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Neural- Network- based Evaluation of the Effect of Variable on Time Contingency Estimation

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Abstract. Implementing the project without considering risk variables is practically impossible .The consequences of these variables such as non-estimated raw material, lack of coordination with sub-contractors, boycott, economical conditions, financial resources, etc. directly affect the estimated time. In major industries, regarding the large scope of work and exorbitant cost; clients tend to conclude the EPC contract in order to transfer the consequence of risks. The failure of executing projects within the predicted time schedule is not only due to surplus cost imposed on contractors to eliminate the obstacles, but also causes some delay penalties, opposing to release Good Performance Guarantees, any Payment Reduction and additional related to the extension of the insurances. Estimating safety time to present time schedule to the clients is applied in this paper. In this research, a back-propagation neural network is used to learn the relationship between real and forecast time. This is achieved by training the network with dwelling on 120 projects of engineering, procurement and construction (EPC project) in one of the Iran Power Plant projects Management Companies, 20 projects for validation and tests the model by focusing on 20 projects. According to the validation cross and results, it was found that the relation between the actual output and network output with the average value of 0.68 was relatively good. Furthermore, MAD, Bias and tracking signal were demonstrated the positive estimation trend in training data.

Keyword: Risk factor, time estimated, EPC Contract, Back-propagation neural net work.

1. Introduction:

Competition in domestic and foreign markets, considering international indices, has caused the companies to improve their technical and financial capacities. Although, competitive time schedule is a positive point to gain credibility for companies, but failure to accomplish their obligations imposes surplus cost to extend Good Performance Guarantees or insurance, release any Payment Reduction, Liquidate damages, etc. Furthermore, if contractor delays on fulfilling her responsibilities, issuance of the Provisional Acceptance Certificate would be hold so transmission of the electricity to the network may be face with difficulties, especially in pick season which this would cause her loses and income. All 3 sections of EPC projects, Engineering, Procurement and Constructionis always surrounded by many uncertainties, which cause risk. Project management institute (PM Industies,2004) defines contingency as the amount of the fund, budget and time needed more than the estimation to reduce the risk of overruns of projects objectivities to a level acceptable to the organization.(Rohman , Idrus & Nuruddin,2011).

The research methodology consists of 4 sections as follows: In section 1: Risk management literature is reviewed based on EP & EPC projects. Other resources like reports of past and current projects in Power

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Plant industries, academic journals and professional body interviews have confirmed risk variables. In section 2: Following risk factor identification, a questionnaire was developed based on the above literature survey results. The questionnaire aims to investigate relative importance of each variable to estimated time. This questionnaire survey was conducted with the experts in Iranian Electric Power industry. A sample of 90 experts received the questionnaire and 80 valid questionnaires were returned for analysis. 20 of risk variables were identified were then reduced to make it easy for Model application purpose. Using factor analysis with SPSS.18, variables were reduced to 14 and classified these extracted variables in 5 Components. Although, to measure of sampling adequacy was selected KMO[1] and Bartlettś test of sphericity in SPSS.18. Neural network design, training and model application have been defined in third section to find the relationship between extracted variable & real time of the execution of projects. In conclusion, a detailed treatment of the result is given and suggests some strategy to manage critical variables.

The research methodology consists of four sections. In section 1, risk management literature wass reviewed based on EPC projects. The risk variables in this research have been confirmed by valid resources like reports of previous and current projects in Power Plants Industries, academic journals and professional body's interview. In section 2, since the number of significant risk variables may vary from the projects and Contractors, a questionnaire was developed based on common variables that mostly considered significant to EPC projects. The questionnaire aims to investigate relative importance of each variable to estimated time. This questionnaire survey was conducted with the experts in Iranian Electric Power industry. A sample of 90 experts received the questionnaire and 82 valid questionnaires were returned for analyse. 14 variables were finalized using factor analysis by SPSS.18, which were classified in 4 Component. Neural network design, training and model application have been defined in third section to find the relationship between extracted variables and real time of project´s execution. A detailed treatment of the result is given in section four. and some strategies to manage critical variables.

1.1 Risk variables identification

The step is aimed in identifying every potential risk variables which could happened during the engineering, procurement, construction and installation the projects. This step was conducted by reviewing several previous researches on risk factor in projects such as by Roman(2011),Chung kang and Min feng(2009),Ebrahimnejad and Mosavi(2010),Wang and Yuan(2010) and Wiguna and Scot(2006). (x_1) Political conditions, (x_2) client managing - abilities , (x_3)Unforeseen requirement at site, (x_4) social conditions(such as strike and ...), (x_5) suggested time offering with competitors, (x_6) Failure in procurement according to the predicted time, (x_7) Standards, (x_8) Consults, (x_9) Terms and laws, (x_{10}) Delay on opening and operating Letter Of Credit, (x_{11}) Problems in transport, Custom clearance and unloading at site, (x_{12})Economical conditions, (x_{13}) Resources of financing, (x_{14}) Any mistakes during Power Plant Construction, (x_{15}) Possible accidents during Installation, (x_{16})Subcontractors, (x_{17}) Failure to estimating in basic design, (x_{18}) Price fluctuations, (x_{19}) Contractual claims, (x_{20}) Force majors were nominated to this research.

1.2 Factor analysis

As mentioned, research questions was done by conducting with 90 experts in Iranian Electricity's Power Plants, 82 valid questionnaires were returned to analysis factors, we factor analysis the 20 extracted variables to identify the major underlying dimensions of these variables, factor score based on these rating provide the variables measures used as independent variables in our analysis of time using factor analysis with SPSS.18, variables were reduced to 14 and classified in 5 Components. Table 1 provides the result of the Component Matrix obtained using Equifax rotation respectively. The results of Component Matrix shows (x_9)Terms and laws , (x_4) social conditions, (x_5) suggested time offering with competitors, (x_2) client managing abilities, (x_7) Standards and (x_{20}) Force majors must be omitted. The value of KMO should be greater than 0.5 if the sample is adequate. (Clingard and Rowlinson,2005). A value close to 1 indicates that patterns of correlations are relatively compact and so factor analysis should yield distinct and reliable factors. Kaiser (1974) recommends accepting values between 0.7 and 0.8 are good.(Field,2005).Also, Bartlett ´s measure tests the

1 . Kaiser-Meyer-Olkin

null hypothesis that the original correlation matrix is an identity matrix. For these research data the value is 0.78, so we should be confident that factor analysis is appropriate for these data. Bartlett ´s test is highly significant ($p < 0.000$), and therefore factor analysis is appropriate.

Table 1.Factor analysis of risk variables: Rotated Component Matrix

	Components			
	1	2	3	4
Variables	x_1, x_4, x_9, x_{12}	x_5,, x_7, x_{18}, ,x_{19}	x_{13}, x_8, x_2	x_3, x_{10}, , x_{11},, x_{15},, x_{17},, x_{20}
Factor name	**General & national risks**	**Industrial risks**	**Client risks**	**Operational risks**

1.3 Artificial Neural Network:

Several researches propose that the rapid growth of the amount of data collected by firms not only leads to a complicated and disorganized data structure but also results in the inability to apply traditional statistical methods due to extreme complexity. Hidden knowledge in this data volume can therefore not be used directly. The nature of our problem and the ability of artificial neural networks (ANN) in analyzing the non-linear relations among the variables was our main objective in applying ANN in the problem. The idea of neural networks was derived from how neurons operate in the brain. Real neurons are connected to each other, and accept electrical charges across synapses (small gaps between neurons). They in turn pass on an electrical charge to other neighboring neurons. The relationship between real neuron systems and artificial neural networks probably end at that point (Churchland, 1997). Neural networks can be applied to a variety of data types, and they can deal with continuous data input or categorical data input, making them flexible models (Nelson & Illingworth, 1994).

ANNs are usually arranged in at least three layers, and have a defined and constant structure that is capable of reflecting complex nonlinear relationships, although they do not have anything close to the capacity of the human brain. Many neural network models are available. About 95 percent of business applications were reported to use multilayered feed-forward neural networks with the back propagation learning rule (Wong, Bodnovich, & Selvi, 1997). This model supports prediction and classification when fed inputs and known outputs. Back propagation is a supervised learning technique in that it uses a training set to fit relationships. This model uses one or more hidden Layers of neurons between inputs and outputs. Neural networks have relative advantages in that they make no assumptions about data properties or statistical distributions. They also tend to be more accurate when dealing with complex data patterns, such as nonlinear relationships.

The introduced neural network is a supervised one in its training and therefore it is necessary to determine four variables: 1. Network inputs 2. Network outputs 3.Terminating network learning 4. Activation f unction. In this research, to achieve the desired input and output data, a data based were designed, by using reports of 140 previous and current Gas Power Plant projects. With regards to the probability and impacts of approved risk variables, which are the basis of risk management, these two factors have been considered as the input and real time of EPC projects for output. Measuring the Inputs and output for neural networks were demonstrated in table 2. We see a neural network with 14 input neurons, 12 neurons in the hidden layer, and 1 output neuron. In this study, the authors used the Neuro solution*6 software application to build the back propagation neural network model. For building a model that estimates performance based on the values of the real time, the neural network was trained using a supervised training algorithm. Each time, an input pattern was given to the network and the network estimated the corresponding performance. The training procedure was continued for all the observations pertaining to the data samples repeatedly. For verifying and validating the ANN, (Hagen et al. 1996) suggest investigating the reaction of the MSE in each epoch. To avoid over fitting, 100 projects were allocated to train the model, 20 projects to validation and 20 projects to test the model. The neural networks computing are working correctly, when the validation cross are increased and the MSE value should be decreased (Hagen et al., 1996). Training ended when iteration epochs reached 7000.

Table 2: Input and Output of Neural network for predicting real time

NO	*Input*	*Desired output*
	Risk=(probability × impact(day))	Delay on PAC[2](day)

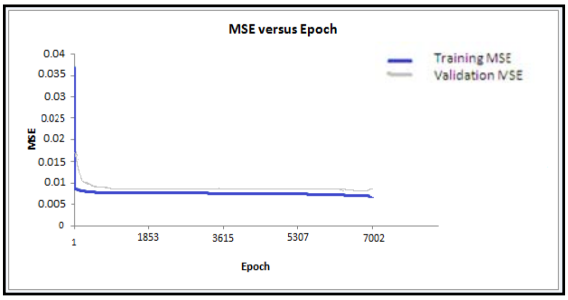

Fig 1: MSE (vertical) versus epochs

A quantitative examination of the fit of the predictive models was made using error measurement indices commonly used to evaluate forecasting models (obersone, 1990). The accuracy of the models was determined by: Mean Square Error (MSE), Correlation Coefficient(r) and Mean Absolute Error (MAE) are evaluated by Neuro solution*6 software application. In addition to investigating the estimation trend 3 criterias: Mean Absolute Deviation (MAD), Bias and Tracking Signal are computed by using equations(1),(2),(3). Where y_t : Equals the observed value at time t, $\hat{y}_t$: Equals the estimated value and n: Equals the number of observations..

$$MAD = \frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{n} \quad (1)$$

$$Bais = \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)}{n} \quad (2)$$

$$Tracking\ Signal = \frac{Bias}{MAD} \quad (3)$$

1.4 Result and discussion:

In this research, through the use of a neural network, we were able to measure the amount of influence of risk variables on real time of Gas Power Plant projects in a more reliable manner than other statistical methods. Table 3 shows the result for the developed Neural Network. Forecasting error measurements based on the difference between the model and the observed values are shown. The results of overall calculated statistical values MSE, MAE, MAD, Bias, r^2 and Tracking signal have shown that Neural Network may be used efficiently to provide the accurate fit to predict real time. Descending curve of MSE and MAD are demonstrated meaningful measures of error. Since times vary from 24 to 30, it is important to compare the amount of the error with the corresponding base real time and predicted time of network. Timing error is negative when the model underestimates the real time and is positive when the model overestimates the real time. Besides, we calculated the correlation coefficients between the actual outputs, and the network outputs, for the test data sets. If the network performance is high, the correlation coefficients between the actual outputs and the network outputs should take the values that are very close to one. The correlation coefficient (r) between the actual output and the network output is relatively high with the average value of 0.68.the value of Tracking Signal is demonstrated that our estimating trend is positive.

[2] .Provisional Acceptance Certificate

Table 3: architecture, specification and statistic information of the neural network

Measurements	***Values***
No. nodes in the input layer	14
No. nodes in the hidden layer	12
No. nodes in the input layer	1
Epoch	7000
Transfer function	Sigmoid
r^2	0.68
MSE	0.01
MAD	0.04
MAD	0.22
Bias	0.02
Tracking Signal	0.24

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3. References:

[1] S. Ghosh, J. Jintanapakanont. Identifying and assessing the Critical risk factors in an underground rail project in Thailand: a factor analysis approach, International Journal of Project management. 2004, 22: 633-643.

[2] M. Hagen, T. Demuth. Neural Network Design. Boston. USA: PWS Publishing Company, 1994.

[3] I. Dikmen, I. Birgonul. Using fuzzy risk assessment to rate cost overrun risk in international construction project. International Journal of Project Management. 2007, 25:494–505.

[4] J. Paek, H. Lee. Pricing construction risk: Fuzzy set application. Journal of Construction Engineering and Management.1993, 119: 743–756.

[5] M. Nelson, W.T. Illingworth. Practical guide to neural nets. USA: Addison Wesley, 1994.

[6] H. Lingard, S. Rowlinsone. Sample Size in Factor Analysis, Psychological Methods. 2008, 3: 231-251.

[7] Publishing Company.

[8] J.H. Tah Thorpe, R. McCafer. Contractor project risk contingency allocation using linguistic approximation. Computing Systems in Engineering. 1993, 4:281–293.

[9] M.T. Wang, H.Y. Chou. Risk allocation and risk handling of highway 791 projects in Taiwan. Journal of Management in Engineering. 2003, 19(2): 60–68.

[10] A. Idrus, M. Nuruddin. Development of project cost contingency estimation model using risk analysis and fuzzy expert system, Expert system with application. 2011,38: 1501-1508

[11] C. Yin, L. Rosendahl. Methods to improve prediction performance of ANN models. Simulation Modeling Practice and Theory .2003, 11(3): 211–222.

[12] Z. Yu Zhao, J. Zuo. Critical success factors for BOT electric Power Projects in China: Thermal Power versus wind power, An international Journal of Renewable Energy. 2009, 35:1283-1291.

[13] D.T. Larose, J. Wiley. Discovering Knowledge in Date.2003.

[14] R. Sonmez , A. Ergin. Quantitative methodology for determining of cost contingency in international project. Journal of Management in Engineering. 2003, 23: 35–39.