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Predicting Intellectual Capital Efficiency of the Companies Listed in Tehran Stock Exchange Using Integrated Artificial Neural Networks-Data Envelopment Analysis Approach

(Case Study: Automotive and Automotive Parts Manufacturing Companies)

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ABSTRACT

Due to the advent of the knowledge-based economy and the developments in activity nature of the companies at international level, intellectual capital is taken to be one of the fundamental pillars of the companies for achieving efficiency. The aim of this study is to predict the effectiveness of intellectual capital of the companies listed in Tehran Stock Exchange using an integrated artificial neural networks-data envelopment analysis approach. In this research, the effectiveness of intellectual capital of the selected companies, from 2006 to 2010, was first addressed using data envelopment analysis (DEA), considering intellectual capital value added coefficient as the input variable and dividend yield, return of assets, and return of equities as three output variables of the model. In the next stage, the multilayer perceptron neural networks have been used to predict the efficiency of intellectual capital. The results demonstrate that the artificial neural network model is highly accurate in predicting intellectual capital of the companies listed in stock exchange.
KEYWORDS: Intellectual Capital, Data Envelopment Analysis, Artificial Networks.

1. INTRODUCTION

At present, knowledge is recognized as the primary pillar of social and economic developments not only in Iran's fourth development plan but also throughout the world. In that, today's economy is called knowledge-based economy. In the knowledge-based economy environment, intellectual capitals are more important and valuable than physical capitals. In other words, intellectual capitals are counted as the requirements of scientific, technological, and economic developments in every country (Mehralizadeh et al., 2011). Intellectual capital is theoretically a new topic which has recently been put forward globally. However, as it is considered to be a valuable resource for the countries and organizations, its degree of development and growth is rapidly transforming to countries development index. On the other hand, this intangible resource is one of the most value adding resources of the companies and a key capital in entrepreneurial growth. According to the researchers, intellectual capital is an intangible value that is not visible in the financial statements; it is actually guiding the companies towards gaining a competitive advantage (Madishen et al, 2011). Today, the necessity of development and management of intellectual capital has been turned into a serious requirement at national macro-level and at business arena. Therefore, moving towards knowledge-based economy has caused change in the industrial economy dominant paradigm, in that possessing intellectual capital and managing it are counted to be the key of success in today's challenging and turbulent environment (Chen et al., 2004). In the knowledge-based economy, intellectual capital is more valuable and significant than financial and physical capitals for the organizations and companies. Put is differently, intellectual capital as an actual wealth is one of the most important capitals of today's organizations and companies.

One way to optimize combination of intellectual capital factors is the use of performance concepts employing different methods. Efficiency is a criterion that gives a helping hand on an uninterrupted improvement of existing conditions. The first step in performance improvement is measurement. Efficiency measurement lays the ground for decision makers to determine their current status and enables them to take a measure for present condition improvement planning (EmamiMeibodi et al., 2011) . Several techniques have been given in the studies for measuring performance. However, among all of the mentioned models, data envelopment analysis is the best one for organization and analysis of data. The underlying reason is that it allows efficiency alternation over the time and does not require any prior assumptions about the efficiency boundary (View wt al, 2005). Therefore, it has been used more often that other views in performance assessment and is considered to be a suitable technique for comparing the units in efficiency evaluation.

In this research, along with the companies' performance assessment of the companies using DEA, neural networks approach has also been used for predicting the companies' efficiency. Statistical and econometric

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methods are accompanied with limitations in the area of prediction. That is, in such methods the incidental form of dependent and independent variables may not be explained properly, in the absence of sufficient knowledge. In addition, the majorities of time series models are linear, and so are incapable of describing nonlinear behaviors. In the recent studies, artificial neural networks have widely been employed as nonlinear approximate instruments, in that they can be utilized to tackle above problems. The neural networks can diagnose the linear and nonlinear relationships between input and output products based on training data. They also can discover the fundamental relationships between such data and then generalize them to other data. Consequently, with proper neural network architecture design and training data selection, a structure capable of time series prediction can be obtained.

Therefore, in this study DEA techniques and artificial neural networks have been deployed, in turn, for performance assessment and predicting the performance of the companies that are active in automotive industry and automotive parts manufacturing sections, listed in the stock exchange. Hence, the present study is organized according to following routine: In the second section, artificial neural networks are introduced; in the third section, literature review is addressed; the fourth section deals with research method explanation; the fifth section examines the findings; and the last part is devoted to conclusion and recommendation.

2. Artificial Neural Networks

Artificial neural networks are a group of mathematical models that imitate human brain function. They can extract patterns from the observed data, without any needs for assumptions about the relationships between the variables (Azadeh et al., 2011). These networks are a series of highly accurate comprehensive, flexible, and powerful instruments for data analysis and nonlinear relationships modeling. One of the most common neural networks is the multilayer perceptron neural network. Multilayer perceptron is a standard combination of inputs, linear and nonlinear neural units and outputs. The output of all processing units is transported from each layer to all processing units of the next layer. Processing units of the input layer are all linear. However, neurons with tangent sigmoid, hyperbolic, or any other nonlinear and continuously differentiable function can be used in the hidden layer. Usually, linear form of output layer neurons is selected for increasing the speed. The main debating issue in these types of networks is determination of the number of hidden layers and their neurons. Hidden layers are remarkably significant in neural network models. The adequate number of such layers in the units of a neural network model plays an effective part in learning process. This layer is merely an intermediate result in the process of output value calculation, so is unique in econometrics. The number of hidden nodes is important due to their substantial role in nonlinear configuration properties of the neural networks (Xang, 2003). The input layer as the recipient of external resources is compared to the five senses with respect to the brain. In determining the number of input nodes, using trial and error method has the highest application. However, in general, the number of input layer neurons indicates the number of input variables (Malik and Naserdin, 2006). In this regard, Nilson (1987) proved that in the neural networks with a hidden layer with $f(x) = \frac{1}{1+e^{x}}$ sigmoid function in the middle layer, and a linear function in the output layer would be able to approximate all of the desired functions with any approximate degrees, providing that there are sufficient neurons in the hidden layer. This is known as global approximation model (Menhaj, 2005).

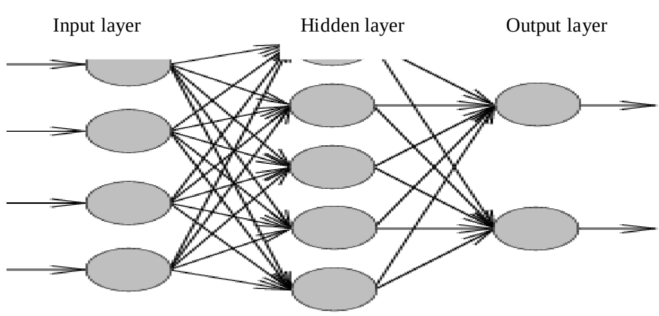

Figure 1. Structure of multilayer perceptron network with a hidden layer

In this study, root mean square error (RMSE), which can be calculated by the below equation, was used for assessing the neural network efficiency in prediction of intellectual capital (Sarmadian et al., 2010).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_0 - Z_p)^2} \tag{1}$$

Where, Z0 is the predicted values, Zp denotes observed values, and n stands for the number of data.

3. REVIEW OF LITERATURE

Tan et al. (2007) investigated the relationship between intellectual capitals as well as its components, and financial performance of the companies listed in Singapore Stock Exchange. The results indicate a positive correlation between intellectual capital as well as its components, and financial performance. Cohen and Kaimenakis (2007) conducted a research titled "Intellectual Capital and Corporate Performance in Knowledge-Intensive SMEs." The findings indicate a reciprocal relationship of specific properties of intellectual capitals in such companies at some different aspects of the patterns observed in other studies which have analyzed large companies. In addition, the experimental information have provided supportive evidences maintaining that specific classes of intellectual capital positively affect organizational performance. Makki et al. (2008) have conducted an investigation titled The Performance of Intellectual Capital in Pakistani Companies. In this study, it was clarified that in addition to financial performance assessment, intellectual capital performance evaluation is also highly significant. The findings show that chemical, oil, gas, and cement sections have high level of intellectual capital, banking section possesses average intellectual capital performance, and public sector companies hold low intellectual capital performance. Ting and Lin (2009) investigated intellectual capital performance and its correlation with financial efficiency among Malaysian companies using Palic's model for intellectual capital assessment. The results demonstrate that intellectual capital is significantly and positively affect profitability. Mohammad and Esmail (2009) in a case study on a financial part of 18 Malaysian companies in 2007 investigated their intellectual capitals and performances and showed a positive relationship between intellectual capital and performance. They also depicted that in Malaysian financial sections, the market value was created mostly through the physical than intellectual capital. Zeynal et al. (2009) in a study titled The Board Structure and Corporate Performance in Malaysia have investigated 75 companies listed in Malaysia Stock Exchange. In this study, they used Palic's model to look into the effect of the board structure on intellectual capital performance of the companies. Their findings showed a significant correlation only between a percentage of independent non-executive members on the board and intellectual capital. Zeynal et al. (2010) in a study addressed profitability of the resources, competitive intellectual capitals, and corporate performance in the health care industry. The experimental findings indicate a significant correlation between intellectual capital and corporate performance. These results also demonstrate that initiative capacities and modification are counted to be the first process. In addition, corporate performance improvement can be achieved by corporate human capital value added. Zo and Han (2011) first measured the efficiency of business units under investigation by taking fiscal data, especially financial ratios, and using DEA techniques. They, then, studied the impact of intellectual capital on the performance of the business unit. The results demonstrate a negative correlation between the used capital and structural capital, and performance. In addition, a positive correlation is reported between human capital and positive performance. Demetrius et al. (2011) examined the impact of intellectual capital on corporate market value and investigated corporate performance of 96 companies listed in Athens Stock Exchange during 2006 to 2008. The results indicate that in Greece, human resource improvement seems to be one of the most important factors of economic success. Mondale and Kumar (2011) investigated the effect of intellectual capital on the fiscal performance of Indian banks during 1999 to 2008. The results show a positive and significant correlation between intellectual capital and fiscal performance indices (profitability and efficiency). Sri Kumar and Mahapatra (2011) in a research studied the performance of Indian educational centers using integrated DEA-NN approach. The results imply that this integrated approach has introduced precise outputs for investigating the performance of those centers. Costa (2012) in a study on racing sailboats manufacturing section, in Italy, investigated the intellectual capital productivity and efficiency of 17 companies during 2005 to 2008. In this study, DEA techniques and Malmquist index have been used for performance and intellectual capital efficiency growth evaluation, respectively. The results divided the companies into four categories: high competitive and rapid growth, high competitive and slow growth, low competitive and rapid growth, and low competitive and slow growth groups. They finally gave suggestions for productivity and performance improvement of inefficient industrial companies. Mehralian et al. (2013) in a study prioritized intellectual capital indices in the knowledge-based industries using fuzzy TOPSIS model. The results indicate that human capital, especially knowledge and skills of the managers and employees, are superior with respect to intellectual capital.

Despite the large importance of intellectual capital in different areas and regarding the conducted studies by the researcher, no study has been ever done on corporate intellectual capital performance using DEA model and on the capability of neural networks in predicting the performance obtained from DEA. Therefore, this study aims to fill this gap.

4. RESEARCH METHOD

4.1. Data Collection Instrument and Data Analysis

The research method is selected based on the objective, nature, topic, and executive facilities. The present research is among applied research. The employed strategy is mathematical modeling based analysis. Since artificial neural networks are based on data, preparation of data is a significant step, or actually the key of success, in utilizing neural network. The bigger the number of data is, the approximation of the hidden structure in the model is more reliable (Menhaj et al., 2010). In this study, the performance obtained from DEA model, using WINQSB, was employed as the output variable of prediction models. In addition, annual dividend yield data, return of equity, return of assets, and intellectual capital indices (inputs and outputs of DEA) were deployed as input variables of prediction models. These data belong to a period from 2006 to 2010. Neuro Solution application was used for data analysis. This study consists of several stages. At the first stage, data were categorized into testing and training data. Then, neural network algorithms were employed for predicting intellectual capital performance. At the final stage, the results from different assessment algorithms and an effective and appropriate model for predicting intellectual capital performance were determined.

4.2. Statistical Population and Sample Size

The research statistical population consists of the automotive and automotive parts manufacturing companies listed in Tehran Stock Exchange. The underlying reason for selecting this population is that the fiscal information of the companies listed in Tehran Stock Exchange is accessible. The other reason is the homogeneity of their fiscal data due to specific regulations of the stock market, leading to better data analysis. In this study, the sample was selected using systematic elimination sampling based on five criteria:

1. The investigated firms should be among the technical and manufacturing companies listed in Tehran Stock Exchange, not those in over the counter stocks and not those to be listed
2. Detailed and complete annual financial statements of them along with stock market prices at the end of that year on Tehran Stock Exchange board over a course of five years (2006-2010) should be available.
3. The investigated firms should be among the companies listed in Tehran Stock Exchange at least one year prior to the onset of the study (2005) to the end of 2010.
4. The selected companies should be among profitable ones over these five years
5. The financial year of the selected companies should be the end of Iranian calendar (20^{th}, 21^{st}, or 22^{nd} of March), in order to improve or maintain fiscal information comparative capability.

In this research, the automotive and automotive parts manufacturing companies listed in the stock exchange were selected as pilots. In this regard, a total number of 15 companies were selected as sample size. The chosen companies are Iran Khodro, Pars Khodro, Saipa, Bahman Group, Electric Khodro, Charkheshgar, Iran Radiator, Ringsazi, Zamiyad, SazehPouyesh, Fanarsazi-e-Khavar, Lent-e-Tormoz, Mehvarsazan, and Mehrkam-e-Pars.

4.3. Input and Output of DEA Model and Artificial Neural Networks

Tables 1 and 2 represent inputs and outputs of DEA model and the selected artificial neural networks:

Table 1: Input and output of DEA model

Input	**X1**	**Value Added Coefficient of Intellectual Capital**	**Intellectual Capital indicator**
Output	Y1	Stock returns	Financial performance indicators
	Y2	Rate ofreturn on equity	
	Y3	Rate ofreturn on assets	

Table 2: Input and output of the artificial neural network

Input	**Stock returns**
	Rate ofreturn on equity
	Rate ofreturn on assets
	Value Added Coefficient of Intellectual Capital
Output	Unitperformancebased onDEAmodel

5. RESULTS

5.1. Calculating the performance of the units on the basis of DEA model

In this study one input index and three preliminary output indicators were selected to assess the chosen companies' performance by investigating the background, reviewing the literature, and considering the experts' comments. All of the mentioned companies are active in the automotive and automotive parts manufacturing areas listed in the stock Exchange. There are a number of limitations in employing DEA, such as: the bigger variables number is, the basic models possess less discriminatory power between efficient and inefficient units. In addition, as the number of organizational units is less than a certain amount discriminatory power of the basic models of DEA decreases (Mehregan, 2006). Therefore, regarding the number of companies selected in this research (15) and that it was not possible to add more companies, it was attempted to tackle this issue by decreasing the number of input and output variables of DEA model. Hence, intellectual capital index alone was selected as the input variable and return of equity, return of assets, and dividend yield were taken to be the outputs of DEA model.

At the next stage, relative efficiency of intellectual capital for each of these chosen companies was determined considering the information relevant to each of them and using DEA output-oriented CCR technique. The results are summarized in Table 3. The reason for output oriented selection is that while the companies possess a fixed amount of resources, the maximum output is expected from them. Therefore, their outputs depend on the activities and the way they allocate resources to different sections.

Table 3: The efficiency of intellectual capital of the units for 2006-2010

Row	Company	1385	1386	1387	1388	1389
1	Iran Khodro	0.436	0.705	0.410	0.436	0.811
2	Pars Khodro	0.800	0.737	0.920	0.782	0.405
3	Saipa	0.396	0.411	0.551	0.881	0.930
4	Bahman Group	0.226	0.264	0.290	0.183	0.950
5	KhodrosharghElectric	0.982	0.944	1	0.694	0.836
6	Charkheshgar	1	0.667	1	1	0.660
7	Iran Radiator	0.771	0.701	1	0.389	0.556
8	Mashahd Ring	0.904	0.813	0.861	0.631	1
9	Zamyad	0.370	0.547	0.674	0.817	1
10	SazehPouyesh	0.770	0.783	0.657	0.667	1
11	FanarsaziKhavar	0.823	0.614	0.761	0.681	0.547
12	Lent Tormoz	1	1	1	1	1
13	MehvarSazan	0.974	0.834	0.491	0.651	0.866
14	Mehrkam Pars	1	1	0.693	0.349	0.139
15	NiruMoharakeh	0.858	1	0.987	0.952	0.908

As can be seen in Table 3, the efficiency degree of the automotive and automotive parts manufacturing companies listed in the Stock Exchange over the given years is within 0-1 range. The companies with efficiency value of 1 are taken to the efficient ones, and others are taken to be inefficient firms. Regarding that in DEA model the calculated weights are the most suitable ones for maximizing units' performance, it is expected that the efficiency of all units to be obtained equal to 1; however, it is not so, according to the table, and significant differences can be observed in the performances. Of the chosen companies, only Lent-e-Tormoz Company showed the highest efficiency over the study years, since it achieved the maximum intellectual capital performance. In other words, over all these years, this company has taken the maximum advantage of its resources to gain access to the performance outputs. Other companies do not perform at optimal level in most of or all the study years with respect to performance indicators. Iin order to be able to show how inefficient decision-making units can reach efficiency boundary, the subject should be investigated from the views of inputs or outputs, or combination of them. It is obvious that for moving the usints efficiency boundary from inputs view, the number of inputs to those units should be decreased until the weighted outputs set/inputs ratio reach the efficiency threshold. From the outputs perspective, the number of outputs would be increased until weighted outputs set/input ratio reach efficiency threshold. From outputs window, inputs reduce to a certain amount and outputs increase to some extent. From the inputs view, the efficiency value obtained from various DEA models are multiplied by preliminary values of the inputs. It is obvious that for efficient decision-making units efficiency score of 1, there is no inputs change. In other units, the number of recommended inputs is reduced via multiplying it by preliminary values of the inputs. From outputs perspective as well, the inverse value of the performance obtained from different DEA models is multiplied by the preliminary values of the outputs. Again, there is no change in the outputs with respect to the decision-making units. In other units with efficiency score lower than 1, the recommended output value is increased through multiplying inverse value of the performance by the preliminary values of the outputs.

5.2. The results from artificial neural network testing

In designing a neural network, the size of learning and experimental set, data normalization, network's hidden layers number, neurons number in each layer, learning algorithm, conversion function, performance function, learning rate, and number of repetitions should be determined. For this purpose, there is no systematic method. Therefore, the best way for network design is using experience, and trial and error. In this study, after determination of testing and training data sets, the input data were standardized using Equation 2. In case the network is feed with raw data, due to big data changes, they exert different impact on the network in that some neurons reach ignition threshold too soon, while some other neurons has not arrive at activation threshold yet. This will cause reduction of model prediction capacity (Menhaj, 2005). Therefore, data are first standardized using the below Equation. It means that they are given a value within a numerical range that usually is between 0.1 and 0.9 (Sarmadian et al., 2010).

$$y = 0.8 \times \frac{X_i - X_{min}}{X_{max} - X_{min}} + 0.1 \qquad (2)$$

Where, Xmin and Xmax are, in turn, the smallest and the biggest input data series. Using this equation, the input data would be placed between 0.1 and 0.9.

In this research, the network is with f(x)=1/ 〖1+e〗^x sigmoid activation function in the hidden layer, linear activation function in the output layer, and a number of 1-10 neurons. The optimum number of neurons was determined though trial and error. Moreover, for efficiency, simplicity, and speed considerations, Levenberg-Marquardt training algorithm was employed. To predict the efficiency of intellectual capital, the inputs of network included dividend yield, return of equity, return of assets, and intellectual capital value added coefficient. The minimum value of RMSE is related to a network with seven neurons in the hidden layer. The changes in RMSE do not follow a certain trend. Since neural network is a black box model and the weights are selected randomly, this trend cannot be explained completely. Therefore, the only way for obtaining the best structure is trial and error. The underlying reason to be mention is that when the model becomes more complicated, the neural network is over-trained and so is incapable of fitting new data properly.

Chart 1 presents the distribution of test data for the neural network with 1-7-4 structure which has the highest performance rate. Regarding this figure, it can be seen that the best fitting line is with an angle close to 45 degrees, indicating high accuracy.

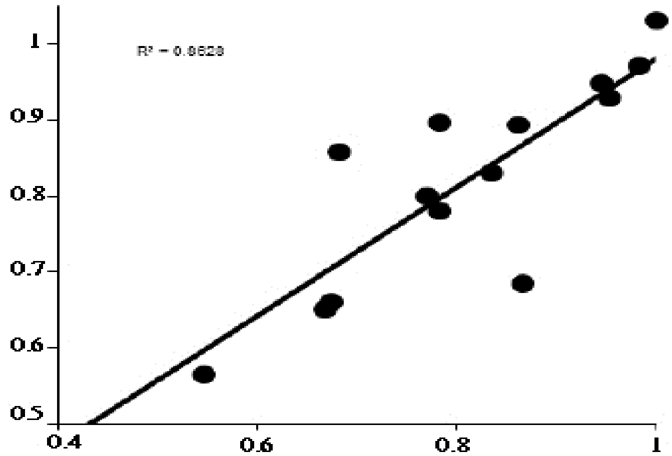

Chart 1: Distribution curve for the predicted and observed values using neural network model

5.3. The results and prediction models assessment

The results from the artificial neural network model and multivariate regression related to the measured parameter are summarized in Table 4. According to this table, it can be observed that in general artificial neural network accounts for the highest performance in predicting the feature under investigation. It also is better than multivariate regression with respect to both criteria.

Table 4: Actual and predicted intellectual capital values and the performance of different models

Year	Actual Values	Regression	Neural Network
MehvarSazan (1386)	0.834	0.791	0.831
KhodrosharghElectric (1386)	0.944	1.046	0.948
SazehPouyesh (1385)	0.770	0.841	0.800
MehvarSazan (1389)	0.866	0.678	0.683
KhodrosharghElectric (1385)	0.982	0.953	0.972
NiruMoharakeh (1388)	0.952	0.885	0.930
Mehrkam Pars (1389)	0.139	0.530	0.254
Zamyad (1387)	0.674	0.638	0.659
SazehPouyesh (1386)	0.783	0.891	0.780
Mashhad Ring (1387)	0.861	0.864	0.894
Pars Khordro (1388)	0.782	0.816	0.897
SazehPouyesh (1387)	0.667	0.650	0.651
FanarsaziKhavar (1389)	0.546	0.653	0.564
Lent Tormoz (1385)	1	0.985	1.031
FanarsaziKhavar (1388)	0.681	0.839	0.858
Model assessment indicators	R^2	**0.650**	**0.860**
	RMSE	**0.130**	**0.07**

6. CONCLUSION AND RECOMMENDATION

Modern economic growth comes from knowledge and information. This has caused increased intellectual capital importance as a research and economic subject. The role and contribution of intellectual capital in management, technical, and socioeconomic development have been picked as the topic for recent studies. In that, organizational knowledge has been known as the main factor in competitive advantage and value creation (Nikomaram and Eshaghi, 2010). The purpose of this study is to investigate the performance of artificial neural networks in predicting intellectual capital performance of the companies listed in the Stock Exchange. In this research, automotive and automotive parts manufacturing companies listed in the Stock Exchange were selected as pilot, intellectual capital index (intellectual capital value added coefficient) was chosen as the input index, and dividend yield, return of assets, and return of equity indicators were picked as the output variables of DEA model for the mentioned 15 companies within 2006-2010. Then, in order to predict the efficiency of intellectual capital, artificial neural network was used. In addition, four indices of intellectual capital value added coefficient (as intellectual capital measurement criterion), dividend yield, return of assets, and return of equity were taken as input, and the performance (calculated in DEA model) was considered to the output. The results from the present study showed that with respect to intellectual capital relative performance, Lent-e-Tormoz, Charkheshgar, and Mehrkam-e-Pars companies were superior than other companies in the relevant industry. The findings also indicate the superiority of artificial neural network over multivariate regression model in predicting intellectual capital performance. In addition, input indices sensitivity analysis by neural network showed that the input index of intellectual capital value added coefficient (intellectual capital measurement index) had the greatest impact on the output, i.e. units' efficiency. At the end, it should be mentioned that regarding the approximate nature of the measured values and parameters, they seem to be the reason for better performance of artificial neural network in predicting intellectual capital. Therefore, other companies which experience lower relative efficiency with respect to intellectual capital can move toward relative efficiency boundary using the experiences of Lent-e-Tormoz, Charkheshgar, and Mehrkam-e-Pars: educated, committed, and polite personnel, better training for personnel, proper use of modern management methods, customer-orientation and actual respect to clients, diversifying services, and use of modern industry related technologies and information. Considering intellectual capital as one of the key and strategic factors in promoting the efficiency and productivity of the selected companies listed in Tehran Stock Exchange: regarding the attained results, companies can keep the employees satisfied, motivate, and involved by investing more on human resources and training and by using incentive programs. The underlying reason is that creative and skilled people question the existing conditions to improve the processes, and these improvements provide the customers with better services and productions, and finally loyal and satisfied customers lead to organizational performance and efficiency improvement. However, regarding random search of the solution space by neural network for interpolation of complicated problems, this model with more input variables leads to better results. This can be a topic for future studies. Following list includes other recommendation for further investigations:

- Developing competitiveness infrastructure in the automotive and automotive parts industries listed in Tehran Stock Market
- Since ineffective companies in automotive and automotive parts industries listed in the Stock Exchange did not perform at optimal level with respect to output indicators such as return of equity (ROE), return of assets (ROA), and dividend yield. Therefore, the managers of the respective companies should exclusively take this into consideration during policy-making, since the improvement of these indicators causes better performance.
- Inefficiency is a scale for one of the factors affecting technical inefficiency. It means that the majority of companies in automotive and automotive parts industries do not perform at optimal level in production zone. It is recommended that those companies which act in increasing and decreasing return to scale, in turn, increase and decrease their activity level to move toward optimal scale.
- One of the most influential factors in productivity changes in the selected companies has been technological developments. However, it experienced a small rate of annual growth. Therefore, in order to enhance technical efficiency and improve technology, and finally to increase productivity, it is recommended that the selected companies become involved in training, counseling, and promoting new technologies.
- Due to the low managerial efficiency and its impact on the productivity of intellectual capital in the respective industry, managerial efficiency should be enhanced to increase productivity and achieve higher growth. This increase should be achieved by providing managers with more training and by acknowledging the principle of meritocracy in placing executives in management pyramid.

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