Applied Mathematics and Computational Intelligence
Volume 7, No.1, 2018 (13-22)

Investment Planning Problem in Power System Using Artificial Neural Network

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ABSTRACT

This paper presents a model to solve Distribution Expansion Planning (DEP) problem. An effective method is proposed to determine an optimal solution for strategic investment planning in distribution system. The proposed method will be formulated by using mean-variance analysis (MVA) approach in the form of mixed-integer quadratic programming problem. Its target is to minimize the risk and maximize the expected return. The proposed method consists of two layers neural networks combining Hopfield network at the upper layer and Boltzmann machine in the lower layer resulting the fast computational time. The originality of the proposed model is it will delete the unit of the lower layer, which is not selected in upper layer in its execution. Then, the lower layer is restructured using the selected units. Due to this feature, the proposed model will improve times and the accuracy of obtained solution. The significance of output from this project is the improvement of computational time and the accurate solution will be obtained. This model might help the decision makers to choose the optimal solution with variety options provided from this proposed method. Therefore, the performance of strategic investment planning in solving DEP problem certainly enhanced

Keywords: Mean-variance analysis, Hopfield network, Boltzmann machine, Distribution expansion planning.

1. INTRODUCTION

Due to the economic growth in the world's population, the demand for electricity has grown. To obtain a reliable and sustainable electricity supply, a well-organized power operation system becomes more vital. Since the demand of electricity keep increasing, thus a meticulous planning should be provided in to enhance the delivering process of electricity to consumer. Distribution Expansion Planning (DEP) has been a very hot topic in the 21st Century [1]. DEP is the service of increasing or rebuild the distribution system so that it fulfills the predicted load requirement that satisfy all operational and technical constraint and at the same time it lower the operational, investment, annualized and planning cost [2].

In real situations, DEP used to face complicated investment planning problems and most of them are non-linear programming problem which is hard to solve. To minimize the misdirect investment a method based on the mean-variance approach is proposed by referring the past data.

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Markowitz initially proposed the mean-variance analysis (MVA) approach in view of the portfolio selection problem and it is then defined as the mixed integer programming (MIP) problem[3]. The portfolio selection problem is formulated as the mathematical programming problem of minimizing the risk since the return has been fixed into certain condition, thus considering the efficient frontier in the portfolio selection [4]. Several publications have appeared in recent years documenting about employing MVA in investment planning for the power system [5,6]. This method attempts to solve the long-term DEP problem by defining the share of each asset found in a territory's energy portfolio. According to Beurskens *et al.* and Hickey *et. al,* [7,8] the strengths of MVA is the fact that the approach has a greater ability and conceptual richness than that provided by the perspective of the simple individual lowest cost of each technology.

In this research, the combination of Hopfield network and Boltzmann machine (BM)named as Double-layered BM is a proposed method to solve DEP problem. Hopfield network can easily trap in local minimum and cannot find the exact solution of optimization problems[9]. As for Boltzmann machine, it requires many hours of computational time. This due to it has to reach its thermal equilibrium, so if the weights are hand coded, there must be a precaution to avoid the energy barriers that are too high for annealing searches to know how to change the weight but at the same time the weights must be changed in order to construct a good model to produce a quality solution based on the selected solution. Thus, by combining these two neural network and transform the objective function into an energy function of BM, an accurate and quality solution can be obtained with various options for decision makers. By combining Hopfield and BM into two layers, the computational time can be reduced by applying Hopfield function in first layer to select a limited number of units. The number of units selected then used BM in second layer to determine the optimum solution. This two layers model connects corresponding units in the upper and lower layer so it produced an effective problem solving method. The objective of this paper is to develop an efficient and flexible method to minimize misdirects investment and improves the computational performance and execution time.

2. MATHEMATICAL MODEL

2.1 Mean-Variance Analysis (MVA)

H. Markowitz originally has proposed the mean-variance analysis [4, 10]. He has stated that most of decision makers have aversion risk even if its return might be less. Since the utility function is hard to identify due to different utility structure of the decision makers, thus, Markowitz formulated MVA as the following quadratic programming problem, under the condition that the expected return rate must be more than a certain specified amount [11, 12].

2.1.1 Formulation 1

$$\text{minimize} \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij}\, x_i\, x_j \tag{1}$$

$$\text{subject to} \sum_{i=1}^{n} \mu_i\, x_i \geq R \tag{2}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{3}$$

$$x \geq 0 \; (i = 1, 2, \ldots, n) \tag{4}$$

where;

R : least acceptable rate of expected return
σ_{ij} : the covariance between stock i and j
μ_i : the expected return rate of stock i
x_i : the investment rate for stock i

2.1.2 Formulation 2

In Formulation 1, the optimal solution with the least risk is searched under the constraint that the given value from the decision makers should be less compared to the expected return rate. The investment rate for each stock determined the solution with the least risk under the given expected return rate. However, the decision makers unsatisfied with the solution since the risk are evaluated under the condition of fixing the rate of the expected return. Thus, an appropriate formula as in Formulation 2 is proposed as in Equation (5) to (10).

$$\text{maximize} \sum_{i=1}^{n} \mu_i m_i x_i \quad (5)$$

$$\text{minimize} \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} m_i x_i m_j x_j \quad (6)$$

$$\sum_{i=1}^{n} m_i x_i = 1 \quad (7)$$

$$\sum_{i=1}^{n} m_i = S \quad (8)$$

$$m_i \in [0,1](i = 1,2,\ldots \quad (9)$$

$$x \geq 0 \; (i = 1, 2, \ldots, n) \quad (10)$$

where;

S : the desired number stocks to be selected in the portfolio
m_i : the decision variable for stock *i*where $m_i$is 1 if any stock *i*is held and m_i is 0 otherwise
σ_{ij} : the covariance between stock *i*and *j*
μ_i : the expected return rate of stock *i*
x_i : the investment rate for stock *i*

Based on Formulation 2;

$$\text{maximize} \sum_{i=1}^{n} \mu_i x_i \quad (11)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_i x_i x_j \quad (12)$$

$$\text{subject to} \sum_{i=1}^{n} x_i = 1 \tag{13}$$

$$x \geq 0 \; (i = 1, 2, \ldots, n) \tag{14}$$

The formulation is a mixed-integer quadratic programming problem which comprises two target works, the expected return rate and the degree of risk. It is difficult to acquire the ideal and quality solution from a large set of possible in mixed quadratic programming. Hence, a proper method with the combination of the Hopfield network and Boltzmann machine is invented to achieve the quality solution by changing over the portfolio into energy function.

2.1.3 Boltzmann Energy Function

A BM is an interconnected neural network proposed by G. E. Hinton [13-15]. This model is based on a Hopfield network. The BM is a model that improves a Hopfield network by means of probability rules which are employed to update its state of the neuron and the energy function. If $V_i(t+1)$ is an output value of neuron i in next time $t+1$, $V_i(t+1)$ is 1 according to the probability P which is shown in the following. On the other hand, $V_i(t+1)$ is 0 according to the probability $1-P$.

$$P[V_i(t+1)] = f\left(\frac{u_i(t)}{T}\right) \tag{15}$$

where;

$f(\cdot)$	:	the sigmoid function
$u_i(t)$	:	the total input to neuron i
T	:	the network temperature (control parameter)

The energy function, which is proposed by J. J. Hopfield, is written in the following equation:

$$E = \frac{1}{2} \sum_{ij=1}^{n} w_{ij} V_i V_j \tag{16}$$

2.1.4 Double-Layered Boltzmann Machine

Double-layered BM is a model that deletes the units of lower layer, which are not selected in the upper layer in its execution. Then the lower layer is restructured using the selected units. Due of this feature, a Double-layer BM converges more efficiently than original BM. This is an efficient method for solving a portfolio selection problem by transforming its objective function into the energy function since the Hopfield and BM converge at the minimum point of the energy function. Based on MVA theory, it show a condition for x_i to sum to 1 as in Equation (13) (not that for each x_i cannot be less than 0).The condition equation is rewrite where the total of investment rates of all units is 1.

$$\left(\sum_{i=1}^{n} x_i - 1\right)^2 = 0 \tag{17}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j - 2\sum_{i=1}^{n} x_i + 1 = 0 \tag{18}$$

Next, the condition equation and the expected return equation are transformed into energy function as in Equation (19) and (20) respectively.

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\right) - \sum_{i=1}^{n} x_i \tag{19}$$

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\right) - \sum_{i=1}^{n} x_i + K\sum_{i=1}^{n} \mu_i x_i \tag{20}$$

Where K is a real number and must not less than 0. The algorithm of original BM is show as in Algorithm 1.

Algorithm 1.

Step 1: Set parameter *K,* number of units, value *h* and initial value of each unit.
Initialize the control parameter T (temperature).
Set the control parameter update frequency *M.*

Step 2: Choose a certain unit *i* at random between 1 and *n.*

Step 3: Compute a total of input $u_i(t) = \sum_{j=1}^{N} w_{ij} V_j$ for the *i*th unit; the difference $\Delta i = u_i - \theta_i$, and the probability $P = \frac{1}{1+\exp\left(-\frac{\Delta i}{T}\right)}$

Step 4: If $u_i > 0$, then with probability P, subtract a small constant *h* from $V_i(t)$ and with the probability *1-P* , add *h* to $V_i(t)$.
If $u_i < 0$, then with probability P, add *h* to $V_i(t)$ and with the probability *1-P* , subtract *h* to $V_i(t)$.
However, the output value is not changed in the case of $u_i(t) = 0$.

Step 5: The chosen *i*will be up date with the following equation:

$$V_i(t+1) = \begin{cases} V_i(t) + h : & u_i(t) > 0 \\ V_i(t) - h : & u_i(t) < 0 \\ V_i(t) \quad : & u_i(t) = 0 \end{cases}$$

Step 6: After iterating M for z times from Step 2 to Step 5, the control parameter; *T(z)* will be reduced; $T(z) = \frac{T_0}{M*z}$

Step 7: Repeat Step 2 to Step 6 until reaching the stopping condition *T(z)* = 0.00001 and divide the output value of each unit by the sum of the output value for all units.

The Double-layered BM converted the objective function into the energy functions of the upper layer, E_u and lower layer, E_l as described as in Equation (21) and (22) respectively. Upper layer is called as “supervise layer” meanwhile lower layer is used to decide the optimal units from the limited selected in upper layer. It is called as “executing layer”.

$$E_u = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}s_i s_j + K_u\sum_{i=1}^{n}\mu_i s_i \tag{21}$$

$$E_l = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j + 2\sum_{i=1}^{n}\sum_{j=1}^{n}x_i x_j\right) + 2\sum_{i=1}^{n}x_i + K_l\sum_{i=1}^{n}\mu_i x_i \tag{22}$$

Here K_u and K_l are the weight of the expected return rates of upper and lower layer respectively. The algorithm of the Double-layered BM is shown as in Algorithm 2. Detail idea of the proposed method is sketched as in Figure 1.

Algorithm 2.

Step 1: Set the number of units, an initial value of each unit and value *h.*
Set the start, restructure and end of the control parameter *T* (temperature).
Set the control parameter update frequency *M.*

Step 2: Set K_u and K_l

Step 3: Execute the first layer.
Start running the Hopfield network in the first layer.

Step 4: If the output value of a unit in the first layer is 1, add *h* to the corresponding unit in the second layer. Start running the second layer.

Step 5: After executing the second layer at a constant frequency *M,* decrease the temperature.

Step 6: If the output value for certain units are sufficiently large, add *h* to the corresponding unit in the first layer.

Step 7: Iterate from Step 3 to step 6 until the temperature reaches the restructuring temperature.

Step 8: Restructure the second layer using the selected units in first layer.

Step 9: Execute the second layer until the termination condition is reached.

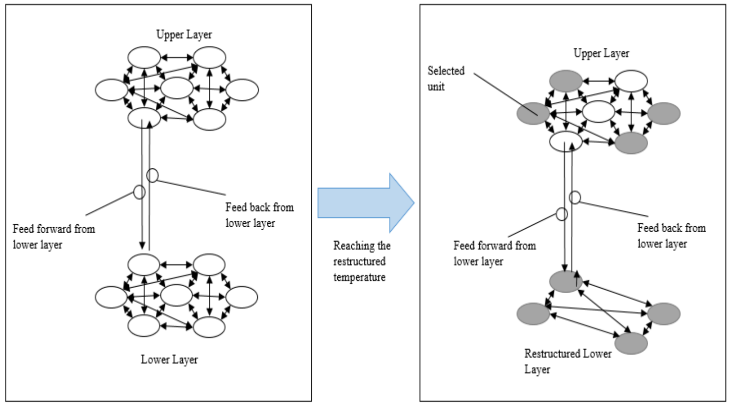

Figure 1. Double-layered boltzmann machine

3. CASE STUDY

The following numerical example is employed to illustrate the DEP problem in power systems. In the distribution system investment problem, the optimal maintenance investment to each substation is decided based on its past downtime cost rates. The power system consists of fifteen substations, defined as $SS1$ through $SS15$. In this analysis, the downtime cost rates for five years were employed to analyse the investment over fifteen substations as shown in Table 1. The analysis was carried out for values of $K = K_u = K_l$ of 0.3, 0.5, 0.7 and 1.0. The effectiveness of the proposed method is demonstrated by performing an optimisation of 1286 substations and making a comparison of the computational time between a conventional BM and proposed method.

Table 1 Annual downtime cost rates of substations

Year/	**Downtime cost rates (%)**					
Substation	**1**	**2**	**3**	**4**	**5**	**Mean**
SS 1	2.17	2.31	2.22	2.47	2.11	2.256
SS 2	2.38	1.79	2.81	2.35	2.63	2.392
SS 3	2.91	2.39	1.95	2.87	2.19	2.462
SS 4	2.84	2.56	1.81	2.12	2.56	2.378
SS 5	2.95	2.91	2.02	2.63	2.73	2.648
SS 6	2.31	2.22	2.74	1.87	1.96	2.22
SS 7	1.99	2.78	2.46	2.17	2.76	2.432
SS 8	2.08	1.89	2.18	2.00	1.99	2.028
SS 9	2.15	2.19	2.95	1.93	2.00	2.244
SS 10	2.87	2.59	2.75	2.43	2.17	2.562
SS 11	2.18	1.92	2.68	2.78	2.45	2.402
SS 12	2.99	2.43	2.63	2.31	2.23	2.518
SS 13	2.75	2.00	2.31	2.76	2.61	2.486
SS 14	1.97	2.76	2.19	2.41	2.31	2.328
SS 15	2.71	2.31	2.79	2.53	2.77	2.622

Table 2 Result of simulation in investment rate for each substation

Substation	K=0.3	K=0.5	K=0.7	K=1.0
SS1	-	-	-	-
SS2	-	-	-	-
SS3	0.530	0.244	0.176	0.019
SS4	-	-	-	0.488
SS5	-	-	0.115	0.105
SS6	-	-	-	-
SS7	-	-	-	-
SS8	-	-	0.119	-
SS9	-	-	-	0.104
SS10	0.470	0.365	0.216	-
SS11	-	-	-	-
SS12	-	0.291	0.216	0.114
SS13	-	-	-	0.001
SS14	-	-	-	-
SS15	-	0.099	0.146	0.189

Based on Table 2, for K = 0.3, 53.0% of the maintenance investment should be made in SS 3 and 47.0% should be made in SS10. No investment should be made in the substations not included in the list of units after restructuring. For K = 0.5, four substations were selected from the list of units after restructuring. For K = 0.7, six substations were selected, and for K = 1.0, seven substations were selected from the list of units after restructuring. The number of substations selected from the restructured list is directly proportional to K.

The results in Table 2 shows four different risk aversion levels (K) that reflected the different preferences of the decision maker. Since the results are variety, thus the decision making process can be enhanced as the proposed method produced effective solutions. The various solutions obtained suit with decision maker preferences. According to the value of K, a decision maker can determine the optimum solutions which the larger value of K leads to riskier option while small value of K leads to conservative ones. Since this proposed method is flexible thus it produced a strategic planning investment for decision maker.

Figure 2. Computational time with efficiency for conventional and proposed methodology.

Figure 2 compares the performance of the double-layered BM and the conventional BM, employing various system sizes from 10 to 1286 substations. Computational efficiency is given by the Equation (23).

$$C_e = \left(\frac{t_{CBM} - t_{DBM}}{t_{CBM}}\right) x100 \quad (23)$$

Where Ce denotes computational efficiency, t_{DBM} is the computational time of the Double-layered BM, and t_{CBM} is the computational time of a conventional BM. The computational time of the Double-layered BM is drastically shorter than that of a conventional BM. The reason is because the double-layered BM deletes useless units during the restructuring step. By contrast, a conventional BM computes all units until the termination condition is reached. Comparing computing efficiency, the double-layered BM is more efficient, especially when the initial number of units is large. The proposed method provides a more effective selection by using the Hopfield network in the upper layer to choose a limited number of units, and the BM in the lower layer to decide the optimal solution/units from the limited number of units selected by the upper layer.

4. CONCLUSION

In this case, the optimal maintenance investment was decided according to its past five years downtime cost rate. The simulation was performed for 15 substations. The analysis was continued up until the number of substations is 1286. Note that in this case the value for K_u is equal to K_l. The simulation was done by comparing the conventional method and proposed method. Based on the simulation result, the computational time for proposed method is less as the number of substations is increased compared to conventional method which the computational time is high as the number of substations increased. Since the simulation resulted the fast computational time for the proposed method, thus the efficiency for this proposed method can be enhanced as the number of units increased. It showed that the proposed method is efficient for big data since it has improved the computational time and efficiency. The decision making process can be enhanced as there are effective solutions for decision maker. Since the solutions are variety, thus a decision maker can make a decision based on their preferences which the larger value of K leads to riskier option while small value of K leads to conservative ones.

ACKNOWLEDGEMENT

The authors would like to thank Universiti Malaysia Perlis (UniMAP) and Ministry of Higher Education Malaysia for providing research facilities and funding for the project via Fundamental Research Grant Scheme (Grant No. 9003-00577).

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