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Full Length Research Paper

Modeling and evaluating the strategic effects of improvement programs on the manufacturing performance using neural networks

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Selecting the most effective improvement programs is the main challenge of business managers to achieve superior operational performances. This paper, in an effort to develop new insights into practice-performance relationships, investigates improvement programs, strategic priorities, environmental factors, manufacturing performance dimensions and their interactions via a data mining approach. The results of implementing improvement programs in 91 Iranian small and medium sized companies were gathered by means of a questionnaire-based survey and an artificial neural network was trained to model the relationships between input and output variables. Using a series of regression analysis on the same data shows that the proposed model outperforms all estimated regression models. Also, to understand and evaluate the strength of strategic effects on performance dimensions, a sensitivity analysis method was conducted on the trained model which indicates that implementing a program may be supportive of some performance dimensions and simultaneously incompatible with the others. The results are aimed at providing guidance for decision makers using the prediction power of the proposed model to estimate performance changes before investment in implementing programs.

Key words: Operations strategy, neural network modeling, strategic decision-making, practice-performance relationships.

INTRODUCTION

Improving the economics of manufacturing and making companies more competitive are the main goals of business managers. Skinner (1969) argued that managers needed to give serious thought to the role that manufacturing strategy could have on a firm's competitive abilities and the resulting effect on the firm's performance by providing a structured decision making approach.

Contrary to the thirst for the concept of manufacturing strategy among academicians, the adoption of manufacturing strategy concepts into practice has been quite modest (Kim and Arnold, 1996). Skinner (1969) argues that an important reason for that is the fact that despite the massive research in the past no appropriate tool has been suggested to help manufacturing managers make strategic decisions to meet manufacturing strategic objectives. Skinner (1969) concludes that there is a need for research that would improve understanding of links between manufacturing strategic objectives and specific manufacturing policies (Skinner, 1992).

De Meyer and Ferdows (1990) introduced some questions in this area, like as: Which programs contribute to improvement of manufacturing performance along specific measures? What is the relationship between the effect of an improvement program and the extent of the efforts and resources dedicated to its implementation? Are there synergies between different improvement programs?

They conclude that success in manufacturing does not come easily and seems to require investment in a wide

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portfolio of programs and the relationship between programs and performance is perhaps complex and might be indirect.

Considering the literature, it seems that there are many researches that explain the linkages among different dimensions of operational performance and the relationships between dimensions of manufacturing capabilities or the effects of manufacturing practices on operational performance but there is no normative generic model for the linkage (Acur et al., 2003).

In this paper the topic of decision making in manufacturing strategy is addressed, especially the modeling of manufacturing capabilities and operational performance of manufacturing plants, so the overall research objective is to investigate how manufacturing companies make use of different manufacturing practices or bundles of manufacturing practices to develop certain sets of capabilities, with the ultimate goal of supporting the market requirements. Following this objective two areas are identified to be of particular interest; to investigate (i) modeling the relationship among different dimensions of operational performance and simultaneously (ii) the way different performance dimensions (operational performance) are affected by manufacturing practices or bundles of manufacturing practices.

The research objectives are accomplished via an empirical study of some small and medium sized Iranian companies. A questionnaire-based survey methodology has been selected and a data mining approach was conducted on the data survey using Artificial Neural Networks (ANNs) modeling. The results are aimed at providing guidance for decision making in manufacturing companies.

The rest of this paper is organized as follows. The next section reviews the relevant literature. Subsequent sections describe the modeling method, study sample and data gathering approach and finally, the sensitivity analysis results of the proposed method. The discussion section includes the implications of the study for business managers to improve their strategic decisions and also identifies limitations and areas of further research.

LITERATURE REVIEW

Since the main interesting area of the research is the practice- performance relationships and strategic priorities trade-off in manufacturing strategy operationalizing, literatures closely related to this area are examined in this section.

After the seminal work by Hayes and Wheelwright (1984) that identified a set of manufacturing practices as being fundamental to achieving manufacturing success, the subject of the "best practices" was introduced by other researchers (Flynn et al., 1997, 1999) to support companies in achieving superior performance (Laugen et al., 2005).

Hayes and Wheelwright (1984) introduced the term World Class Manufacturing (WCM), and described this as a set of practices, including quality management, continuous improvement, training and investment in technology.

Testing best practice propositions is usually performed using statistical samples from a given population (Ketokivi and Schroeder, 2004a) and so, most of best practice studies measures the adoption or degree of implementation of specific practices and examines their relationship to measures of operational or financial performance using regression analysis, path analysis, structural equation modeling etc (Flynn et al., 1999; Ahmad and Schroeder, 2003; Sakakibara et al., 1997; Kim and Arnold, 1996). The practices with a significant link to performance are then interpreted and prescribed as the factors that contribute to higher performance and competitive advantage.

Laugen et al. (2005) argues that the WCM and best practice studies suffer from some weaknesses. First, the field is rather scattered with many articles focusing on one or a limited set of new practices, while the reasons why these practices are considered best are often not accounted for. For example quality management practices and JIT is included in some researches (Flynn et al., 1995) and the others (Hanson and Voss, 1995; Voss, 1995) focused on TQM, concurrent engineering (CE) and lean production or Ketokivi and Schroeder (2004a) included computer- aided design (CAD), computer-aided manufacturing (CAM) and statistical quality control (SQC).

Secondly, too little effort is put into analyzing the relationship between the different practices and relative effects both individual practices and their interaction have on performance. Thirdly, the potential influence of factors like: type of industry, country economic conditions, company size, processes and products is considered in little surveys (Cua et al., 2001; Amoako-Gyampah, 2003; Moattar Husseini and O'Brien, 2004; Mellor and Hyland, 2005).

Based on a review literature, Davies and Kochhar (2000) defined the methodological issues for practice-performance studies. They concluded that there are three main structures for studies linking practices to performance: the ideal model, benchmarking and testing a hypothesis method. After defining advantages and disadvantages of structures, they argued that although there is an increasing interest in studies of practice-performance relationships, much of the work remains descriptive. This is due to the complexity of attaching mathematical relationships to an environment in which many variables exit. Although most of the works indicates that the relationships between some performance and practices do exist; however, there is little indication of the strengths of the relationships (Davies and Kochhar, 2002; Acur et al., 2003) . Also, Rusjan (2005) identified short-comings related to empirical research in the relationships between manufacturing strategic decision making and strategic performance.

Another locus which has been much attention in operations management research is the relationships among manufacturing capabilities. Typically, the research involves assessing the operational performance (Ward et al., 1998), identifying the relationships among different operational performance dimensions (Ferdows et al., 1986; Ferdows and De Meyer, 1990).

The trade-off theory initiated by Skinner (1969) and the notion of cumulative capabilities by Ferdows and De Meyer (1990) are two well known theories about these relationships. One common interpretation of Skinner's argument is that manufacturing firms can not perform well on all capabilities and that superior performance in some capabilities can be gained only at the expense of others (Safizadeh et al., 2000).

Ferdows and De Meyer (1990) have argued that for lasting improvements, manufacturing firms build their capabilities sequentially in a pre- specified order that is quality, dependability, speed and cost (Ferdows et al., 1986; De Meyer, et al. 1989; Noble, 1995). They contended that the nature of the trade-offs among manufacturing capabilities is more complex than has been assumed; so, depending on the approach taken for developing each capability, the nature of the trade-offs change. They suggested that the order and manner in which manufacturing capabilities are built can change the nature of trade-offs, so that one capability is not necessarily at the expense of another (Ferdows and De Meyer, 1990).

Many studies found evidence supportive of cumulative and trade-off models and the others that are apparently incompatible with these concepts (Flynn and Flynn, 2004; Silveira and Slack, 2001; Größler and Grübner, 2006; Silveira, 2005). In keeping with the expectations of the cumulative model, findings by Roth and Miller (1992) and by Noble (1995) indicate that better performing firms compete simultaneously on the basis of multiple capabilities (Noble, 1997) . Most of the studies (Silveira and Slack, 2001; Hayes et al., 2005) have still only described bi-dimensional trade-off situations and multi-dimensional trade-offs rapidly become extremely complex (Winroth et al., 2006).

Definition of the research problem

Respect to the literature, the complex, nonlinear and indirect cause and effect relationships between improvement programs and performance and the relationships among manufacturing capabilities made the process of improvement programs selection so difficult for managers.

There is a need for modeling and evaluating the effects of programs and capabilities trade-offs simultaneously. Using some statistical methods, studies like Acur et al. (2003), Ketokivi and Schroeder (2004b), Laugen et al. (2005) and Cagliano et al. (2005) exploratory investigated manufacturing practices, manufacturing performance and their relationships via the empirical studies. They developed these methods in order to find which programs have most influence on manufacturing performance. The most important shortcoming of their studies is independency of estimated models and they have thus not been able to capitalize on the relatedness of models (Ketokivi and Schroeder, 2004a), for example the matter of simultaneous effects of implementing improvement programs on the performance and consequently trade-offs between all manufacturing capabilities of the companies have not been understood.

The other problem is that these models have no prediction power based on the empirical data gathered to estimate the changes in the performance of companies under future events and so they could not be able to help decision makers selecting the best complementary combination of improvement programs.

This research proposes a method to build a predicting model that satisfies research objectives. In order to do this, an Artificial Neural Network (ANN) will be utilized, which has been found to be successful prediction tool for this type of business problems. Below, a short review and the use of ANNs for similar problems are given.

ANNs are information-processing systems that have specific performance characteristics common to biological neural networks. A standard ANN comprises numerous simple processing elements called neurons or nodes. Each neuron is connected to other neurons through directed communication links, each with an associated weight. These weights represent information utilized by the net to solve a given problem (Deng et al., 2007).

ANNs are particularly useful in recognizing patterns in data, abstracting the gist of input data from seemingly unrelated factors and capable of delivering accurate predictions of future events because of their training procedure on archival data (Gupta and Sexton, 1999; Sexton et al., 1998). The fundamentals of ANNs can be found in Fausett (1994) and Galushkin (2007).

Based on the literatures by Lam (2004), Garver (2002), Kim and Street (2004) and Vellido et al. (1999), numerous studies applied ANNs for prediction and classification research in the sciences and social sciences problems as well as many other fields, such as technology, medicine, agriculture, engineering, education, pattern recognition, financial management, medical diagnosis and forecasting for tourism demand, sales, service quality management, innovation performance and stock market returns (Behara et al., 2002; Lam, 2004; John et al., 2000; Burke and Ignizio, 1992; Smith and Gupta, 2000).

Since ANNs generally have high degrees of freedom, they can model the non-linearity of a process under study significantly better than the statistical approaches. In situations where non-normal data, non-linear relationships and multicollinearity are present, ANNs outperform statistical models such as regression and discriminant analysis, because they are model-free estimators that allow them capture the interaction effects between variables without explicit model formulation from users (Sexton et al., 2005; Bishop, 1994; John et al., 2000) and do not require any data distribution assumptions (Hornik et al., 1989). They are applicable even for unknown logical relationships since they self- organize the mapping relationship by learning (Takagi and Hayashi, 1991).

Data collection and analysis

Data were collected by means of a postal and E-mail survey with a questionnaire containing the principal objectives of the research in the middle of 2009. the manufacturing plant is selected as a unit for analysis, which commonly operates in an industry with its own objectives and strategies.

The population is made of small and medium sized companies located in Iran such as automotive suppliers, oil and gas industry suppliers, electronics, machinery and so on. At each plant, the director of operations/ manufacturing/research and development department (or equivalent) was asked to participate in the study. Most of the plant research coordinators were consulted to identify the right respondents in the plant who had pertinent knowledge, experience and ability to provide accurate and unbiased answers to the questions in the survey.

The survey was sent with a covering letter to respondents and instructions for completing the survey were provided as well as highlighting the purpose of the study. Total number of mailed surveys was 534 and at the end of the field work, 105 completed questionnaires were received. And because of the effort for contacting personally the managers and pursuing to send the results, the goodish response rate of 19.66% was met.

The validity of the questionnaires was insured by selecting the most of the scales from the existing literature. The reliability of data collection instrument was pre-tested using 5 industry experts and academics. After the pilot testing, some of the items were clarified or changed to be more representative of the intended constructs. As a result of these tests, some of the scales were significantly revised.

Description of decision variables

Investigating a complementary questionnaire that meet the objectives of the research, the existing international/ national surveys (International Manufacturing Futures Survey (IMFS), World Class Manufacturing Study (WCMS), International Manufacturing Strategy Survey (IMSS) (Christiansen et al., 2003; Urgal-Gonzalez and Garcia-Vazquez, 2007; Swink et al., 2007; Tan and Wisner, 2003)) were considered and most of the required questions were selected from them with least changes to save reliability. The structure of the survey is divided into three sections: (i) Description of strategic capabilities and environmental factors of the company; (ii) Manufacturing performance of the company; (iii) Past implemented improvement programs.

Definition of inputs and outputs

Strategic capability

Ketokivi and Schroeder (2004a) argued that what the management views as important certainly should have implications on performance and proposed that the performance effect of practices is contingent, on the manufacturing goals. They entered the strategic fit and the perceived importance of performance dimensions into the inputs of their model as an interaction between the priority and practice variables. In this regard, the importances of company's strategic capabilities (goals) are selected as a group of the inputs in this paper. Six questions form the questionnaire and are related to the strategic capabilities of the company which consider the importance of the following capabilities: Lower selling prices, superior product design and conformance quality, more dependable deliveries, faster deliveries, superior customer service and wider product range. From the viewpoint of major customers to win orders, the importance of indicators in last three years were asked on a scale of 1 to 5 in the range of (Not Important to Very important).

Past improvement programs

Selection from the long list of improvement programs used in the literature is so difficult and surely not exhaustive. The proposed categorization of the programs by the IMSS IV survey which raised from 3 previous rounds of survey, was selected with a little add/remove changes in programs to be adaptable and applicable for the small and medium-sized companies of this research.

There are 16 questions to measure the degree of implementation of these practices during the last three years on a five-point Likert scale from 1 to 5 (1 = no usage, 5 = high usage). The averages of the results from six main categories (Planning and control, Quality, Product development, Technology, Organization and Supply chain related programs) are entered to the model as another independent input.

Manufacturing performance

The study includes 10 questions which refer to the manufacturing performance of the company. Considering the average performance of competitors, respondents were asked to determine the change of the indicators over the last three years on a scale of 1 to 5(deteriorated more than 10%, stayed about the same, improved 10 - 30%, improved 30 -50%, improved more than 50%).

The indicators were Manufacturing conformance and Product quality, Volume and mix flexibility, Time to market, Customer service and support, Delivery speed, Delivery dependability, Unit manufacturing cost, Manufacturing lead time, Labour productivity and Inventory turnover. These were grouped into 5 main categories: Quality conformance, Cost efficiency, Dependability, Speed and Flexibility.

Environmental/control variables

One of the important variables which affects the performance beside the other practices and priorities are the environmental factors of the company which is considered in the literature as control variables or environmental dynamism (Ward and Duray, 2000; Amoako-Gyampah, 2003; Hoque, 2004; Ketokivi and Schroeder, 2004b).

The plant size measured by the number of employees, the plant ownership from public to private ownership and the plant age as the company's history are three examples of these variables which were selected in this study. Plant age and ownership are included as there may be differences in efficiency and flexibility between old and new plants and between public and private sectors. Ketokivi and Schroeder (2004b) argued that size is a proxy for complexity; larger organizations tend to be more complex than smaller ones. Another three questions are considered to describe the external environment of the companies: Market dynamics on a scale of 1 to 5 (declining rapidly to growing rapidly), Market span on a scale of 1 to 5 (few segments to many segments) and Market concentration on a scale of 1 to 5 (few competitors to many competitors).

Neural network modeling

The most successful prediction and classification applications of ANNs use a feed- forward design (Burke and Ignizio, 1992; Behara et al., 2002). However, this model depends on the datas gathered on past successful/unsuccessful experience of companies from implementing improvement programs; the supervised learning method is selected to modeling.

The ANN model chosen for this research is a 2-layer, fully connected feed-forward network with a back-propagation training rule to predict manufacturing performance. To construct this ANN model, the detailed descriptions of input/output variables, training and generalization, net-work topology and activation function will be discussed below.

The input/output indicators are the input/output vectors of ANN. Generally the decision makers use the input vector, along with output vector, to train the ANN and subsequently to obtain the weights. The importance of six strategic capabilities of the company, the degree of implementation of six improvement practices bundles, three features of the plant (age, ownership and size) and three external factors as the environmental variables are entered to the model as 18 input variables; five manufacturing performance measurements are used as output variables (Figure 1).

Although this modeling method is slightly liken to the six statistical regression models of the work done by Ketokivi and Schroeder (2004a), there is a main differrence. They estimated six models independently and have thus not been able to capitalize on the relatedness between the six models and performance dimensions trade-offs. The ANN selected structure for modeling simultaneously considers all the effects of improvement programs, strategic capabilities contin-gencies and environmental factors on the all of manufacturing performance indicators.

Between all 105 completed questionnaires, only 91 have been considered to the study because of the missing or noisy data in related questions. In cases where the quantity of available data is small, it is desirable to keep all the good parts of various observations and the literature suggests using the cross validation training technique (Hristev, 1998; Kovacheva and Toshkova, 2006).

In the K-fold cross validation method, an integer K (preferably a factor of total number of dataset) is chosen and the training set is divided randomly into K subsets. Then one subset is used to test the performance of model trained on the union of the remaining K-1 subsets. This procedure is repeated K times, choosing a different part for testing each time. Then the efficiency of the model is calculated by making an average over all K estimates. When K = N, the method is called the leave-one-out.

And because of the small number of observations in this study, the leave-one-out cross validation method is selected in order to use as much as possible of the data to build the model (training) and also as much as possible unseen data to test its performance more thoroughly (testing). Although in this method all observations in the dataset are eventually used for both training and testing but also its disadvantage is the computational time which will be very large as well. In this case, 91 different ANNs were built during this process using different data subsets which made a question about which of them should be used at the end.

Hristev (1998) discussed that it would be much better to combine several networks to form a committee which is even not required to be a network; it may be any kind of model. Kovacheva and Toshkova (2006) suggested to

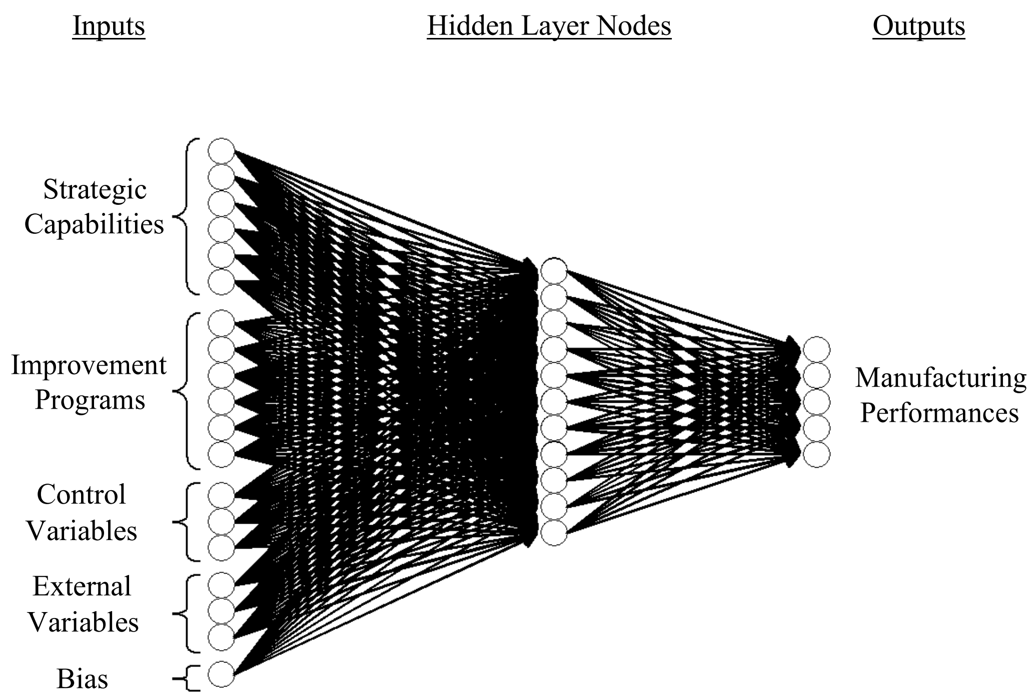

Figure 1. The neural network architecture.

keep the ANNs built throughout the training and considered using them together in an ensemble. In order to do this, the simplest way of building a committee of *M* networks was used which consider the output of the whole system y_{com} as being the average of individual network outputs $y_m(x)$ (Hristev, 1998):

$$y_{com} = \frac{1}{M} \sum^{M} y_m(x)$$

Networks parameter setting

However, there are no good theoretical methods for choosing the learning parameters (constants); the practical hands- on approach is still the best, for example usual values for learning rate are in the range [0.1; 1] and [0; 0.1] for the momentum. In this regard, after testing some combinations of these constants during the model training, the learning rate and the momentum were set at 0.5 and 0.1. Also, the weights were initialized with small random values and the adjusting process was continued by iteration.

Achieving better trained ANNs, based on comparing the achieved results of error terms from changing the number of epochs, for each ANN the epoch's number differently ranges from 1000 to 3000 with testing every 25 runs. Another criterion to stop learning will be a change less than 0.01 in the Mean Square Error (MSE) between the two sequential epochs.

Duda et al. (1998) argued that the number of hidden units determines the total number of weights in the network -which is considered informally as the number of degrees of freedom- and thus ANNs should not have more weights because of the loss in the degrees of freedom. In this regard, using two or more hidden layers in this study would not be applicable because of too number of inputs and outputs. Therefore, for each network, only one hidden layer was used and the number of hidden nodes for each network was determined by training the initial network with one hidden node and then systematically adding additional hidden nodes until the error ceased to decrease. Figure 2 shows the MSE results for comparison. Although up to twelve hidden nodes were tried, it was found that 11 hidden nodes were sufficient for finding this study objective because further additional hidden nodes would increase the number of weights which is not suitable regard to the insufficient existing data (Figure 2).

The activation function is a mathematical formula that calculates a layer's output from its network input. In a standard back propagation ANN, input layer neurons typically use linear activation functions, whereas all other neurons use a sigmoid/log-sigmoid function/ hyperbolic tangent and so on (Deng et al., 2007). After testing some functions during the training process, the log-sigmoid function was finally selected, because a fixed-point data type is used in the output layer which represents numbers within a finite range, overflows could occur if the result of an operation was larger or smaller than the numbers in that range. To handle this, positive overflows

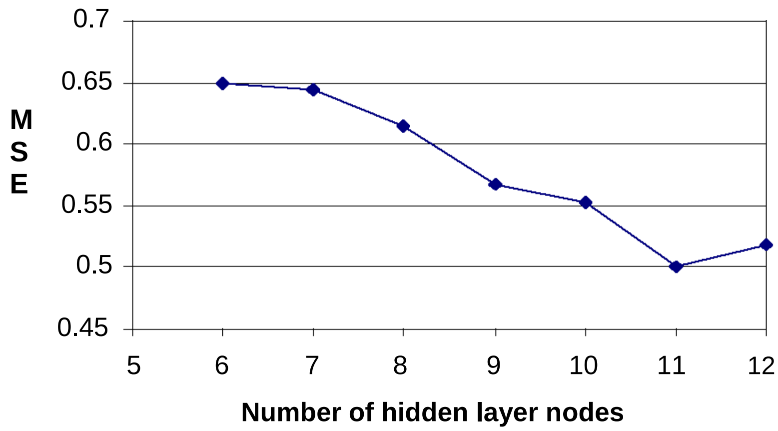

Figure 2. Selecting the best number of hidden layer nodes.

Table 1. Summery of the 5 multiple regression models.

Dependent variables	R^2	Adjusted R^2	F(18,72)	p<
Quality conformance	.389	.236	2.54	.0027
Flexibility	.434	.292	3.07	.0003
Dependability	.351	.189	2.17	.0109
Speed	.347	.184	2.13	.0125
Cost efficiency	.244	.055	1.29	.2174

Table 2. MSE comparison between ANN model and multiple regressions.

Dependent variables	MSE of multiple regression model	MSE of ANN model
Quality conformance	0.51	0.47
Flexibility	0.55	0.46
Dependability	0.57	0.40
Speed	0.47	0.36
Cost efficiency	0.91	0.63
Total MSE	0.602	0.464

were set as the largest positive number in the range being used and negative overflows as the largest negative number in the range, using a saturating linear function. All of the computer models in this research were conducted with the MATLAB 7.1. software and carried out in a desktop computer.

RESULTS

For a baseline comparison, multiple regression analysis was conducted on these observations to show how well the ANN model performed. For each of 5 outputs of ANN model (dependent variables), a separate multiple regression analysis was estimated on the same 91 observations and MSE (Mean Squared Error) was the base to compare the ANN and regression models. Table 1 shows the summery of the 5 multiple regression models. Since there were 5 separate regression models, the average MSE of them was reported to compare with the MSE of the ANN. As can be seen in Table 2, the ANN model (MSE = 0.464) outperformed the regression models (MSE = 0.602).

The rest of this section is organized to understand the effect of the improvement programs, strategic capabilities and control variables on the manufacturing performance. Although ANNs are known as the model-free estimators and black box methods, but there are some proposed methods in the literature (the sensitivity analysis, rule extraction, etc.) to show the effects of each input variable on the output (Lisboa and Taktak, 2006; Lam, 2004).

In this study, this was done using a sensitivity analysis on the trained ANN as proposed by Behara et al. (2002). In this regard, each input variable was systematically

Table 3. Effects of improvement programs on performance dimensions.

		Improvement programs [a]					
		PC	Q	PD	T	Or	SC
Dependent Variable	Quality conformance	-0.039	0.395	0.124	-0.062	0.013	0.079
	Flexibility	0.296	0.047	0.188	0.062	0.098	0.195
	Dependability	0.158	0.088	-0.063	0.161	0.132	0.177
	Speed	0.093	0.111	-0.013	0.247	0.053	0.198
	Cost efficiency	0.045	0.217	0.189	0.041	0.112	0.296

Note: [a]PC = Planning and control, Q = Quality, PD = Product development, T = Technology, Or = Organization and SC = Supply chain.

Table 4. Effects of strategic capabilities, external environment and company characteristics on performance dimensions.

		Dependent variables (outputs)[a]				
		QC	F	D	S	CE
Company characteristics	Age	0.094	0.043	0.041	-0.008	0.070
	Size	-0.069	-0.102	-0.084	-0.103	-0.133
	Ownership	0.064	0.050	0.067	-0.056	0.050
External environment [b]	MD	0.082	0.007	0.170	0.088	0.116
	MS	-0.097	0.044	-0.136	-0.117	-0.092
	MF	0.019	0.058	0.109	0.135	0.160
Strategic capabilities [c]	LSP	0.026	-0.083	-0.066	-0.195	-0.033
	SCQ	-0.082	0.024	-0.192	-0.067	-0.077
	FD	-0.012	-0.012	-0.050	-0.025	-0.006
	MDD	-0.026	-0.033	0.013	0.066	0.026
	SCS	0.052	-0.013	-0.083	0.019	-0.141
	WPR	0.032	-0.038	0.095	-0.115	0.006

Note: [a]QC = Quality Conformance, F = Flexibility, D = Dependability, S = Speed, CE = Cost efficiency, [b]MD = Market Dynamics, MS=Market Span, MF=Market Focus, [c]LSP = Lower Selling Prices, SCQ=Superior Conformance Quality, FD = Faster Deliveries, MDD = More Dependable Deliveries, SCS=Superior Customer Service, WPR = Wider Product Range.

varied up and down in a fixed percent from its original value for each observation and the resulting change in the output variables was recorded.

To accomplish this, each 91 observations was applied to the trained model. For each observation, one input was changed, one time from its original value to the next point on its likert scale and another time to the previous point, holding another's at original values. Then two resulted outputs with these increment and decrement variations in that input were calculated by the prediction power of the trained ANN.

The difference between resulted outputs and their original values is the change measure. The calculation was repeated for every input and every output. Then for a given output, resulted changes for all increments in a given input, were averaged across 91 observations and also resulted changes for all decrements were averaged. Finally the total effect of the input i on the output j was given by:

$$\frac{\text{(Average changes in output j from increments in input i)} - \text{(Average changes in output j from decrements in input i)}}{2}$$

The mean changes in performance outputs for a given plus and minus percent change in the corresponding ANN inputs are presented in Table 3 for improvement programs inputs and in Table 4 for strategic capabilities, external environment and company characteristics inputs. In these Tables, each positive value represents that an increase in the corresponding input value increases the related output and there is a direct relationship between input and output. So the negative values identifies that an increase in input will cause a decrease in the output. Table 3 depicts that between all improvement programs, planning and control and technology based programs have a negative low effect on the performance of quality conformance. The other negative effects are the effect of the programs that aimed at improving product development on the both dependability and speed performance. The most effective programs on the quality conformance are those aimed at improving quality and product development with high strengths. The flexibility and cost efficiency performances are positively affected by all of the improving programs.

As expected before based on the literature, there are some positive and negative relationships between improvement programs and operational performance which shows the matter of interactions between programs and also depicts that some capabilities can be gained only at the expense of others (implementing a program may be supportive of some performance dimensions and simultaneously incompatible with the others).

Table 4 shows that age and ownership variables have positive effects on all performance dimensions except the speed. It means that there are differences in efficiency not only between old and new plants but also between public and private sectors. It seems that old companies with a big history in the background and also companies with private ownerships were more successful in implementing improvement programs and achieving better performances. Another conclusion from Table 4 is the negative effect of increase in the company's size on all performance measures.

Considering values of the external environment variables in Table 4 indicates that companies encountered with market dynamics growing rapid, markets with many competitors and few segments were more successful in implementing improvement programs.

Finally, Table 4 identifies about two-third of strategic capabilities have negative effects on several operational performances which means that if those capabilities are more important for companies the achieved performance in some dimensions is less which in some dimensions maybe surprising results. However in some dimensions of performance, relationships have a pre-expected effect and direction for example in an environment that more dependable deliveries is more important, manufacturing performance in delivery, speed and cost efficiency dimension may better improved. It seems that in this environment the related improvement programs such as technology and supply chain based programs fit better.

CONCLUSION

This study aims to increase the understanding of the practice-performance relationships and contributes to the literature by improving the decision making process in manufacturing strategy modeling in a Middle East context with respect to Iranian small and medium sized companies. There are two outcomes that deserve some discussion. The first and the most important outcome is the contribution to provide a new approach that simultaneously models the relationship among different operational performance dimensions and the way manufacturing practices affect operational performances.

In this regard, considering the importance of strategic capabilities, degree of use of improvement programs and environmental factors as the control variables (all as inputs), an ANN model was constructed to predict the operational performance of the company (as outputs). The proposed ANN considers any trade-offs and interactions between input/output variables in modeling process which is the most interesting area of the research. A significant conclusion can be identified in this study is that the ANN model provides a more useful approach to interpreting the data of practice-performance relationships than the other methods mostly used in the literature. Results reported in Table 2 support this conclusion that the ANN model outperformed the regression analysis method by the total MSE of 0.46.

The other outcome of the study concerns the strength /effectiveness of each improvement program on the all operational performances using sensitivity analysis experiments in the proposed model. Referring to the questions introduced by De Meyer and Ferdows (1990) in introduction section, the results of sensitivity analysis reported in Table 3 and Table 4 states several insights to these questions.

From these considered improvement programs, the planning and control as well as technology based programs have a negative low effect on the performance measure of quality conformance, also programs that aimed at improving product development have a negative low effect on the both dependability and speed performance. The most effective program for each output and the other interesting relationships between variables were depicted in Table 3.

Using the prediction power of the proposed model, mangers would be able to compare between the predicted performances of alternative bundles of improvement programs and make better decisions before implementation.

There are some limitations in this study affected the generalizability of the model and validation of the outcomes that could present as opportunities for future researches. An obvious limitation is the limited number of observations collected by questionnaires particularly for neural network training. To validate the outcomes of the proposed ANN model, future works are needed with too many observations or it is better to train a new model based on data from existing international surveys such as IMSS.

There are some control variables that not included in the proposed model such as process type, industry sector, economical situations and etc. Comparative studies could be conducted on the other countries and contexts to validate the results and using large firms for more generalizability.

Also data gathering process in this study suffers from another weakness which is the number of respondents in each company. Certainly, surveys which asked more respondents to answer the questions have more ability to provide accurate and unbiased data.

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