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A Genetic Algorithm-based Neural Network for Forecasting the Risk of High-Tech Projects

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Abstract

Investing on high-tech projects always includes some unexpected risks. The lack of a systematic mechanism to forecast the risk of such projects is believed to be as one of the most important barriers for evaluating them. To provide project managers with a reliable framework for evaluating high-tech projects, this paper combine two different computational intelligence methods viz., Genetic Algorithms (GA) and Artificial Neural Networks (ANN) for forecasting the risk value of high-tech projects to build a model. This model firstly utilizes the Principal Component Analysis (PCA) to select the most related subset of input variables that can predict the desired output with an acceptable level of accuracy. Secondly, it uses the approximation ability of ANNs for modeling the complex relationships between input and output variables and the random search ability of GA for finding optimal values of ANN's parameters viz., weights and biases to enable neural network for refraining from being trapped in local optima and ploddingly converging to global optimum. Using four statistical indicators, the performance of this hybrid model (ANN-GA) has been compared with classical back-propagation neural network (BPP). The results show that ANN-GA outperforms BPNN in terms of convergence speed and approximation accuracy. This Model can be used for forecasting the risk value of high-tech projects.

Keywords

High-tech Project Risk, pharmaceutical industry, Risk Assessment Index System, Principal Component Analysis, Genetic Algorithm, Artificial Neural Network

Introduction

Risk analysis has been the subject of several management studies (Lee, Wei, & Lee, 2010; Francis, Gupta, & Hasan, 2011; Ackermann, Howick, Quigley, Walls, & Houghton, 2014; Ansaripoor, Oliveira, & Liret, 2014; Mitra, Karathanasopoulos, Sermpinis, Dunis, & Hood, 2015). Among management issues, project management has received a great deal of attention in terms of risk studies (Williams, 1995; Tavares, 2002; Zhang & Elmaghraby, 2014). As a type of project, development project of high-tech products is always influenced by several risks neglecting each of which will dramatically undermine the success rate of such a project (Wang *et al*., 2015, Zhang *et al*., 2013, Liu *et al*., 2011, De Maio *et al*., 1994). Likewise, because of the fact that investment on development projects of high-tech products require the utilization of different resources (i.e. both physical assets & intellectual capitals) and will not always result in desired predictions, failure of such projects will doubtlessly inflict massive economic costs on organizations (Liu *et al*., 2011, Wei *et al.*, 2009). Therefore, if project planners are enabled to measure and analyze the risk of such projects, they can forecast their success or failure more confidently. The purpose of this study is to construct a model by which project managers can forecast risk value of investing on high-tech products. Thus, it contributes largely to pinpoint and stop investing on those projects which are more likely to fail with regard to organization's current resources. This model is formulated through three main phases. In the first phase, a number of risk-related variables (of high-tech projects) are gleaned. Then, the Principal Component Analysis (PCA) is used for analyzing them in order to construct a Risk Assessment Index System (RAIS) for high-tech products development projects. The second phase deals with developing an Artificial Neural Network (ANN) for forecasting risk value of high-tech projects in a pharmaceutical industry. Third and the last phase is focused on improving proposed ANN through embedding a Genetic Algorithm within it.

Literature Review

In the field of Artificial Intelligence (AI), an Artificial Neural Network (ANN) is known as a powerful computational data model that is able to extract and represent nonlinear input/output relationships among

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variables (Somers & Casal, 2009) As stated in Neurosolutions (2014) "The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain ".ANNs are basically presented as systems of interconnected "neurons" that are able to compute values from inputs, and have the capability of machine learning as well as pattern recognition because of their adaptive nature. In real world problems, ANNs have been applied in a large number of fields ranging from aerospace engineering to banking industry.

John, Balakrishnan, and O. Fiet (2000) used ANN to model the relationship between corporate strategy and wealth creation. This study shows that ANN outperforms conventional methods such as discriminate analysis in terms of modeling nonlinear relationships. In another study, Lam (2004) designed a supervised feed forward neural network for forecasting financial performance through integrating both fundamental and financial analysis. In an effort to study and forecast the innovation performance of Taiwanese manufacturing industry, Wang and Chien (2006) proposed a supervised back propagation neural network model. During this study, they showed the superior performance of their proposed methodology as compared to the multi-regression method. Paliwal and Kumar (2009) developed an ANN to measure the performance potential of graduates of an Indian business school. Through this research, they compared their presented model with some of standard traditional statistical techniques and showed the superiority of ANN over regression analysis for prediction problem. Tollo, Tanev, Davide, and Ma (2012) used both supervised and unsupervised neural networks for analysis and assessment of the relationship between firms' innovativeness and their degree of engagement in co-value creation activities.

Some researcher (Li, 1994; Vellido, Lisboa, & Vaughan, 1999; Smith & Gupta, 2000 ;) have tried to survey the business application of ANN in verity of sub fields. In another effort, Hakimpoor, Arshad, Tat, Khani, and Rahmandoust (2011) conducted a survey on ANNs' applications in management in which they classified its applications based on four main areas and their related problem types. Table 1 shows this classification.

Table 1. ANNs' reported applications

Main Area I	Marketing and Sales
Problem Type	Forecasting costumer respond, Market development forecasting, Sales forecasting, Price elasticity modeling, Target marketing, Customer satisfaction assessment, Customer loyalty and retention , Market segmentation, Customer behavior analysis, Brand analysis, Market basket analysis, Storage layout, Customer gender analysis, Market orientation and performance, Marketing strategies, strategic planning and performance, Marketing data mining, Marketing margin estimation, Consumer choice prediction, Market share forecasting.
Main Area II	Finance and Accounting
Problem Type	Financial health prediction, Compensation assessment, Bankruptcy classification, Analytical review process, Credit scoring, Signature verification, Risk assessment, Forecasting, Stock trend classification, Bond rating, Interest rate structure analysis, Mutual found selection, Credit and evaluation.
Main Area III	Manufacturing and Production
Problem Type	Engineering design, Quality control, Storage design, Inventory control, Supply chain management, Demand forecasting, Monitoring and diagnosis, Process selection.
Main Area IIII	Strategic Management and Business Policy
Problem Type	Strategic planning and performance, Assessing decision making, Evaluating strategies

Regarding Table 1, it can be seen that ANN has been widely used in various types of business problems. In terms of risk assessment of high-tech products, some researchers have done good works. Badiru and Sieger (1998) developed a neural network as a simulation meta-model in economic analysis of risky projects. Zheng'ou, Tao, Shuxin, Qi, and Rongchun (2000) proposed a radial basis function neural network and applied it to the risk evaluation of high-technology project investment. Jiang and Ruan (2010) designed an ANN for assessing investment risks on high-tech projects.

Most of the researches conducted on application of ANNs in assessment of high-tech projects' risk have more focused on approximating the risk value of high tech projects through conventional back propagation ANNs (Hashemi & Stafford, 1993; Rahmat, 2005; Saracia, Cantone & Basili, 2007; Goonawardene, Subashini, Boralessa & Premaratne, 2010) while this paper's main assumption is to develop a more improved ANN for forecasting the risk value of investing on high-tech projects (Porto, Fogel, & Fogel, 1995; Curry, & Morgan, 1997; Gupta & Sexton, 1999; Sexton & Gupta, 2000).

Technology Classifications

Technologies can be studied in terms of various types (Aunger, 2010). A technology classification system enables researchers to understand technologies-related types and view them from various angles. Different methods of technology classification have been so far proposed (Schmoch, 2008; Ghezzi, Nogueira Cortimiglia & Balocco, 2012; Thorleuchter & Van den Poel, 2013) each of which possess a set of pros and cons. . As a matter of fact, there are some criteria based on which technologies can be classified into some types. A typical classification is represented in Table 2 (Aarabi & Mennati, 2014).

Table 2. Technology types' classification

Criterion	Technology
Life Cycle	Emerging, Pacing, Key and basic Technologies
Labor or Capital	Labor and capital Intensive Technologies
Place	Intramural and extramural technologies
Complexity	Absorbable & non absorbable technologies
Output	High-tech, Medium Tech, Low Tech, labor-intensive technologies
Nature	Software & hardware technologies
Codification	Codified & Tacit technologies
background	Current and new technologies
Application area	Product and Process technologies
Appropriateness	Appropriate and inappropriate technologies
Importance	Critical /distinctive, basic and external technologies

Development of High-tech projects every so often needs both a lot of financial resources and too much supervision time (Feldman, 1985; Shenhar, 1993; Miles, 1998; Verma & Sinha, 2002). Moreover, investment of such projects entails a lot of risk and can't certainly lead to success. Therefore, some organizations have suffered enormous resource losses in process of investing on such projects because of the ignorance of risk assessment or using improper assessment methods (Himmelberg & Petersen, 1994; Jiangn & Ruan, 2010).

Development of a Risk Assessment Index System

To assess the risk of investing on high-tech projects, a Risk Assessment Index System (RAIS) should be developed at first. To do so, after interviewing some subject matter experts and studying related literature (Shenhar , 1993; Han & Ma, 2001; Wei & Liu,. 2009; Meredith, & Mantel Jr, 2011; Liu, Zhang, & Liu 2011; Mirza, Pourzolfaghar, & Shahnazari, 2013; Zhang, He, & Zhou, 2013; Gueymard , 2014), twenty five variables related to the risk of high-tech project were captured and classified into six main risk contents as represented in Table 3. Then, the Principal Component Analysis (PCA) was used to construct an index system. As a statistical multivariate method, PCA is widely used for data analysis. Basically, researchers apply this method to transform a group of correlated data to a group of uncorrelated data which are ordered by decreasing variance. The uncorrelated data are actually linear combinations of the initial data whose last ones are erased with minimum loss of real data. The first PC is a combination of data explaining the highest amount of variance. The second PC represents the next highest variance and depends on the first one and so on (Jolliffe, 2002). The final result of using PCA to construct a RAIS from Table 3 is presented in Table 4.

Table 3. Risk contents and their risk variables

Risk Contents	Risk variables
A: R & D Risks	A1:The financial resources availability
	A2:Capable human resources
	A3:Knowledge resources
B: Technical Risks	B1:Technical maturity
	B2:Technology substitutability
	B3:Technology advantage
C: Production Risks	C1:The standardization degree of the production tools
	C2:The standardization degree of the production process
	C3:The supply capability of the raw material
D: Marketing Risks	D1:Market prospects
	D2:Substitute products
	D3:The Product life cycles
	D4:Product competitiveness
	D5:Possibility of new entrants
E: Management Risks	E1:The degree of managers' technical competencies
	E2:The maturity of Project management methods
	E3:The scientific weights of decisions
	E4:The quality of managers' behavior
F:Environmental Risks	F1:The quality of conformation to cultural norms
	F2:The degree of governmental support

Table 4. RAIS of high-tech project investment

Risk Contents	Risk variables
A: R & D Risks	A1:The financial resources availability
	A2:Capable human resources
	A3:Knowledge resources
B: Technical Risks	B1:Technical Maturity
	B3:Technology advantage
C: Production Risks	C1:The standardization degree of the production tools
	C2:The standardization degree of the production process
	C3:The supply capability of the raw material
D: Marketing Risks	D1:Market prospects
	D2:Substitute products
	D4:Product competitiveness
	D5:Possibility of new entrants
E: Management Risks	E1:The degree of managers' technical competencies
	E3:The scientific weights of decisions
	E4:The quality of managers' behavior
F:Environmental Risks	F1:The quality of conformation to cultural norms
	F2:The degree of governmental support

Case study and Samples

This study was a part of a larger study which had been previously conducted in the pharmaceutical industry. As a matter of fact, there are lots of reasons for selecting pharmaceutical industry as the case study. First, it is the regarded as the highest R&D intensive industry and consequently possesses the highest level of R&D intensity among all industries. Secondly, because of its tremendously competitive nature, all pharmaceutical industries have made a large number of systematic efforts for protecting their intellectual properties and thereby, generated a lot of recorded data in forms of technical reports, academic researches and patents (Zhang et al., 2012).

During the original study, a main survey was constructed based on RAIS presented in Table 4 in order to measure the risk factors and record their corresponding results from the viewpoint of engaged subject matter experts. After constructing the survey, it was distributed among 12 firms which were active in pharmaceutical industry. These firms which were directly engaged in developing drug (as a high-tech product) had a lot of recorded data about their past experiences in developing drug products. The survey was justified to all firms' managers and distributed to them from November 15, 2014 to November 16, 2014. The due time of questionnaire's reception was set for 10 days later (i.e. November 26, 2014). Among all 12 firms that received the survey just 10 of them responded to it up to the end of due time.

Data Requirements

In the original study, the data of 220 projects were collected which in current study only the data of 63 projects could be used. This was mainly because of the fact that the problem of this research structurally differs from that of original one. The used data are shown in Table 5 according to their firms.

Table 5. Firms' used data

	Number of implemented projects based on different periods				Sum
	2010	2011	2012	2013	
Firm 1	1	3	2	1	6
Firm 2	2	5	1	2	10
Firm 3	1	2	2	2	7
Firm 4	1	2	1	2	6
Firm 5	1	1	2	2	6
Firm 6	1	2	1	1	5
Firm 7	1	1	1	1	4
Firm 8	1	1	3	2	7
Firm 9	1	2	1	2	6
Firm 10	2	1	1	2	6
Sum	12	20	15	17	63

Model Development

Artificial Neural Network

The ANN developed in this paper is represented in Fig 1: All input vectors of proposed ANN have 17 elements of RAIS. The number of these input vectors is equal to that of implemented projects (i.e. 63). The proposed ANN has 12 neurons (i.e., Nodes) in its hidden layers each of which has a Hyperbolic Tangent Sigmoid transfer function. This function's structure is shown is Equation (1).

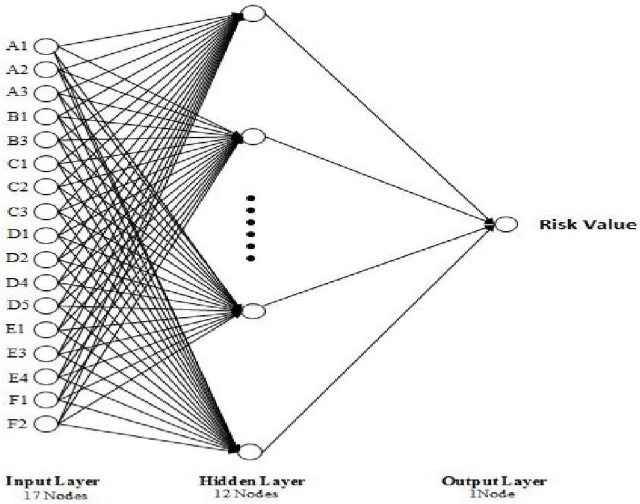

Fig 1. Proposed ANN

$$f(n) = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \tag{1}$$

Mathematically, it compresses all of its inputs to a range from -1 to +1, as it is shown in Fig. 2 for an interval of [-10, 10]. In the output layer there is just 1 neuron equal to the value of risk. The transfer function used in this neuron is presented in Equation (2)

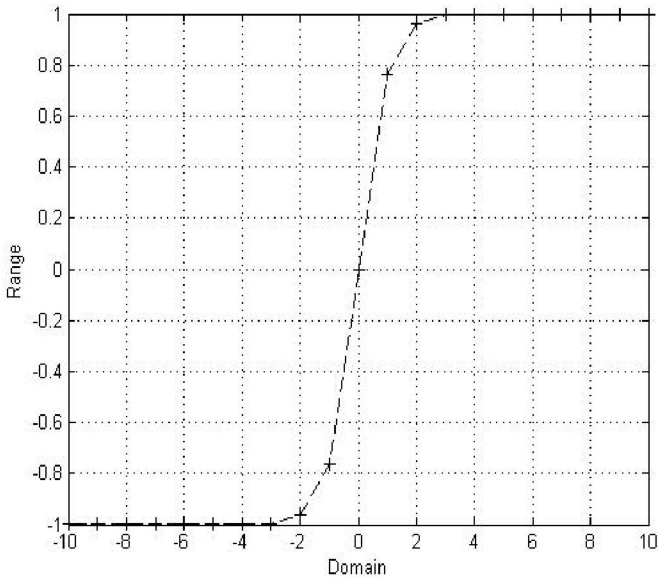

Fig 2: Hidden layer's function diagram

$$f(n) = n \tag{2}$$

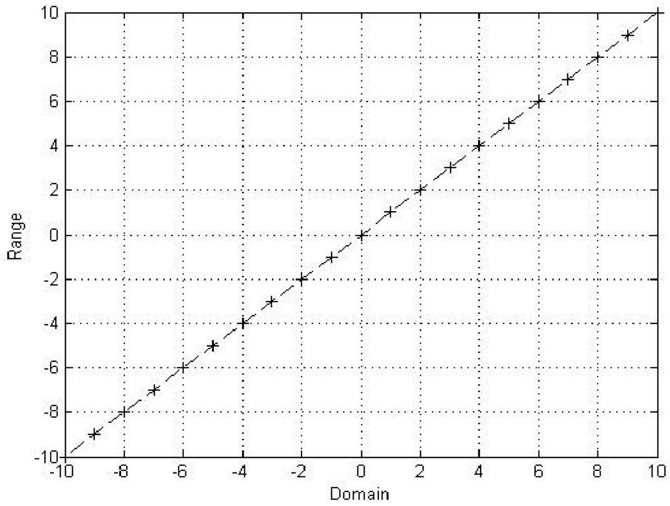

Fig 3. Output layer's function diagram

The performance function of proposed model is shown in Equation (3)

$$MSE = \frac{\sum_{i=1}^{N} e_i^2}{N} \qquad (3)$$

Where e_i stands for the error of i_{the} neuron and N represents the number of all neuron of the network.

The model's most important purpose is to reduce this performance function as much as possible. This is what a training algorithm is responsible for doing. Actually, a training algorithm tries to reduce this index as much as possible through network's parameter updating. The better algorithm can update parameters, the more it can reduce error function. Most often, gradient descent research methods are used for training ANNs, but since these methods are inclined to get trapped in local minima during optimization, (Montana & Davis, 1989; Gupta & Sexton, 1999; Sexton & Gupta,2000; Mandal, Pal & Saha, 2007)a Genetic Algorithm is used do to so.

Genetic Algorithm

A large number of researches conducted in Artificial Neural Networks (ANNs) mainly use gradient methods for training ANNs. As a well-known gradient descent-based method, back propagation (BP) trains ANN one the basis of its error function's gradient descent. This method which has been developed by Rumelhart, McClelland, PDP Research Group (1986) and Werbos (1994) is frequently used for training various types of supervised ANNs.

However, since ANNs generate complex surfaces of error with several local optima points, even for a simple function approximation problem, gradient research algorithms mainly intend to get trapped in local solutions which are not global. Therefore, BP and other gradient research methods seem not to be able to offer the best and fastest mechanisms for neural networks training (Gupta & Sexton, 1999). To prevent ANN from being trapped in local solutions, especially when a nonlinear problem is supposed to be modeled, Genetic Algorithm as one of the most applied evolutionary algorithms has been found very effective for ANN training. Some studies conducted by Porto, Fogel, and Fogel (1995), Curry and Morgan (1997), Gupta and Sexton (1999) and Sexton and Gupta, (2000) have pointed to the fact that meta heuristics outperform BP varieties in terms of ANN training ().

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

Unlike BP, which moves from one single solution to another based on gradient information, the GA simultaneously searches in a population of solutions, which enhances the probability of finding the global optimum (Montagno, Sexton, & Smith, 2002) The flowchart of a simple GA is shown in Fig 4.

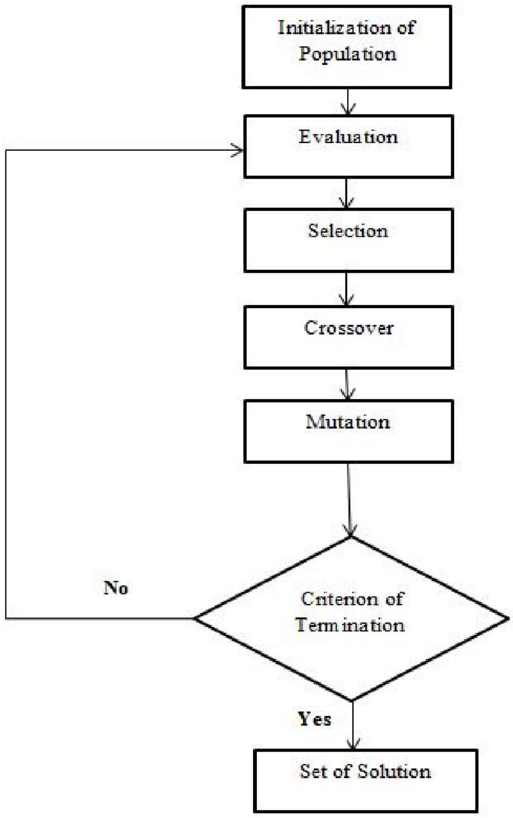

Fig 4. Flowchart of a simple GA

As can be seen from Fig. 4, like other nature inspired algorithms' first step, GA starts with an initial population which is set to 500 in this study. In the second step, the individuals of this population (i.e. chromosomes) are evaluated through cost function. In the third step, a number of population's individuals are selected for crossover and mutation operations. Generally, methods such as random selection, roulette wheel selection and tournament selection are used for doing so which in this study, the roulette wheel method has been used for selection.

Like selection, there are some operation methods for crossover and mutation which in this study, the uniform operator and boundary operator have been used for crossover and mutation respectively. The crossover and mutation percentages are also set to 0.50 and 0.35 (of initial population) respectively. In the fourth step, by merging the initial population, off springs and mutants, a new population is created. Then, this population is sorted based on evaluating its individual' cost and then worse chromosomes are truncated and a new population which is a big as the first one is extracted. In the last step, if this population satisfies problem's criteria, the algorithm ends, otherwise it is goes to the loop and starts from the beginning until the end of the maximum number of generations which is set to 100 in this study.

Hybrid Model

A supervised ANN is trained based on the difference between its output and real output. Actually, this difference is presented by an error function such as Mean Squared Error (MSE) presented in Equation (1). A training algorithm tries to reduce this index as much as possible through network's parameter updating. The better algorithm can update parameters, the more it can reduce error function. Usually, gradient descent research methods are used for training ANNs, but since these methods are inclined to get trapped in local minima during optimization, evolutionary optimization methods are used do to so. The hybridization of GA with ANN is shown is Fig 5. As can be seen from Fig 1, instead of a gradient research method, a GA is used for optimizing ANN's error.

Results

After writing and solving the proposed model by MATLAB Software, the results indicated a good performance for it. Model's overall performance is shown in Fig. 6. As can be seen, by training ANN through a real valued GA, the MSE index has had a good decreasing trend. After 100 generations, the GA has been able to reduce this index to 0.0704 showing a really good training performance for the ANN shown in Fig.1. The training error value for each sample (out of 50) has been plotted in Fig 7. As can be seen, the distance between ANN's outputs and real outputs is somewhat low for a large number of samples.

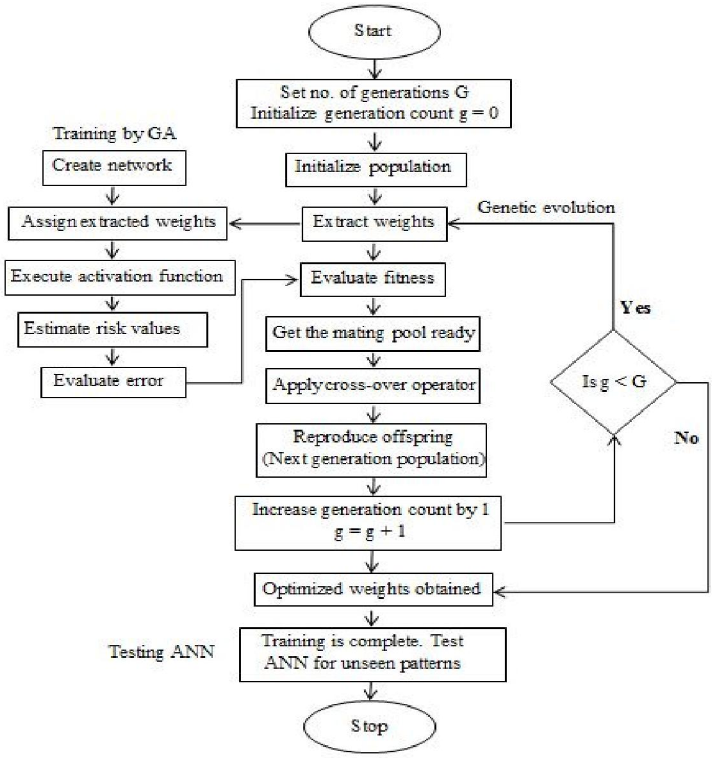

Fig 5.Flowchart for risk estimation by proposed model

The error average value (EAV) of training error for all samples is 13.2639. Apart from training performance which is an indicator for network training quality, another performance indicator is test performance which indicates network's learning quality. The test performance MSE of this model has been reduced to 0.1325 after 100 generations which means the proposed model has had more errors in this performance index than other training one. However, this performance value is acceptable and proves ANN's good learning quality.

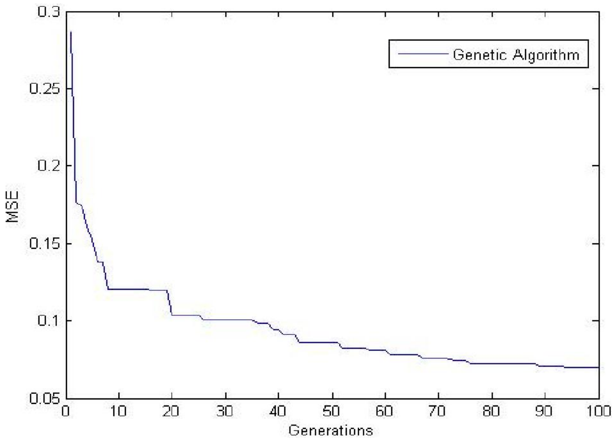

Fig 6. Model's overall performance

The test error value for each sample (out of 13) has been plotted in Fig. 8. As can be seen for test performance, the distance between ANN's outputs and real ones is more than that of training performance. The error average value (EVA) of test error for all samples is 18.2219. All of the results of the proposed model are presented in Table 6. As can be seen, the training performance of proposed model is better than its testing one. However, it should be noted that since 50 of all 63 samples have been used for training set and just 13 of all samples are used for testing set, all performances of the proposed model are really good and this network enables the decision makers to forecast the risk of investing on high tech projects with a high accuracy.

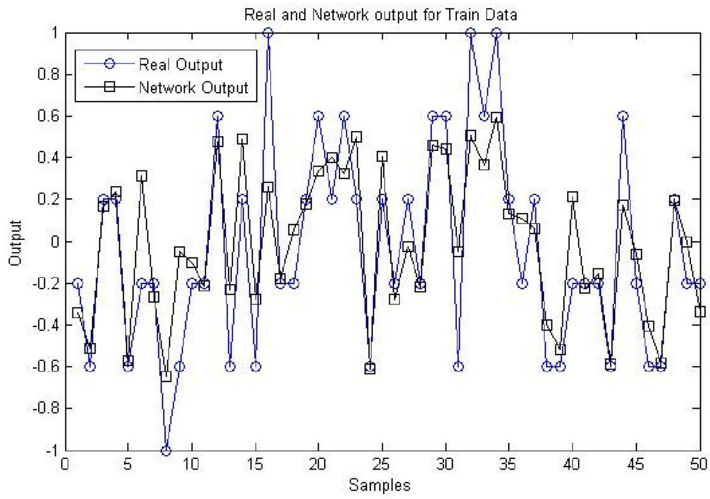

Fig 7. Training error plot

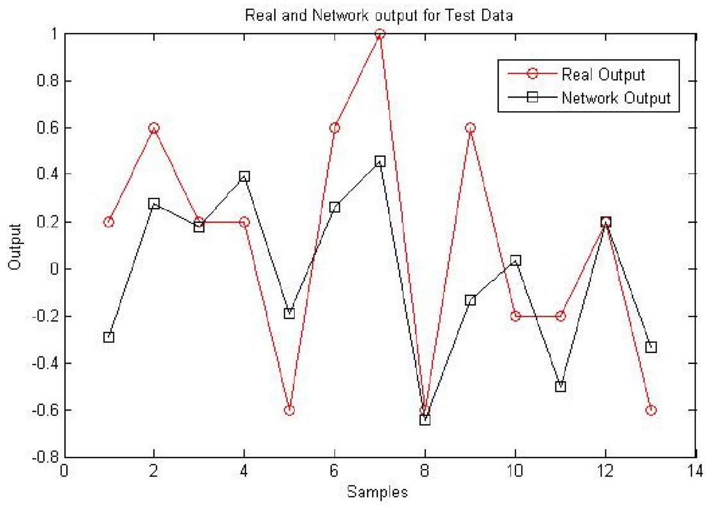

Fig 8. Test error plot

Table 6. Proposed Model's results

Training	MSE	0.0704
	RMSE	0.2653
	EVA	13.2639
	Correlation	0.8501
Testing	MSE	0.1325
	RMSE	0.3644
	EVA	18.2219
	Correlation	0.7361

Comparison of GA with BP

To show the quality of proposed model's results, it was compared with a BP-trained ANN .As shown in the Fig. 9, when ANN is trained by a real valued GA its performance is far better than when it is trained by a BP algorithm. This difference is mainly due to the fact that GA has been more efficient in updating ANN's parameters. The results of these two models have been shown in Table 7.

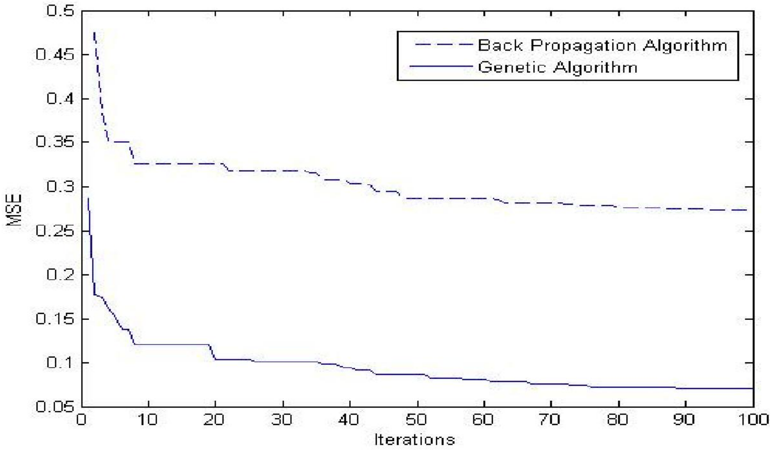

Fig 9. Comparison of GA-trained ANN And BP-trained ANN

Table 7.Results of two models

		GA-trained ANN	BP-trained ANN
Training	MSE	0.0704	0.2734
	RMSE	0.2653	0.5229
	EVA	13.2639	26.1425
	Correlation	0.8501	0.5862
Testing	MSE	0.1325	4304
	RMSE	0.3644	0.6561
	EVA	18.2219	32.8027
	Correlation	0.7361	0.4669

The above Fig. shows a drastic difference between the performance of GA-trained ANN (proposed model) and that of BP-trained ANN (classical networks). This difference shows that the proposed model has outperformed the gradient descent –based ANN in terms of all performance indicators. This shows that the proposed model's outputs are much more accurate than those of BP-trained ANN. So, projects managers are enabled to forecast the risk value of investing on high tech projects far better and more confidentially when they use this proposed model.

Conclusion

Development of high-tech products doesn't always result in planned outcomes and organizations will suffer huge losses if they fail in developing them. To manage high-tech product development projects more confidently, managers should have reliable information about their risk values in advance. The Model developed in this paper is aimed at helping managers to have such precious information and enabling them to forecast the risk value of investing on high tech projects far better than classical BP-trained models. According to a Risk Assessment Index System (RAIS) that has been extracted from valid resources and constructed by Principal Component Analysis (PCA) method, an ANN has been designed and improved by a real valued Genetic Algorithm (GA) for enabling project managers to forecast the risk value of each high-tech project before starting investing on it. The heighted level of model's accuracy and reliability makes it a very reliable mechanism for measuring the risk value of high-tech projects in advance.

However, the proposed model can be improved in three two. The First aspect is that when there are many input variables (elements), it becomes painstakingly difficult to include all of them into the model. So, a mechanism should be developed for selecting more important input variables before they enter the model. Meta heuristics such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO) can be used for doing so (See Sivagaminathan & Ramakrishnan, 2007; Kabir, Shahjahan, & Murase, 2012; Oreski & Oreski, 2014; Das, Pattnaik, & Padhy, 2014). The second aspect is about the nature of model's variables which all can be dealt with in a fuzzy manner; therefore, development of a fuzzy ANN is strongly needed (See Kuo, 2001; Chien, Wang, & Lin 2010).Anyway, pursuing each of these two aspects is of paramount value and can be a subject for future researches.

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