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A Modified Boltzmann Machine for Solving Distribution System Expansion Planning in Malaysia

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ABSTRACT

This paper proposes an effective technique to solve Distribution System Expansion Planning (DSEP) problem by using the artificial neural network. The proposed technique will be formulated by using mean-variance analysis (MVA) approach in the form of mixed-integer quadratic programming problem. It consists of two layers neural network which combine Hopfield network and Boltzmann machine (BM) in upper and lower layer respectively named as Modified BM. The originality of the proposed technique is it will delete the unit of the second layer, which is not selected in the first layer in its execution. Then, the second layer is restructured using the selected units. Due to this feature, the proposed technique will improve time consuming and accuracy of solution. Referring to the case study demonstrated in this paper, the significance outputs obtained are the improvement in computational time and accuracy of solution provided. As the solution provided various of options, the proposed technique will help decision makers in solving DSEP problem. As a result, the performance of strategic investment planning in DSEP certainly enhanced.

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1. INTRODUCTION

Planning of distribution system has been a very hot topic in the 21st century [1]. Distribution System Expansion Planning (DSEP) is dealing with the continuous increasing load demand. In DSEP, the stages of the plan and overall time span; the methods of treating distribution feeders and substations in terms of cost representation, location and sizing problems; radiality and voltage drop considerations; and the mathematical programming techniques used to solve this problem [2]. It uses a fundamental economic criterion, the 'cost-benefit analysis', in a heuristic selection process of plan options, starting from the terminal year and propagating backward to the initial year, to arrive at a plan solution [3].

On the other hand, the demand for electricity has grown due to the rapid economic development and gradual increase in the world's population [4]. According to Malaysia Statistic Energy Handbook [5], the total generating capacity in Peninsular Malaysia is 24,105 MW. It is predicted that if the current global energy consumption pattern continues, the world energy consumption will increase by over 50% before 2030 [6]. Since the demand keeps increasing, thus a meticulous planning should be provided to enhance the power delivery to the consumer.

Efficient operation and planning of power systems become more important for a reliable and sustainable electricity supply [7]. Optimization is playing a vital and dominant role in the electric power system. Optimization problems in power system are diversified and can be categorized in terms of the objective function characteristics and type of constraints [8, 9]. Basically, system failure is caused by lack of maintenance. Thus to prevent any electrical failure, maintenance on electrical equipment is important and should be taken as a precautionary measure [10], [11]. Since maintenance costs are significant portion of the investment planning problem, so, an efficient tool is needed to minimize misdirected investment. In real situations, investment planning problems are complicated and non-linear program. Thus, soft computing is a valid and convincing approach to solve the problem.

Previous research papers have appeared to solve DSEP problem by using soft computing and mathematical optimization techniques. Tafreshi et al. [12] proposed Genetic Algorithm (GA) to calculate the optimum system configuration that can achieve the customers required loss of power supply probability (LPSP) with a minimum cost of energy (COE) while Falaghi [13] used the same approach to solve multistage DSEP which solved installation of substations, feeders and DG that suit to capacity expansion. Another approach that consists the capability of solving DSEP is Artificial Immune System (AIS) that proposed by Souza et al. [14]. AIS produced a systematically set of solutions and able to solve DSEP problem in planning smart grid and obtaining DG optimal solution. Mixed Integer Linear Programming (MILP) that solved by Simulated Annealing (SA) is proposed by Popovic et al. [15] while Tabu Search proposed by Ramirez-Rasado et al. [16] to solve DSEP problem.

The MVA approach is used to solve the portfolio selection problem in this paper. The formulation that proposed by Markowitz is in the form of mixed integer programming problem which minimising the risk while the return has been fixed into a certain condition. Since the problem is hard to solve, thus soft computing approach wil be use by employing the combination between Hopfield Network and Boltzmann Machine named as Modified BM. The further explanation will be discussed in Section 2. Section 3 provided the discussion based on the simulation result. Lastly, Section 4 will be explaining the conclusion and future recommendations.

2. MATHEMATICAL MODEL

2.1. Mean-Variance Analysis

The MVA is a quantitative tool that allows the decision maker to make asset allocation by considering the interchange between expected return rate and the measure of risk [17–19]. The portfolio optimization employed mean and variance that solved expected return rate for each asset, standard deviation which is measure of risk and covariance matrix between these assets. The output is in form of the efficient frontier where the expected return greater than any other with the same or lesser risk [20]. Basically, MVA is formulated as mixed-integer programming problem as in Equation (1) to (4).

Formulation 1

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

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

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

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

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.

Formulation 2

Based on Formulation 1, the optimal solutions are offered with the least risk. However, the constraint faced by the decision maker is the given value cannot exceed the expected return rate. The investment rate for each stock determined the solution with the least risk under the given expected return rate. Since the risk are evaluated under the condition of fixing the rate of expected return and lead to decision maker dissatisfaction, thus Formulation 2 is proposed as in Equation (5) to (10).

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

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

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

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

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

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

where *S* is the desired number 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*, 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.

In Formulation 2, there are two objective works that have been comprised which are the expected return rate and risk. Since Formulation 2 is in the form of mixed-integer programming problem, hence an appropriate technique is invented. The combination of Hopfield network and BM is formulated to achieve the quality solution by changing over the portfolio into energy function.

2.2. Boltzmann Machine

A BM is an interconnected neural network proposed by G. E. Hinton [21]. This model is based on a Hopfield network. BM is the updated version of Hopfield network that employed simulated annealing to escape the local optimum. The probability rule in BM is used to update the state of neuron and 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. Meanwhile, $V_i(t+1)$ is 0 according to the probability $1-P$.

$$P[V_i(t+1)] = f\left(\frac{u_i(t)}{T}\right) \tag{11}$$

where V_i is the state of unit *i*, $f(\cdot)$ is the sigmoid function, $u_i(t)$ is the total input to neuron *i* and *T* is the network temperature (control parameter).

$$u_i(t) = \sum_{j=1}^{n} w_{ij} V_j(t) - \theta_i \tag{12}$$

where w_{ij} is the weight of the connection from neuron *j* to neuron *i*, V_j: is the state of unit *j* and θ_i is the threshold of neuron *i*.

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

$$E = \frac{1}{2} \sum_{ij=1}^{n} w_{ij} V_i V_j - \sum_{j=1}^{n} \theta_i V_i \tag{13}$$

2.3. Modified Boltzmann Machine

Theoretically, Hopfield network can solve the mixed-integer programming problem within minimal period of time despite providing less accurate and optimum solutions. On the other hand, Hopfield network is easily trapped into the local minimum, thus a modification was made by employing simulated annealing to escape the local minimum in the form of BM [22], [23]. The advantage of BM is it can select the optimum and accurate solutions since it yields the global optimum solutions and at the same, it requires more computational time. The idea of Modified BM is originally taking into account the advantages of both BM and Hopfield network. Hopfield network in the upper layer will select units quickly, and then the lower layer which is BM will choose the selected units from the upper layer. It will be restructured using those selected units. Based on MVA theory, the 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.

$$\left(\sum_{i=1}^{n} x_i - 1\right)^2 = 0 \tag{14}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j - 2\sum_{i=1}^{n} x_i + 1 = 0 \tag{15}$$

Next, the condition equation and the expected return equation are transformed into energy function as in Equation (16) and (17) respectively.

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\right) - \sum_{i=1}^{n} x_i \tag{16}$$

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

where K is in the range from 0 to 1.

Equation (18) and (19) represent the objective function that has been converted into energy function for the upper layer, E_u and the lower layer, E_l. The upper layer is called as "supervise layer" meanwhile the lower layer is used to decide the optimal units from the limited selected in upper layer. It is called as "executing layer".

$$E_u = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} s_i s_j + K_u \sum_{i=1}^{n} \mu_i s_i \tag{18}$$

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

Based on Equation (18) and (19), K_u and K_l represented the weight for expected return rates for both upper and lower layer respectively. Figure 1 shows the flowchart for the algorithm of Modified BM.

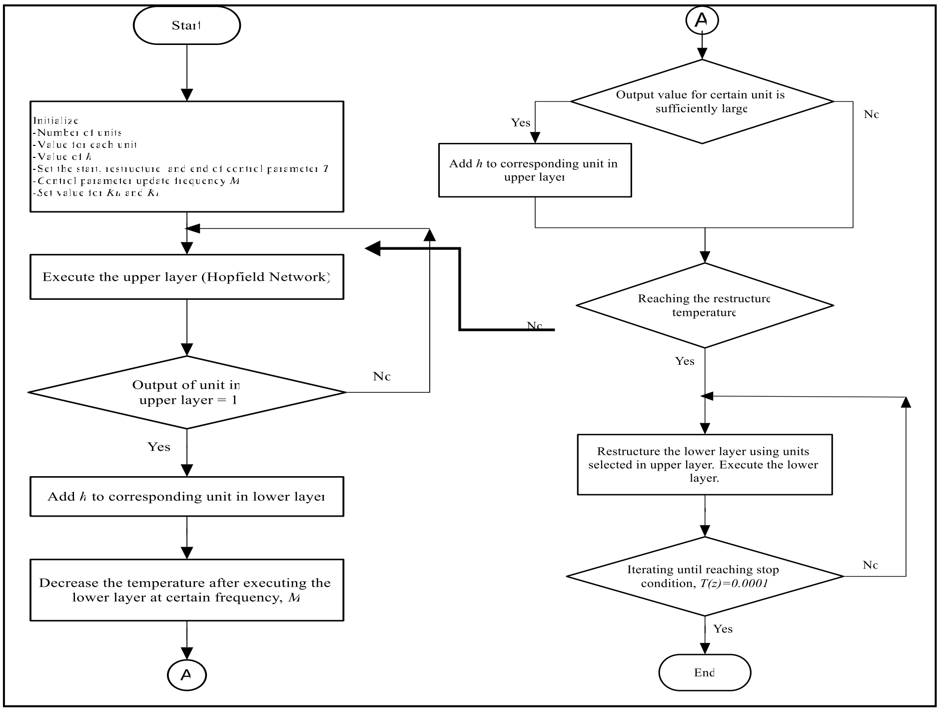

Figure 1. Algorithm of modified BM

2.3. Data and Analysis

There are 13 states in Malaysia that have been taken with their 15 years average interruption durations, in which portfolios of investment can be analyzed and optimized. The analysis of interchange between interruption duration and variance that employed MVA and Modified BM is more efficient as the number of states is increased dramatically. Decision makers are concerned with risk and return, thus these should be measured for the portfolio as a whole.

The simulation steps are listed as follows:

a. The temperature *T* of the Boltzmann machine is moved decrementally from 100 to 0.0001.
b. The change is implemented with an interarrival temperature of 0.001.
c. The initial setting for each unit is 0.1.
d. The constant *K* = *Ku* = *Kl* is simulated for 0.3, 0.5, 0.7 and 1.0.
e. As the Boltzmann machine behaves probabilistically, the result is taken to be the average of the last 10,000 trials.

The following steps are described as the process of implementing the proposed technique:

Step 1.Determining the Right Uncertainty

The MVA process is initiated by determining the right uncertainty. In this case, the uncertainty is the average interruption duration for each state within 15 years in Malaysia.

Step 2.Quantifying Individual Uncertainties

The following data that has been quantified as in Table 1 is the average interruption duration by the state in Malaysia. The data was collected per hour per customer per year within 15 years from 2001 to 2015. In DSEP, the optimal maintenance for each state is decided by referring to average interruption duration.

Table 1. Average Interruption Duration by State

State \ Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean
Johor	6.16	3.06	3.00	3.56	3.50	2.33	1.51	1.71	1.33	2.00	1.30	1.03	1.18	0.97	0.98	2.24
Kedah	4.20	1.50	2.89	2.69	4.12	1.96	1.25	1.94	1.29	2.13	1.45	1.36	1.24	1.41	0.96	2.02
Kelantan	4.05	1.75	3.46	2.27	1.95	1.14	0.87	1.65	1.37	1.42	1.21	1.21	1.16	0.94	0.94	1.69
Kuala Lumpur	2.20	1.38	1.69	1.65	1.46	1.16	0.96	1.13	0.79	0.70	0.56	0.56	0.60	0.55	0.54	1.06
Melaka	1.14	0.87	1.31	1.72	4.28	1.83	1.06	1.65	1.01	1.01	0.73	0.76	0.64	0.75	0.71	1.30
N. Sembilan	1.45	1.99	1.30	1.43	4.91	1.67	1.47	1.32	0.89	1.36	0.93	0.91	1.17	0.90	0.95	1.51
P. Pinang	3.09	1.24	5.50	1.13	1.71	1.26	1.39	1.74	1.86	1.83	1.28	1.22	1.15	0.84	0.91	1.74
Pahang	3.35	4.67	4.36	2.35	3.03	3.19	1.81	1.71	1.03	1.24	1.48	1.04	1.06	1.15	1.04	2.17
Perak	4.26	2.00	2.71	1.91	1.75	1.65	0.83	1.02	1.13	3.25	2.00	1.39	1.32	1.15	0.86	1.81
Perlis	0.87	0.59	4.18	0.91	1.00	0.98	0.62	0.95	0.89	1.08	0.63	0.59	0.61	0.65	0.57	1.01
Putrajaya	0.00	0.00	0.59	0.03	0.02	0.04	0.04	0.11	0.00	0.15	0.00	0.14	0.02	0.00	0.01	0.08
Selangor	3.34	2.45	1.60	1.84	1.77	1.64	1.45	1.17	0.82	1.33	1.02	0.94	0.91	0.93	0.85	1.47
Terengganu	1.93	4.46	2.79	2.96	1.50	1.52	0.79	1.22	0.82	0.93	0.90	0.84	0.74	0.72	0.69	1.52

Step 3. Post-processing the Uncertainties

The next step is post-processing the uncertainties. In this step, the quantified uncertainties have to undergo the process of mean and variance calculation. Table 2 shows the covariance matrix for the interruption duration index for each state in Malaysia.

Table 2. Covariance Matrix of Average Interruption Duration for Each State in Malaysia

	Johor	Kedah	Kelantan	Kuala Lumpur	Melaka	N. Sembilan	P. Pinang	Pahang	Perak	Perlis	Putra-jaya	Selangor	Terengganu
Johor	1.888	1.187	1.077	0.649	0.470	0.537	0.725	1.162	0.984	0.272	0.012	0.867	0.843
Kedah	1.187	0.976	0.714	0.412	0.593	0.597	0.581	0.661	0.627	0.299	0.027	0.471	0.347
Kelantan	1.077	0.714	0.809	0.399	0.162	0.144	0.802	0.707	0.650	0.450	0.058	0.454	0.499
Kuala Lumpur	0.649	0.412	0.399	0.252	0.192	0.191	0.330	0.483	0.288	0.178	0.017	0.295	0.356
Melaka	0.470	0.593	0.162	0.192	0.773	0.780	0.093	0.362	0.028	0.095	-0.001	0.142	0.122
N. Sembilan	0.537	0.597	0.144	0.191	0.780	0.923	0.032	0.494	0.077	0.019	-0.014	0.219	0.236
P. Pinang	0.725	0.581	0.802	0.330	0.093	0.032	1.287	0.754	0.586	0.897	0.138	0.262	0.375
Pahang	1.162	0.661	0.707	0.483	0.362	0.494	0.754	1.470	0.528	0.531	0.063	0.614	1.094
Perak	0.984	0.627	0.650	0.288	0.028	0.077	0.586	0.528	0.851	0.265	0.036	0.448	0.354
Perlis	0.272	0.299	0.450	0.178	0.095	0.019	0.897	0.531	0.265	0.749	0.118	0.057	0.294
Putrajaya	0.012	0.027	0.058	0.017	-0.001	-0.014	0.138	0.063	0.036	0.118	0.021	-0.004	0.034
Selangor	0.867	0.471	0.454	0.295	0.142	0.219	0.262	0.614	0.448	0.057	-0.004	0.448	0.466
Terengganu	0.843	0.347	0.499	0.356	0.122	0.236	0.375	1.094	0.354	0.294	0.034	0.466	1.117

Step 4. Applied Portfolio Theory

In order to enable the decision maker to solve DSEP problem, a set of assets is used to maximize return while considering risk aversion. The specific class of optimization is quadratic optimization based on an appropriate balance of risk and returns. These risks and returns are typically derived from historical average interruption duration. The quadratic programming problem can be solved by MVA that employed Modified BM efficiently.

Step 5. Determining the Optimal Maintenance Strategy

The results offer sets of solutions following an efficient frontier which the optimal solution can be chosen. The decision maker can find an indifferent curve between the value and the uncertainty that accurately reflects his interest. Table 3 shows the simulation result for investment rate for each state in Malaysia while Table 4 is the table of computational time comparison between conventional BM and Modified BM.

Table 3. Simulation Result for Investment Rate for Each State in Malaysia

States	K=0.3	K=0.5	K=0.7	K=1.0
Johor	0.317	0.289	0.242	0.204
Kedah	0.229	0.237	0.261	0.270
Kelantan	0.000	0.000	0.018	0.034
Kuala Lumpur	0.000	0.000	0.000	0.000
Melaka	0.000	0.000	0.000	0.000
N. Sembilan	0.000	0.000	0.000	0.009
P. Pinang	0.000	0.000	0.065	0.135
Pahang	0.248	0.201	0.173	0.118
Perak	0.206	0.176	0.119	0.077
Perlis	0.000	0.000	0.000	0.000
Putrajaya	0.000	0.000	0.000	0.000
Selangor	0.000	0.097	0.122	0.132
Terengganu	0.000	0.000	0.000	0.021

Table 4. Computational Time Comparison Between Conventional BM and Modified BM

Number of states	Computational times (sec)	
	Conventional BM	Modified BM
10	7.21	6.42
40	12.11	8.52
80	20.08	10.03
160	43.41	12.61
320	100.14	20.07
640	223.01	39.96

3. RESULTS AND DISCUSSION

The simulation result for each state in Malaysia was tabulated as in Table 3.0. During K equal to 0.3, there were only four states selected which are Johor with the highest portion of the investment, 31.70% followed by Pahang with 24.80%, Kedah and Perak with 22.90% and 20.60% respectively. As the value of K was increased to 0.5, the selected states were increased as well. The selected states are Johor, Kedah, Pahang, Perak and Selangor with 28.90%, 23.70%, 20.10%, 17.60% and 9.70% respectively. The simulation was repeated by changing the value of K to 0.7. In this situation, there were seven states chosen which are Kedah with the highest portion of 26.10% and Kelantan with the least portion of 1.80%. Meanwhile Johor should receive 24.20%, Pulau Pinang with 6.50%, Pahang with 17.30%, Perak with 11.90% and Selangor with 12.20%.

There were nine states selected as the value of K equal to 1.0. 20.40% of investment should be received by Johor, 27.00% for Kedah and 3.40% for Kelantan. The least portion goes to Negeri Sembilan with 0.90% only. Pulau Pinang, Pahang and Perak should receive 13.50%, 11.80% and 7.70% respectively followed by 13.20% for Selangor and last but not least 2.10% for Terengganu.

According to Table 3.0, there were four level of risk aversion, 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 decision maker can determine the optimum solutions where the larger value of K leads to riskier option while the small value of K leads to conservative ones. Since this proposed technique is flexible, thus it produced a strategic planning investment to solve DSEP problem.

In order to demonstrate the efficiency of the proposed technique, a comparison was made for the computational time between conventional BM and Modified BM as tabulated in Table 4.0. Based on the table, the conventional BM consumed 7.21s compared to 6.42s for the Modified BM when the number of state equal to 10. As the number of state was set to 160, the Modified BM consumed 12.61s only while conventional BM needed 43.41s to complete the task. When the number of state was 640, the conventional BM consumed 223.01s meanwhile Modified BM consumed less than a minute which is 39.96s only. Notice that, the conventional BM required time-consuming compared to Modified BM. This is due to the Modified BM deleted useless units during the restructuring step. By contrast, a conventional BM computes all units until the termination condition is reached. Comparing computing efficiency, the Modified BM is more efficient, especially when the initial number of unit is large. The proposed technique provides a more effective selection by using the Hopfield network in the upper layer to choose a limited number of unit, and the BM in the lower layer to decide the optimal solution from the limited number of unit selected by the upper layer.

4. CONCLUSION AND FUTURE RECOMMENDATION

In this paper, the Modified BM can deal well with DSEP problem that consists of mixed-integer programming problem. By following the investment expenses rate for each state as proposed, the cost saving can be increased. The results also show that the proposed technique for incorporating structural learning into BM is effective and can enhance the decision-making process.

Other than that, the appropriateness of Modified BM has been verified as the proposed technique able to solve the problem of choosing the most potential states to receive the investment. As the result, the proposed technique can successfully determine the optimal solutions for each stated at different *K.* The simulation results also show that there is significant decrease in computational time compared to original BM.

In future, several further works could be explored to enhance the effectiveness of 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 Modified BM 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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REFERENCES

[1] Liu J, Gao H, Ma Z, et al. Review and prospect of active distribution system planning. *Journal of Modern Power Systems and Clean Energy* 2015; 3: 457–467.
[2] Gönen T, Ramirez-Rosado IJ. Review of distribution system planning models: a model for optimal multistage planning. *Gener Transm Distrib IEE Proc C* 1986; 133: 397–408.
[3] Bin Humayd AS, Bhattacharya K. Distribution system planning to accommodate distributed energy resources and PEVs. *Electr Power Syst Res* 2017; 145: 1–11.
[4] Trebolle D, Gomez T, Cossent R, et al. Distribution planning with reliability options for distributed generation. *Electr Power Syst Res* 2010; 80: 222–229.
[5] Suruhanjaya Tenaga Energy Commission. Malaysia Energy Statistics Handbook 2015. *Suruhanjaya Tenaga Energy Comm* 2015; 84.
[6] Suganthi L, Samuel AA. Energy models for demand forecasting - A review. *Renew Sustain Energy Rev* 2012; 16: 1223–1240.
[7] DeLlano-Paz F, Calvo-Silvosa A, Antelo SI, et al. Energy planning and modern portfolio theory: A review. *Renew Sustain Energy Rev* 2017; 77: 636–651.
[8] Yaakob SB, Watada J, Takahashi T, et al. Reliability enhancement of power systems through a mean-variance approach. *Neural Comput Appl* 2012; 21: 1363–1373.
[9] Watada J, Yaakob SB. Structural learning model of the neural network and its application to LEDs signal retrofit. *Stud Comput Intell* 2011; 372: 11739.
[10] Publications USG. National Fire Protection Association Report Related Public Inputs for This Document. 2014; 5: 1–93.
[11] *NFPA 70B Recommended Practice for Electrical Equipment Maintenance*. 2013.
[12] Tafreshi SMM, Zamani HA, Ezzati SM, et al. Optimal unit sizing of distributed energy resources in microgrid using genetic algorithm. In: *Proceedings - 2010 18th Iranian Conference on Electrical Engineering, ICEE 2010*. 2010, pp. 836–841.

[13] Falaghi H, Singh C, Haghifam MR, et al. DG integrated multistage distribution system expansion planning. *Int J Electr Power Energy Syst* 2011; 33: 1489–1497.
[14] Souza BB, Carrano EG, Neto OM, et al. Immune system memetic algorithm for power distribution network design with load evolution uncertainty. *Electr Power Syst Res* 2011; 81: 527–537.
[15] Popović ZN, Kerleta VD, Popović DS. Hybrid simulated annealing and mixed integer linear programming algorithm for optimal planning of radial distribution networks with distributed generation. *Electr Power Syst Res* 2014; 108: 211–222.
[16] Ramirez-Rosado IJ, Dominguez-Navarro JA. New Multiobjective Tabu Search Algorithm for Fuzzy Optimal Planning of Power Distribution Systems. *IEEE Trans Power Syst* 2006; 21: 224–233.
[17] Gasser SM, Rammerstorfer M, Weinmayer K. Markowitz revisited: Social portfolio engineering. *Eur J Oper Res* 2017; 258: 1181–1190.
[18] Delarue E, De Jonghe C, Belmans R, et al. Applying portfolio theory to the electricity sector: Energy versus power. *Energy Econ* 2011; 33: 12–23.
[19] Silva T, Pinheiro PR, Poggi M. A more human-like portfolio optimization approach. *Eur J Oper Res* 2017; 256: 252–260.
[20] Fulga C. Portfolio optimization under loss aversion. *Eur J Oper Res* 2016; 251: 310–322.
[21] Ackley D, Hinton G, Sejnowski T. A learning algorithm for boltzmann machines. *Cogn Sci* 1985; 9: 147–169.
[22] Yaakob SB, Watada J, Fulcher J. Structural learning of the Boltzmann machine and its application to life cycle management. *Neurocomputing* 2011; 74: 2193–2200.
[23] Tahar SHM, Yaakob SB, Ahmed A. An improved Boltzmann machine for strategic investment planning in power system environment. *Indones J Electr Eng Comput Sci* 2017; 6: 259–267.