International Journal of Applied Operational Research
Vol. 3, No. 2, pp. 53-65, Spring 2013

Journal homepage: www.ijorlu.ir

A Reliability Approach on Redesigning the Warehouses in Supply Chain with Uncertain Parameters via Integrated Monte Carlo Simulation and Tuned Artificial Neural Network

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Received: 4 September 2012 ; **Accepted:** 26 December 2012

Abstract In this paper, a reliability approach on reconfiguration decisions in a supply chain network is studied based on coupling the simulation concepts and artificial neural network. In other words, due to the limited budget for warehouse relocation in a supply chain, the failure probability is assessed for determining the robust decision for future supply chain configuration. Traditional solving approaches can find the failure probability in problems with small scenarios and limited dimensions, while huge number of scenarios needs to be optimized by an efficient approach in terms of accuracy in obtained solution and improving the computational time simultaneously. Hence, the tuned artificial neural network (ANN) is applied to forecast the failure probability while network's parameters and available budget are stochastic. The results show that simulation of problem using ANN can work appropriately in selecting the configuration with considerable less time consumption and forecasting error.

Keywords Tuned Artificial Neural Network, Reliability, Monte Carlo Simulation, Warehouse Relocation.

1 Introduction

In two last decades, reliability approaches have attracted significant attention in published researches. In an uncertain environment, decision makers want to take a robust decision based on quantitative criterion, which can be assessed for each decision. Reliability approaches specially failure probability have wide applications in uncertainty situation. One of the applicable approaches for evaluating the reliability in each system is Monte Carlo Simulation (MCS). Moreover, in limit state function or nonlinear limitation of first and second order of reliability approaches, MSC cannot find a precise solution and has considerable error [1, 2]. Therefore, using a sensible approach and by its integration with suitable forecasting tools it can help us to solve the uncertain problems with desirable error and computational time.

In this paper, we show the applicability of tuned ANN in forecasting the failure probability in two examples. The first one is a mathematical function with stochastic inputs and in the second example, we deal with a supply chain network with stochastic parameters that it is active now and we want to select the best decision about its reconfiguration based on

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available random budget. It is obvious that according to a crisp approach or inappropriate approach, obtained decision cannot be reliable and may be followed considerable costs for each wrong decision. In his regard, top managers want to compute the failure probability according to stochastic threshold budget. As will be shown, this problem needs sizable computational time; hence, ANN's applicability will be discussed in complex problem.

The reminder of paper is organized as follows: in the second section, a literature on reconfiguration models and existing simulation approaches is discussed. In section 3, reliability concepts and the way of using the neural networks in the problems are explained. Section 4 presents the proposed simulation approach using neural network and failure probability. Two hypothetical numerical examples, containing a mathematical example and a relocation model, are discussed for validating the integration of tuned ANN and simulation procedure in section 5. Finally, conclusion and remarks are suggested in the last section.

2 Literature Review

In this section, some existing works in simulation approaches are presented. Then, relocation models are surveyed according to their uncertainty or deterministic nature.

In recent researches, neural network has demonstrated its applicability in a wide range of engineering problems. These networks are applied in problem with considerable computational time or in cases that there is no solving methodology for overcome them. Moreover, they have even been applied for obtaining the better solution comparison with traditional methods.

In this regard, Papabrakadis et al. [3] have examined the application of Neural Networks (NN) for the reliability analysis of systems with complex structure. The failure of the system is associated with the plastic collapse. Papabrakadis and Lagaros [4] have used ANN to reduce time consuming required for forecasting the failure probability in a case study. Moreover, using integrated MSC and ANN they have studied for determination of terminal network reliability. Ratana et al [5] have surveyed application of neural network in a NP-hard problem and results showed its efficiency in reducing the time and obtaining reliable solutions. Kuo et al [6] have proposed a novel approach on clustering through NN, and they have proved the efficiency of their approach by simulation concepts. There are other related investigations which have applied ANN and MCS in other applications such as damage detection [7], structural safety [8], etc. but according to authors' knowledge, there is no research in redesigning the supply chain based on integration of failure probability and ANN. Moreover, mentioned researches have not evaluated using the multiple response optimizations for tuning the ANN's parameters.

Since the proposed example in this investigation is related to relocation models, some relocation models are described briefly. Relocation models have begun to appear in the literature in the past decade because of their necessity. According to Ballou and Masters investigation [9], of 200 logistics executives, 65% of the respondents indicated that they decided to evaluate their current warehouse network and consider relocating it in the near future. In this area, Melachrinoudis and Min [10] have presented a relocation model on warehouse design for reducing the cost and assessing the current situation of the system. Also, Melachrinoudis and Min [11] and Min and Melachrinoudis [12] focused on the relocation of facility with deterministic parameters. The mentioned models in [11] and [12] were presented for only single facility and they cannot be extended to multi-facility relocation. It is obvious that all of the relocation models are evaluated in a deterministic environment.

In real cases, managers would like to predict the shortfall probability in budget for each decision. Therefore, in this paper failure probability is studied using integrated tuned ANN and simulation approach.

3 Problem descriptions

In this section, at first, we studied a reliability approach named failure probability. As will be shown, using the common optimization approaches for computing the failure probability has the high computational time so that for numerous scenarios, using them is unjustifiable. Therefore, we discussed neural network concepts and its tuning procedure.

3.1 Reliability Approach

The main probabilistic nature of system parameter (system may be a supply chain or any probabilistic structure), demands, production, capacity and transportation costs are important factors that influence failure probability of budget comparison with a stochastic threshold cost. The probability of failure can be computed using the relationship:

$$p_f = p[R < S] = \int_{-\infty}^{\infty} F_R(S) f_S(S) dS \tag{1}$$

where R indicates the threshold budget and S presents obtained cost resulting from reconfiguration decision taken by manager. The randomness of R and S can be described by known probability density function $f_R(S)$ and $f_S(S)$, respectively. Moreover, $F_R(S)$ is cumulative probability density function of *S*. It's worthwhile to note that stochastic nature of threshold budget and network's cost are the main reasons for applying the reliability concepts, because if one of the mentioned stochastic factors, influence the result directly, and if it is deterministic, we could use the other stochastic approaches such as deterministic equivalent or chance programming,

By defining a performance (failure) function $G(R,S) = R - S$, we can reformulate Eq. (2) as follows:

$$p_f = p[G(R,S) \le 0] = \int_{G \le 0} f_R(r) f_S(s) ds \tag{2}$$

For complex system with large number of uncertain parameters, the large number of combinations of events leads to considerable computational time so that sometimes the problem cannot be solved. In this regard, probabilistic methods are needed to calculate the integral of Eq. (2). The Monte Carlo simulation is applied to approximate Eq. (2) as follows:

$$\bar{p}_f \approx \frac{1}{N} \sum_{i=1}^{N} I(X_i) \tag{3}$$

where $I(X_i)$ is an indicator defined as:

$$I(X_i)=\begin{cases}1 \text{ if } G(X_i)\le 0\\ 0 \text{ if } G(X_i)>0\end{cases} \tag{4}$$

Thus, N independent random samples of a specific probability density function (of X) are generated so that failure function is calculated for each sample X_i. If $G(X_i)\le 0$, so a successful simulation is counted. The Monte Carlo Simulation determines failure probability as below estimation:

$$\bar{p}_f \approx \frac{N_H}{N} \tag{5}$$

where N_H is the number of successful simulations and N is the total number of simulations.

3.2 Artificial neural networks

Artificial neural networks are used for solving a variety of problems such as function approximation, pattern recognition, clustering, time series, etc. Multiple layer perceptron (MLP) is the most common type of neural network which is formed from one input layer, one or more hidden layers and one output layer. In general, backpropagation method is used for this type of networks [13, 14]. Gradient descent, conjugate gradient descent, resilient, BFGS quasi-Newton, one-step secant, scaled conjugate gradient, Levenberg-Marquardt and Bayesian regularization are some different algorithms which can be used for training in backpropagation method [15]. Type and complexity of the problem determine which algorithm is proper to train neural network.

3.2.1 Tuning effective parameters of neural networks

In MLP neural networks, number of neurons in first and last layer is determined according to number of inputs and outputs, but there is no explicit method for determining number of neurons in hidden layers. Almost for this purpose, trial and error method is used, but it needs more computational time and is not a precise method. For finding optimum values of effective parameters in performance of neural network, there are some methods based on design of experiments. Some researches like Khaw et al. [16], Packianather et al. [17] and Tortum et al. [18] used Taguchi's method to find the best combination of effective factors in neural network and also analyzed the effect of each parameter in performance of the neural network. Bashiri and Farhsbaf Geranmayeh [19] has applied the CCD and genetic algorithm for finding optimal parameters of neural network in a continuous space while others have used Taguchi's method and optimal parameters and have selected between a finite combination of controllable factor levels. So in this paper, the described method in [19] with some changes in performance criteria which is described in the next section is used.

4 Failure probability determination based on tuned ANN using CCD design

In this section, the proposed approach is explained systematically as follows:

Step1. Tune the NN's parameters as follows:
As it is shown in fig. 1 there are five steps to tune parameters of neural network in this method in which each step is described briefly as follows.

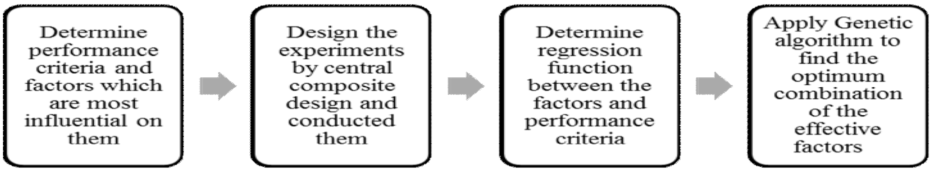

Fig. 1 Flow chart of ANN's parameter tuning

- **Determine performance criteria and factors which are most influential on them**

For training the ANN, the data are divided into 3 subsets: training, validation and testing set. In this study, the Mean Absolute Percentage Error (MAPE) of testing and validation set is considered as a performance criterion. The MAPE is regarded as one of the standard statistical performance measures and it is shown in the first Equation.

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{y_i - \tilde{y}_i}{y_i}\right|.100\,\% \tag{6}$$

where y_i is the target $\tilde{y}_i$ is the neural network's output and M is the numbers of testing and validation sets.

It is clear that the Smaller this criterion is the better (STB) type will be achieved. It's crucial to determine controllable factors which would have the most important effects in performance of ANN. These factors are described as follow:

(A) The percentage of training data: In this study, percentage of validation data is considered as 10 percent of data assumed to be a constant value. In other words, for example if the parameter level is taken as 0.7, it means that 70 percent of data are used for training the network while 20 and 10 percent of data are used for testing and validating, respectively.
(B) The number of neurons in the first layer: This factor is one of the most effective parameters in performance of ANN.
(C) The number of neurons in the second layer: This factor determines the number of neurons in the second layer; moreover, it helps us to determine that network is one-layered or not. In other words, for example if the parameter level is taken zero, it means that the network has only one hidden layer.

- **Design of experiments by Central Composite Design**

Central composite design (CCD) is a rapid technique which extracts relationship between responses and controllable factors [20]. This design can be used as the experimental design of ANN parameter tuning. For designing of experiments by CCD, parameter α should be specified. For example for 2 controllable factors, points in the axial (star) portion of the design are at :(+ α, 0), (-α, 0), (0,+ α), (0,- α). In this study, because of finding the controllable factors as integer values, parameter α are defined as 2.

- **Determine the regression function between the factors and performance criterion**

For applying analysis of variance (ANOVA), some conditions such as normality of residuals should be considered. In this study, Box-Cox transformation is used for this purpose; then, ANOVA is applied for determining more effective controllable factors. Ineffective terms can be eliminated from the model. Finally, regression coefficients for performance criterion and effective factors are extracted.

- **Apply Genetic algorithm to find the optimum combination of effective factors**

After establishing regression relation between performance criterion and effective factors, genetic algorithm is applied for finding the optimum combination set of effective factors.

Step 2: Forecast the output values based on tuned neural network using generated scenarios based on stochastic inputs

In this step, the predicted costs are determined by considering the tuned network. Note that the inputs in ANN are stochastic parameters.

Step3: Compare outputs of ANN and stochastic threshold budget.

Step 4: Compute the failure probability according to Equations (3)-(5).

5 Numerical Examples

The main purpose in this paper is to apply the mentioned approach on a relocation model. However, we use it on a mathematical function to check the applicability of proposed approach. The first example focuses on the error of forecasting the outputs by tuned ANN, but the second one justifies the reason of using ANN to compute the failure probability in a relocation problem with considerable computational time in simulation procedure.

5.1 Example 1

To show capability of tuned neural network in function approximation simulated process according to a complex mathematical function is trained by using tuned ANN. Considered mathematical function is defined in Equation 2, and its surface is shown in **Error! Reference source not found.**. For this purpose, 1000 data which is distributed uniformly between -6 and 6 is used. For small or medium size networks in function approximation problems, Levenberg-Marquardt algorithm often has better performance. Nevertheless, for large networks using scaled conjugate gradient algorithm would be suitable [21]. In this numerical example, Levenberg-Marquardt algorithm is selected for training neural network.

$$f(x, y) = x\sin(4x) + 1.1y\sin(2y) \tag{7}$$

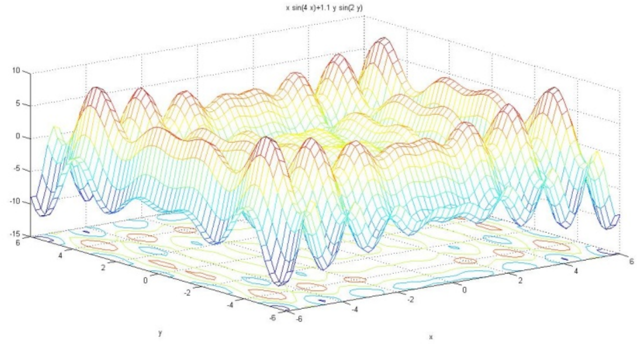

Fig. 2 Surface of function

- **Tuning effective parameters of ANN**

The performance criteria and effective parameters of them were defined in the previous section. By considering dimension of training data, axial points for designing of experiments by CCD is determined as Table 1. In CCD experiment design, each designed experiment is conducted with 10 replications.

Table 1 Parameters and their levels studied in the experiments based on CCD design in the ANN parameter tuning for example 2

	Factors	Cube points		Central points	Axial points	
		Low	High		Low	High
A	Percentage of training set	0.6625	0.7875	0.725	0.6	0.85
B	The number of neuron in first layer	21	47	34	8	60
C	The number of neuron in second layer	15	45	30	0	60

After conducting the designed experiments, regression relation between effective parameters in performance of ANN and MAPE is determined by applying ANOVA. The regression relation is illustrated in Equation (8).

Genetic Algorithm is used to find optimal values of effective parameters in performance of ANN by minimizing MAPE. Results of tuning effective parameters are shown in Table 2. Confirmation experiment is done in the obtained optimum parameters and the result is illustrated in fourth column of Table 2. Results show capability of tuned ANN in function approximation.

$$MAPE = (0.140592 + 0.010497A - 0.001155B - 0.002227B^2 + 0.000051C^2 - 0.000028BC)^{(-100/52)} \quad (8)$$

Table 2 Optimum values of effective parameters in example 1

Percentage of training set	The number of neurons in first layer	The number of neurons in second layer	Confirmation MAPE
0.84	8	60	7.3%

5.2 Example 2

5.2.1 Reconfiguration of supply chain

In this section, the proposed model for redesigning the warehouses configuration in a supply chain network based on Melachrinoudis and Min 's reassert [10], and its extension in a stochastic environment are introduced.

The mathematical model contains three echelons (plant, warehouse and customer nodes) and is presented as follows:

5.2.1.1 Indices and sets

s=index for scenarios($s \in S$),
p=index for manufacturing plants ($p \in P$),
k=index for customers ($k \in K$),
o=index for product ($o \in O$),
i=index for existing warehouses and new candidate sites for relocation and consolidation ($i \in A$).
$A = E \cup N; (j,i) \in (E \times A)$, Where E is set of existing warehouses and N is set for new candidates. Note that existing warehouses can be consolidated with both N and E sets.

5.2.1.2 Parameters

d_{sko}= demand of customer k in scenario s for product o,
v_{spio}= unit production cost at plant p for product o under scenario s (including manufacturing cost and shipment cost between plant p and warehouse i),
w_{siko}= unit warehousing cost at warehouse i and shipment cost between warehouse i and customer k for o^{th} product under scenario s,
r_{ji}= cost of moving and relocating the capacity and facilities of warehouse j to warehouse i ($j \neq i$) and saved cost achieved (income) from closure of existing warehouse j excluding its relocated equipment,
c_{io}= throughput capacity of warehouse i for product o,
cp_{ik}= Capacity to carrying goods between warehouse i and customer k,
q_{spo}= production capacity of plant p for product o under scenario s,
fv_{io}= cost per unit capacity of warehouse i for product o,
fc_i= fixed cost of retaining warehouse i excluding capacity cost,
fs_i= saved cost achieved from closure of existing warehouse i (both of the warehouse and equipment),
fl_{ik}=fixed cost of relation between warehouse i and customer k,
ce_{po}= cost of extra unit for extending the manufacturing capacity for product o,
re_o= Space usage of one unit of product o,
b_{ik}=coverage matrix (warehouse i and customer k),

5.2.1.3 Decision variables

y_{spio}= volume of product o shipped by plant p to warehouse i under scenario s,

x_{siko}= volume of product o shipped from warehouse i to customer k under scenario s,
e_{spo}= volume of extra production capacity (at plant p, for product o) needed for satisfying customer demands under scenario s,

$$z_{ji} = \begin{cases} 1, \text{if capacity of warehouse } j \in E \text{ is relocated to site } i \in A, i \neq j \text{ or if existing warehouse } j \in E, i = j \\ \text{remains open} \\ 0, \text{other wise} \end{cases}$$

$$z_{nn} = \begin{cases} 1, \text{if a new warehouse } n \in N \text{ stablishes in candidate site } n \in N \\ 0, \text{other wise} \end{cases}$$

5.2.1.4 Mathematical Model

The objective function and the constraints of the model are presented as follows:

$$\begin{aligned} Min \quad [O.F_s] = & \sum_{p \in P} \sum_{i \in A} \sum_{o \in O} v_{spio} y_{spio} + \sum_{i \in A} \sum_{k \in K} \sum_{o \in O} w_{siko} x_{siko} + \sum_{j \in E, (j \neq i)} \sum_{i \in A} r_{ji} z_{ji} + \sum_{i \in A} \sum_{o \in O} fv_{io} \sum_{j \in E} c_{jo} z_{ji} \\ & + \sum_{(i=j) \in E} \sum_{j} fc_i z_{ji} + \sum_{i \in N} fc_i z_{ii} - \sum_{j \in E} \left[fs_j \left(1 - \sum_{i \in A} z_{ji} \right) + fc_j \sum_{i \in E, i \neq j} z_{ji} \right] + \sum_{p \in P} \sum_{o \in O} ce_{po} e_{spo} \end{aligned} \tag{9}$$

$s.t.$

$$\sum_{i \in A} y_{spio} \leq q_{spo} + e_{spo} \quad , \forall p \in P, \forall o \in O, \forall s \in S \tag{10}$$

$$\sum_{p \in P} y_{spio} = \sum_{k \in K} x_{siko} \quad , \forall i \in A, \forall o \in O, \forall s \in S \tag{11}$$

$$\sum_{k \in K} x_{siko} \leq \sum_{j \in E} c_{jo} z_{ji} \quad , \forall i \in E, \forall o \in O, \forall s \in S \tag{12}$$

$$\sum_{k \in K} x_{siko} - c_{io} z_{ii} \leq \sum_{j \in E} c_{jo} z_{ji} \quad , \forall i \in N, \forall o \in O, \forall s \in S \tag{13}$$

$$\sum_{i \in A} b_{ik} x_{siko} \geq d_{sko} \quad , \forall k \in K, \forall o \in O, \forall s \in S \tag{14}$$

$$\sum_{o \in O} x_{siko} re_o \leq cp_{ik} \, , \forall i \in A, k \in K, \forall s \in S \tag{15}$$

$$\sum_{j \in E} z_{ji} \leq |E| z_{ii} \quad , \forall i \in E \tag{16}$$

$$\sum_{j \in E} z_{ji} \leq |E| z_{ii} \quad , \forall i \in N \tag{17}$$

$$\sum_{i \in A} z_{ji} \leq 1 \quad , \forall j \in E \tag{18}$$

$$y_{spio} \geq 0 \quad , \forall p \in P, \forall i \in A, \forall o \in O, \forall s \in S \tag{19}$$

$$x_{siko} \geq 0 \quad , \forall i \in A, k \in K, \forall o \in O, \forall s \in S \tag{20}$$

$$z_{ji}, z_{ii} \in (0,1) \, , \forall j \in E, i \in A \tag{21}$$

The objective function minimizes the total supply chain cost comprised of production, transportation and relocation in which, related costs include moving and relocating the consolidated warehouses, maintaining the existing and new warehouses and cost savings resulting from the closure or consolidation of redundant warehouses. Also, the cost of extending the capacity and maintaining the warehouses are given in equation (9). Constraints (10) insure that the volume of products shipped to warehouses do not exceed the capacity of a manufacturing plant supplying such products and needed products for extension of capacity. Equations (11) assure that the total volume of products supplied by the plant to each warehouse equals to the total volume of products shipped from that warehouse to its customers. Constraints (12)-(13) insure that the total volume of products shipped to customers after consolidation cannot surpass throughput the capacity of the warehouse serving them. Constraints (14) emphasize on demand satisfaction considering coverage radius. Constraint (15) denotes that the volume of products shipped from warehouse to a customer do not exceed the maximum transit capacity. Constraints (16) state that an existing warehouse cannot be consolidated into another existing one, unless such consolidated warehouse remains open. Also, $|E|$ is the cardinality of set E resulted from aggregation of constraints over set E with the equal right hand side (RHS) constraint (16). Similarly, constraints (17) have the same concept of previous constraint but for consolidation of existing warehouses into new warehouses. Constraints (18) denote that each warehouse can merge with only one of the destination warehouses. For more understanding, we describe the whole possibilities for z_{ii}. For $j \in E$, $z_{jj} = 1$ if the existing warehouse j remains open. Also, for $i \in A$ and $z_{ji} = 1 (i \neq j)$, existing warehouse j is consolidated into warehouse i. Note that for $n \in N$ and $z_{nn} = 1$, the new warehouse n is established in nth candidate site. Also, $\sum_{i \in A} z_{ji} = 0$ demonstrates that warehouse j has been redundant and should be eliminated from the supply chain network. Constraints (19) and (20) assure decision variables positivity. Constraints (21) states that variables are of binary type.

5.3 Failure probability determination

5.3.1 Traditional approach

In this example, at first we used GAMS software for obtaining the cost of each decision for particular scenario $\xi^s = (q^s, d^s, v^s)$ and stochastic threshold cost (f^s) where the symbols indicate a scenario of ξ containing production capacity, demand and the unit cost of producing and transmitting the goods, respectively. Moreover, f^s denotes randomly amount for budget. By solving the problem with small scenarios, three candidate decisions for reconfiguration are selected for simulation procedures which are labeled by D1, D2, and D3. Then by computing the failure probability for each reconfiguration decision, the failure probability and its computational results will be reported in table 5.

5.3.2 ANN approach

In this example, the scaled conjugate gradient algorithm is applied for training of neural networks, since network's size is relatively large. In some situations, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant).

Reducing the dimension of the input vectors can improve training phase in neural network. Principal component analysis is an effective procedure for performing operation of input reduction. This technique has three effects: it orthogonalizes the components of the input vectors (so that they are uncorrelated with each other), it orders the resulting orthogonal components (principal components) so that those with the largest variation come first, and it eliminates those components that contribute the least to the variation in the data set. In this example by using the principle component analysis technique, dimension of input vectors is reduced from 37 to 14 and it is expected to improve training of ANN.

In this example, 10^3 of 10^4 data are selected for training phase (which is divided to three subsets) and others are predicted by trained neural network.

For tuning effective parameters of ANN, experiments with 10 replications are designed by CCD. Effective parameters and their levels for this example are shown in Table 3.

Table 3 Parameters and their levels studied in the experiments based on CCD design in the ANN parameter tuning for example 2

	Factors	Cube points		Central points	Axial points	
		Low	High		Low	High
A	Percentage of training set	0.6625	0.7875	0.725	0.6	0.85
B	The number of neuron in first layer	21	47	34	8	60
C	The number of neuron in second layer	15	45	30	0	60

After obtaining regression relation between effective parameters and corresponding MAPE, genetic Algorithm is used to find optimal values of effective parameters in performance of ANN by minimizing MAPE. Results of tuning effective parameters are shown in Table 4. After finding the optimum parameter of neural network for problem, under optimum situation neural network is trained and final MAPE which is used for approximate failure probability is shown in fifth column of Table 4.

Table 4 Optimum values of effective parameters in example 2

Percentage of training set	The number of neurons in first layer	The number of neurons in second layer	MAPE
0.6	22	2	6.97%

After training phase, 10^4-10^3 the remaining data are predicted by trained ANN. Mean absolute percentage error for prediction of these data is calculated 7.14% which shows generalization capability of tuned neural network. Number of data which has value more than 1.84e7 is 931. In a case whose failure probability is calculated by simulation, this number is 902. So obtained the result by ANN is in 95 percent confidence, and the proposed method can be a good alternative because of less time consumption.

Moreover, table 5 shows the results of possible decisions. For computing the failure probability, GAMS software has considerable computational time so that for scenarios that are larger than 10^5, the computational time is out of memory. For evaluating the ANN applicability, failure probability of D1, D2 and D3 are calculated. The results show reducing the computational time with reasonable error (95% confidence level). According to table 5, D1 has the best situation for redesigning the warehouse (0.079).

Table 5 Comparison results for simulation based on ANN and common approach

	D1		D2		D3	
Approach	GAMS	ANN	GAMS	ANN	GAMS	ANN
Failure probability	0.079	0.081	0.0851	0.0838	0.0902	0.0931
Computational time(sec) (Tuning+Training+Forecasting)	13860	2225	13440	2183	13500	2189

Note that all of inputs for training the ANN extracted from GAMS software are considered in computational time. Table 5 demonstrates that using ANN not only can forecast the failure probability in a desirable confidence level, but it also can solve the problem with considerable reduction in computational time. Table 5 shows that D1 has the less failure probability among all decisions. In the proposed approach, we used 10% of data as outputs of GAMS software and inputs of the proposed approach. Thus, other costs and their parameters predicts according to discussed approach. Considering the number of tests and time consumption in the experiments especially in each reliability test that has considerable cost, the proposed approach seems to be capable and economical.

6 Conclusions

In this paper, for computing the failure probability of stochastic budget respected to network's costs in a relocation model (for finite possible reconfiguration decisions), tuned neural network was applied. For this purpose, central composite design and genetic algorithm were used for tuning the important parameters of ANN so that the network could forecast the failure probability precisely with considerable reduction in computational time and number of tests. Moreover, we checked the failure probability determination based on tuned neural network for a mathematical function, and results showed the efficacy of the proposed approach. As a future research, a problem considering correlation between parameters can be evaluated.

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