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An Exploration Study on Quality Performance Casual Path Model Based on BN Method

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Abstract
According to MBNQA:1997 standard and scale, empirical data was obtained through a questionnaire survey from Chinese railway construction enterprise, and used Bayesian Networks for PC algorithm, the path model of the causal relationship between QMP and QP is acquired. The CPT parameter is obtained by EM algorithm, reasoning analysis and diagnosis research are conducted, and some conclusions and suggestions are drawn. Finally, the methodological and practical value of the BN model is discussed.
Key words: RAILWAY CONSTRUCTION ENTERPRISE, QMP, QP, BN STRUCTURE LEARNING, PC ALGORITHM, SENSITIVITY ANALYSIS.

1. Introduction

Since Flynn ,B. and Powell, C. et al. introduced empirical methods to research on the relationship between Quality Management Practice (QMP) and Company Performance (CP) in the 1990s, another research hotspot has appeared in the field of quality management after statistical process control theory [1,2]. Research on the relationship between QMP and QP (Quality Performance) is a subtopic of the former. Garvin (1984) was one of the earliest scholars who studied this issue and proposed a famous 2-path model based on manufacture and market [3]. Flynn, B. (2001), Tito Conti (1997) and Anderson, J.C. (1995) et al. based the items of three international quality award criteria(MBNQA, EQA and DAP) and derived three QP path models through empirical research [1,4]. Ahmad, M.F.(2012) based his theories on five QMP practice items, while Juan, J.T. (2007) obtained another QP causal path models through theoretical hypothesis and empirical analysis, with ten QMP practice items [5,6].

2. Introduction to BN Theories and Methods

2.1. Introduction to BN Theories

Bayesian Networks are referred to as “BN”. They were first raised by Judea Pearl in 1986 [7]. A complete BN consists of two parts (G, P). G stands for Directed Acyclic Graph (DAG). It is composed of several nodes and some connecting edges. It is also known as BN structure. P refers to Conditional Probability Table (CPT). It stands for conditional probability between variables.

BN theories build a bridge between data and graphic structures, achieve the formal expression of relationship between variables through joint probability distribution or CPT, and realize visual expression through DAG structural diagrams between nodes [8].

BN learnings include parameter learning and structure learning. The goal of structure learning is to obtain a DAG structural diagram. Parameter learning is usually a process based on structure learning, in which CPT parameters are obtained in specific ways. After a complete BN is obtained, we can further infer and diagnose and get some quantitative, scientific and objective results, to provide reference for management decisions.

2.2 BN Structure Learning Based on CI Tests

There are two common methods of BN structure learnings: one is based on score function and the other is based on conditional independence tests (CIs for short). Compared with score function algorithms, CI test algorithms are generally applicable to the condition with fewer variables system, sparse network structure and small sample data [9].

Definition1: Assume that A, B and C are three mutually disjoint subsets of the random variable set $V=\{x_1,x_2...x_n\}$. If for $\forall x_i \in A, x_j \in B$ and $x_k \in C$, we have $P(x_i \mid x_j,x_k)=P(x_i \mid x_j)$, when C is given, then A and B are conditionally independent.

Definition2: For a DAG (G) with $V=\{x_1,x_2...x_n\}$ as the node set, if any nodes, x_i and x_j in V, as well as W, a subset of V, meet the following criteria:

(1)All converging-connected nodes(as"$\rightarrow X \leftarrow$") in the connected path of x_i and x_j and offspring nodes of its converging-connected nodes are not in W: (2) At least one serial-connected (as "$\rightarrow X \rightarrow$")or diverging-connected node(as "$\leftarrow X \rightarrow$") in the connected path of x_i and x_j is in W, then we say W node (set) D-separates the path between x_i and x_j. If all paths between x_i and x_j are D-separated by W node (set), then we say W node (set) D-separates x_i and x_j.

CI between variables is corresponding to D-separation between nodes. Through a whole test on CI between all variables in joint probability distribution, we can determine D-separation sets between variables and build a BN to reflect these CIs, to the maximum probability [10].

Traditional CI test methods mainly include SGS, PC, TPDA, FCI and other algorithms [11]. PC, TPDA and FCI algorithms are actually an improvement on the basis of SGS algorithm. The basic idea and calculation steps of SGS algorithm are as follows:

Step I: Connect any two nodes in the node set V and obtain a complete DAG (G).

Step II: For any two nodes x_i,x_j in a complete DAG (G), a CI test is performed with any order subset of S ($S=\{V \setminus (x_i,x_j)\}$) as the condition. If test results show that x_i and x_j are D-separated by certain S_k ($S_k \subset S$), then delete the undirected edge between x_i and x_j in Figure G.

Step III: When determining the direction of adjacent edges, SGS algorithm first finds out any unclosed triple (x_i,x_j,x_k).If there are connecting edges between x_i and x_j, between x_j and x_k, but no connecting edges between x_i and x_k, if and only if x_j doesn’t belong to any D-separation set of x_i and x_k, we define $(x_i-x_j-x_k)$ as a V structure: $(x_i \rightarrow x_j \leftarrow x_k)$.

Step IV: After finding out all V-structures, we apply the following two rules repeatedly to determine the direction of remaining undirected edges:

1) If there is a directed edge $(x_i \rightarrow x_j)$ between x_i and x_j, and an adjacent edge $(x_j - x_k)$ between x_j and x_k, but no adjacent edge between x_i and x_k and no other arrows point to x_k, then we define $(x_j - x_k)$ as $(x_j \rightarrow x_k)$;

2) If there is a directed path from x_i to x_j and an adjacent edge between x_i and x_j, then we define $(x_i - x_j)$ as $(x_i \rightarrow x_j)$.

Step II in SGS algorithm involves many CI tests and a large amount of calculation and a small sample training data cannot guarantee structural reliability [10]. So PC algorithm is mainly focused on Step II, that is, CI tests are conducted in the sequence of 0-order subset S_0, first-order subset S_1 and second-order subset S_2, and so on. After reaching the actual objective value, calculations end automatically. There is no need to test all orders. It greatly reduces the time and complexity of algorithm. For detailed information about PC algorithm, see References [12, 13, 14]

BN parameter learning is very simple. Common methods mainly include: maximum likelihood estimation, Bayesian estimation, EM algorithm and MCMC algorithm, etc. [14].

2.3. BN Inference and Diagnosis

After structure and parameter learnings, we obtain a complete BN, and we can begin BN inference and diagnosis. The core of BN inference is to calculate posteriori probabilities (distributions). Set all variable sets as X, evidence variable sets as E and query variable sets as Q, the basic task of BN inference is to calculate the conditional probability distribution of query variable Q, provided that a set of evidence variables E=e are given, namely:

$$P(Q|\mathrm{E}=\mathrm{e})=\frac{P(\mathrm{Q},E=e)}{P(E=e)}$$

BN inference can realize causal inference from left to right, or diagnostic inference from right to left, sensitivity analysis and any other forms of inference and diagnosis.

3. QP Path Structure Learning

3.1. Reliability and Validity of the Scale

This paper chooses items in MBNQA: 1997 standards as the object of structure learning. A measurement scale of 7 variables is shown in Table 1.

Research sample data came from questionnaires filled by project managers or supervisors of units participating in Nanning-Guangzhou Railway construction. They were civil construction units subordinate to China Railway Construction Corp and China State Construction Engineering Corp. The questionnaire contained 24 items and adopted a 5-point Likert scale. A total of 293 valid questionnaires were collected. Since the questionnaire was designed with reference to MBNQA: 1997 standards and combined the specific characteristics of railway building construction enterprises, it was reliable in contents validity. We mainly used Cronbach´s α to test the reliability of the scale and tested the structural validity of the scale with the variance contribution rate of the first principal component. Specific test results are shown in Table 1.

What Cronbach´s alpha reflects the degree of consistency between various measurement items of latent variables. If Cronbach´s α is greater than 0.7, then there is good consistency between items. What variance contribution rate of the first principal component reflects is the percentage in which latent variables variance can be explained with a single questionnaire item. If the value is greater than 50%, then the scale has good structural validity. The setting of questionaire item is reasonable.

It can be seen from Table 1 that except two variables -"human resource management" and "quality performance" are slightly smaller, other latent variables and their items have good reliability and structural validity.

As BN structure learning is mainly based on index data of observed variables. For latent variables as nodes, we need to calculate the scores of latent variables. Common calculation methods for the scores of latent variables include simple weighted average method, AHP method, principal component analysis and entropy weight method, etc. This paper uses entropy weight method to calculate the score weight of each observed variable(questionnaire item) in latent variables. First, a judgment matrix for scores of all observed variables in 293 samples is built, then normalize processing is performed. The entropy of each observed variable is calculated, to figure out their entropy weights and finally get the scores of 7 latent variables in each sample[15].

3.2. QP Path Structure Learning

GeNIe (Graphical Network Interface) is an application software used to establish graphical decision models. It was developed by Decision Making System Laboratory, the University of Pittsburgh, U.S.A. Since released in 1998, GeNIe 1.0 has received extensive praises from academia and industry. The latest GeNIe 2.0 has a more friendly operation interface than GeNIe 1.0 and provides many new algorithm.

We run sample data on a GeNLe2.0 software platform. In learning methods, we choose CI-based PC methods. For the maximum number of parent nodes, we select 6. For significance level, we select 0.05.

PC algorithm is suitable for structure learning with small sample data and sparse network, but sample data is not too big to learn. To make up for small sample deficiency, we increase objective prior information to achieve the effect of enlarging sample data[14]. Combining with some common sense and conclusions in References [1-6], we input the follow-

Table 1 Contents, Reliability and Structural Validity Tests for QMP And QP Scales

Variables	Index Items	Cronbach´s α	Variance Contribution Ratio
Leadership	1. Have a clear mission, vision and values and communicate to all stakeholders.	0.898	70.307%
	2. Have an organizational guarantee system for quality management and improvement. Each department head has his own quality responsibilities.		
	……… ……… ………		
Information and Communication	1. Acquire the company's internal and external information through various channels.	0.776	59.483%
	2. Make a statistical causal analysis, according to competitors' benchmark data.		
	……… ……… ………		
Strategic Planning	1. Have long-term strategic plans and goals in document, while consider the interest demands of relevant parties. Have clear strategies and action plans	0.805	69.930%
	2. The production system is competitive and has good production strategies.		
	……… ……… ………		
Customer and Market Focus	1. Understand customers' demands. Customers participate in product designs.	0.704	67.324%
	2. Implement customer satisfaction surveys. The customer complaint handling process is standard. Establish a good relationship with customers.		
Human Resource Management	1. Employees receive standard trainings. Versatile employees are paid by capabilities.	0.688	47.970%
	2. Factories solve problemd through groups and teams. Team participation factors are taken into account in performance evaluation.		
	……… ……… ………		
Process Management	Multi-functional teams from different departments involve in the design of production process.	0.772	50.305%
	Before production, production engineers take an active part, make efforts to improve and reduce employees' work difficulty.		
	……… ……… ………		
Quality Performance	Compared with competitors, our project has a higher quality level.	0.654	46.039%
	Compared with competitors, our projects win more awards for construction quality.		
	……… ……… ………		

ing two types of prior knowledge:

- QP variables serve as final nodes, namely, to set up reverse inhibitor arcs between QP and other QMP factors;
- Leadership serves as the first driver in the system, namely, leadership variable is placed in the first layer of the software dialog box.

Calculate and learn structure from GeNLe2.0 directly. The ultimate path structural model between QMP and QP is shown in Figure 1 below.

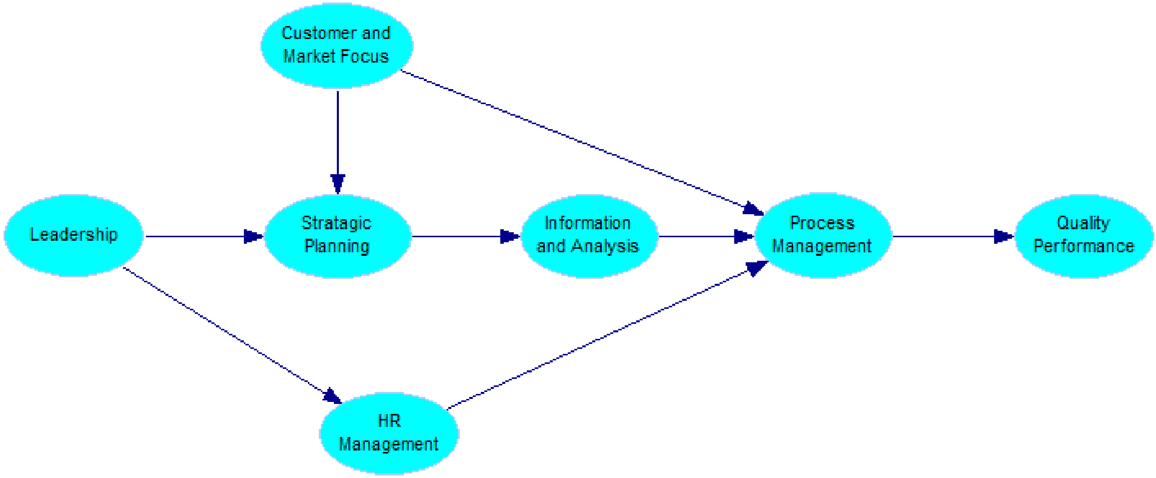
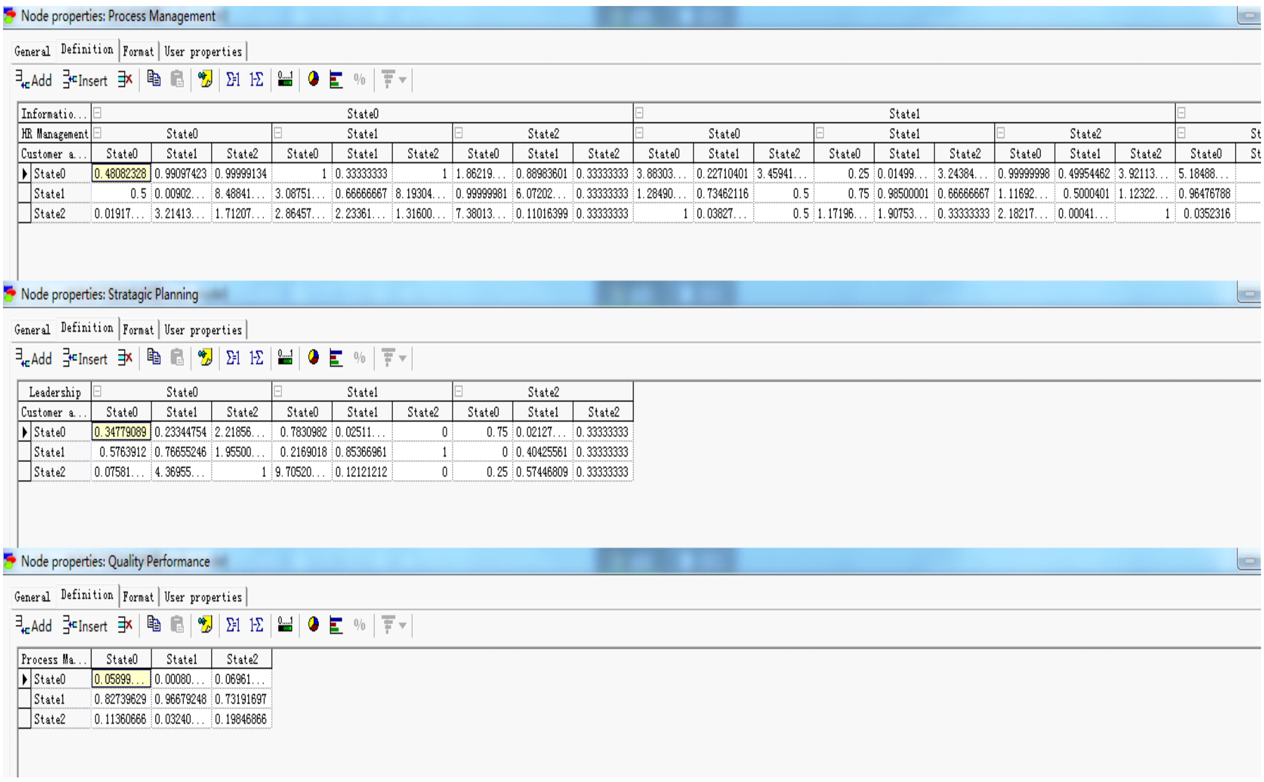


Figure 1. Quality Performance Path Structural Model Derived from BN Structure Learning Methods

3.3. Parameter Learning of the Model

Based on the derived BN structural model, we need to learn parameters further, to obtain a complete BN.

EM algorithm is a common algorithm which estimates parameters from incomplete data sets. EM algorithm is composed of two parts, i.e., expectation step (E Step) and maximization step (M Step), through repeated iteration of E Step and M Step to convergence (namely the estimate of parameters tends to be stable). In GeNIe2.0 software, we learn BN network parameters through EM algorithm and obtain CPT. Due to the limited length of this paper, we only list CPT of three nodes, i.e., "process management", "strategic planning" and "quality performance".(_see Figure 2)



Node properties: Process Management

Informatio...	State0									State1									
HR Management	State0			State1			State2			State0			State1			State2			St
Customer a...	State0	State1	State2	State0	State1	State2	State0	State1	State2	State0	State1	State2	State0	State1	State2	State0	State1	State2	State0
State0	0.48082328	0.99097423	0.99999134	1	0.33333333	1	1.86219...	0.88983601	0.33333333	3.88303...	0.22710401	3.45941...	0.25	0.01499...	3.24384...	0.99999998	0.49954462	3.92113...	5.18488...
State1	0.5	0.00902...	8.48841...	3.08751...	0.66666667	8.19304...	0.99999981	6.07202...	0.33333333	1.28490...	0.73462116	0.5	0.75	0.98500001	0.66666667	1.11692...	0.5000401	1.12322...	0.96476788
State2	0.01917...	3.21413...	1.71207...	2.86457...	2.23361...	1.31600...	7.38013...	0.11016399	0.33333333	1	0.03827...	0.5	1.17196...	1.90753...	0.33333333	2.18217...	0.00041...	1	0.0352316

Node properties: Stratagic Planning

Leadership	State0			State1			State2		
Customer a...	State0	State1	State2	State0	State1	State2	State0	State1	State2
State0	0.34779089	0.23344754	2.21856...	0.7830982	0.02511...	0	0.75	0.02127...	0.33333333
State1	0.5763912	0.76655246	1.95500...	0.2169018	0.85366961	1	0	0.40425561	0.33333333
State2	0.07581...	4.36955...	1	9.70520...	0.12121212	0	0.25	0.57446809	0.33333333

Node properties: Quality Performance

Process Ma...	State0	State1	State2
State0	0.05899...	0.00080...	0.06961...
State1	0.82739629	0.96679248	0.73191697
State2	0.11360666	0.03240...	0.19846866

Figure 2. CPTs Derived with EM Methods

3.4. Inference and Diagnosis

Upon the completion of structure learning and parameter learning, we perform BN inference and diagnosis. Figures 3 and 4 list the results of BN inference when "leadership" is in an "excellent" and "poor" state. After a comparative analysis of data in the figure3 and figure 4, we find that the direct impact of leadership on QP is not obvious, but the impact on human resources and strategic planning is great.

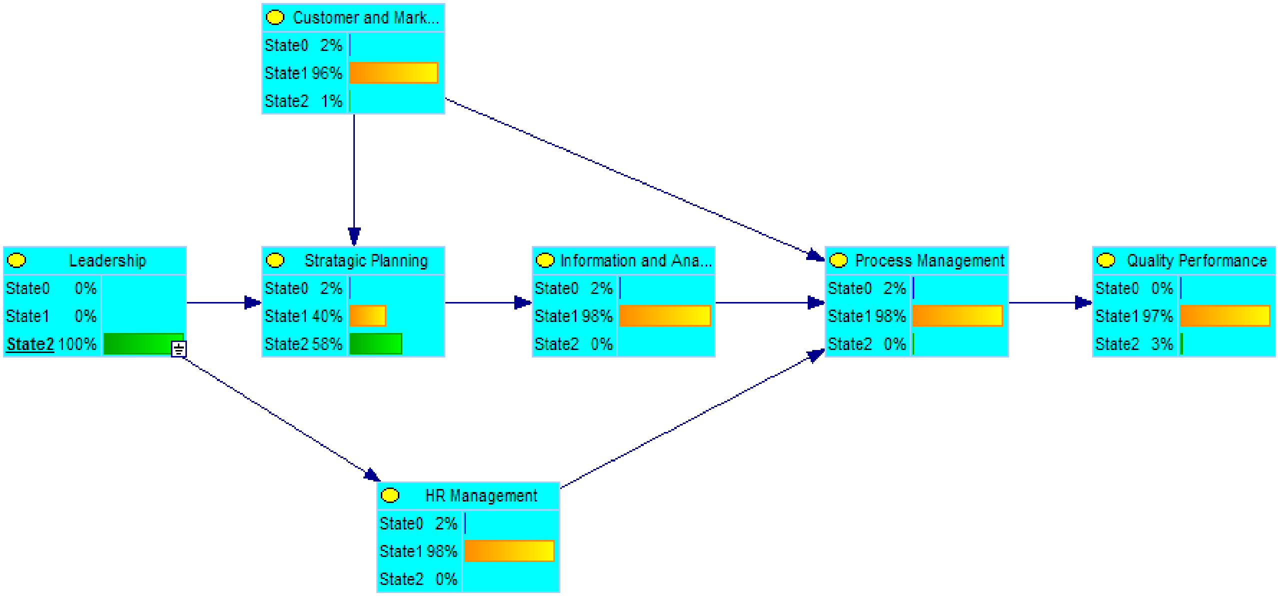


Figure 3. Results of BN Inference When Leadership is in an "Excellent" State

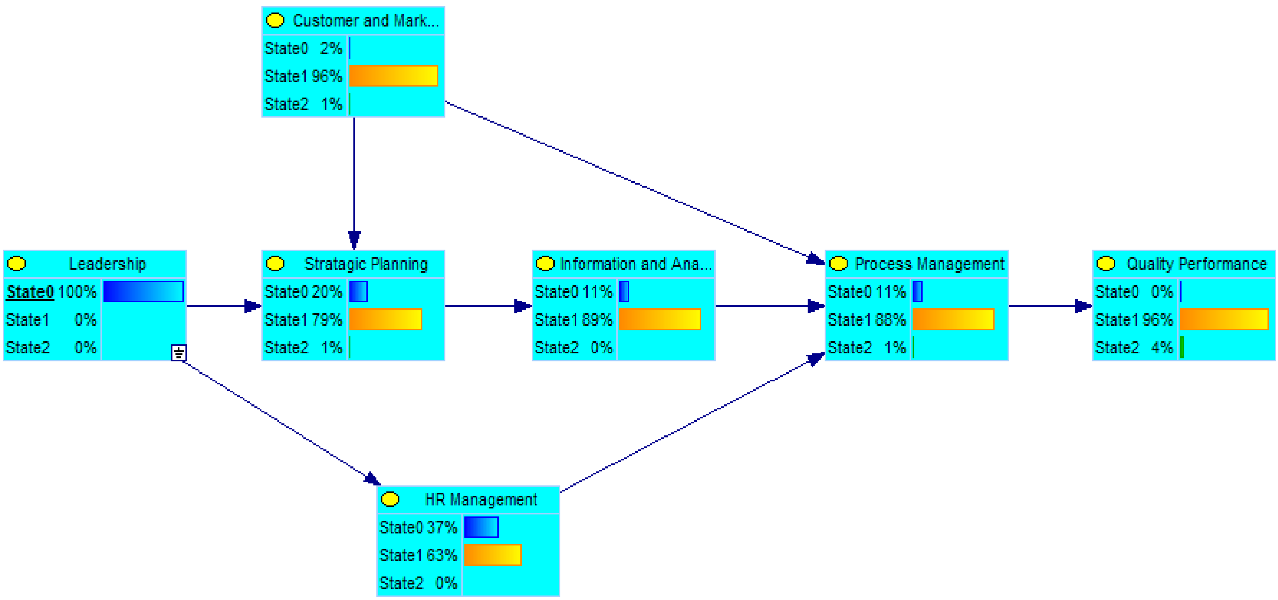


Figure 4. Results of BN Inference When Leadership is in a "Poor" State

Figures 5 and 6 are results of sensitivity analysis when "quality performance" is in an "excellent" and "poor" state. Through a comparative analysis of two figures, we find that when QP is in an "excellent" state, its sensibility affecting factors are five node variables, "customer and market focus", "strategic planning", "human resources management," "information and analysis" and "process management". When QP is in a "poor" state, sensibility affecting factors are three node variables, "strategic planning" "human resource management" and "process management".

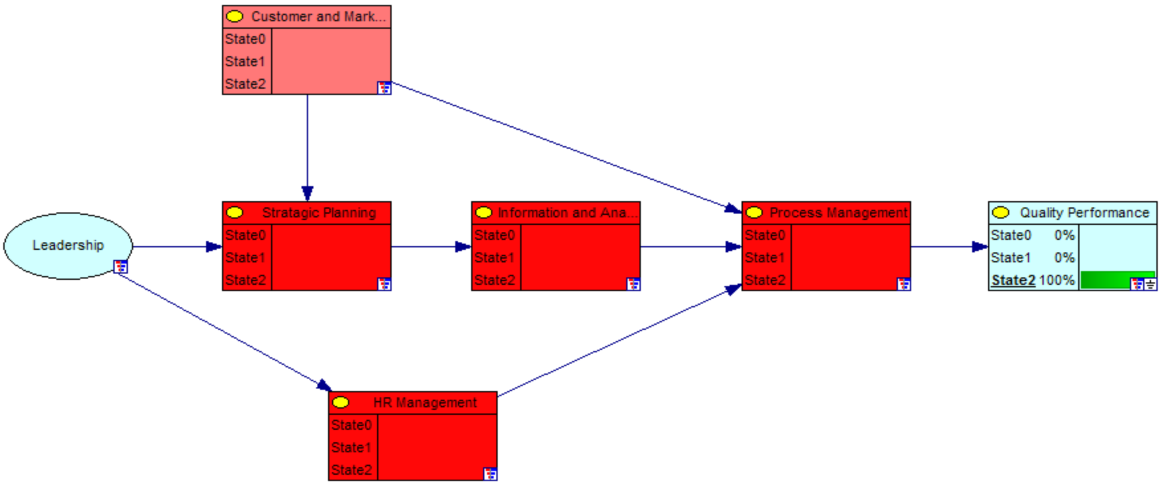


Figure 5. Results of Sensitivity Analysis When QP Variables are in an "Excellent" State

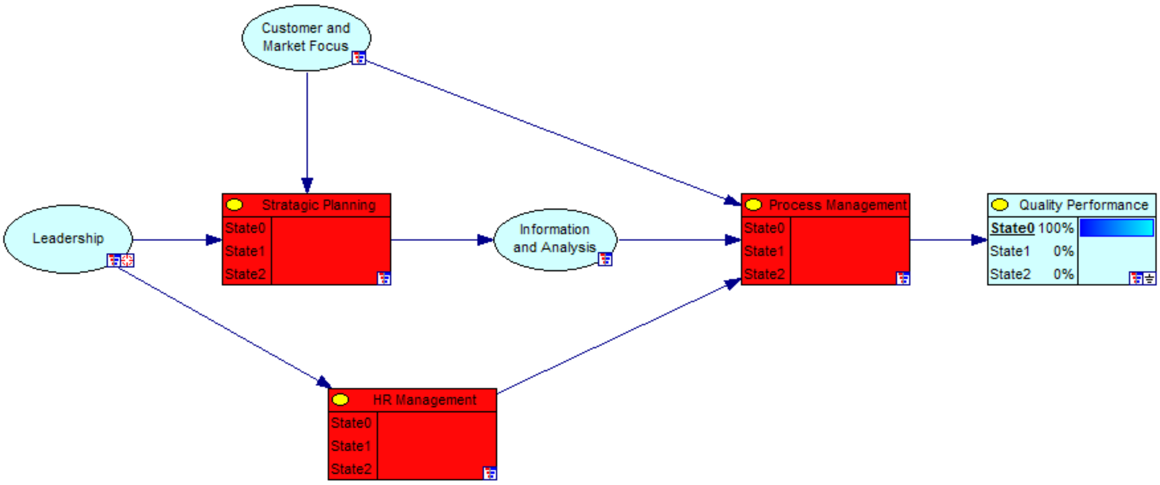


Figure 6. Results of Sensitivity Analysis When QP Variables are in a "Poor" State

4. Further Analysis and Discussion

4.1. About BN Methods

This paper adopts BN methods based on CI tests to explore the causal relationship between variables. Compared with traditional correlation analysis or regression analysis, it reveals the causal relationship between variables, from a more substantial sense. In this research field, some literatures combined SEM and BN methods, modelled structurally with SEM method first and applied BN method to inference and diagnosis[16,17]. But no literature has been reported that the above contents can be completed only by BN.

Besides, in the application field of BN, a large number of literatures applied its inference and diagnosis tools to quantitative research. But almost all of these literatures built models by qualitative "theoretical" analysis. The structure of model is similar to a "fishbone chart" or "tree" structures, rather than a network structure. This will bring certain errors to subsequent inference, diagnosis and quantitative analyses[18,19]. This paper employs structure learning, parameter learning, inference, diagnosis and almost all BN methods to study and analyze QP issues. It has very good reference value.

4.2. About the Structural Model

First of all, from Figure 1, it is not hard to find that there is only one factor that has direct impact on project QP, that is, process management. Other QMP factors act on QP indirectly through process management. The enlightenment on project quality managers is that when designing a quality system, they must grasp the core factor "process management" firmly. Any efforts to ignore process management and pursue other QMP one-sidedly are likely to be in vain. While the ISO9001 quality assurance system is a paragon of stress on process management. Therefore, doing a good job in "implementing" ISO9001 standards is a basis and guarantee of QP for building construction enterprises.

Secondly, direct motive factors affecting the quality of process management include human resources management, information and analysis, customer and market focus. In commonly, "process" generally refers to production process of which human resource management and information analysis based on data are an important content factor. While the direct impact of customer and market focus on production process is not very noticeable. But in the building construction industry, sometimes, the demands of property owners are ambiguous, and design and construction drawings often change. This requires building construction units to pay attention to "customer and market focus". They are supposed to communicate with owners and design units actively and frequently, and improve the effectiveness and efficiency of process management.

Moreover, "customer and market focus" is an exogenous variable. It is not affected by any other variables, but affects strategic planning and process management. It hints that the more attention paid to markets and customers, the more effective quality strategic and goals will be, the more pertinent process control and process management will become. For this reason, building construction units are required to study owner or customer demands, pay attention to gathering standard information of benchmarking enterprises in the industry, satisfy owners or customers and improve QP of project.

Finally, it is noteworthy that Reference [1] used path analysis method to obtain a structural model between 7 factors, based on MBNQA: 1997 standards. It is shown in Figure 7 below.

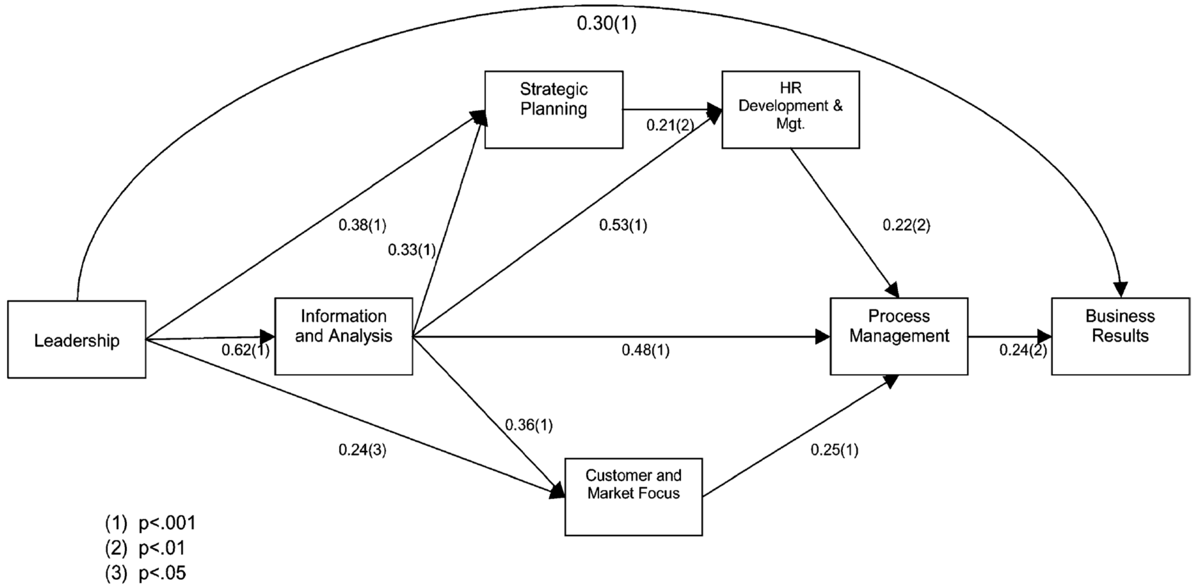


Figure 7. TQM Structural Model Based on MBNQA: 1997 (Flynn, B. 2001)

However, this paper is focused on QP, rather than CP. Compared with the model in Figure 7, Figure 1 has more sparse structure and clearer logic. It is an ideal model that can guide quality management practice and improve QP effectively.

4.3 About Inference and Diagnosis

In European and American countries, there are plenty of literatures on the impact of QMP on QP, but research findings are often confusing. No final conclusion has been drawn yet.

In this paper, empirical results show that the sensitivity factors of affecting QP are mainly "strategic planning", "human resources management" and "process management", while leadership (belonging to basic practice or soft practice) doesn't have a significant direct impact on QP. This empirical result emerged in previous literature, but such a conclusion seemed to deviate from the view of "stress on the role of leadership" in ISO9000 standards. A plausible explanation is that quality leadership is the foundation of other QMP factors in quality system. Leaders affect the final QP indirectly through a direct impact on "strategic planning", "human resources management", by setting strategic goals for enterprises, drawing up quality policies and quality goals, establishing quality organizations and quality responsibility systems, giving quality consciousness educations to employees and building quality culture, etc.

5. Conclusion

Based on QP issues in China's railway construction industry as research object, with MBNQA:1997 standards as the medium, this paper derives a causal path structural model between QMP and QP by applying PC algorithm to BN structure learning, obtains CPT parameters of the model by employing EM algorithm, infers and diagnoses this BN structural model and draws several conclusions and suggestions. This paper uses structure learning, parameter learning, inference, diagnosis and other BN tools to study and analyze QP issues. From the perspective of research methods, it has a certain reference value.

Besides, this study obtains a QP path structural model for China's railway construction industry, with more sparse structure, clearer logic and more reliable conclusions. It makes certain contributions to enriching the theoretical studies in QMP and QP. Meanwhile, the results of model inference and diagnosis derived from this study also have certain guiding significance for QMP activities in the engineering field in China.

In the future, if more sample data are collected, the other learning algorithms of BN, such as K2 algorithm, will be adopted for further tests. All these work need to be conducted in similar studies in the future.

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