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Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance

JIHONG YAN[1], YUE MENG[1], LEI LU[1], AND LIN LI[2]
[1]School of Mechatronics Engineering, Harbin Institute of Technology, Harbin 150001, China
[2]College of Mechanical and Electrical Engineering, Qingdao University of Science and Technology, Qingdao 266061, China

Corresponding author: Lei Lu (lulei71@gmail.com)

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ABSTRACT Industry 4.0 can make a factory smart by applying intelligent information processing approaches, communication systems, future-oriented techniques, and more. However, the high complexity, automation, and flexibility of an intelligent factory bring new challenges to reliability and safety. Industrial big data generated by multisource sensors, intercommunication within the system and external-related information, and so on, might provide new solutions for predictive maintenance to improve system reliability. This paper puts forth attributes of industrial big data processing and actively explores industrial big data processing-based predictive maintenance. A novel framework is proposed for structuring multisource heterogeneous information, characterizing structured data with consideration of the spatiotemporal property, and modeling invisible factors, which would make the production process transparent and eventually implement predictive maintenance on facilities and energy saving in the industry 4.0 era. The effectiveness of the proposed scheme was verified by analyzing multisource heterogeneous industrial data for the remaining life prediction of key components of machining equipment.

INDEX TERMS Industrial big data, multisource heterogeneous data, structuralization and characterization, multiple invisible factors, predictive maintenance.

I. INTRODUCTION

Big data has prevailed in recent years with its potential to ascertain valued insights for enhanced decision-making, and becomes a hot spot in both academic research and practical application [1]. Tremendous amounts of industrial data are increasingly generated by manufacturing companies [2]. Due to the rapid development and application of advanced sensor technology, computer science, internet, communication technology, big data, artificial intelligence technology (AI), the internet of things (IOT), etc., the manufacturing industry is facing a major leap forward, which is regarded as a new industrial revolution [3], [4]. To accelerate economic recovery and further seize new opportunities for development in this industrial revolution, developed countries have proposed several manufacturing-based stimulus policies to promote the integration of industry, information technology and other related advanced technologies. The Industry 4.0 concept in Germany [5] and Cyber Physical Systems (CPS) in the US [6] are the most representative overall schemes that have aroused a new round of worldwide interest in advanced manufacturing [7].

An intelligent/smart factory operates using advanced sensors and information technologies; thus, large amounts of data are generated and collected in a smart factory, requiring big data processing technology to build an integrated environment in which the production process can be represented transparently and controlled and managed in a more efficient way [8]. Reliability and safety are regarded among the most crucial factors of the intelligent system, which are now challenged by the highly complex, automated and flexible industrial system. Industry big data analytics will have great benefits, such as improving system performance, achieving near zero downtime, ensuring predictive maintenance and more.

The processing of industrial big data involves data formatting, dimensionality reduction, hidden pattern identification, performance evaluation and prediction, etc. [9], [10]. Advanced techniques were widely used for the signal

processing and data mining of industrial system, time-frequency analysis approach was applied to process mechanical vibration signal with high background noise [11], intelligent optimization algorithm was employed to select the most representative feature subset with low dimensionality [12], and system performance was evaluated and predicted by intelligent approaches [13]. However, industrial big data is regarded having "5V" characteristics [14], that is, volume, velocity, variety, veracity, value, which much challenged the utilization of traditional signal processing techniques to analyze industrial big data.

This paper explores industrial big data processing and proposes a novel framework for the structuralization and characterization of multisource heterogeneous industrial big data, and invisible factors modeling for the manufacturing process transparency. Then, predictive maintenance on facilities and energy saving are considered using industrial big data.

II. SOURCES, CHARACTERISTICS AND CHALLENGES OF INDUSTRIAL MULTISOURCE HETEROGENEOUS SPATIAL DATA

There is no doubt that data plays and will continue to play an increasingly important role in modern and future industry, as the amount and type of industrial data is continuously growing. Industrial big data mainly accumulates from the following sources:

- Design data, such as data from the product and machine design.
- Machine operation data, such as data from the control system, equipment operation.
- Staff behavior data, such as manual operation record, staff working process videos.
- Cost information, such as cost of manufacturing process, operations.
- Logistics information.
- Environmental conditions, such as weather information, indoor temperature, humidity, noises.
- Fault detection and system status monitoring data.
- Product quality data, such as the defective rate of each facility.
- Product usage data, such as availability, repair rate.
- Customer information, such as customer features, feedback data, suggestions.

The "5V" features of industrial big data make it possible to provide comprehensive and systematic information through data mining and knowledge discovery. Data mining technologies are used to discover the following information:

- Equipment design defects
- Product design defects
- Equipment health conditions
- Production processing defects
- Staff behavior and work habits
- Customer behavior, habits and demands

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This is only a small portion of the valuable information that can be extracted from industrial big data, namely, the tip of the iceberg. Knowledge and information collected from humans, machinery, the environment and the manufacturing process could also assist to reduce production cost and improve product quality.

In future, when considering the whole product lifecycle, including the design, manufacturing, marketing, service, recycling and other links, countless pieces of data, such as customer behavior, will be generated. Thus, multisource heterogeneous spatial data will be formed given the multiple independent systems and various sensors in a manufacturing enterprise. This data can be divided into three types: (1) structured data, including sensor signals, controller data, etc.; (2) semi-structured data, such as information from a website or customer feedback information in XML format; (3) unstructured data, consisting of sound, image and video records, etc.

Since the sources of industrial big data are quite different, characterization of industrial big data must be carried out and regarded as the foundation of data mining and knowledge discovery. To extract useful information from multisource heterogeneous spatial data, unstructured and semi-structured information should be transformed into structured data in advance so that data barriers due to differences in source, format, dimension and other factors can be eliminated.

With the non-structural data and semi-structural information converted into a structured format, the characterization of a complex process of an intelligent manufacturing system should be carried out with the consideration of the unique spatiotemporal property. It should be noted that industrial big data usually has two attributes: special attribute and time attribute. (1) The spatial attribute: a complex process generally consists of several subsystems that are spatially independent, and the output of the complex process can be regarded as an integration of each subsystem. For instance, overall energy consumption may be the summation of independent consumptions caused by machining, air conditioning, factory illumination, AGV transportation, etc. For analysis of energy consumption information, one can make the complex system more clear with consideration of spatial attributes. (2) The time attribute: one industrial objective may be monitored by different sensors with diverse sampling frequencies. For instance, to evaluate health condition of a cutting tool, the corresponding temperature may be acquired with a frequency smaller than 100 Hz. Meanwhile, vibration signals can be collected with frequencies from 10 kHz to 100 kHz, and extraction from these diverse signals should be carried out in different time scales. These two aspects are what we called the spatiotemporal property of industrial big data. Characterizing or featuring industrial big data with the consideration of this unique spatiotemporal property can make the system clear and transparent and can provide more accurate features for data mining in an intelligent manufacturing system.

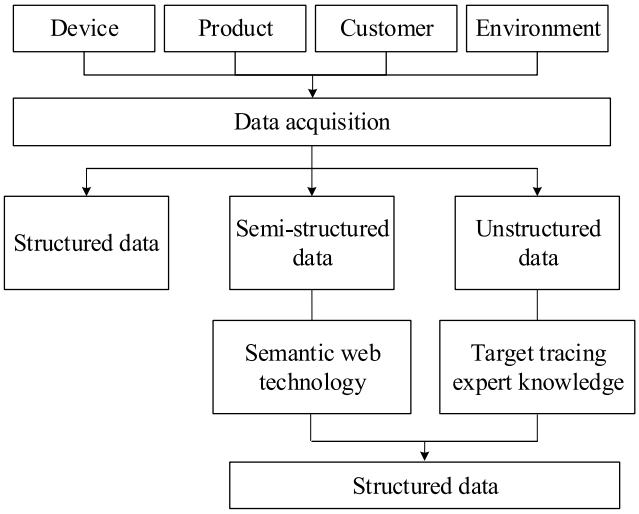


FIGURE 1. Acquisition and structuralization of industrial data.

III. FRAMEWORKS FOR MULTISOURCE HETEROGENEOUS SPATIAL DATA PROCESSING

A. STRUCTURALIZATION OF INDUSTRIAL BIG DATA

The proposed strategy for industry big data structuralization is shown as figure 1. In an intelligent manufacturing system, massive amounts of data can been collected, for the semi-structured data such as XML, semantic web technology is used to make knowledge interpretable, through tagging or annotation of data with the ontology concepts, unstructured or semi-structured data becomes standardized [15]. For the unstructured data, it usually has high instantaneity, for instance, operating characteristics of personnel could be represented by variable quantity of voice signal, video surveillance, etc. Thus, structuralization of multisource heterogeneous spatial data in industrial big data environments requires feature extraction technology and expert knowledge in related application areas. In addition, the purpose of collecting unstructured data, such as manufacturing videos, is to analyze an operator's efficiency and environment safety. The operator is regarded as a "target"; then, target detection and tracking models of target motions need to be built via the procedures of noise eliminating, information rehabilitation and enhancement. In this way, motion parameters and motion trails of the target could be obtained, based on feature extraction and clustering analysis of target motion trail, establishing a structuralization model that helps to understand target behavior.

B. CHARACTERIZATION OF INDUSTRIAL BIG DATA

With the non-structural data and semi-structural information converted into a structured format, the characterization of data can be carried out with the consideration of the unique spatiotemporal property. The procedures are shown in figure 2 and include the following:

- Identify spatially independent subsystems of a manufacturing process; since the collected signals can be regarded as synthesized information from independent subsystems, the envelope analysis technique would be an alternative way to extract intrinsic modes from the synthesized signal by shifting process;
- Analyze association to select intrinsic modes that have high correlations with the process and eliminate redundant modes;
- Acquire signals from subsystems with different time scales, extracting features from the signal by optimized wavelet function and decomposition level using wavelet transformation;
- Carry out feature fusion to accumulate features for data mining.

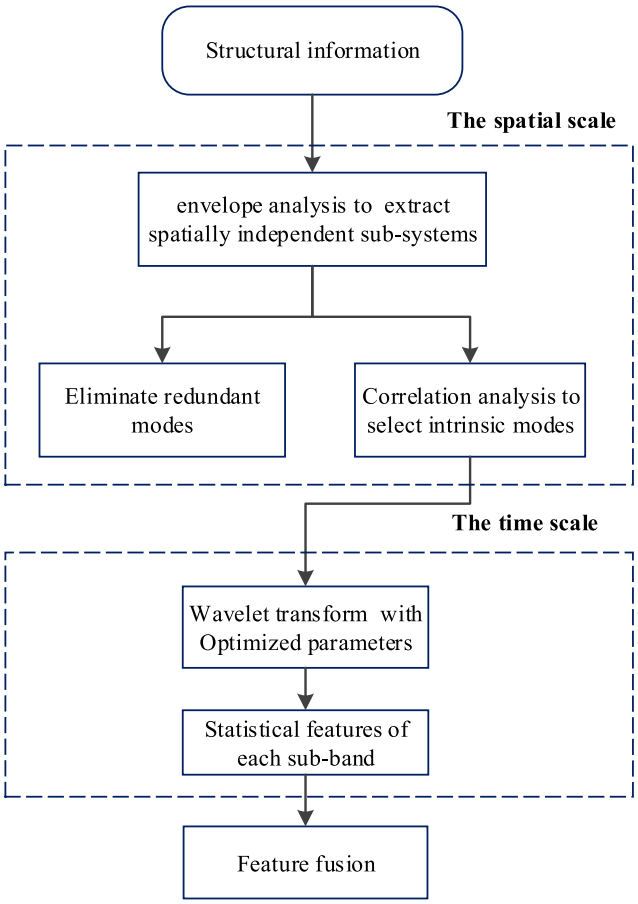


FIGURE 2. Characterization with multi-scale analysis.

IV. MULTIPLE INVISIBLE FACTORS MODELING AND MANAGEMENT BROUGHT BY INDUSTRIAL BIG DATA

Traditionally, invisible factors, such as the health condition of facilities, capability of operators, environmental data, i.e., weather forecast data, temperature of work space, and cutting noise, have not been considered in analytics of conventional manufacturing processes because information is isolated and sensoring is limited [11], [16]. In an industrial big data environment, it is possible to mine the correlation and causal relationship of multisource information and reveal

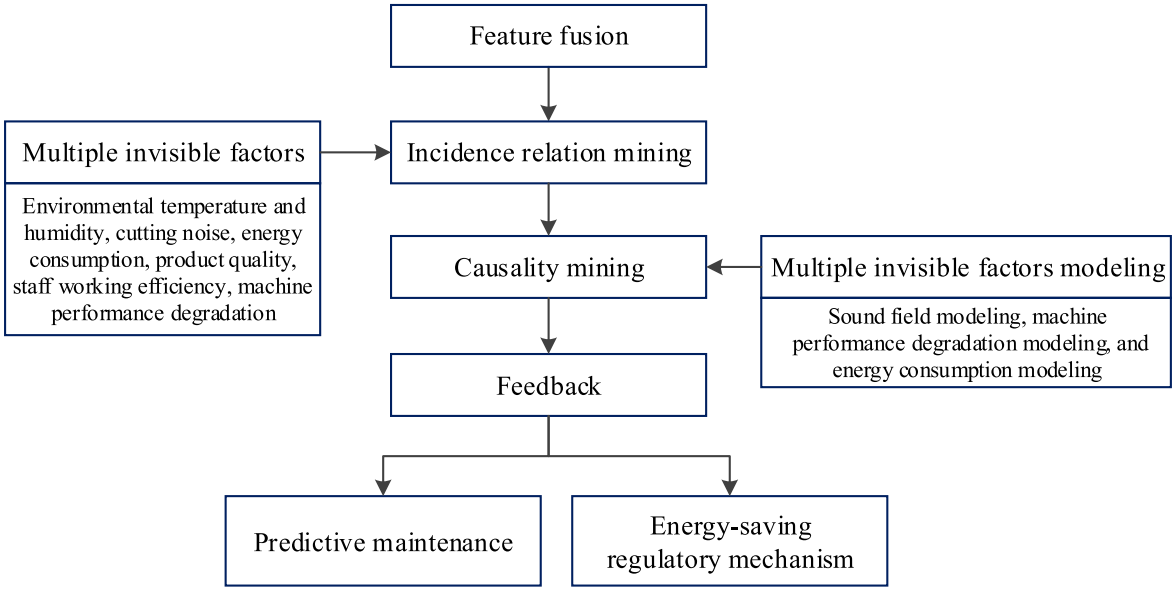


FIGURE 3. Scheme for invisible information mining and energy saving.

invisible factors among human-machine-environment. Therefore, uncertainty information in the process of production could be quantified to comprehensively understand a manufacturing process. Industrial big data provides the opportunity to fully explain the state of a manufacturing process. By utilizing the intelligence of data processing and forecasting techniques, the performance of system decision-making could be improved.

Typical invisible factors in an intelligent manufacturing process from the perspective of human-machine-environment include staff work efficiency, machine performance and environment index. A comprehensive relationship among productivity, cost and these invisible factors can be modeled based on the information provided by industrial big data. Therefore, predictive maintenance on machineries and efficiency evaluation on workforce and energy-aware machining could be achieved by feeding back these traditionally invisible factors to the decision-making system, as shown in figure 3.

A. MULTIPLE INVISIBLE FACTORS MODELING

In the case of ideal light layout, environmental temperature and humidity, cutting noise and sound field distributions are important hidden factors that affect staff working efficiency, which might have a direct influence on production quality, energy consumption and machine performance degradation. Therefore, the coupling mechanism of human-machine-environment in big data environment should be studied based on sound field modeling, machine performance degradation modeling and energy consumption modeling. Using large datasets, these models can help explain the evolution of consumption patterns, predict performance degradation and energy consumption trends and provide the basis for optimizing the performance of large-scale manufacturing systems.

B. CLOSED-LOOP FEEDBACK FOR PREDICTIVE MAINTENANCE AND ENERGY-SAVING

1) PREDICTIVE MAINTENANCE

Equipment failure and short downtime of manufacturing process often cause huge economic losses for an enterprise. Based on degradation severity of machine performance and knowledge mining of multiple inputs, performance degradation models of different types of equipment and the same type of equipment, but with different human-machine-environment factors, can be established. With the maintenance effectiveness evaluation on different maintenance policies, relevant cost, resources, etc., the optimal maintenance strategy can be determined.

2) ENERGY-SAVING REGULATORY MECHANISM

From a production operations perspective, machine tools at idle state that are waiting for an upstream work piece consume significant amounts of energy. When machine tools are idle, the introduction of a machine dormancy mechanism can introduce potential energy savings.

There are many ways to make energy efficient, such as switching off lights, pulling out plugs, optimizing machine tools and minimizing energy consumption of heating, ventilation and air conditioning (HVAC) systems. The HVAC system provides a comfortable temperature for a workshop, which is not only used to control the workshop temperature by comparing the actual and expected temperature in the workshop but also as a forecasting controller considering dynamic weather big data, by which energy usage for HVAC could be minimized.

To explore the potential of energy saving for production management, intelligent optimization algorithms are employed to optimize make-span and total energy

FIGURE 4. HAAS vertical milling center.

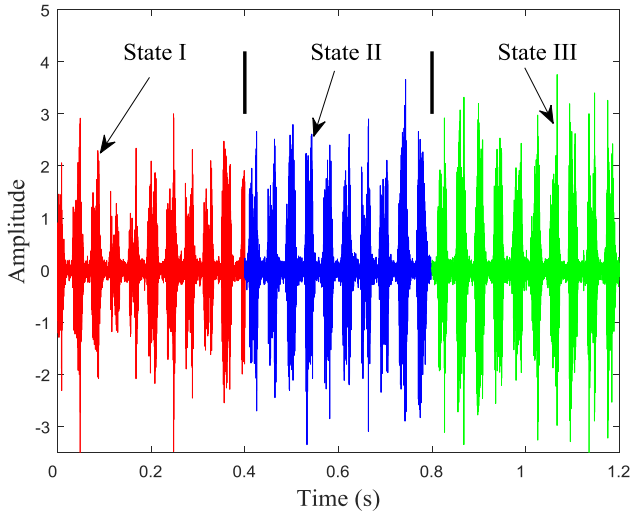


FIGURE 5. Vibration signal of the cutting tool.

consumption simultaneously at a big data processing platform.

V. CASE STUDY AND DATA ANALYSIS

The proposed case study was conducted in a complex intelligent manufacturing system to validate the effectiveness of the developed method on predictive maintenance. The analysis of energy saving and optimization were verified in the authors' previous work [17], [18]. The intelligent manufacturing system consisted of machining equipment, mixed flexible assembling line, a 3D printer, a joint manipulator, AGVs, a cloud computing platform, etc. Multisource heterogeneous big data was employed to evaluate the performance and predict the remaining life of key components of a CNC machining center, as shown in figure 4. The experiment was conducted by machining the surface of type 45 iron with dimensions of $100\times100\times60$ mm^3. The information collected on the cutting process included vibration signal from the cutter, images captured by a 3D laser scanner, acoustical signal collected by sound sensors and power data obtained from power meters with type CW240.

The vibration signal shown in figure 5 was collected every minute from the machining process with a sampling frequency of 1 MHz in LabVIEW platform. The cutter ran from brand new to slightly worn and worn out. The corresponding vibration signal changed from the normal state (State I) to slight vibration (State II) and drastic vibration (State III). With the proposed industrial big data characterizing technique, the vibration signal was processed in two steps: (1) envelope analysis was employed to identify the dominant component and noisy signal produced by the spatial independent equipment, such as the vibration signal from working table moving; (2) time scale analysis was carried out to select frequency bands that represent equipment performance. Then, widely used typical statistical features including the mean value, maximum point, minimum value, standard deviation, kurtosis, pulse index, energy of each mode, waveform factor, peak-to-peak value and fifth central moment, were extracted from sub-frequency bands, which were regarded as input features in the following prediction model I.

With the continuous cutting process, the tool flank wear gradually increased. As shown in figure 6, the 3D laser scanner (Microscope OLS3000) was employed to measure the tool wear size every 20 minutes and obtained the wear information in 3D images that were in the BMP format and regarded as typical unstructured data. The width of the flank surface (WFS) was used to indicate the cutter's performance [19]. As shown in figure 7, ten discrete flank wear values were obtained in the whole cutting process, and the cutter changed from brand-new to worn-out with WFS value of 275.29μm. The two sub-images in figure 7 corresponding to the point B with WFS value of 119.35μm and point G with WFS value of 232.11μm, which clearly illustrate that the WFS value gradually increased in a continuous cutting process. The tool wear principle was obtained by the cubic curve fitting of measured discrete flank wear values, which presented the relationship between cutting time and tool wear and can be used as a benchmark of the cutter's life.

The CW240 power meter was used to measure power data of the machining center in the cutting process every minute. A total of 200 measured power values were shown in figure 8, which showed that the power value volatilely increased with continuous cutting time. The power model was obtained by the cubic curve fitting of measured power values. It should be noted that the tool wear data and power data shown in figure 8 were normalized to the range from 0 to 1.

For the remaining life prediction, the research focused on employing vibration signal to evaluate the current performance and predict the remaining life. Unlike traditional methods, information collected from the multiple sensor nodes in an Industry 4.0 environment provided new solutions for remaining life prediction. Figure 9 presented the prediction result obtained by traditional single source data (prediction model I) and multisource data (prediction model II).

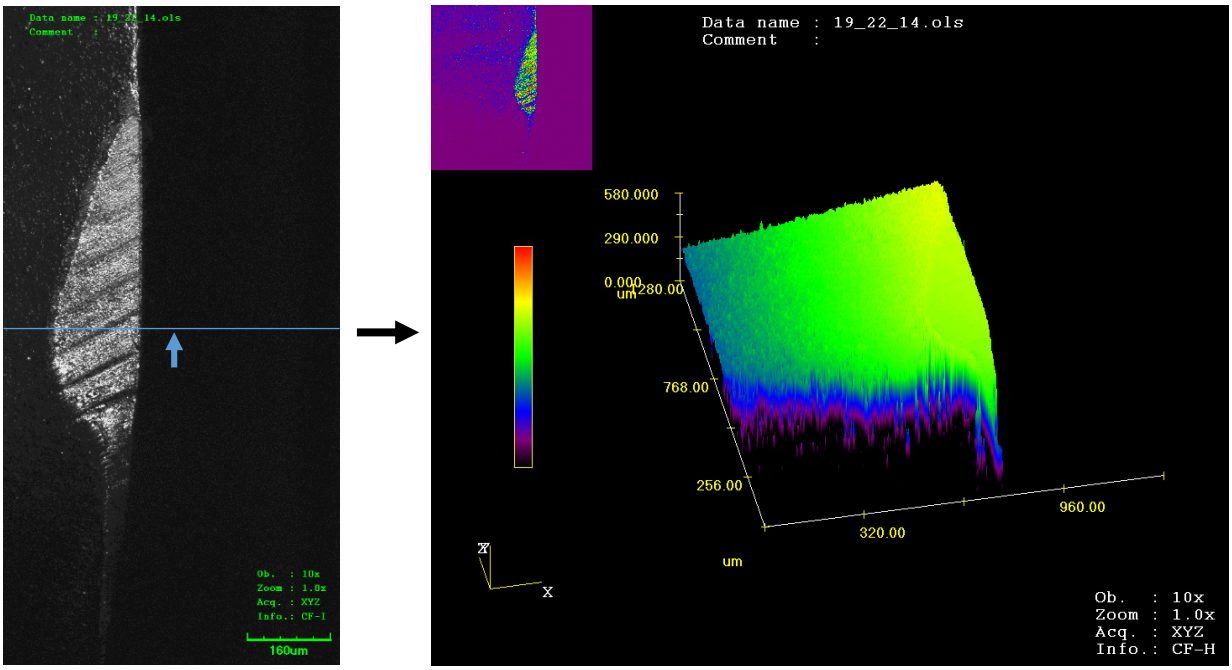


FIGURE 6. Tool wear measured by the 3D laser scanner.

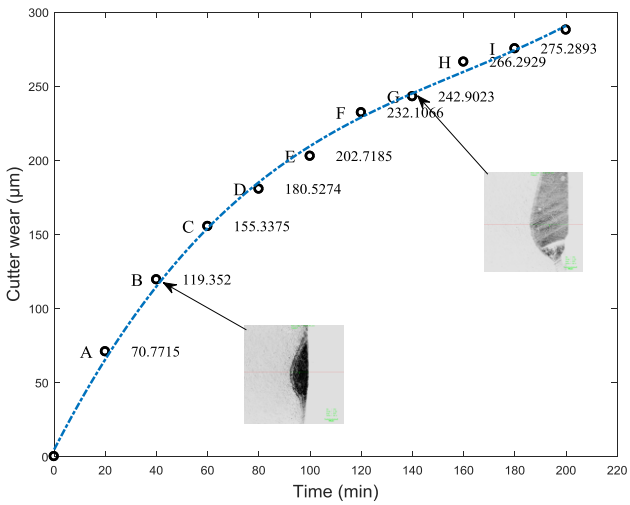


FIGURE 7. Tool wear of the cutting process.

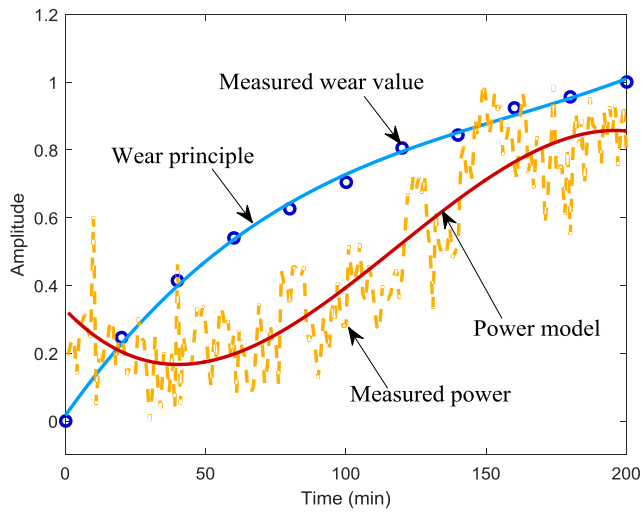


FIGURE 8. The measured data and fitted model.

Parameters and prediction results can be found in Table 1. For prediction model I, the measured vibration data was used to predict the cutter's remaining life based on ANN model, and each input sample consisted of the above discussed 10 statistical features. It can be seen that there were large fluctuations during the prediction part, especially in minutes 146 and 149. For prediction model II, as shown in figure 9, despite the 10 statistical features, the power model was combined, and 11 total statistical features were employed as input features to predict the cutter's remaining life. Compared with prediction model I, the proposed prediction technique by analyzing multisource heterogeneous data obtained a flatter prediction curve.

To obtain statistical results of the two models, the two prediction processes were repeated 100 times. As shown in Table 1, for prediction model I, the mean value of the 100 mean square deviation (MSE) values was calculated to be 0.1823, and the corresponding standard deviation was 0.0482. For prediction model II, the mean value of the 100 MSE values was 0.1504, which was smaller than the value of prediction model I, and the corresponding standard deviation was 0.0482, which was slightly larger than the value of prediction model I. However, it can be calculated that the upper boundary of the mean square deviation was 0.2158, which was smaller than the corresponding value 0.2305 of

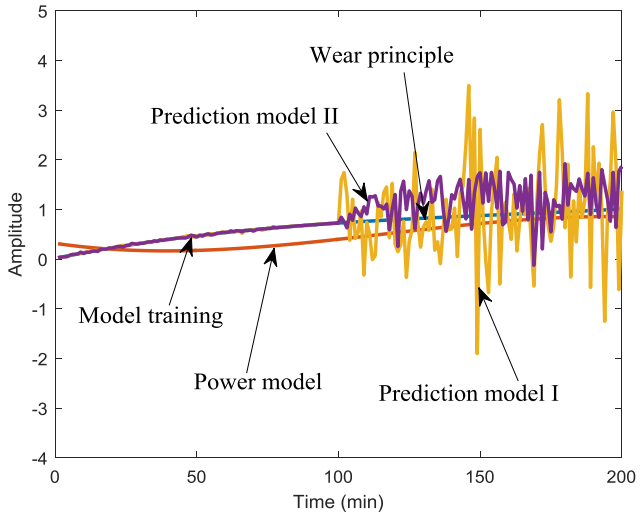


FIGURE 9. Remaining life prediction by two models.

TABLE 1. Parameters and results of the prediction process.

	Prediction Model I	Prediction Model II
Number of training samples	100	100
Number of testing samples	100	100
Neurons in hidden layer	30	30
Input features	10	11
Multisource data	No	Yes
Testing times	100	100
Mean value	0.1823	0.1504
Standard deviation	0.0482	0.0654

prediction model I. The results demonstrated that prediction model II with multisource input data can obtain more accurate prediction results.

VI. CONCLUSIONS

The unique properties of industrial big data, which were distinctly different from big data in social networks, require special processing techniques. A systematic procedure was proposed to structuralize industrial big data in the first place, with semantic web technology for semi-structured data and target recognition, detection and tracking for unstructured data. Then, the structured data would be characterized with multi-scale analysis in two areas to help identify hidden patterns and improve transparency of the manufacturing system, using envelope analysis to extract spatially independent subsystems and time frequency analysis for signal decomposition. A fusion method was then employed to achieve more efficient features for data mining. Finally, data mining for predictive maintenance in industrial big data environment was discussed.

The case study was conducted to predict the remaining life of a key component of a piece of machining equipment by analyzing multisource heterogeneous data. The results demonstrated that the proposed method had superior performance for predicting remaining life compared to the method with a single source of information. In addition, the results illustrated that traditional machine learning methods, such as ANN, can still play a role in the Industry 4.0 environment in some conditions. The findings of this paper indicated that multisource heterogeneous data can provide new solutions for predictive maintenance, scheduling and machining process optimization for energy saving. The proposed industrial big data processing scheme was a systematic project and cannot be covered and verified by one case. Future work will focus on employing more cases to evaluate the developed method, as well as utilizing the recent powerful intelligent techniques, such as deep learning, to analyze industrial big data.

REFERENCES

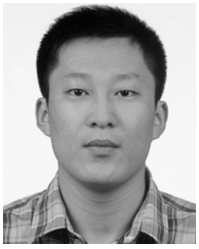
[1] X. Yi, F. Liu, J. Liu, and H. Jin, "Building a network highway for big data: Architecture and challenges," *IEEE Network*, vol. 28, no. 4, pp. 5–13, Jul. 2014.
[2] X. Wu, X. Zhu, G.-Q. Wu, and W. Ding, "Data mining with big data," *IEEE Trans. Knowl. Data Eng.*, vol. 26, no. 1, pp. 97–107, Jan. 2013.
[3] F. Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage. (IEEM)*, Dec. 2014, pp. 697–701.
[4] J. Lee, E. Lapira, B. Bagheri, and H.-A. Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," *Manuf. Lett.*, vol. 1, no. 1, pp. 38–41, 2013.
[5] R. Schmidt, M. Möhring, R. C. Härting, C. Reichstein, P. Neumaier, and P. Jozinovi, "Industry 4.0-potentials for creating smart products: Empirical research results," in *Proc. Int. Conf. Bus. Inf. Syst.*, 2015, pp. 16–27.
[6] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, Jan. 2015.
[7] S. Yin and O. Kaynak, "Big data for modern industry: Challenges and trends [point of view]," *Proc. IEEE*, vol. 103, no. 2, pp. 143–146, Feb. 2015.
[8] H. S. Kang *et al.*, "Smart manufacturing: Past research, present findings, and future directions," *Int. J. Precision Eng. Manuf.-Green Technol.*, vol. 3, no. 1, pp. 111–128, 2016.
[9] P. A. Mathew, L. N. Dunn, M. D. Sohn, A. Mercado, C. Custudio, and T. Walter, "Big-data for building energy performance: Lessons from assembling a very large national database of building energy use," *Appl. Energy*, vol. 140, pp. 85–93, Feb. 2015.
[10] X. Jin, B. W. Wah, X. Cheng, and Y. Wang, "Significance and challenges of big data research," *Big Data Res.*, vol. 2, no. 2, pp. 59–64, 2015.
[11] J. Yan and L. Lu, "Improved Hilbert–Huang transform based weak signal detection methodology and its application on incipient fault diagnosis and ECG signal analysis," *Signal Process.*, vol. 98, pp. 74–87, May 2014.
[12] L. Lu, J. Yan, and C. W. de Silva, "Dominant feature selection for the fault diagnosis of rotary machines using modified genetic algorithm and empirical mode decomposition," *J. Sound Vib.*, vol. 344, pp. 464–483, May 2015.
[13] D. Tumac, "Artificial neural network application to predict the sawability performance of large diameter circular saws," *Measurement*, vol. 80, pp. 12–20, Feb. 2016.
[14] S. Sagiroglu, R. Terzi, Y. Canbay, and I. Colak, "Big data issues in smart grid systems," in *Proc. IEEE Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2016, pp. 1007–1012.
[15] M. Panahiazar, V. Taslimitehrani, A. Jadhav, and J. Pathak, "Empowering personalized medicine with big data and semantic Web technology: Promises, challenges, and use cases," in *Proc. IEEE Int. Conf. Big Data*, Oct. 2014, pp. 790–795.

[16] Y. Zhang, S. Ren, Y. Liu, and S. Si, "A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products," *J. Cleaner Prod.*, vol. 142, pp. 626–641, Jan. 2017.
[17] J. Yan, L. Li, F. Zhao, F. Zhang, and Q. Zhao, "A multi-level optimization approach for energy-efficient flexible flow shop scheduling," *J. Cleaner Prod.*, vol. 137, pp. 1543–1552, Nov. 2016.
[18] J. Yan and L. Li, "Multi-objective optimization of milling parameters—The trade-offs between energy, production rate and cutting quality," *J. Cleaner Prod.*, vol. 52, pp. 462–471, Aug. 2013.
[19] G. Zhang, S. To, and S. Zhang, "Evaluation for tool flank wear and its influences on surface roughness in ultra-precision raster fly cutting," *Int. J. Mech. Sci.*, vol. 118, pp. 125–134, Nov. 2016.

JIHONG YAN is a Professor and the Deputy Dean of the School of Mechatronics Engineering, Harbin Institute of Technology (HIT). She was a Post-doctoral Researcher with Tsinghua University from 1999 to 2001, the IMS center at the University of Wisconsin from 2001 to 2004, and Pennsylvania State University from 2004 to 2005. She was named the Overseas Recruited Talent of HIT and the Chairman of the Industrial Engineering Institute of Mechanical Engineering, Heilongjiang. Her research is mainly focused on industrial big data analysis, sustainable manufacturing, and intelligent maintenance. As a PI, she was involved in and accomplished 20 projects funded by the NSF of China (NSFC), joint NSF-NSFC projects, national high-tech projects, and high-tech funding from industries. She participated in the 973 Project and the Thousand Talents Plan. She has authored two books in Chinese and one in English (Wiley, 2015) and has authored and coauthored over 100 research papers.

YUE MENG received the B.S. degree from the School of Mechatronics Engineering, Harbin Institute of Technology and the M.S. degree from the School of Transportation and Logistics Engineering, Dalian Maritime University. She is currently pursuing the Ph.D. degree with the School of Mechatronics Engineering, Harbin Institute of Technology, under the supervision of Prof. J. Yan. From 2013 to 2015, she was a Visiting Researcher with the University of Cincinnati, USA. Her research interests are industrial big data analysis, predictive maintenance, and data mining.

LEI LU received the Ph.D. degree with the School of Mechatronics Engineering, Harbin Institute of Technology, in 2016. He was a Visiting Scholar with the Department of Mechanical Engineering, The University of British Columbia, Canada, from 2013 to 2015. He is currently a Post-doctoral Researcher with the School of Management, Harbin Institute of Technology. His research interests include industrial big data processing, biomedical data analysis, and intelligent machine health monitoring. He has participated in several projects funded by the NSFC, and also joint NSF–NSFC projects.



LIN LI received the Ph.D. degree from the School of Mechatronics Engineering, Harbin Institute of Technology, in 2016. He was a Visiting Researcher with Purdue University, USA, from 2014 to 2015. He is currently a Lecturer with the College of Mechanical and Electrical Engineering, Qingdao University of Science and Technology. His research interests are energy consumption modeling, sustainable manufacturing, computer aided intelligent design, etc. He has several publications in the field of sustainable manufacturing.