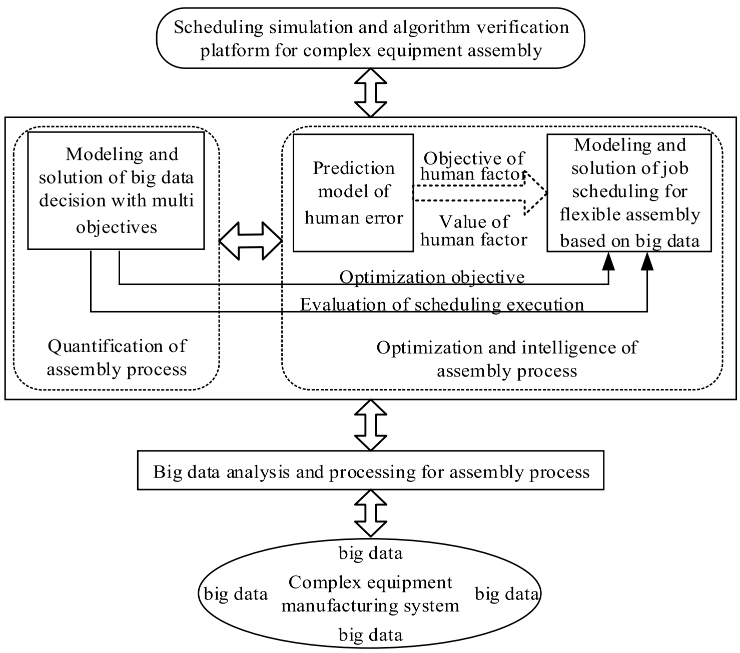


FIGURE 2. The logical structure of the big data analysis and scheduling optimization system.

Database management module: The complex assembly line requires a set of professional assembly orders, which contain assembly process description, relevant inspection quotas, as well as assembly parts, tools, materials *et al.*

IV. THE SUPPORT TECHNOLOGIES OF THE BIG DATA ANALYSIS AND SCHEDULING OPTIMIZATION SYSTEM ORIENTED COMPLEX EQUIPMENT ASSEMBLY

To realize the function and architecture of the system, the key technologies are focused on four aspects: the big data analysis and processing of assembly process, big data decision, human error prediction, and assembly scheduling based on big data. Their relationship is illustrated in Fig. 2. The decision-making and scheduling optimization models are based on the big data produced in the equipment assembly system. The detailed methods of implementation are shown in Fig. 3.

A. BIG DATA ANALYSIS AND PROCESSING

The dynamic, diverse and conflicting big data generated in the manufacturing process is the fundamental factor for the

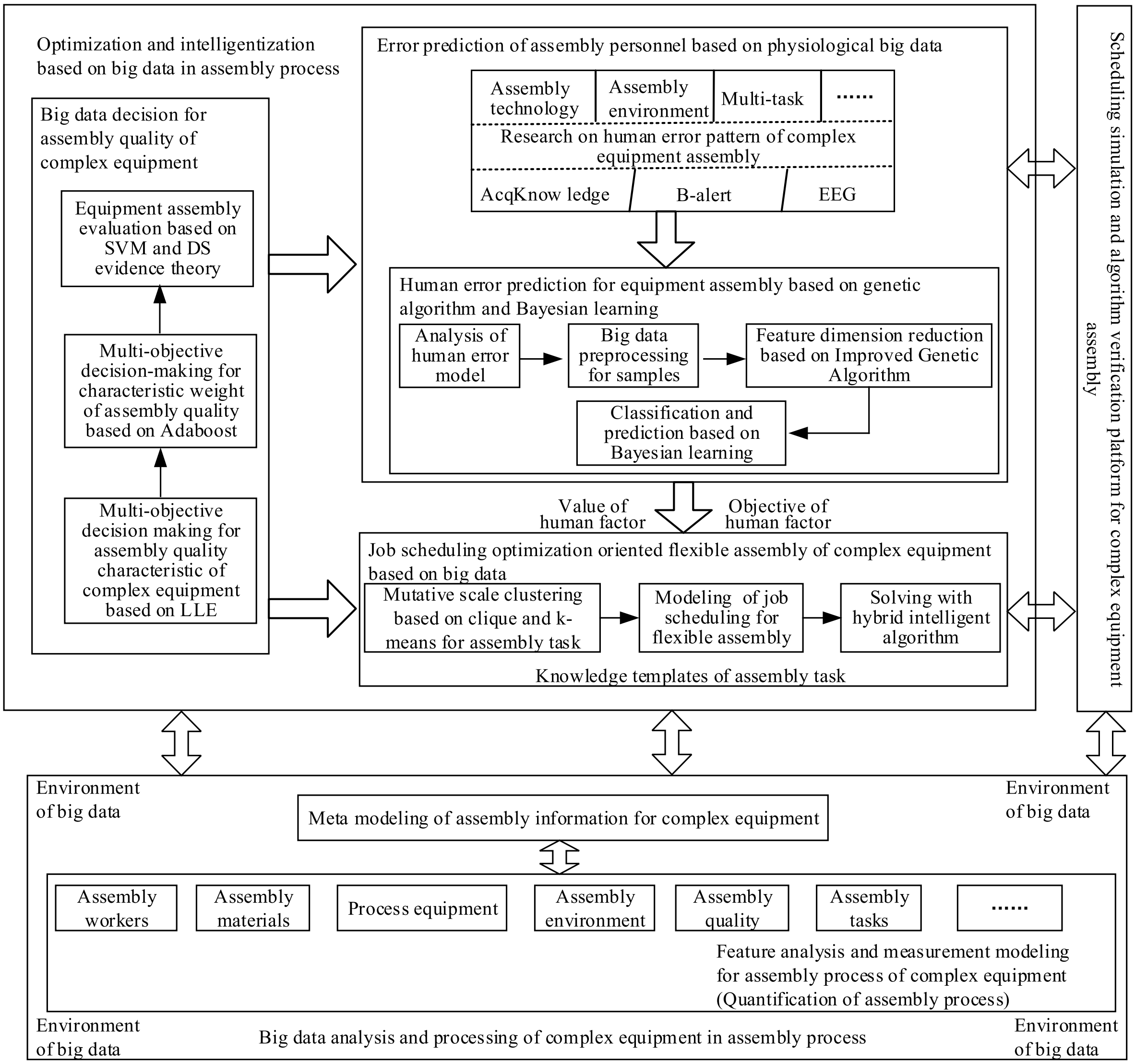


FIGURE 3. The key methods for implementation.

complexity of the manufacturing system. The factors that affect the assembly quality of complex equipment come from many aspects. Tang [17] divided the unascertained information into entity elements and non-entity elements : Entity elements cover the information of equipment, personnel, materials, and energy. Non-entity elements cover the information of operation standards, process specifications and production management. They all may cause the quality fluctuations of the finished products. In order to establish the index system of assembly quality and develop measurement method of assembly quality, the work involved include:

Sensor networks and measurement modeling for multi-source assembly quality data. According to the types of signal input, the big data related to assembly quality is divided into mechanical quantity, electrical quantity, thermal quantity, etc., to design the corresponding perception quantity of quality source. Secondly, analyze the applicability of the perception equipment and technology oriented different perception objects, assembly conditions, assembly personnel and other factors, to establish an intelligent quality sensor system of assembly data for the complex equipment. The sources of data that affect the assembly quality are shown in Fig. 4.

Meta modeling of assembly information for complex equipment. Consider the time-dependent behavior of assembly resource, and encapsulate the knowledge of assembly activity into the assembly information model, to construct a reconfigurable meta model of assembly with knowledge association.

B. BIG DATA DECISION FOR ASSEMBLY QUALITY OF COMPLEX EQUIPMENT

The execution process of manufacturing involves many multi-attribute or multi-objective decision-making problems.

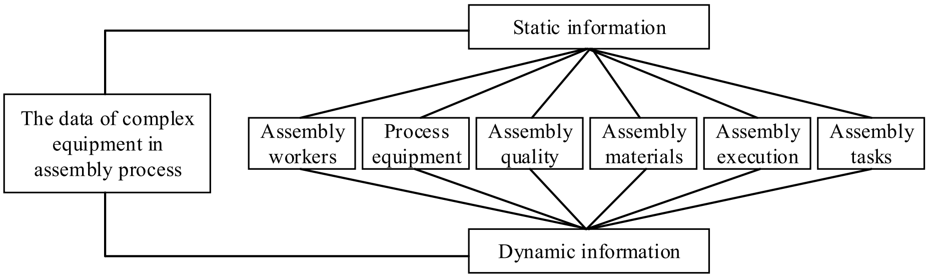


FIGURE 4. The sources of assembly data for complex equipment.

The actual data environment contains a large amount of uncertain information, and the collected data is often filled with noise and incomplete information. Therefore, it is necessary to analyze and process the assembly big data before making a decision. The purpose is: a) to establish a decision table after invalid or weak efficient data reduction; b) to complete the incomplete information; c) consistency processing for conflicting and inconsistent information.

To deal with uncertain information many scholars have proposed knowledge reduction methods based on Rough Set Theory [18] to [20]. However, the classical Rough Set Theory has some difficulties in big data processing. This paper proposes to integrate Locally Linear Embedding (LLE), Adaboost (Adaptive Boosting), Support Vector Machine (SVM) and D-S evidence theory (Dempster-Shafer evidence theory) for big data decision.

The quality evaluation of complex equipment assembly involves a series of multi-objective decision-making problems, which can be summarized as several key steps:

Multi-objective decision-making for quality features of complex equipment assembly. For a huge amount of nonlinear data in manufacturing process, Locally Linear Embedding is a widely used method for dimensionality reduction of nonlinear data. Its characteristic is that the processed low-dimensional data can maintain the same topological relationship as the original high-dimensional data of observation sample. By dimensionality reduction, the main features or attributes of assembly quality for complex equipment are determined.

Multi-objective decision-making for feature weight of assembly quality. The weights of features that affect the assembly quality should be given to different conditions by AdaBoost. AdaBoost updates the weights of the weak classifiers according to the error rate of classification by iterating the assembly big data, so that the big data can be used to make a decision for feature weights efficiently [21].

Assembly evaluation of complex equipment based on assembling big data. Combined with the feature variables of complex equipment assembly to input the actual assembly data, the assembly quality evaluation is carried out. Using support vector machine and D-S evidence theory, the process of quality evaluation of complex equipment assembly is shown in Fig. 5. The combination of support vector machine

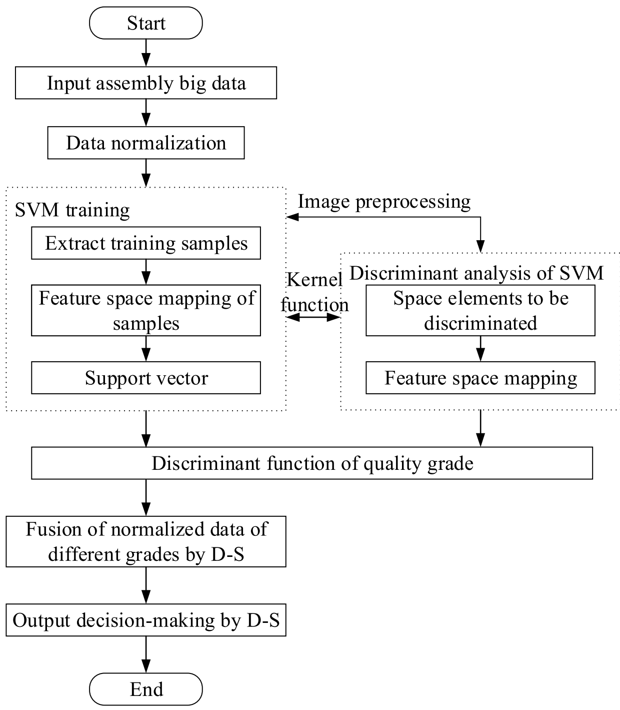


FIGURE 5. Assembly evaluation of complex equipment based on SVM and D-S evidence theory.

and D-S evidence theory has been widely used. The output of support vector machine is mapped to the probability of quality grades, which is used as the discriminant function of quality grade in the D-S evidence theory (i.e. Basic Probability Assignment, BPA) to realize the objectivity of BPA assignment. Finally, the data of different grades are fused to make a decision by D-S evidence theory.

C. ERROR PREDICTION OF ASSEMBLY PERSONNEL BASED ON PHYSIOLOGICAL BIG DATA

Due to the complexity of thinking, physiology of bodies and the interaction and restriction of human, organization, technology and environment, the error behavior of assembly workers is extremely complex. In order to predict human error, the neural industrial engineering can be applied to the assembly field of complex equipment to study the influence mechanism of various factors on human error in assembly

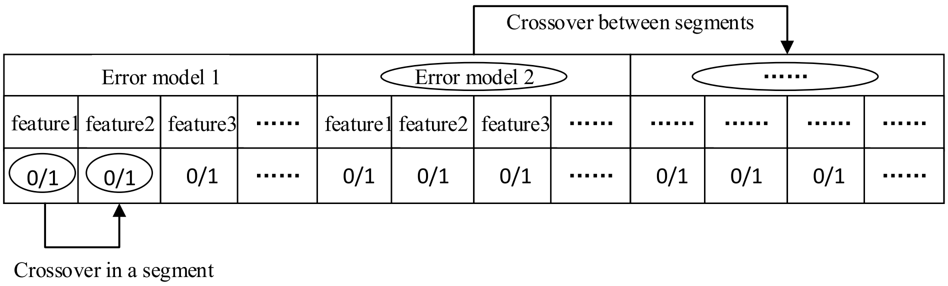


FIGURE 6. **Operation diagram of improved genetic algorithm.**

work. Furthermore, predict human error in assembly work by genetic algorithm and Bayesian learning based on physiological big data of assembly workers. The key problems involve the following contents:

Research on human error pattern of complex equipment assembly. The physiological data (participation degrees, distraction, workload, heart rate, electrocardiography(ECG), electroencephalography(EEG), electromyography(EMG), electro-oculogram(EOG), nerve potential, etc.) of assembly workers can be collected by a multi-lead physiological recorder. Furthermore, from the influence of assembly technology, assembly environment, multi-task and other aspects on human mental workload and cognitive ability, a coupled human-machine-environment model is established to study the influence mechanism of various factors on human error in assembly process.

The prediction of human error in complex equipment assembly based on physiological big data. Based on the obtained physiological big data, the genetic algorithm and Bayesian learning are used to predict the human error in assembly process:

Step 1: analysis assembly human error model.

Step 2: input sample data.

Step 3: feature dimension reduction based on improved genetic algorithm.

Step 4: construct classifiers based on Bayesian learning.

Step 5: error prediction of assembly personnel.

In the process of feature dimension reduction of big data by improved genetic algorithm, the sample data is coded by segment, and genetic manipulation is implemented by crossover of code between segments (Fig. 6). This method not only reduces the amount of calculation on big data processing, but also makes use of the powerful parallel computing ability of MapReduce [22] to process sample data.

D. JOB SCHEDULING OPTIMIZATION ORIENTED FLEXIBLE ASSEMBLY OF COMPLEX EQUIPMENT BASED ON BIG DATA

In order to realize the maximization of the productive efficiency, line balance and intelligent assembly, the crux is to solve the modeling problem of mixed-model assembly line based on the big data from assembly process, and find an efficient solution to the dynamic programming model.

The solution is as follows:

- Make full use of historical information of assembly execution to establish the knowledge templates of assembly activity.
- Cluster of assembly tasks and work breakdown by station.
- Combined with the description of multi-objective scheduling problem of flexible assembly, achieve the multi-objective scheduling optimization of complex equipment assembly with the optimization objectives of maximization of productive efficiency, minimization of cost, equipment utilization and human factors (mental workload) within a reasonable range.

The difficulties and the explanation lie in these two points:

1) VARIABLE METRIC CLUSTERING OF ASSEMBLY TASK OF COMPLEX EQUIPMENT

Through the similarity analysis of assembly tasks, the similar assembly tasks that belong to different assembly stages are integrated in a same batch to ensure the maximization of assembly productive efficiency and line balance.

- Process the assembly tasks preliminarily by variable metric clustering of clique based on grid and density.
- According to different processes of different assembly tasks, establish the high-dimensional space of clustering for assembly tasks by different assembly parameters in k- dimensional space (described with the data-set of D, feature parameter ε and threshold τ).
- Clip space through the MDL (minimum description length) technique, and construct the optimized clustering space of samples composed of dense cell.
- Cluster the assembly tasks by the k-means algorithm based on the optimized clustering space.

2) ASSEMBLY SCHEDULING AND SOLVING OF FLEXIBLE COMPLEX EQUIPMENT

It is the primary task to define the objectives and their quantitative expressions of assembly scheduling decision-making based on assembling big data. The scheduling objective integrates productive efficiency, equipment utilization, human factors (mental workload) etc., which lays the foundation for the construction of scheduling problem. Moreover, analyze the assembly constraints involved in the assembly scheduling problem, including delivery time, resource capability, cost, task priority, etc. Scheduling optimization of complex equipment assembly can be solved by hybrid intelligent algorithm.

V. CONCLUSION

In this study, a multi-objective decision making and scheduling optimization platform is proposed for complex equipment assembly. The paper also expounds the support technologies of the big data analysis and scheduling optimization system to provide decision-making support for the quantitative and information-based equipment manufacturing. The contribution of the research can be summarized as follows:

1) Through analyzing assembling big data with uncertain information, this paper discovered a relationship between the assembling big data and comprehensive performance of assembly task execution in the complex equipment manufacturing. On this basis, the reconfigurable meta model of assembly resource with knowledge association is constructed, which lays the foundation for the decision-making of the complex equipment assembly.

2) A general solution to the multi-objective decision-making problems involved in the assembly process of complex equipment is provided, including dimensionality reduction of assembling big data, feature weight evaluation, assembly quality evaluation based on assembling big data, human performance prediction and assembly task scheduling.

3) The Locally Linear Embedding method can reduce the interference of uncertain information, and improve the adaptability and accuracy of assembly scheduling system in dynamic big data environment. Meanwhile, feature weight evaluation by Adaboost algorithm based on big data is more objective and scientific than the traditional artificial evaluation methods.

4) Before the scheduling optimization of complex equipment assembly, an accurate prediction of assembly personnel performance by the neural industrial engineering contributes to explore the influence pattern of various factors on assembly quality and obviously improve the reliability of assembly task execution.

5) The assembly task planning of complex equipment through variable metric cluster analysis based on assembly features can take into account different assembly stages, different assembly processes and other assembly features to cluster the similar tasks of different stages in the same batch. It is conducive to maximize the production efficiency and production balance.

Compared to the traditional scheduling model based on basic manufacturing data, the big data analysis and scheduling optimization system presented in this paper has the advantage of big data mining. It includes the dynamic and uncertain information in the assembly execution, which helps to get a more accurate and comprehensive assembly evaluation and optimization result. This paper also provides a way to solve the Curse of Dimensionality.

In some cases, the small-batch production of complex equipment may lead to the shortage of historical manufacturing data and affects the optimization effect. In the future, it is required to improve the model and algorithm to better adapt to insufficient data in the proposed system.

REFERENCES

[1] H. L. Zhao, "The study of CNC machine tool's assembly reliability based on assembly complexity,"M.S. thesis, Chongqing Univ., Chongqing, China, 2014.

[2] M. Z. Liu, Z. B. Zhao, M. G. Ge, X. Q. Wang, and L. Ling, "Online optimization for assembly quality of complex mechanical products based on improved PSO," *Trans. Chin. Soc. Agricult. Machinery*, vol. 44, no. 6, pp. 246–252, 2013, doi: 10.6041/j.issn.1000-1298.2013.06.043.

[3] Q. Wang, L.-Q. Wen, J.-X. Li, Y.-L. Ke, T. Li, and S.-J. Zhang, "Modeling and optimization for aircraft final assembly line based on Petri net," *J. Zhejiang Univ., Eng. Sci.*, vol. 49, no. 6, pp. 1224–1231, 2015, doi: 10.3785/j.issn.1008-973X.2015.07.004.

[4] Y. H. Liu, D. W. Zuo, and D. Zhang, "Assembly process modeling method based on matrix technique," *J. Nanjing Univ. Aeronaut. Astronaut.*, vol. 46, no. 6, pp. 938–944, 2014, doi: 10.3969/j.issn.1005-2615.2014.06.018.

[5] B. Wang, X. Q. Tang, and R. J. Geng, "Modeling for assembly structure in mechanical product," *J. Beijing Univ. Aeronaut. Astronaut.*, vol. 36, no. 1, pp. 71–76, 2010, doi: 10.13700/j.bh.1001-5965.2010.01.005.

[6] E. G. Minca, V. Stefan, A. Filipescu, A. Serbencu, and A. Filipescu, Jr., "Two approaches in modeling of assembly/disassembly line with integrated manipulator mounted on mobile platform," in *Proc. IEEE ICSTCC*, Sinaia, Romania, Oct. 2012, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6379285

[7] T. Aized, K. Takahashi, and I. Hagiwara, "Modeling and optimization of multiple product FMS using colored Petri net and design of experiment," in *Proc. IEEE Int. Conf. Netw., Sens. Control*, Apr. 2007, pp. 334–339, doi: 10.1109/ICNSC.2007.372801.

[8] J. Miltenburg, "Balancing and scheduling mixed-model u-shaped production lines," *Int. J. Flexible Manuf. Syst.*, vol. 14, no. 2, pp. 119–151, 2002, doi: 10.1023/A:1014434117888.

[9] J. Pereira and M. Vilà, "An exact algorithm for the mixed-model level scheduling problem," *Int. J. Prod. Res.*, vol. 53, no. 19, pp. 5809–5825, 2015, doi: 10.1080/00207543.2015.1005771.

[10] G. M. Jiao, D. W. Zuo, D. Zhang, and M. Wang, "Scheduling models of aerospace product agile mixed-model assembly," *J. Southeast Univ., Natural Sci. Ed.*, vol. 40, no. 4, pp. 717–721, 2010. [Online]. Available: http://kns.cnki.net/KCMS/detail/detail.aspx?filename=dndx201004011 &dbname=CJFD&dbcode=CJFQ

[11] R. Hwang and H. Katayama, "Sequencing problem for mixed-model assembly line in a manual boiler plant," in *Proc. IEEE CIE*, Jul. 2010, pp. 1–5, doi: 10.1109/ICCIE.2010.5668430.

[12] J. Bautista and A. Cano, "Solving mixed model sequencing problem in assembly lines with serial workstations with work overload minimisation and interruption rules," *Eur. J. Oper. Res.*, vol. 210, no. 3, pp. 495–513, 2011, doi: 10.1016/j.ejor.2010.10.022.

[13] X.-Z. Pi, X.-M. Fan, and J.-Q. Yan, "Appication of genetic algorithm based on task sequences to assembly line balancing," *Mech. Sci. Technol.*, vol. 22, no. 1, pp. 35–38, 2003, doi: 10.3321/j.issn:1003-8728.2003.01.012.

[14] J. L. Wang, J. Zhang, W. Qin, L. Yin, and D. Chen, "Robust scheduling on flexible job shop with uncertain processing time," *China Mech. Eng.*, vol. 26, no. 5, pp. 627–632, 2015, doi: 10.3969/j.issn.1004-132X.2015.05.010.

[15] M. Z. Liu, X. Zhang, C. Liu, M. X. Zhang, and M. G. Ge, "Optimization method of remanufacturing reprocessing shop scheduling under uncertain conditions," *J. Mech. Eng.*, vol. 50, no. 10, pp. 206–212, 2014, doi: 10.3901/JME.2014.10.206.

[16] Y. Liu, R. Z. Li, X. J. Fan, and T. Gao, "Human reliability in assembly based on improved double-factor model," *Syst. Eng.*, vol. 33, no. 2, pp. 50–57, 2015.

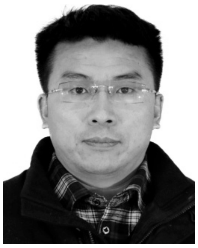
[17] J. Tang, "Research on prediction method about production logistics bottleneck shifting of manufacturing shop in uncertain environment," M.S. thesis, HeFei Univ. Technol., Hefei, China, 2009.

[18] E. J. Gardiner and V. J. Gillet, "Perspectives on knowledge discovery algorithms recently introduced in chemoinformatics: Rough set theory, association rule mining, emerging patterns, and formal concept analysis," *J. Chem. Inf. Model.*, vol. 55, no. 9, pp. 1781–1803, 2015, doi: 10.1021/acs.jcim.5b00198.

[19] M. T. Rezvan, A. Z. Hamadani, and S. R. Hejazi, "An exact feature selection algorithm based on rough set theory," *Complexity*, vol. 20, no. 5, pp. 50–62, 2015, doi: 10.1002/cplx.21526.
[20] J. H. Liu, J. Yu, and M. Y. Zhu, "Technical state control technology of aerospace product in production process based on Internet of manufacturing-related things," *Comput. Integr. Manuf. Syst.*, vol. 21, no. 7, pp. 1781–1789, 2015, doi: 10.13196/j.cims.2015.07.013.
[21] N. Yao, "Research of monocular vision based target tracking and positioning techniques," Ph.D. dissertation, Shanghai Jiao Tong Univ., Shanghai, China, 2014.
[22] J. Anjos, I. C. Izurieta, W. Kolberg, A. L. Tibola, L. Arantes, and C. Geyer, "MRA++: Scheduling and data placement on mapreduce for heterogeneous environments," *Future Gener. Comput. Syst.*, vol. 42, pp. 22–35, Jan. 2015, doi: 10.1016/j.future.2014.09.001.

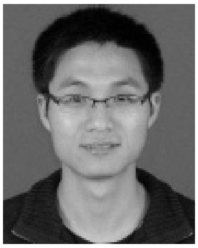
XINYE WU received the B.S. degree in industrial engineering from the Nanjing University of Science and Technology in 2016, where she is currently pursuing the master's degree in industrial engineering.

Her research interest is complex assembly management and decision.



JIANBO ZHAO received the M.S. degree in mechanical engineering science. He is currently the Vice Research Laboratory Director with the 713 Research Institute, China Shipbuilding Industry Corporation.

His research interest is advanced ship system.



YIFEI TONG received the Ph.D. degree in mechanical engineering science from the Nanjing University of Science and Technology. He is currently an Associate Professor with the Nanjing University of Science and Technology.

His research interests are in the areas of modern product development and advanced manufacturing system management and control.

He was a recipient of the third Award of the Jiangsu Provincial Science & Technology.