Performance evaluation of discrete manufacturing workshop based on key performance indicators and BP neural network

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Abstract
Evaluation on the performance of discrete manufacturing workshop is a tough problem. This paper builds a performance evaluation model based on key performance indicators and BP neural network algorithm to achieve the goal from vertical executing strategy and horizontal operations management perspective. Empirical analysis has proved this method is feasible.

Key Words: Discrete Manufacturing Workshop, Key Performance Indicators, BP Neural Network

INTRODUCTION

The instability that diversity and variability of workshops' demand for external market leads to and the workshops' own features including the material diversity caused by variety diversity, random disturbance and uncertainty caused by complicated manufacturing process make the workshop management of discrete manufacturing company complex and the production data miscellaneous. Managers of workshop get into a dilemma where they can't identify the weakness of production process faced with mass data and can only make provisional decisions based on their experience. How to improve the production efficiency has become the initial problem for discrete manufacturing workshops to gain and promote competence. Discrete manufacturing workshop is an organic integration composed of staff, equipment, material, hardware and software which has discrete manufacturing and assembling features and aims to finish regulated production plan. Performance evaluation provides a kind of mechanism to improve products and process. Effective performance evaluation plays a positive role in promoting production and operations management efficiency(Bond,1999), business process reengineer, continuous improvement(Fullerton,2002; Kuwaiti,2000; Shaeffer,1996; Neely,1995), and realizing lean management. Processing mass data comprehensively needs to eliminate the disturbance of unimportant data, which requires the recognition of critical success factors and key performance indicators(Rochart,1979).

International standard ISO 22400 for manufacturing operations management makes a specific definition for calculating key performance indicators(JISO/DIS 22400-2). This paper builds a key performance indicator evaluation system for entire discrete manufacturing workshops from longitudinal company's strategy execution process and horizontal workshop's production and operations management process to meet the evaluation demand for corporate management and workshop management at the same time. Performance evaluation approach based on BP Neural Network algorithm is proposed on the basis of bionics theory and linear approximation method is also used based on benchmarking theory to optimize the performance of discrete manufacturing workshops. It will help workshops to evaluate performance effectively using historical information and current state, find practical and potential problems to provide reference for the production improvement and finally realize lean management.

LITERATURE REVIEW

Performance evaluation has direct relationships with critical success factor which is the driving factor of performance evaluation and process management(Dixon et al.,1990;Bititci,1997;Bassionli,2004; Luu,2008). Therefore much literature analyze and decompose critical success factor of specific workshop’s production by brainstorming and Fishbone Diagram to get the performance evaluation system. Performance indicator selection of many papers focus on enterprise- level or plant-level leaders’ requirement for performance(Dixon et al.,1990; Vokurka,1995; Vora,1992) and they usually regard cost, quality and delivery time as critical success factors of workshop(Li,2011), which lacks comprehensive evaluation from production process management perspective.

Qualitative performance evaluation method is mainly benchmarking management including competitive benchmarking, function benchmarking, general benchmarking and interior benchmarking management. However, only interior benchmarking management is feasible(Mayle et al., 2002) here because performance evaluation for discrete manufacturing workshop is special and rivals can’t gain realistic data to compare with other production departments with the same function in the same industry. Quantitative performance evaluation methods are mainly Analytic Hierarchy Process(AHP) and Analytic Network Process(ANP). Although existing manufacturing performance evaluation method gives quantitative process to performance indicators, the weight of indicators relies on valuator’s subject judgment and it depends on expert's experience and mind. Recently, domestic and overseas scholars apply neural network method for performance evaluation and conduct a lot of studies which achieve success. Back, Sere, and Vanharanta (1997) analyzed enterprise's performance of many stages through building self-organizational neural network. Zheng and Harrison (2002) built an enterprise template with probabilistic neural network to evaluate the enterprise's performance and analyze the problems by comparing the enterprise's realistic condition with the template. Zheng and Li (2010) built a dynamic supply chain performance evaluation model by BP neural network to provide reference for analysis and decisions. Literature above indicate that neural network algorithm can build mathematical relationships by training historical data, calculate weight of indicators and then build a objective performance evaluation model which can predict performance conditions in a certain period.

KEY PERFORMANCE INDICATORS DESIGN OF DISCRETE MANUFACTURING WORKSHOP BASED ON HIERARCHY

This paper uses critical success factors method to build a discrete manufacturing workshop performance evaluation framework according to KPI design thinking based on hierarchy, which provides reference for the development of workshop's performance management system and information system such as MES. Our research objective is discrete manufacturing workshop which can be ascribed to division- level KPI. Besides, we only focus on workshop's performance level to find the weaknesses and potential problems so individual- level KPI is not considered here. The design process of KPI system is as Figure 1.

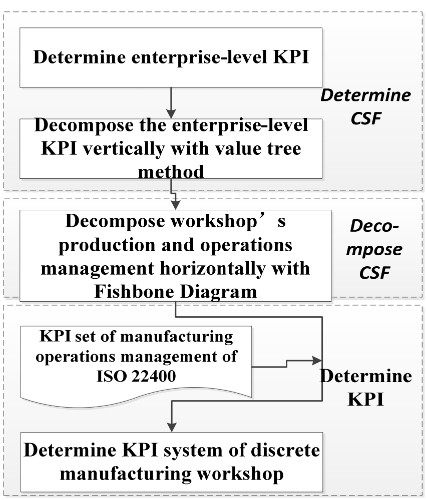

Figure1-KPI Design Process of Discrete Manufacturing Workshop

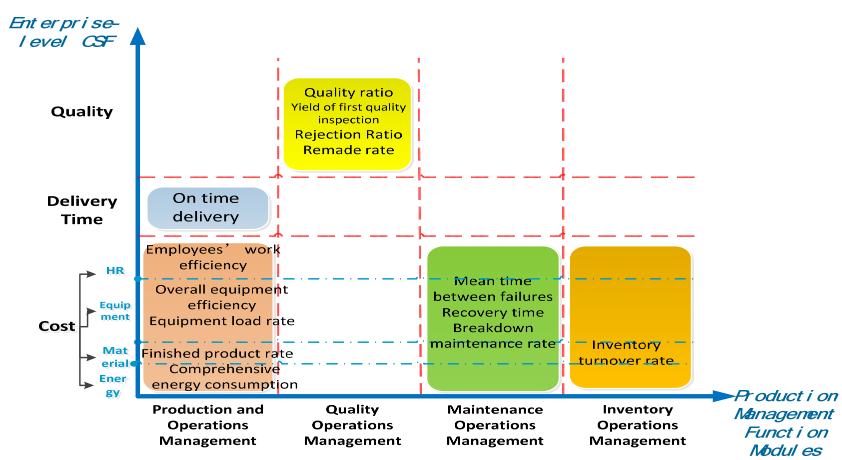

Figure 2-KPI Matrix Model of Discrete Manufacturing Workshop

This paper doesn't illustrate analysis process due to space constraints and only shows the two-dimensional discrete workshop KPI. The two-dimensional matrix model of KPI is as Figure2. This model involves the longitudinal process of enterprise management which is decomposing strategy objective top to bottom and the horizontal process of workshop production management which is analyzing production management function modules. It can illustrate the longitudinal enterprise's strategy objective's realization in the horizontal workshop's production management process clearly. Among the 14 indicators, on time delivery(P1), employees' work efficiency(P2), overall equipment efficiency(P3), equipment load ratio(P4), finished product rate(P5), inventory turnover rate(S1), quality ratio(Q1), yield of first quality inspection(Q2), mean time between failures(M1) are positive indicators which means larger value of indicator indicates better performance; comprehensive energy consumption(P6), rejection ratio(Q3), remade rate(Q4), recovery time(M2) and breakdown maintenance rate(M3) are negative indicators which is converse.

PERFORMANCE EVALUATION MODEL OF DISCRETE MANUFACTURING WORKSHOP

The process of discrete manufacturing workshop's performance evaluation is a complex evaluation system containing many indicators' input and output. The indicators are uncertain and fuzzy and they have nonlinear relationships. Besides, the indicators raised above are all quantitative without setting a specific indicator hierarchy which accord with neural network's input standard. Neural network algorithm can train a systematic model rapidly through learning quantitative samples and evaluate performance clearly. Considering above reasons, this paper adopts the most widely used BP neural network algorithm to build a dynamic performance evaluation model for discrete workshops(Chen et al.,2006; Fan,2013).

Discrete Manufacturing Workshop Performance Indicator Reprocessing

The input performance indicators should be normalized according to expertise and statistics to make the indicators comparable. Concretely speaking, it is quantifying positive indicators and negative indicators to dimensionless indicator values on closed interval [0,1] and then normalizing them by effect coefficient.

Normalization formula of positive indicators:

$$F_j = (X_j - X_{jmin})/(X_{jmax} - X_{jmin}) \tag{1}$$

Normalization formula of negative indicators:

$$F_j = (X_{jmax} - X_j)/(X_{jmax} - X_{jmin}) \tag{2}$$

F_j is effect coefficient of objective value of indicator j. X_{jmin} is the minimum value of indicator j. X_{jmax} is the maximum value of indicator j. j is the number of performance evaluation indicators(Fan, 2013).

The Determination of BP Neural Network Structure

(1) Determine the number of layers of BP neural network

This paper selects a three-layer BP network as the basic structure for discrete manufacturing performance evaluation system.

(2) Determine the number of input layer nodes of BP neural network

14 indicators are determined as the performance evaluation system above so the number of nodes of input layer is 14.

(3) Determine the number of hidden layer nodes of BP neural network

Existing theories can't precisely predict the number of nodes in hidden layer. Generally speaking, the larger the number of hidden layer nodes is, the more precisely the sample set can learn, however, the worse the generalization ability of applying network for input vector without learning yet is. Therefore the number of hidden layer nodes is determined by comparing approximation ability with generalization ability of training result. It is generally recognized that the number of nodes in hidden layer is related to the number of nodes in input and output layer. The relationship is as relation (3)(Li, 2009).

$$N_{\mathrm{hidden}} < N_{in} - 1 \quad \text{or} \quad N_{hiddenn} < \sqrt{N_{in} + N_{out}} + a \tag{3}$$

N_{in} is the number of nodes of input layer. N_{out} is the number of nodes of output layer. N_{hidden} is the number of nodes of hidden layer. a is between 0 and 10. N_{hidden} is predefined as 6.

(4) Determine the number of output layer nodes of BP neural network

The performance evaluation result is the output of BP network in this paper so the number of nodes in output layer conforms to the evaluation scale. Output result is divided into three classes which are excellent, average and poor and are represented by three-dimension unit vectors. In the expected output, [1,0,0] represents excellent class of workshop's performance; [0,1,0] represents average class; [0,0,1] represents poor class. Therefore the number of nodes is 3.

The BP neural network topological graph of discrete manufacturing workshop based on above analysis is as figure 3.

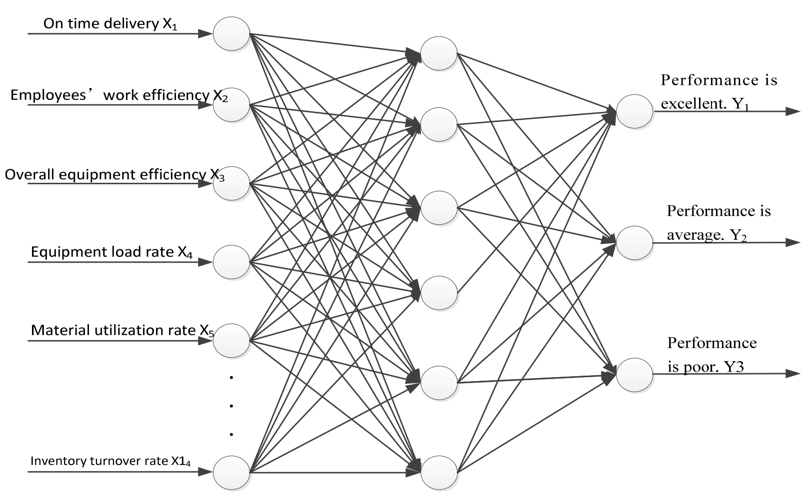

Figure 3-The BP neural network topological network graph of discrete manufacturing workshop

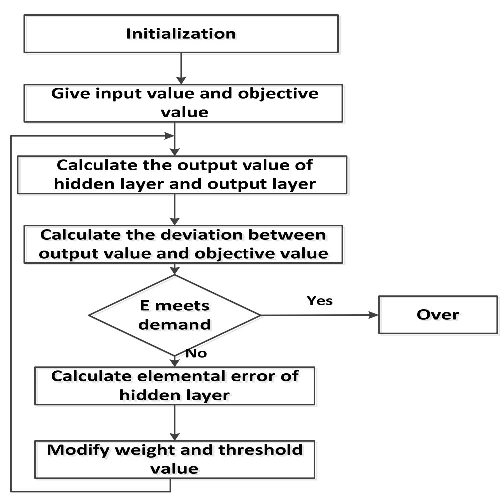

Figure 4-Algorithm process of BP neural

Learning Algorithm of Discrete Manufacturing Workshop's Dynamic

Performance Evaluation Model

The number of input layer nodes of BP neural network is P(P=14). The number of output layer nodes is M(M=3). The number of hidden layer nodes is L(L=6). W_{ij} is the link weight from input layer X_i to hidden layer H_j. V_{jk} is the link weight from hidden layer H_j to output layer Y_k. θ_j is the threshold value of hidden layer and θ_k is the threshold value of output layer. In order to stimulate biological neural network's nonlinear characteristic, we choose sigmoid function as transfer function. The hidden layer and output layer both adopts S function as equation (4). The steps of standard BP neural network algorithm is as figure 4. See details of algorithm in reference(Zhang et al.,2008).

$$\text{logsig}=1/(1+e^{-y}) \tag{4}$$

Performance Optimization of Discrete Manufacturing Workshop Based on Benchmarking Method

Benchmarking method is widely used in performance evaluation now(Stewart,1995; Gilmour,1999; Ross and Droge, 2002). This paper analyzes workshop's performance evaluation data based on benchmarking method. The month whose performance evaluation result is excellent is regarded as benchmark and data of the month whose evaluation result is poor is adjusted to approximate the excellent month's data with linear approximation method. The equation is as (5).

$$X_{ap} = X_{ip} + \lambda(X_{ep} - X_{ip}) \tag{5}$$

X_{ep} represents the data of the month whose performance evaluation result is excellent. X_{ip} represents the poor month's data. λ means adjustment coefficient between 0 and 1. X_{ap} represents the indicator value after adjustment. Comparing X_{ap} with X_{ip} and X_{ep}, analyzing all indicators' change under the tendency of optimizing performance result will provide guidance for improving workshop's performance level.

APPLICATION EXAMPLE/ EMPIRICAL ANALYSIS

A company's structural component division has the independent design and manufacturing capability of large steel components, such as electrical cabinet, motor frame, and motorcycle frame, etc. The division adopts discrete manufacturing pattern and contains four workshops which are blanking workshop, parts shop, welding shop and car body (welding) workshop. It is gradually increasing its informationazation level and has implemented ERP and MES in the critical links of enterprise management and workshop business management. Based on the information system above, the division builds and carries out performance evaluation system of blanking workshop on the basis of this paper's theory.

Performance Evaluation Analysis and Optimization of Blanking Workshop

(1)Data preparing

The production data of blanking workshop from November, 2013 to December, 2014 is collected from MES. Performance indicators data is calculated according to ISO 22400 and original data isn't exhibited in this paper due to space restrict.

We preprocess the original data according to the linear function normalization method and get the normalized performance indicator quantization table of blanking workshop, not exhibiting normalized data due to space restrict as well.

(2)BP neural network training

The number of input layer nodes is 14. The number of output layer nodes is 3. The number of hidden layer nodes is 6 according to the trial. Weight from input layer to hidden layer is W_{ij} and weight from hidden layer to output layer is V_{jk} whose initial value is a random number within [-1,1]. Standard BP learning algorithm has the property of falling easily into local optimal solution and slower convergence speed so we adopt BP neural network accelerated learning method here. Hidden layer and output layer uses Sigmoid function as equation (4). The improved network learning rate is set to 0.1 at first and change the learning rate factor in the operating process. When error increases, learning rate should be reduced. The minimum of error allowed is 0.001 and the maximum of learning times is 6000. We build BP neural network by MATLAB 7.0 and train the inputted normalized data. The changing curve between output error and training times is as figure 5.

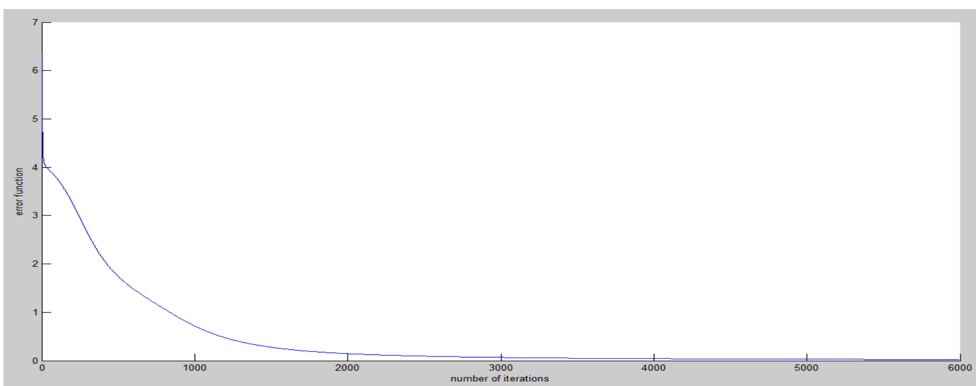

Figure 5-The relationship between output error and training times of BP neural network

BP network becomes stable when training times is 5300 and the learning process is over now. Output result after training is as table 1. The maximized error is less than 7.5% which is less than the acceptable error scope 10%. Thus it proves the evaluation model is accurate and efficient.

Table 1-Performance evaluation result of blanking workshop in 14 months

P1	**P2**	**P3**	**P4**	**P5**	**P6**	**Q1**	**Q2**	**Q3**	**Q4**	**M1**	**M2**	**M3**	**S1**
0.9632	0.9805	0.0005	0.0007	0.0190	0.0160	0.0377	0.9836	0.0174	0.0109	0.0281	0.0146	0.9823	0.9666

0.0525	0.0216	0.0707	0.0563	0.9819	0.9734	0.9634	0.0228	0.9740	0.9497	0.9547	0.9256	0.0232	0.0469
0.0003	0.0002	0.9516	0.9503	0.0094	0.0152	0.0068	0.0002	0.0153	0.0450	0.0151	0.0457	0.0002	0.0002

The BP network after training can predict discrete manufacturing workshop's performance data in next stage. The performance data of January and February, 2015 is collected by investigation and sampling in table 2.

Table 2-Performance indicator original data of blanking workshop in January and February, 2015

Month	**P1 (%)**	**P2 (%)**	**P3 (%)**	**P4 (%)**	**P5 (%)**	**P6(10^4 KW·H)**	**Q1 (%)**	**Q2 (%)**	**Q3 (%)**	**Q4 (%)**	**M1 (h)**	**M2 (h)**	**M3 (%)**	**S1 (%)**
1	95.00	81	86	95.8	85.95	99	86	90	8	6	168.8	4	0.45	0.7
2	96.10	86	90	97	90.45	95	89	93	4.8	4.2	173	2.4	0.31	0.88

We normalize the data in table 5 and then input it into trained BP neural network. Prediction result is (0.0006, 0.1544, 0.9233) and (0.0163, 0.9881, 0.0094). It can be seen that evaluation result of January, 2015 is poor and result of February is average. This result accords with the realistic performance condition gained by survey and it proves the performance evaluation method of discrete manufacturing workshop based on BP neural network raised in this paper is effective.

(3)Performance Optimization of Blanking Workshop

Data of blanking workshop of 12 months in 2014 is analyzed based on benchmarking method. Performance evaluation result of June is excellent so we select June as the benchmark and try to adjust January's data whose performance evaluation result is poor to approximate to the excellent month with linear approximation method mentioned above. When λ equals 0, 0.25, 0.5 and 0.75, original data changing result of 14 KPI is in table 3.

Table 3-Performance level of January when approximating to June linearly

λ	P1(%)	P2 (%)	P3 (%)	P4 (%)	P5 (%)	P6(10^4 KW·H)	Q1 (%)	Q2 (%)	Q3 (%)	Q4 (%)	M1 (h)	M2 (h)	M3 (%)	S1 (%)
0	95.20	82	85	96	80.95	99	86	88	7.9	6.1	168.9	6	44	72
0.25	95.9	85.3	88.3	97.0	83.6	98.0	88.8	90.5	6.5	4.8	170.4	4.6	35.8	77.5
0.5	96.6	88.5	91.5	98.0	86.2	97.0	91.5	93.0	5.1	3.4	172.0	3.3	27.5	83.0
0.75	97.3	91.8	94.8	99.0	88.9	96.0	94.3	95.5	3.7	2.1	173.5	1.9	19.3	88.5

① $\lambda = 0$: 14 KPI of January don't change so performance evaluation result doesn't adjust which is still poor;

② $\lambda = 0.25$: 14 KPI of January approximate to the excellent month by 25% at the same time and performance result changes to (0.0066, 0.8750, 0.1228) which means performance has been increased to average level. It indicates that if 14 KPI increases to the data when λ equals 0.25, overall performance of blanking workshop can be improved to average level.

③ $\lambda = 0.5$: 14 KPI of January approximate to the excellent month by 50% at the same time and performance result changes to (0.1286, 0.7887, 0.0061) which means performance remains average level.

④ $\lambda = 0.75$: 14 KPI of January approximate to the excellent month by 75% at the same time and performance result changes to (0.8983, 0.1089, 0.0006) which means performance has been improved to excellent level. It indicates that if 14 KPI increases to the data when λ equals 0.75, overall performance of blanking workshop can be improved to excellent level.

From the analysis above, we can know that this model provides guidance for improving blanking workshop's performance level. It not only points out the increasing objective of all indicators, but also predicts the influence of performance indicators' change on overall performance to guide the formulation of performance optimization scheme.

CONCLUSION

This paper builds a two-dimension KPI model for discrete manufacturing workshops based on ISO 22400 standard and realize the two-dimension performance evaluation from vertical enterprise level strategy execution process and horizontal workshop production and operations management process. Based on KPI model, it applies BP neural network for learning, predicting and optimizing performance evaluation result. The application example shows the quantitative analysis of one company's blanking workshop's performance and indicates the feasibility and operability of this performance indicator system and performance evaluation method which contribute to evaluating discrete manufacturing workshop's performance objectively and efficiently.

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