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The business model of intelligent manufacturing with Internet of Things and machine learning

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ABSTRACT

To establish a business model of intelligent manufacturing, the sequence Generative Adversarial Network (SeqGAN) was used to optimise the Back Propagation (BP) neural network algorithm improved by multi-objective Genetic Algorithm to propose the sequence Generative Adversarial Network-Genetic Algorithm Back Propagation Algorithm (SeqGAN-GABP). Meanwhile, the Elman algorithm was optimised by the SeqGAN model to propose the SeqGAN-Elman algorithm. The algorithms were constructed and trained and were applied to the Internet of Things platforms. The results showed that the SeqGAN-GABP algorithm outperforms the SeqGAN-Elman algorithm in terms of minimal error, fitting accuracy, training time and internal memory usage.

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KEYWORDS

Business model; intelligent manufacturing; Internet of Things; machine learning; neural network

1. Introduction

At present, the domestic and foreign manufacture industries are moving towards an intelligent and digital era, and the influence of intelligent manufacturing on various aspects of manufacture industry is also growing (Peng and Gao 2017; Mousavi et al. 2017). Doubtlessly, it is the developing direction of the automatic manufacture for intelligent manufacturing. The intelligent manufacturing system judges and plans its own behaviour by collecting and analysing its own information and environmental information and enriches the knowledge base in the practice process (Li et al. 2018). Business model refers to various transaction relationships and connection methods between enterprises and enterprises, between departments and departments, between enterprises and customers, and between enterprises and channels (Kaulio, Thorén, and Rohrbeck 2017). A business model is a conceptual tool that contains a set of elements and their relationships to illustrate the business logic of a particular entity (Ding et al. 2017). It describes the value that a company can provide to its customers, as well as the internal structure, partner network, and relationship capital of the company to achieve (create, market, and deliver) this value and generate sustainable profits (Yun, Won, and Park 2017).

The Internet of Things (IoT) refers to real-time collection of any object or process that needs monitoring, connection, and interaction through various information sensors, radio

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frequency identification technology, global positioning system, infrared sensor, laser scanner, and other devices and technologies, which collects various information required for sound, light, heat, electricity, mechanics, chemistry, biology, location, etc., through various possible network accesses, to achieve ubiquitous connection between objects and objects, objects and people, as well as the intelligent perception, identification, and management of items and processes (Guijarro et al. 2017; Wollschlaeger, Sauter, and Jasperneite 2017). Machine learning refers to the acquisition of new skills or knowledge and the improvement of the performance through computer simulation or the realisation of human learning behaviours (Helma et al. 2018). The intelligent manufacturing system has the characteristics of high-dimensional features and strong-weighted comprehensive scoring subjective factors. In addition, the adaptive learning, generalisation ability, feature extraction ability and large-scale parallel-distributed structure of the neural network can support its adaptive mode according to the environment for identification, which is convenient to expand its capacity and add functional modules. In the context of the rapid development of intelligent manufacturing, enterprises lack the evaluation tools for intelligent manufacturing systems. Under such circumstances, it is particularly important to build a complete and scientific intelligent evaluation system for the intelligent manufacturing system.

The way to closely integrate the IoT business model, machine learning and intelligent manufacturing has become the main research direction of the future of intelligent manufacturing. Therefore, based on the theories of IoT and machine learning, a neural network algorithm based on the Internet of Things platform was proposed in this study, which was optimised, modelled and trained to explore the business model of intelligent manufacturing, providing a reference for relevant r enterprises. The organisational structure of this study is divided into five sections. The first section is the introduction, which briefly introduces the background of the research. The second section is the literature review, which introduces the research progress in recent years. The third section introduces the intelligence manufacture business model in the environment of the Internet of Things and machine learning. The SeqGAN generative adversarial networks were used to optimise the BP neural network algorithm improved by a multi-objective Genetic Algorithm to propose the SeqGAN-GABP algorithm. In addition, the Elman algorithm was optimised by the SeqGAN model to propose the SeqGAN-Elman algorithm. The algorithms were constructed and trained and were applied to the IoT platforms. The fourth section is the feasibility analysis of the artificial neural network algorithm in the intelligent manufacturing business model, which analyses and compares the two algorithms for the verification of feasibility. The fifth section is the conclusion, which summarises the research results, deficiencies and subsequent works. The pattern recognition of intelligent manufacturing systems is realised in this study to meet the developmental needs of enterprises, which has great significance for the innovation and restructuring of business models.

2. Literature review

The comprehensive analysis of key literature at home and abroad was mainly achieved through the illustration of the overall concept, system design and implementation, and advantages and development of intelligent manufacturing.

2.1. The overall concept of intelligent manufacturing

Research by Penn et al. showed that in the aspects of intelligence and manufacture, the intelligent manufacturing would be developed in the future; all products would be the entity of some kind of algorithm, i.e. the era of 'pan-robot' (Preuveneers et al. 2017). The importance of developing intelligent manufacturing for Chinese manufacture industry and even the Chinese economy is self-evident. With the integration of manufacture industry and information technology, the manufacturing industry is gradually digitised, and more data are gathered on the same data platform (Penn, Pennerstorfer, and Jungbauer 2018). Data analysis has made the manufacturing industry truly intelligent (Cardin et al. 2017). Based on the digitalisation of manufacture and the big data generated by 'Internet+', the system platform conducts data analysis to form knowledge and value (Lim et al. 2018). Guo et al. suggested that intelligent manufacturing would promote the formation of vertically integrated business models, horizontally integrated business models, and intelligent platform business models (Guo, Pang, and Li 2018). Intelligent manufacturing would reconstruct the future business models with the platform as the core, which not only helps manufacture companies to achieve cost reduction and efficiency but also gives enterprises the opportunity to rethink value positioning and reconstruct business models (Mohtar 2017).

2.2. The design and implementation of the intelligent manufacturing system

Ozay et al. proposed that machine learning can be applied to intelligent manufacturing systems. One way is to build a single system with machine learning functions. The other way is to build an enterprise-level machine learning platform to provide capabilities and services of machine learning for other systems in the enterprise. The latter machine learning platform system architecture can be divided into data acquisition layer, source data layer, data storage layer, data analysis layer and application layer (Ozay et al. 2017). Expert systems and pattern recognition technologies in modern manufacture processes have been widely used and have been applied in visual recognition, natural language understanding and robotics in many disciplines (Klaine et al. 2017). The original expert system defines the experience and experimental data of the business professionals in the system in a regular way, and then integrate the mathematical programming algorithm to find the optimal solution of the problem according to the given conditions, such as the dynamic scheduling in multi-objective programming, while the pattern recognition is based on the characteristics that have been set, and the identification model is given by the parameter setting method to achieve the discriminating purpose, focusing on solving the sensing problem of small data change and single business targets, such as production signal processing, image recognition and statistical process control (Giusti et al. 2017). Machine learning can use standard algorithms to learn historical samples to select and extract features to build and continuously optimise models so that the ability of independent learning of the original system in the enterprise is increased, which solves the uncertain business in the production process and enhances the intelligent level of the system (Ge et al. 2017).

2.3. The advantages and development of intelligent manufacturing

Wang et al. believed that the application of the Internet of Things technology to intelligent manufacturing systems would promote the development of intelligent manufacturing business models (Wang et al. 2017). Yang et al. discussed the problems of artificial intelligence in intelligent manufacturing and proposed related recommendations (Yang et al. 2018). Day et al. pointed out that intelligent manufacturing technology is based on information communication technology and manufacturing technology and discusses the advantages of small-scale intelligent manufacturing systems (Day 2018). Lv et al. suggested that the complete separation of machines and people has become a trend in technology development. To survive in a highly competitive and ever-changing market, manufacturers must improve the model flexibility, competitiveness, sustainability and timely response of their intelligent manufacturing business through innovative management methods and advanced technologies (Lv and Lin 2017).

At present, most of the literature on intelligent manufacturing focuses on three aspects, i.e. the overall concept description, the system design, and the implementation, advantages and development. The research on intelligent manufacturing systems based on machine learning for relevant analysis and evaluation is rare, which is exactly the current needs of manufacturing enterprises. Therefore, based on domestic and foreign research, an evaluation system for the intelligent manufacturing business model was proposed in this study so that enterprises can clearly understand their status and shortcomings to make the next-step decisions.

3. The business model of intelligent manufacturing under the environment of the Internet of Things and machine learning

3.1. Theories and key technologies of machine learning

3.1.1. Artificial neural network algorithm

Artificial Neural Network (ANN) is usually used to solve feature selection problems. It has the advantages of simple structure and strong practicability, which is widely used (Bose 2007). Wu et al. applied ANN to the prediction of cleanliness level (Wu et al. 2009). Rawat et al. reviewed the various applications of neural networks in the synthesis of smart antenna arrays (Rawat, Yadav, and Shrivastava 2012). Sustrova designed several neural network models with different structures to optimise the inventory level of companies and proposed that the optimised neural network had an excellent effect on the prediction of subsequent orders, reduction of inventory purchase and cost reduction (Sustrova 2016). However, the number of exercises is high, the learning efficiency is low, and the trend of forgetting old samples is easy; in addition, ANN is easy to fall into local optimum. In this study, the ANN was optimised for these shortcomings.

3.1.2. The generative adversarial network algorithm based on adversarial ideas

The generative adversarial network (GAN) consists of two modules: generative model and discriminant model. The game learning among modules can produce quite good output. The two ANNs learn from each other to perform training optimisation, and the training process is shown in Equation (1).

$$\min_{g}\max_{D} E_{x-p_{data}} \log[D(\chi)] + E_{Z-p_Z} \log[1 - D(g(Z))] \tag{1}$$

In Equation (1), P_{data} was the distribution of real data, P_z was the noise data in compliance with the arbitrary distribution. GAN can produce better samples and is suitable for all generator training without having to make a pre-judgement. However, traditional GAN has certain limitations. For example, it is difficult to achieve a Nash equilibrium, and the loss function is missed. It is difficult to judge whether the progress is made during the training process, and it is difficult to generate discrete data. In view of these limitations of the GAN, in this study, the SeqGAN Generative Adversarial Network was applied to discrete data generation for optimisation. First, the random long-term and short-term memory network method was used to perform distributed sampling, and a positive sample was obtained, and the generator was pre-trained to generate a discriminatory and adjust the generator to weight the loss function. The Monte Carlo tree search was used to complete the possibility of each action, get the feedback value and pass the feedback value back to the generator for updating.

3.1.3. Multi-objective genetic algorithm

Multi-objective optimisation problems often conflict, which can be solved by intelligent optimisation algorithms. Intelligent optimisation algorithms include Genetic Algorithms and Particle Swarm Optimisation Algorithms. The Genetic Algorithm (GA) is a method to simulate the natural evolution of the Darwin biological evolution theory and the biological evolution process of genetic mechanism to search for optimal solutions. The main operational steps are chromosome coding and decoding, designing the fitness function, genetic operation and parameter adjustment. In this study, an improved algorithm, i.e. the Quick Non-dominated Sorting Genetic Algorithms-II (NSGA-II) was used. The algorithm could run fast and had good convergence, which could be used as a method for updating the weight of neural networks. By initialising the weights and thresholds of the neural network, the possibility of the neural network algorithm falling into local optimum was reduced, and the learning efficiency was improved.

3.1.4. The SeqGAN-GABP algorithm

The SeqGAN-GABP algorithm used in this study was formed by the SeqGAN optimised multi-objective GA improved by Back Propagation (BP) neural network algorithm. The SeqGAN was used to expand the discrete sample data against the network, and feature extraction was performed. The BP neural network algorithm improved by the multi-objective GA was trained. The GABP algorithm could be divided into three parts, i.e. the BP neural network model, the GA optimisation of BP neural network and the prediction of BP neural network after optimisation. First, the training error was set to the chromosome fitness value. The selection operation, cross operation and mutation operation was performed. Then, the optimal initial weight and threshold required by the network were obtained by the genetic algorithm, which was substituted into the BP neural network for prediction. The predicted results were output after training. The specific flow chart is shown in Figure 1. The algorithm was proposed for the case where the evaluation sample data was small, and the feature data was not robust enough in the intelligent manufacturing system. The SeqGAN-Elman algorithm was improved by combining the SeqGAN generation-based anti-network BP algorithm optimised by the multi-objective genetic algorithm. The core

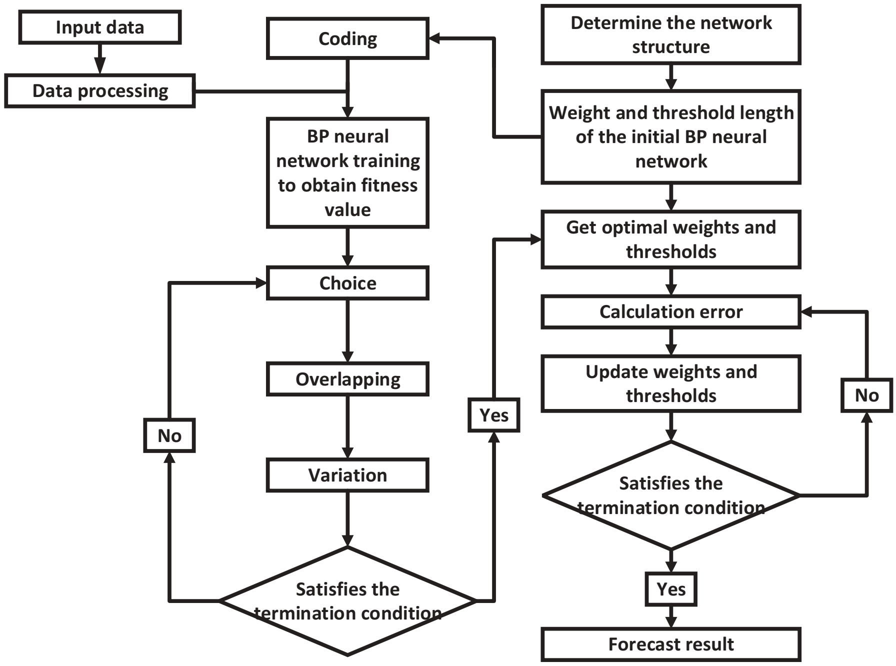

Figure 1. The flowchart of BP neural network algorithm optimised by genetic algorithm.

idea was to use the SeqGAN generative adversarial networks to expand and robust the discrete sample data. Then, the feature extraction of the expanded sample data was performed. The extracted data were input into the GABP network for training.

First, the training error was set to the chromosome fitness value according to Equation (2).

$$F = K \left. \sum_{i=1}^{n} abs(y_i - o_i) \right) \tag{2}$$

In Equation (2), n was the number of output nodes, y_i was the actual result of the i-th node and O_i was the prediction result of the i-th node. Then, the roulette method was used to select operations, as shown in Equations (3) and (4).

$$f_i = K/F_i \tag{3}$$

$$P_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{4}$$

In the Equations, K was the coefficient, F_i was the fitness value of the individual i and N was the total number of chromosomes. A pair of chromosomes in the individual was found for cross-processing, as shown in Equations (5) and (6).

$$a_{mj} = a_{mj}(1 - b) + a_{ij}b \tag{5}$$

$$a_{ij} = a_{ij}(1 - b) + a_{mj}b \tag{6}$$

In the Equations, b was a random number between 0 and 1. The mutation of the y-th gene a_{xy} on the chromosome x is shown in Equations (7) and (8).

$$a_{xy} = a_{xy} + (a_{xy} - a_{max}) * f(g),\ r > 0.5 \tag{7}$$

$$a_{xy} = a_{xy} + (a_{\min} - a_{xy}) * f(g),\ r \leq 0.5 \tag{8}$$

In the Equations, max and min respectively represented the upper and lower bounds of the chromosomal gene and g represented the number of iterations. The optimal initial weights and thresholds of the neural network were obtained based on the GA and were substituted into the BP neural network for prediction and output.

3.1.5. The SeqGAN-Elman algorithm

The SeqGAN-Elman algorithm used in this paper was formed by the SeqGAN model optimised Elman neural network algorithm. The SeqGAN was used to expand the discrete sample data against the network, and feature extraction was performed. The Elman neural network improved by the multi-objective GA was trained. The main structure of the neural network was feedforward connection, including input layer, hidden layer, receive layer and output layer. The weight and threshold of the Elman neural network were optimised by GA. The specific flowchart is shown in Figure 2. The SeqGAN-Elman algorithm was proposed for the case where the evaluation sample data was small, and the feature data was not robust enough in the intelligent manufacturing system. The Elman algorithm was improved by combining the SeqGAN model to form the SeqGAN-Elman algorithm. The

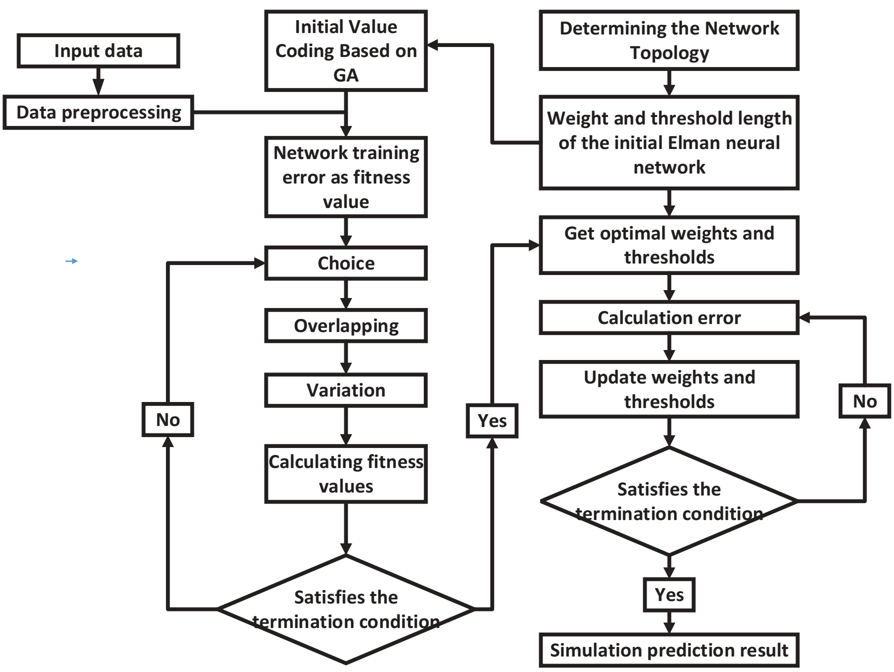

Figure 2. The flowchart of Elman neural network algorithm optimised by genetic algorithm.

core idea was to use the SeqGAN generative adversarial networks to expand and robust the sample data. Then, the feature extraction of the expanded sample data was performed. The extracted data were input into the Elman network for training.

3.2. Construction and training of the artificial neural network

Key technologies for neural network modelling and training included learning mode selection, network type selection, topology design, hyperparameter design, optimisation algorithm design, network detail design, modelling and coding, data training, and performance testing and comparison. It was modelled by the SeqGAN-GABP algorithm. The model structure is shown in Figure 3. In the input layer, the vector with the 52-dimensional feature was input. In the hidden layer, tanh was used as an activation function to capture features. In the output layer, the seven rows and seven columns of unique heat vectors were output, which respectively represented seven levels of the industry. It was modelled by the SeqGAN-Elman algorithm. The model structure is shown in Figure 4. The model structure of the SeqGAN-Elman algorithm consists of four layers, i.e. the input layer, the hidden layer, the receiving layer and the output layer. The receiving layer receives the feedback signal from the hidden layer, memorises the data of the previous iteration of the layer and inputs the data to the hidden layer, which are linearly weighted by the output layer.

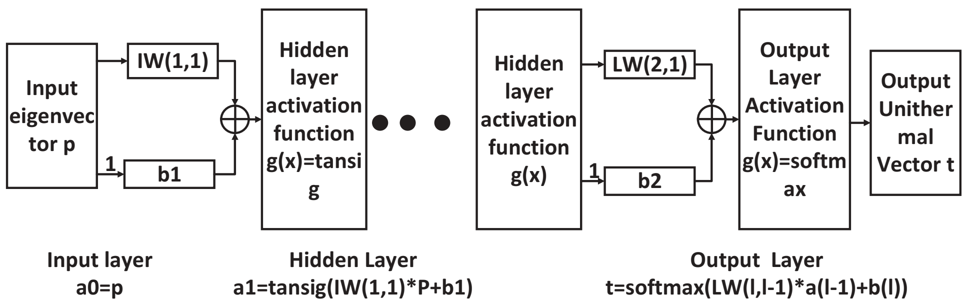

Figure 3. The constructive flowchart of SeqGAN-GABP algorithm model.

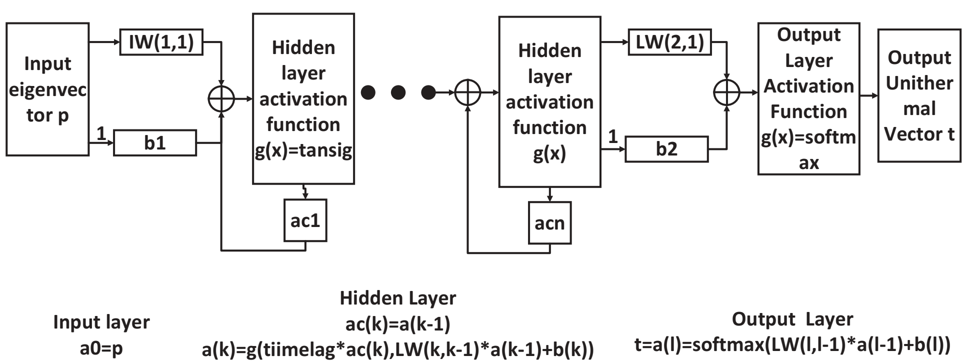

Figure 4. The constructive flowchart of SeqGAN-Elman algorithm model.

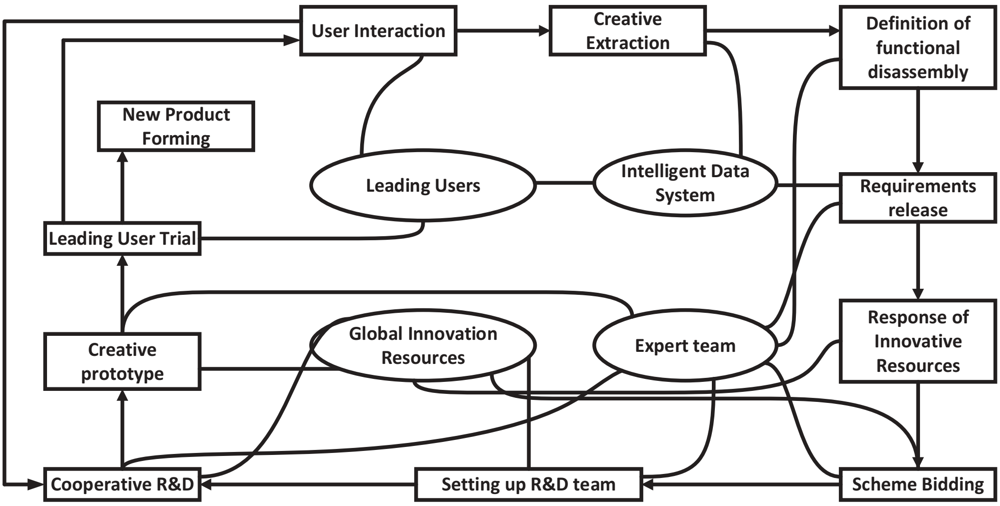

Figure 5. The operative mechanism of the open innovation platform.

3.3. The module introduction of Internet of Things platform

3.3.1. The open innovation platform

The operating mechanism of the open innovation platform is shown in Figure 5. Through the open innovation platform, users could obtain relevant information and services, and interact with other users and the platform, thereby colliding with more ideas, thoughts and needs. First, a leading user community was established. The leading users were from the high-end technology forums, the frontier technology and technology sharing, and the recruitment of partners and other means. Leading users could share scientific and technological achievements, relevant industry dynamics, and expert knowledge in the community, and could discuss product features and service models. The big data collection system of the platform automatically pushed the relevant and accurate information resources to demand users. At the same time, through professional search tools, it could find suitable information resources to assist users in screening and matching technical candidates. In addition, the platform could identify valuable information based on industry and technology, solve technical and functional problems, and provide decision-making reference for users based on current development trends.

3.3.2. The interactive individualised platform

The individualisation process of the interactive individualised platform is shown in Figure 6. In order to meet the needs of users, it was divided into custom creation, module customisation and exclusive customisation. In addition, the P-creation individualisation referred to that the user released the product requirements on the platform; the individualised designer designed the product according to the needs of users and published it on the platform, and then became a specific product through the prototype manufacture and crowd-funding pre-sale. Module individualisation was that the user selected different functional modules through several ‘N-select ones’ and combined them to obtain products. The exclusive individualisation was to provide the user with the appearance and pattern of the

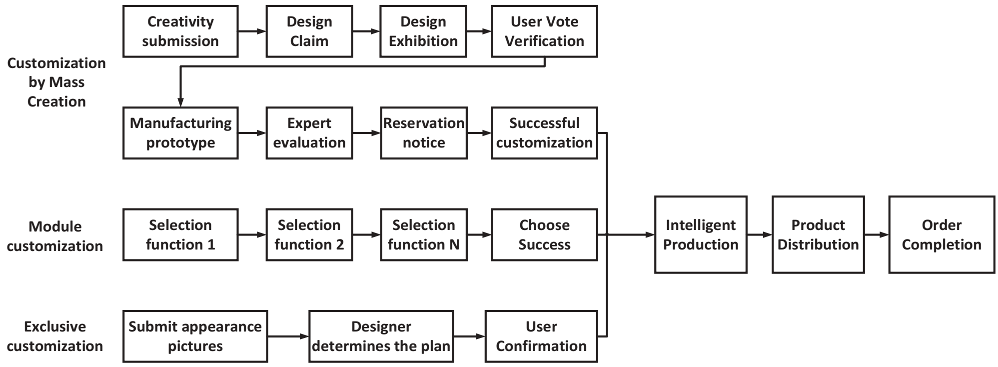

Figure 6. The individualised flow of the interactive individualised platform.

product. The individualised designer designed the solution according to the needs of users, and the two parties negotiated and communicated to finalise the product.

3.3.3. The precision marketing platform

User-related data were obtained through product sales, online clubs, collection and analysis of intelligent products, after-sales and logistics services, product production, etc., and the data were integrated to establish a user demand predictive model. The predictive model could quantify the potential needs of the user. Based on the user data of the social networking site and the e-commerce platform, the user segmentation data model and the user activity data model could be established to obtain accurate and refined user data for accurate advertisement and precision marketing.

3.3.4. The intelligent manufacturing platform

The intelligent production platform included planning and scheduling, on-site statistical process control analysis, workshop personnel management, cost management, quality management and production execution. It interfaced with the interactive customisation platform and the module procurement platform enabled on-site production and user requirements to inter-operate and directly provided solutions for related problems of personalised customisation. The intelligent production platform realised the flexible and agile production of the assembly line and could meet the needs of the informationized deployment, transformation and intelligent upgrade of the manufacturing enterprise.

3.3.5. The module procurement platform

The module procurement platform was open to all suppliers. Suppliers provided corporate qualifications to register and improve relevant information and pay deposits. After the registration was successful, the supplier could interact with the user through the docking interactive customisation platform and grab the order on the platform in response to the demand. After the transaction was successful, the user evaluated the execution result on the platform as the performance of the supplier.

3.3.6. The IoT intelligent platform

The IoT intelligent platform used an open design and had strong compatibility to provide users with various forms of interaction. The platform collected data generated by user interactions for big data systems performed precision marketing and product innovation iterations and interacted with customers through artificial intelligence. The IoT intelligent platform connected the third-party hardware and software resources at the same time, thereby providing possibilities for cross-product and cross-ecological development.

3.3.7. The intelligent logistics platform

The intelligent logistics platform could automatically classify, store and outbound goods, thereby providing visual data for each node of the warehouse. In the delivery process of the goods, the travel trajectory of the delivery vehicle was monitored in real-time to provide a delivery inquiry service. In addition, the user was provided with a distribution and installation service to increase the chance of contact with the user.

4. The feasibility analysis of artificial intelligent neural network algorithm in the business model of intelligent manufacturing

4.1. System environment and parameters setting

The index, configuration details and optimisation algorithm of the neural network are designed, modelled and coded on the Matlab platform. The input of the network is a 52-dimensional eigenvector. Among the probabilities of each mode of the output network, the one with the highest probability is the identified mode. By comparing the feature vectors with those of poor and excellent samples in the same industry, the feature with the largest gap is obtained as a guide. The indexes of the neural network are sampled from randomly selected cross-validation data samples, and the networks with different parameter configurations are screened. Genetic algorithm will be used to initialise the weight threshold of the optimised neural network.

First of all, the total precision and training time of confusion matrix are selected as the optimisation index, high precision and low training time are the best, and memory usage is selected as the screening condition. The performance index of neural network is regarded as the target of super parameter selection and the index of orthogonal experiment analysis. The combination of regularisation coefficient, the number of layers of neural network and the number of neurons in hidden layer are optimised by orthogonal experimental design. The main indicators of the network are the ability to fit the training data and the ability to generalise the test data. The mean square error of the output vector and label vector is regarded as one optimisation objective, and the sum of the squares of the weights is another optimisation objective, which controls the fitting degree and generalisation ability, respectively. Moreover, combined with multi-objective optimisation algorithm, the optimal weight and threshold are solved. The output of the neural network is the pattern and the gap eigenvector of the sample. From the softmax layer, the recognition probability of each pattern of the network is obtained. Among them, the model with the highest probability is the model of the sample. The eigenvectors of samples are compared with those of excellent and poor samples of the same industry, and the absolute value of the difference is taken. After normalisation, the feature gap vector is obtained. In descending order, the corresponding feature number is output. It is necessary to focus on improving the characteristics of the larger gap in output. After completing the design of neural network, each matrix dimension is analysed. The algorithm is vectorised to speed up the operation speed, and Matlab is used for coding.

4.2. Dataset collection and pre-processing

Analytic Hierarchy Process/Fuzzy Comprehensive Evaluation (AHP/FCE) is used to analyse and evaluate the noise data extracted, and preprocess the input data of network training. First, the hierarchical structure of the evaluation system is established, which is the highest level, the middle level and the lowest level. Combined with the index system, AHP is used to calculate and determine the weight of each index. Through the fuzzy comprehensive evaluation method, the noise data is comprehensively evaluated and analysed, and the comprehensive score, the comprehensive membership degree and the index score rate are calculated.

Less data can be collected. In order to ensure the performance of fitting, increase the data enlargement, rearrangement and grouping of Gaussian noise, and further increase the robustness of the network, in this study, the principal component analysis (PCA) method is used to compress the input feature vector (52 dimensions) and remove the non-orthogonal features. Table 1 shows the characteristics before data compression. After compression, Table 2 is obtained. The training time is reduced by 25%, but the accuracy is reduced by 3% ~ 6%.

Before training the neural network, min-max standardised form is used to normalise the dimension characteristics of input samples. Program Train_GABP.m and Train_Elman.

Table 1. Characteristics before data compression.

Characteristics	Data
Productivity	3.75
Production flexibility	2.12
Production mode	1.06
Management culture	2.11
Database level	3.15
Customer satisfaction	0.89
Achievement transformation level	2.86
Total assets growth rate	1.75
Production cycle reduction rate	3.99
Product rate of independent innovation	0.65
Automatic data collection rate	0.51
Growth rate of operating revenue	2.41
Sales logistics expense rate	0.15
Damage rate of handling materials	1.22
Networking rate of mechanical equipment	0.39
IoT equipment level	3.00
Intelligent data processing rate	0.71
Intelligent management level	2.95
Intelligent data entry rate	0.26
Popularity rate of intelligent terminal	0.63
Enterprise Internet of Things coverage rate	0.49
Average R & D equipment per capita	2.46
Popularity rate of intelligent operation	0.54
Cooperation ratio of production, learning and research	1.12

Table 2. Characteristics after data compression.

Characteristic 1	3.41
Characteristic 2	1.21
Characteristic 3	0.79
Characteristic 4	0.51
Characteristic 5	0.47
Characteristic 6	0.33
Characteristic 7	0.16
Characteristic 8	0.06
Characteristic 9	−0.30
Characteristic 10	−0.61

m are run to read training data data1.xlsx. In addition, due to regularisation, it is necessary to prevent the overfitting phenomenon of deep neural network.

4.3. Experimental design and results

The comparison of the two neural algorithms is shown in Table 3. The results showed that the SeqGAN-GABP algorithm outperformed the SeqGAN-Elman algorithm in terms of minimal error, fitting accuracy, training time and internal memory usage. The learning curve of GABP neural network algorithm is shown in Figure 7. The training error, test error and verification error of the GABP neural network algorithm were relatively small; the gap was not large, and no obvious under-fitting or over-fitting state was seen. In addition, the minimum error was 0.042 the fitting accuracy was 95.2%, and the network training time was 1.81 s. Under the scale of the network, the minimum error, network training speed, and fitting accuracy were very impressive, which proved that the neural network training was relatively successful. After multi-objective genetic algorithm optimisation initialisation, the number of iterations would be 4–6 times less. Therefore, after using the optimisation algorithm, only 20–55 steps of iteration were needed for convergence according to the expected precision. When the SeqGAN-GABP algorithm was training, the BP network gradually converged, and the convergence was completed in about 40 iterations. The learning curve of the Elman neural network algorithm is shown in Figure 8. It could be seen that the optimal training state was reached when the number of iterations in the training was 6 times and the minimal error was 0.044. The network size of the Elman neural network algorithm was relatively large, and the overall training time was long. However, due to its delay memory effect, the convergence was relatively fast, and the number of iterations required was less. The convergence was completed only in six iterations.

Table 3. The performance comparisons of models based on the SeqGAN-GABP algorithm and the SeqGAN-Elman algorithm.

	The SeqGAN-GABP algorithm	The SeqGAN-Elman algorithm
The minimal error	0.042	0.044
Iterations	40	7
Fitting accuracy (%)	95.2	93.7
Training time (%)	1.81	2.46
Internal memory usage (MB)	971	1005
The number of hidden layers	2	2
The number of neurons in each hidden layer	4	10

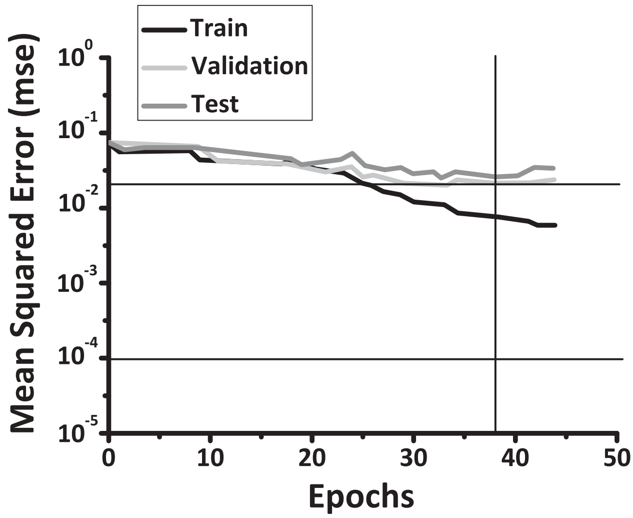

Figure 7. The learning curve of the neural network algorithm.

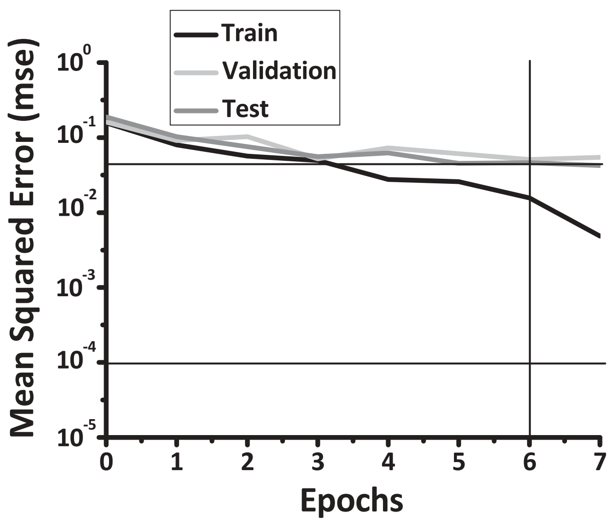

Figure 8. The learning curve of Elman neural network.

The ANN was based on the biological neural network and constructed a practical neural network model according to the actual application needs. By simulating the structure of the brain synaptic connection, the corresponding learning algorithm was designed as a means of information processing (Bahman et al. 2018). Therefore, the biological neural network was mainly used in the research of intelligent mechanism, and the ANN was mainly applied to the realisation of the intelligent mechanism, and they shared a mutually complementary relation (Omrani, Tayyebi, and Pijanowski 2017). The ANN could update the weights and thresholds and fit any function and could also extract features by processing the feature vectors. It had self-learning function, associative storage function and high-speed ability to find optimised solutions. It had a strong nonlinear fitting function, which could map the arbitrarily complex nonlinear relationships; in addition, it had simple learning rules and was convenient for computer implementation. These features had a large application market in large and complex systems. Therefore, it was feasible to use the ANN algorithm as a machine learning algorithm for intelligent manufacturing business model.

ANN had the disadvantages of long training time and was easy to fall into local optimum and cannot obtain a globally optimal solution. The GA could ensure that the ANN had a good initialisation position by initialising weights and thresholds so as not to fall into local optimum (Sengupta, Shim, and Roy 2017). By experimenting with traditional ANN algorithm and GA optimised ANN algorithm, GA optimised ANN algorithm needed to mobilise the GA every time the weights and thresholds were updated. Therefore, in this study, the application of GA to optimise the initialisation of the ANN algorithm was possible.

Through the Internet of Things platform, the enterprise value chain is improved and integrated to form a unified platform. With intelligent manufacturing as the core, a new business model has been created. Value proposition has been reshaped, and new value proposition has been put forward: providing customised products and services for users, producing intelligent products for users and creating intelligent life. Through the interactive customisation platform, the user's needs are put in the first place, directly as the design basis of the scheme. Customisation gives the initiative of choice to the user, which ensures the user a more flexible and diverse choice. New value proposition can bring new market orientation for enterprises and enhance brand image. In terms of sales channels, including micro store platform, online platform and offline stores, the community ecology of 'three stores in one' has been realised, and the marketing mode of online to offline (OTO) has been formed. Taking X company as the research object, the relevant data of its intelligent manufacturing are sorted out and compared with Y company and Z company in the same industry. As shown in Figure 9, it can be seen that the intelligent manufacturing capacity of the three companies in emerging formats is generally low. Among them, Z company's intelligent manufacturing capacity is the weakest, Y company's intelligent manufacturing capacity in system integration is higher, while X company's intelligent manufacturing capacity in production, logistics, resource elements, interconnection and information integration is higher than y company and Z company. In general, X company has strong intelligent manufacturing capacity, and its business model of the Internet of

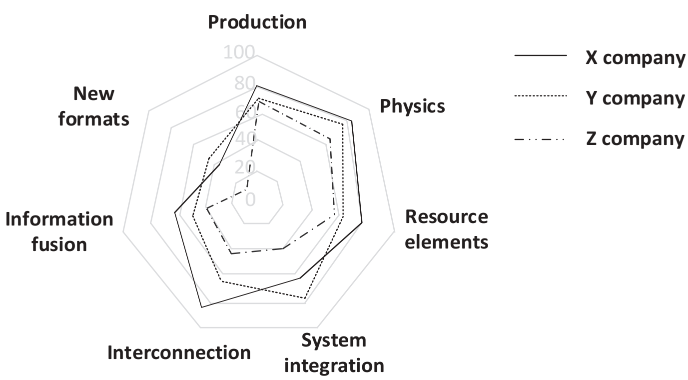

Figure 9. Comparison and analysis of intelligent manufacturing capacity among different enterprises.

Things platform is emerging. With the continuous improvement and maturity of the later stage, it is believed that this role will be more obvious.

4.4. Discussion

The intelligent manufacturing is a study of artificial intelligence, which includes intelligent manufacturing technology and intelligent manufacturing systems (Jianrong et al. 2017). Intelligent manufacturing technology is based on advanced technologies such as network technology, automation technology, modern sensing technology and anthropomorphic intelligence technology; in addition, combined with intelligent sensing, human-computer interaction, decision-making and execution technology, the technology achieves the design process, manufacture process, and intelligent manufacturing equipment (Mittal et al. 2019). Intelligent manufacturing plays an important role in various manufacturing activities such as design, production, management and service. It analyzes the plans and policies for intelligent manufacturing that have been introduced in China. It is not difficult to see that the current focus is on the development of intelligent manufacturing technology and intelligent manufacturing equipment industry (Lin et al. 2017). In order to realise the inherent requirements of Chinese manufacture upgrade and meet the needs of industrialisation of intelligent manufacturing technology, it is particularly important to accelerate the development of intelligent manufacturing (Cheng et al. 2018).

At present, the business model of intelligent manufacturing is still in its infancy. In this study, it has been found that intelligent manufacturing could change many operations in the business model, and the business model could lead intelligent manufacturing companies to develop healthily and rapidly. In order to solve the relationship between intelligent manufacturing and business model, in this study, two optimised ANN algorithm models were established, which were trained, tested, and analysed. In addition, the SeqGAN-GABP algorithm outperformed the SeqGAN-Elman algorithm in terms of minimal error, fitting accuracy, training time and internal memory usage (Liu and Wang 2019).

By exploring the working mechanism and impact of each module of the IoT platform, the characteristics of the business model of the IoT platform were summarised. The interactive individualisation platform and the intelligent production platform could provide users with customised products and services. The IoT platform fully exploited the customer groups and subdivided through intelligent manufacturing (Ma et al. 2019), which broke the traditional communication mode between enterprises and users and established an innovative online interaction mechanism. The data obtained through the platform provided users with accurate marketing services and carried out business development on the open innovation platform, interactive customisation platform, intelligent production platform and module business resource platform, which enhanced the original manufacture business and increased the platform business; the two complemented each other. It could be seen that the business model of intelligent manufacturing would become an important revenue channel in the future. The realisation of intelligent manufacturing could greatly reduce operating costs, improve production efficiency, shorten product development time, improve product quality, and reduce resource and energy consumption.

5. Conclusions

Through the business model of intelligent manufacturing based on IoT and machine learning, the artificial neural network algorithm and the IoT platform have reliability in the business model of intelligent manufacturing, which could improve the development of the business model of intelligent manufacturing, facilitate the user interaction and business development, and have broad application prospects. However, in the actual application process, relevant analysts should cooperate and coordinate based on the actual problems to clarify the analysis objectives and feasibility of machine learning. However, there were also deficiencies in the research process. For example, the machine learning model established in this study needs to manually evaluate the underlying indicators. In the subsequent research, the underlying indicators can be judged by computer vision, thereby gradually eliminating the stage of manual data input and evaluation. The scale of the network scale fails to adapt to the background of big data. In the future, the feature vector of the evaluation system model can be raised to high-dimensional space, while the high-dimensional low-level features are extracted through the deep learning network and compressed to low-dimensional advanced features. Therefore, network performance needs to be improved through machine learning. In addition, the innovation and reconstruction of business models involve all aspects of the industry. The distribution of interest by different companies and the better integration of industry resources are also a major obstacle to the implementation of an industrial blockchain.

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References

Bahman, N., F. A. Sina, M. Amir, S. Shamshirband, T. Rabczuk. 2018. "An Intelligent Artificial Neural Network-Response Surface Methodology Method for Accessing the Optimum Biodiesel and Diesel Fuel Blending Conditions in a Diesel Engine from the Viewpoint of Exergy and Energy Analysis[J]." *Energies* 11 (4): 860. doi:10.3390/en11040860.

Bose, B. K. 2007. "Neural Network Applications in Power Electronics and Motor Drives—An Introduction and Perspective[J]." *IEEE Transactions on Industrial Electronics* 54 (1): 14–33. doi:10.1109/TIE.2006.888683.

Cardin, O., D. Trentesaux, A. Thomas, P. Castagna, T. Berger, H. Bril El-Haouzi. 2017. "Coupling Predictive Scheduling and Reactive Control in Manufacturing Hybrid Control Architectures: State of the Art and Future Challenges[J]." *Journal of Intelligent Manufacturing* 28 (7): 1503–1517. doi:10.1007/s10845-015-1139-0.

Cheng, Y., F. Tao, L. Xu, D. Zhao et al. 2018. "Advanced Manufacturing Systems: Supply–demand Matching of Manufacturing Resource Based on Complex Networks and Internet of Things[J]." *Enterprise Information Systems* 12 (7): 780–797. doi:10.1080/17517575.2016.1183263.

Day, C. P. 2018. "Robotics in Industry—Their Role in Intelligent Manufacturing[J]." *Engineering* 4 (4): 440–445. doi:10.1016/j.eng.2018.07.012.

Ding, Y., H. Hui, Z. Lin, M. Zheng, X. Qu, and W. Cui, et al. 2017. "Design of Business Model and Market Framework of Active Demand Response Oriented for Power Demand Side[J]." *Automation of Electric Power Systems* 41 (14): 2–9 and 189.
Ge, Z., Z. Song, S. X. Ding, B. Huang. 2017. "Data Mining and Analytics in the Process Industry: The Role of Machine Learning[J]." *IEEE Access* 5 (99): 20590–20616. doi:10.1109/ACCESS.2017.2756872.
Giusti, A., J. Guzzi, D. Ciresan, F. He, J. Rodriguez, F. Fontana, M. Faessler, C. Forster, J. Schmidhuber, G. Caro, D. Scaramuzza, L. Gambardella. 2017. "A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robots[J]." *IEEE Robotics & Automation Letters* 1 (2): 1.
Guijarro, L., V. Pla, J. R. Vidal, M. Naldi.2017. "Game Theoretical Analysis of Service Provision for the Internet of Things Based on Sensor Virtualization[J]." *IEEE Journal on Selected Areas in Communications* 35 (3): 691–706. doi:10.1109/JSAC.2017.2672239.
Guo, B., X. Pang, and W. Li. 2018. "The Role of Top Management Team Diversity in Shaping the Performance of Business Model Innovation: A Threshold Effect[J]." *Technology Analysis & Strategic Management*, no. 4: 1–13.
Helma, C., T. Cramer, S. Kramer, L. De Raedt. 2018. "Data Mining and Machine Learning Techniques for the Identification of Mutagenicity Inducing Substructures and Structure Activity Relationships of Noncongeneric Compounds[J]." *Journal of Chemical Information and Computer Sciences* 35 (39): 1402–1411.
Jianrong, T., L. Daxin, L. Zhenyu, C. Jin. 2017. "Research on Key Technical Approaches for the Transition from Digital Manufacturing to Intelligent Manufacturing[J]." *Strategic Study of Chinese Academy of Engineering* 19 (3): 34–44.
Kaulio, M., K. Thorén, and R. Rohrbeck. 2017. "Double Ambidexterity: How a Telco Incumbent Used Business-model and Technology Innovations to Successfully Respond to Three Major Disruptions[J]." *Creativity & Innovation Management* 26 (4): 339–352. doi:10.1111/caim.12246.
Klaine, P. V., M. A. Imran, O. Onireti, R. D. Souza. 2017. "A Survey of Machine Learning Techniques Applied to Self Organizing Cellular Networks[J]." *IEEE Communications Surveys & Tutorials* 19 (4): 2392–2431. doi:10.1109/COMST.2017.2727878.
Li, B., X. Chai, L. Zhang, B. Hou, Y. Liu. 2018. "Accelerate the Development of Intelligent Manufacturing Technologies, Industries, and Application under the Guidance of a New-Generation of Artificial Intelligence Technology[J]." *Strategic Study of Chinese Academy of Engineering* 20 (4): 73–78.
Lim, C. H., M. J. Kim, J. Y. Heo, K. J. Kim. 2018. "Design of Informatics-based Services in Manufacturing Industries: Case Studies Using Large Vehicle-related Databases[J]." *Journal of Intelligent Manufacturing* 29 (3): 497–508. doi:10.1007/s10845-015-1123-8.
Lin, Y. C., M. H. Hung, H. C. Huang, -C.-C. Chen, H.-C. Yang, Y.-S. Hsieh, F.-T. Cheng et al. 2017. "Development of Advanced Manufacturing Cloud of Things (Amcot)—a Smart Manufacturing Platform[J]." *IEEE Robotics and Automation Letters* 2 (3): 1809–1816. doi:10.1109/LRA.2017.2706859.
Liu, Z., and C. Wang. 2019. "Design of Traffic Emergency Response System Based on Internet of Things and Data Mining in Emergencies." *IEEE Access* 7,: 113950–113962. doi:10.1109/ACCESS.2019.2934979.
Lv, Y., and D. Lin. 2017. "Design an Intelligent Real-time Operation Planning System in Distributed Manufacturing Network[J]." *Industrial Management & Data Systems* 117 (4): 742–753. doi:10.1108/IMDS-06-2016-0220.
Ma, B., Z. Liu, F. Jiang, Y. Yan, J. Yuan, and S. Bu. 2019. "Vehicle Detection in Aerial Images Using Rotation-Invariant Cascaded Forest." *IEEE Access* 7: 59613–59623. doi:10.1109/Access.6287639.
Mittal, S., M. A. Khan, D. Romero, T. Wuest. 2019. "Smart Manufacturing: Characteristics, Technologies and Enabling Factors[J]." *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 233 (5): 1342–1361. doi:10.1177/0954405417736547.
Mohtar, R. H. 2017. "A Call for A New Business Model Valuing Water Use and Production: The Water, Energy and Food Nexus Holistic System Approach[J]." *Water International* 42 (6): 1–4. doi:10.1080/02508060.2017.1353238.
Mousavi, S. M., A. Bahreininejad, S. N. Musa, F. Yusof 2017. "A Modified Particle Swarm Optimization for Solving the Integrated Location and Inventory Control Problems in A Two-echelon Supply

Chain Network[J]." *Journal of Intelligent Manufacturing* 28 (1): 191–206. doi:10.1007/s10845-014-0970-z.

Omrani, H., A. Tayyebi, and B. Pijanowski. 2017. "Integrating the Multi-label Land-use Concept and Cellular Automata with the Artificial Neural Network-based Land Transformation Model: An Integrated ML-CA-LTM Modeling Framework[J]." *Mapping Sciences & Remote Sensing* 54 (3): 283–304. doi:10.1080/15481603.2016.1265706.

Ozay, M., I. Esnaola, F. T. Y. Vural, S. R. Kulkarni, H. V. Poor. 2017. "Machine Learning Methods for Attack Detection in the Smart Grid[J]." *IEEE Transactions on Neural Networks & Learning Systems* 27 (8): 1773–1786. doi:10.1109/TNNLS.5962385.

Peng, J., J. Gao. 2017. "Foreword to the Special Issue of Journal of Intelligent Manufacturing on Uncertain Models in Intelligent Manufacturing Systems: Dedicated to Professor Mistuo Gen for His 70th Birthday[J]." *Journal of Intelligent Manufacturing* 28 (3): 501–502. doi:10.1007/s10845-014-1019-z.

Penn, J., P. Pennerstorfer, and A. Jungbauer. 2018. "New Generation of Continuous Casting Plants with Intelligent Manufacturing Strategy; Neue Generation Von Stranggie?anlagen Mit Intelligenter Fertigungsstrategie;[J]." *BHM Berg- und Hüttenmännische Monatshefte* 163 (1): 11–17. doi:10.1007/s00501-017-0694-4.

Preuveneers, D., E. Ilie-Zudor, D. Preuveneers, E. Ilie-Zudor.2017. "The Intelligent Industry of the Future: A Survey on Emerging Trends, Research Challenges and Opportunities in Industry 4.0[J]." *Journal of Ambient Intelligence and Smart Environments* 9 (3): 287–298. doi:10.3233/AIS-170432.

Rawat, A., R. N. Yadav, and S. C. Shrivastava. 2012. "Neural Network Applications in Smart Antenna Arrays: A Review[J]." *AEU - International Journal of Electronics and Communications* 66 (11): 903–912. doi:10.1016/j.aeue.2012.03.012.

Sengupta, A., Y. Shim, and K. Roy. 2017. "Proposal for an All-Spin Artificial Neural Network: Emulating Neural and Synaptic Functionalities through Domain Wall Motion in Ferromagnets[J]." *IEEE Transactions on Biomedical Circuits & Systems* 10 (6): 1152–1160. doi:10.1109/TBCAS.2016.2525823.

Sustrova, T. 2016. "An Artificial Neural Network Model for a Wholesale Company's Order-Cycle Management[J]." *International Journal of Engineering Business Management* 8: 2. doi:10.5772/63727.

Wang, J., L. Zhang, L. Duan, R. X. Gao.2017. "A New Paradigm of Cloud-based Predictive Maintenance for Intelligent Manufacturing[J]." *Journal of Intelligent Manufacturing* 28 (5): 1125–1137. doi:10.1007/s10845-015-1066-0.

Wollschlaeger, M., T. Sauter, and J. Jasperneite. 2017. "The Future of Industrial Communication: Automation Networks in the Era of the Internet of Things and Industry 4.0[J]." *IEEE Industrial Electronics Magazine* 11 (1): 17–27. doi:10.1109/MIE.2017.2649104.

Wu, C. H., Y. S. Wong, W. H. Ip, H. C. W. Lau, C. K. M. Lee, G. T. S. Ho. 2009. "Modeling the Cleanliness Level of an Ultrasonic Cleaning System by Using Design of Experiments and Artificial Neural Networks[J]." *The International Journal of Advanced Manufacturing Technology* 41 (3–4): 287–300. doi:10.1007/s00170-008-1471-z.

Yang, S., J. Wang, L. Shi, Y. Tan, F. Qiao.2018. "Engineering Management for High-end Equipment Intelligent Manufacturing[J]." *Frontiers of Engineering Management* 5 (4): 10–40. doi:10.15302/J-FEM-2018050.

Yun, J. J., D. Won, K. Park. 2017. "Growth of a Platform Business Model as an Entrepreneurial Ecosystem and Its Effects on Regional Development[J]." *European Planning Studies* 25 (5): 805–826. doi:10.1080/09654313.2017.1282082.