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Solving financial allocation problem in distribution system expansion planning

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ABSTRACT

This paper introduces a new technique to solve financial allocation in Distribution System Expansion Planning (DSEP) problem. The proposed technique will be formulated by using mean-variance analysis (MVA) approach in the form of mixed-integer programming (MIP) problem. It consist the hybridization of Hopfield Neural Network (HNN) and Boltzmann Machine (BM) in first and second phase respectively. During the execution at the first phase, this model will select the feasible units meanwhile the second phase will restructured until it finds the best solution from all the feasible solution. Due to this feature, the proposed model has a fast convergence and the accuracy of the obtained solution. This model can help planners in decision-making process since the solutions provide a better allocation of limited financial resources and offer the planners with the flexibility to apply different options to increase the profit.

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1. INTRODUCTION

As per present, scenario demand of electric power generation is increasing. Due to the increasing demands, several power supply failures might cause major social losses. Failures are caused by many factors such as type, design, weather condition or geographical location. The distribution system is the most extensive part of the electrical system, and consequently, it is the mainly responsible for energy losses [1-3]. Thus, a meticulous distribution system expansion planning (DSEP) must be provided to supply reliable electricity to consumers. Power system planning is defined as a process of determining a minimum cost strategy for long-range expansion of the generation, transmission and distribution systems so that it is sufficient enough to supply the load forecast within a set of technical, economic and political constraint [4]. As for DSEP, the goal is to fulfill electricity load increment at the lowermost cost and consumer's reliability desires with a level of satisfaction [5].

One of the important factors in the DSEP is included with well-calculated or analyzed investment planning that allowed by the planners. The planners plan a strategic decision related to a whole power system network and also particular individual simultaneously. Nevertheless, planners faced a problem in deciding on how much a portfolio to allocate to the different type of assets. In this case, financial allocation plays a crucial role in solving the planner's problem. Its aim is to balance risk and reward by apportioning a portfolio asset according to an individual goals, risk tolerance and investment horizon [6, 7]. In real situations, financial allocation problems are complicated and non-linear programming problem which is hard to solve. One of the ways of tackling this problem is by using the artificial neural network (ANN) since it is a useful tool for a large area of [8-12]. The previous study in [1] has shown that the Genetic Algorithm (GA) able to provide a better financial allocation. Meanwhile, Particle Swarm Optimization was proposed by [13] to provide a flexibility to apply different options to increase the profit in DSEP. The same approach proposed by [14] that provided the best investment profile for the planner, considering different market opportunities.

In 1952, Markowitz [15] introduced mean-variance analysis (MVA) where it plays an important role in solving financial allocation in DSEP problem. The ultimate objective of MVA is to maximize the profit by allocating wealth among several assets and minimize the risk as low as possible [16, 17]. It can be defined as the process of weighing the risk that expressed as variance against the expected return. Planners commonly used the MVA to decide which financial allocation to be allocated based on planner's preferences in terms of trade off the value of risk and the level of return. In the other hand, Markowitz used the stocks profitability variance as a measure of risk along with the expected returns of stocks for portfolio selection, defining an efficient frontier that determined which portfolio composition would have the highest expected value for a given level of risk [18].

This paper proposed a MVA approach to solve the financial allocation problem in DSEP. Since the formulation is in the form of mixed integer programming (MIP) problem and hard to solve, thus ANN with few modifications are applied following the efficient frontier in the portfolio selection. Hybrid Boltzmann Machine (HBM) is the new technique that will be introduced which consist the hybridization of both Hopfield Neural Network (HNN) and Boltzmann Machine (BM). The proposed technique will employed HNN at the first phase that function to select the feasible solution. Then, BM in the second phase will find the best solution from all the feasible solution. This two-phase model connects corresponding units in the first and second phase and delivering an effective problem solving method.

The further explanations will be discussed in Section 2. In Section 2, the proposed methodology and the mathematical formulation will be presented. Section 3 devoted to discuss the results and finally Section 4 conclude a summary with future recommendations.

2. MATHEMATICAL FORMULATION

2.1. Mean-variance analysis

The present findings confirm that the MVA is widely considered to be a good way to solve the financial allocation problem in DSEP. This methodology able to solve the long-term investment selection problem by defining the share of each of the real power generation assets found in a regional's energy portfolio. To achieve this, MVA assesses costs or returns and economic risks that defined as variability of cost of each technology and set of technologies (portfolio) [19]. As mentioned in the previous section, MVA is in the form of MIP as in Formulation 1.

Formulation 1

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

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

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

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

where R is the least acceptable rate of expected return, σ_{ij} is the covariance between stock i and j, μ_i is the expected return rate of stock i and x_i, x_j is the investment rate for stock i and j respectively.

An appropriate formula is proposed as in Formulation 2 by referring to MVA approach.

Formulation 2

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

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

$$\sum_{i=1}^{n} m_i x_i = 1 \tag{7}$$

$$\sum_{i=1}^{n} m_i = S \tag{8}$$

$$m_i \in [0,1] (i = 1,2,...,n) \tag{9}$$

$$x \geq 0 \; (i = 1, 2, ..., n) \tag{10}$$

where S is the desired number of stocks to be selected in the portfolio, m_i, m_j is the decision variable for stock i and j respectively where m_i is 1 if any stock i is held and m_i is 0 otherwise, σ_{ij} is the covariance between stock i and j, $\mu_i$is the expected return rate of stock i and x_i, x_j is the investment rate for stock i and j respectively. (5) and (6) are the cost function and follow by its constraint as in (8) to (10).

The formulation is a MIP problem which taking into consideration of two target works, the expected return rate and the degree of risk [20, 21]. Basically, it is complicated to acquire the solution from the MIP, therefore a proper technique is proposed based on the hybridization of HNN and BM to achieve the quality solution by changing over the portfolio into energy function.

2.2. Boltzmann machine

A BM is the interconnected neural network proposed by G. E. Hinton [22]. This model is based on HNN. The BM is a model that improves HNN through the probability method which is used to update neuron state and the energy function. The energy function, E which is proposed by J. J. Hopfield, is written in (11).

$$E = \frac{1}{2}\sum_{ij=1}^{n} w_{ij} V_i V_j - \sum_{j=1}^{n} \theta_i V_i \tag{11}$$

where w_{ij} is the weight of the connection from neuron j to neuron i, V_i , V_j are the state of unit j, θ_i is the threshold of neuron i and n is the number of units.

2.3. Hybrid Boltzmann machine

HBM is a model that consists of two-phase connects each unit correspondingly [23-25]. During the execution at the first phase, this model will select the feasible units meanwhile the second phase will restructured until it finds the best solution from all the feasible solution. Due to this characteristic, the HBM converges more efficiently than conventional BM. This is an effective technique for solving a portfolio selection problem by changing its objective function into the energy function since the HNN and BM converge at the minimum point of the energy function [24-26]. Based on MVA theory, it show a condition for x_i to sum to (not that for each x_i cannot be less than 0). The condition equation is rewritten where the total of investment rates of all units is 1.

$$\left(\sum_{i=1}^{n} x_i - 1\right)^2 = 0 \tag{12}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j - 2\sum_{i=1}^{n} x_i + 1 = 0 \tag{13}$$

Next, the condition equation and the expected return equation are transformed into energy function as in (14) and (15) respectively.

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\right) - \sum_{i=1}^{n} x_i \tag{14}$$

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\right) - \sum_{i=1}^{n} x_i + K\sum_{i=1}^{n} \mu_i x_i \tag{15}$$

where K is a real number and must not less than 0.

The HBM converted the objective function into the energy functions of the first phase, E_u and second phase, E_l as described as in (16) and (17) respectively.

$$E_u = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}s_i s_j + K_u\sum_{i=1}^{n}\mu_i s_i \quad (16)$$

$$E_l = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j + 2\sum_{i=1}^{n}\sum_{j=1}^{n}x_i x_j\right) + 2\sum_{i=1}^{n}x_i + K_l\sum_{i=1}^{n}\mu_i x_i \quad (17)$$

Here K_u and K_l are the weight of the expected return rates of the first and second phase respectively.

The overall conceptual framework is shown as in Figure 1 while the detail of the proposed idea is shown as in Figure 2. The average interruption duration data for every state in Malaysia is analyzed by using the proposed technique, HBM. Due to the feature of the HBM, it yields a fast convergence besides provide flexibility solution to planners in solving financial allocation in DSEP problem.

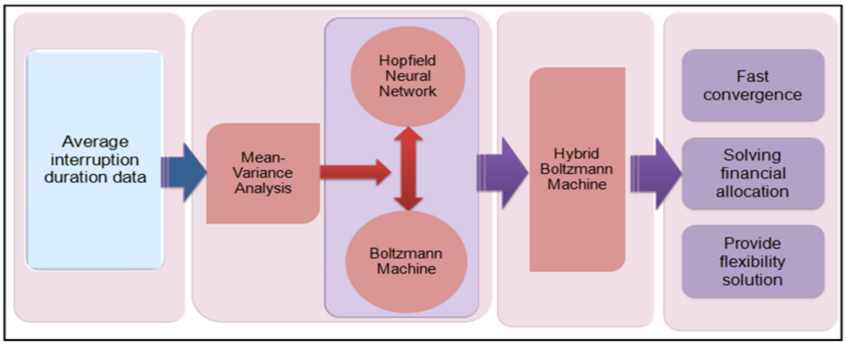

Figure 1. Overall conceptual framework

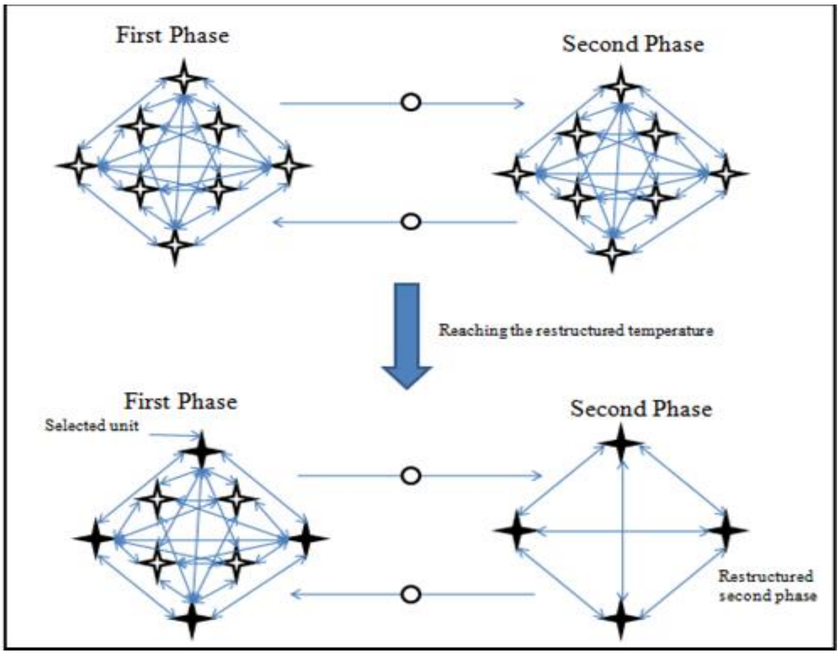

Figure 2. Hybrid Boltzmann machine

Based on Figure 2, the first phase is named as supervising phase and the purpose of HNN applied at the first phase is to select the feasible solution of units from that phase. Meanwhile, the executing phase occurred at the second phase where BM is applied at to determine the optimum and best solution from all feasible solution. The overall flowchart of the HBM is shown as in Figure 3.

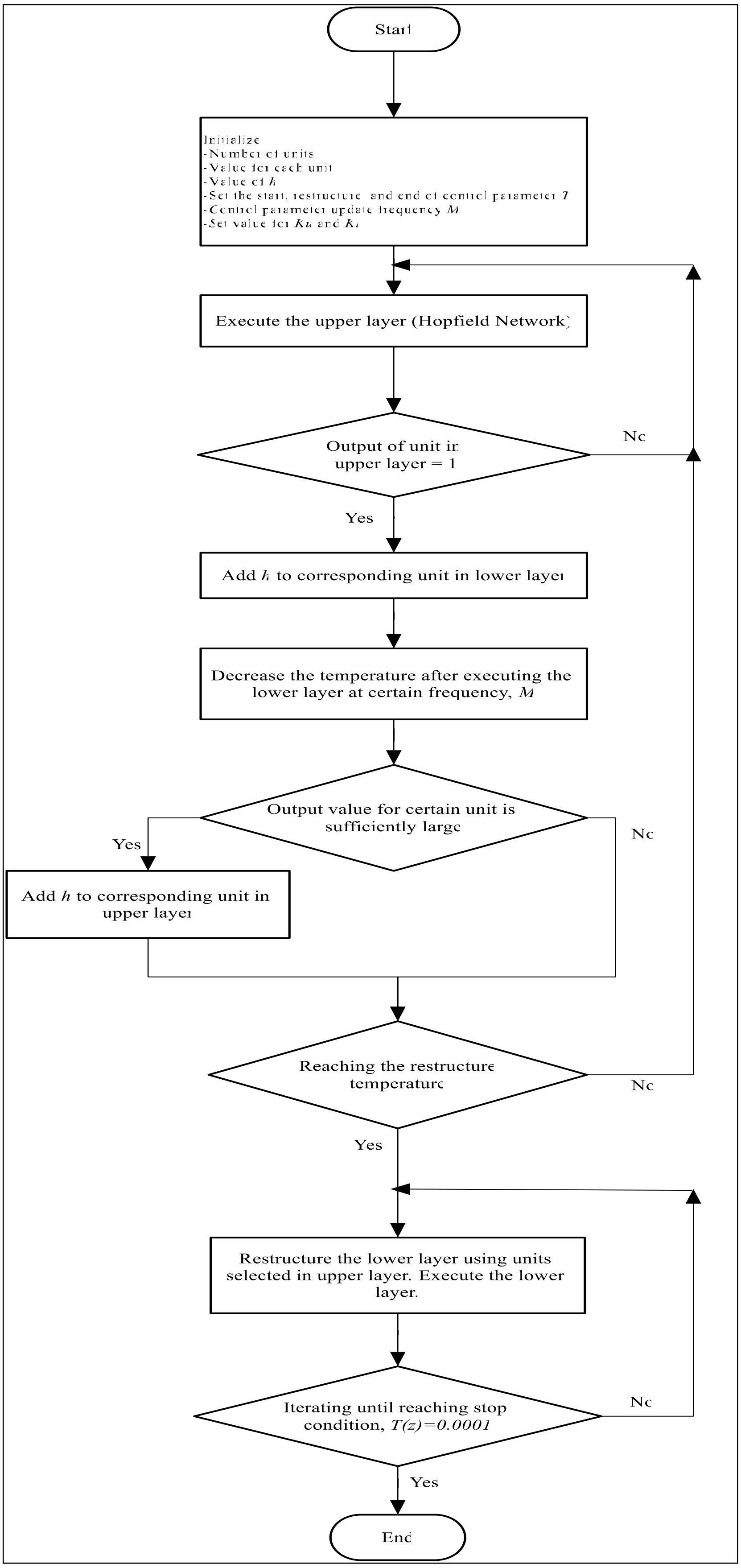

Figure 3. The flowchart of HBM

3. RESULT AND DISCUSSION

3.1. Data

The following data in Table 1 is the average interruption duration by each state in Malaysia. The data was collected per hour per customer per year within eight years from 2008 to 2015. In order to solve financial allocation in DSEP, the optimal maintenance for each state is decided by referring to past downtime rates.

Table 1. The average interruption duration for each state

	2008	2009	2010	2011	2012	2013	2014	2015	Mean
S1	1.708	1.332	1.999	1.301	1.030	1.181	0.966	0.983	0.954
*S*2	1.942	1.287	2.128	1.453	1.356	1.240	1.406	0.957	1.070
*S*3	1.653	1.365	1.417	1.213	1.206	1.160	0.937	0.936	0.899
S4	1.648	1.012	1.008	0.725	0.761	0.635	0.755	0.708	0.659
S5	1.323	0.888	1.356	0.932	0.910	1.166	0.897	0.948	0.766
*S*6	1.740	1.855	1.827	1.276	1.222	1.148	0.840	0.908	0.983
*S*7	1.713	1.030	1.239	1.483	1.036	1.062	1.149	1.044	0.887
*S*8	1.022	1.125	3.245	1.996	1.394	1.316	1.151	0.861	1.101
*S*9	0.947	0.888	1.077	0.630	0.587	0.613	0.649	0.568	0.542
*S*10	1.167	0.815	1.329	1.022	0.945	0.907	0.931	0.846	0.724
*S*11	1.215	0.818	0.926	0.904	0.838	0.744	0.722	0.691	0.624

*Note: *S*1 is Johor, *S*2 is Kedah, *S3* is Kelantan, *S*4 is Melaka, *S*5 is Negeri Sembilan, *S*6 is Pulau Pinang, *S*7 is Pahang, *S8* is Perak, S9 is Perlis, *S*10 is Selangor and *S*11 is Terengganu. All data in hour.

3.2. Analysis

The simulation step is beginning by moving the temperature *T* of the BM decrementally from 100 to 0.0001. Subsequently, the change is implemented with an inter-arrival temperature of 0.001 and the initial setting for each unit is 0.1. Then, the constant $K=K_u=K_l$ is simulated for 0.3, 0.5, 0.7 and 1.0. As the BM behaves probabilistically, the result is taken to be the average of the last 10,000 trials.

3.3. Result and discussion

In this paper, a case study in Malaysia was analyzed to optimize the financial allocation for eleven state maintenance cost. In this analysis, the average interruption duration for eight years is used to analyze the expense investment and at the same time solve the financial allocation problem. Table 2 presented the simulation results for financial allocation for each state in Malaysia.

Table 2. Simulation result for financial allocation for each state in Malaysia

States	*K*=0.3	*K*=0.5	*K*=0.7	*K*=1.0
*S*1	0.306	0.268	0.226	0.191
*S*2	0.241	0.250	0.268	0.273
*S*3	0.000	0.000	0.007	0.031
*S*4	0.000	0.000	0.000	0.000
*S*5	0.000	0.000	0.000	0.014
*S*6	0.000	0.000	0.041	0.088
*S*7	0.233	0.191	0.179	0.162
*S*8	0.220	0.181	0.162	0.117
*S*9	0.000	0.000	0.000	0.000
*S*10	0.000	0.110	0.117	0.124
*S*11	0.000	0.000	0.000	0.000

*Note: *S*1 is Johor, *S*2 is Kedah, *S3* is Kelantan, *S*4 is Melaka, *S*5 is Negeri Sembilan, *S*6 is Pulau Pinang, *S*7 is Pahang, *S8* is Perak, S9 is Perlis, *S*10 is Selangor and *S*11 is Terengganu.

According to Table 2, during *K* equal to 0.3, there were only four states selected that the allocation of financial should be assigned which are *S*1, *S*2, *S*7 and *S*8 with 30.6%, 24.1%, 23.3% and 22.0% respectively. The simulation is repeated by changing the value of *K* to 0.5. The selected states are increased to five where *S*10 also should receive the portion of the financial allocation. As the value of *K* is 0.7, there were seven states selected which are *S*2 with the highest portion, 26.8% followed by *S*1, *S*7, *S*8, *S*10, *S*6 and *S*3 with the least portion of 0.7%. There were eight states selected as *K* increased to 1.0. S2 has the highest portion with 27.30% while *S*4 with the least portion of 1.40%. The rest of states are *S*1, *S*7, *S*10, *S*8, *S*6 and *S*3.

The proposed technique offered the solution with level of risk aversion, *K* compared to conventional method. There was four level of *K* which is 0.3, 0.5, 0.7 and 1.0 that reflected the different preferences of the decision maker. Noticed that the value of *K* influenced the number of states chosen where the selected states are high as the value of *K* increased. A planner can determine the optimum solutions where the larger value of *K* leads to riskier option compared to the small value of *K*.

4. CONCLUSION

This paper proposed an efficient technique to solve financial allocation problem in DSEP by using HBM. As mentioned before, one of the characteristics of HBM is it has fast convergence compared to original BM. Furthermore, the basis for estimating the allocation of limited financial can be obtained by using HBM. The proposed technique is capable to provide adequate participation profile for the market player. Beside that, the planners have the flexibility to decide which financial allocation portfolio based on the various solutions provided, thus it enhance the decision making process. Regarding to the finding in the results, planners are able to choose which solutions that fit into their preference since the results are flexible.

In the future, several further works could be explored to enhance the reliable solutions that used the proposed technique. Recently, data is being generated in large amount with varying number of quality; hence the term of big data was used. Nowadays, big data has started to affect the lives of modern day in almost every area, whether engineering, investment, business, education or healthcare. Since the proposed technique can yield the optimum solution for large unit number with fast computational time, thus the HBM is highly suitable to solve the big data problem. The data is suggested to undergo a specific tool that can help to eliminate the redundancy so that it can require less computational effort and time-consuming.

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