MJFAS MALAYSIAN JOURNAL OF FUNDAMENTAL AND APPLIED SCIENCES
PRINT ISSN: 2289-5981 | ONLINE ISSN: 2289-599X

RESEARCH ARTICLE

An improved cost estimation for unit commitment using back propagation algorithm

Baqer Turki Atiyha [a,*], Salahaldain Aljabbar [b], Ammar Ali [a], Abdullah Jaber [a]

[a] Thiqar Technical College, Southern Technical University, Thiqar, Iraq
[b] Faculty of Engineering, Al-Muthana University, al-Somawa, Iraq

[*] Corresponding author: dr.baqer_turki@stu.edu.iqa

Article history
Received 29 April 2018
Revised 27 June 2018
Accepted 7 August 2018
Published Online 14 April 2019

Abstract

Daily load is the main issue for many power plant industries that are affected by the varying maximum and minimum peak hours. Due to that, electricity is being used less during the weekends, compared to weekdays, where the spending is higher. The same logic is applied to day and night spending, which requires balancing among the units so that it can operate during high demand hours. The main problem is to determine the units that will be affected according to the operation schedule which means which unit, and for how long, will it stay on or off. In this context, the main objective for unit commitment in general was to minimize the total cost of operating a unit, and at the same time maintain the constraints met. Several approaches and techniques were used in existing studies; each has a solution for the optimal unit commitment problem. Some of the approaches presented would use complex methods in order to address the issues, while others would use simple forms to do the same task. The problem of operation scheduling for unit commitment would be different depending on the type of industry and according to the plan of mixing unit and operating constraints.

Keywords: Load, power plant, algorithm, commitment

INTRODUCTION

Unit commitment is the most important issue in the power industry and plays a potential rule to save resource costs in terms of fuel and maintenance costs every year. This problem is complex when making decisions on which units should be powered on at certain times, this decision will help in balancing the power generated by units and demand loads. The main objective of such systems is to find the optimal solution for unit distribution. Several methods have suggested in the literature review to involve algorithms that can achieve acceptable performance but these algorithms are usually not considered the most optimal solution. Currently, there are classical methods used to find near optimal solution such as Newton's method [1], Lagrangian Relaxation [2,3] and gradient method [4]. However, it is not advisable to use these solutions to address the operation schedule problems.

Nowadays, new heuristic methods such evolutionary program [5], Annealing simulated [6], Tabu [7], and fuzzy methods [8] have an adequate performance in choosing the optimal solution but the disadvantage of these methods is that they are slow in convergence due to high computational cost. The problem of unit commitment can be defined as part of scheduling in generating units of thermal power system according to various constraints. The main issue in unit commitment is to make the power generated from units adaptive, in order to validate the loads during the peak/off peak hours [9]. In other words, the power consumption during the day and night is not the same, so it is reasonable to manage the units of power system accordingly. To achieve the main objective of unit commitment (which is to minimize the operating cost when it meets the demand power) the perfect algorithm which can manage these units under critical constraints should be found. Since long time researchers and developers are tried to achieve the best algorithm for unit commitments and suggested algorithm in general that classified into three main classes: classical, non-classical and hybrid models [9]. When new technologies and modern high computational computers are taken into consideration, it is noticeable that hybrid models can open the prospect of using Artificial Intelligent (AI) and its relevant applications. Function of the cost in unit commitment includes sum of fuel conception, shut down for all units and startup cost (minimizing [9]). These costs are varied from one unit to another and may have an effect on the optimization if the order is changed.

In structured environment, unit commitment is considered to be a very important problem. Unit commitment determines the timing where units are on or off and the state of the generators and how they are being dispatched during the scheduling, so that the operation costs can be minimized, thus addressing the contrast mentioned earlier, such as load balance, system reverse requirement, ramp rate limits and minimum up/down time limits. [10]. The unit commitment system uses mixed intergers, and thus, it is difficult to identify or device an optimal solution. It is considered to be a complex optimization problem, with variety of methods are being applied in order to address the issue. All three types of models and techniques have been applied in order to address the issue. Other methods such as dynamic programming are used in order to solve the unit commitment optimization problem. Classical methods such as priority list [9], Lagrangian relaxation, mixed integer programming [11], and branch and bound are not fully capable in devising a solution that can address the problem with the scale of UC. Heuristic methods however, have redounded these limitations. Metaheuristic algorithms such as simulated annealing, uzzy logic, genetic algorithm, neural network [12], swarm algorithms [13] and so on, have been used to address the unit commitment issues. In some cases, more than one algorithm have been used in order to address the problem, these methods are known as hybrid techniques. These type of models and techniques are applied in order to handle complicated problems and known to have a higher average performance.

Table 1 Review on existing methods with their constraints.

Authors	Number of hidden layer	Number of units	methods
Kumar, S. and Palanisamy, V. (2007)	9	10	dynamic programming based on neural network with linear model for input and output for neurons
Ouyang, Z., and Shahidehpour, S. M. (1992).	4	6	A hybrid dynamic programming and neural network to prescheduling each input profile for unit commitment
Ronne-Hansen, P., and Ronne-Hansen, J. (1991)	3	6	Fixed layer considered for generating power plant and treated by neural network to recognize unit commitment structure
Jahromi, M. Z., et al, (2013)	4	15	real time solution for unit commitment generator for plant. Neural network used to arrange the constraints while managing the operating hours load with minimum down time
Nayak, R., and Sharma, J. D. (2000)	variable	10	feeding the forward neural network by annealing method considering units commitment.

The purpose of the proposed system was to minimize the production cost with or without neglecting the shut down of isolated unit. The proposed system would address the optimization of demand loads with economic units.

Related work

The main issues have been addressed in previous studies that related with compatibility between consumption and production. Demands on the power are deferred from one time to another according to the daily life of the people. There are many constraints that affecting the generation power plants in general, such as environmental conditions (temperature, humidity and the wind), economical with physical conditions (age of generation plants, fuel cost and schedule of operation) and technical used in designing power plant. Good units commitment satisfies the demands on the power under certain conditions and vice versa for bad units commitment. Technically, good system can achieve better result when using Artificial Intelligent via generating such neural network and classifiers to organization units commitment. Table 1 shows a review ~~of~~ on existing methods of units commitment.

Kumar and Palanisamy (2007) have developed a new dynamic programming based on neural network to direct computation of Hopfield to generate economic dispatch. Proposed method used a linear model for input and output for neurons, in which iterations were ignored in this method by using direct computation instead to solve the problems. Ten generating units were used in this study.

A hybrid dynamic programming suggested by Ouyang and Shahidehpoud [19] used neural network to preschedule each input profile for unit commitment. Dynamic search was performed for the stages of uncertain units in the system. Execution time was reduced significantly for hybrid dynamic programming without degrading any quality of scheduling the generators.

Start-up costs were considered by Ronne-Hansen, P. and Ronne-Hansen, J.[20] and treated by neural network to recognize some kinds of unit commitment structure. Number of neurons was considered the same as number of operating hours, where three layers were used for each of varying 10 neurons (for single layer). Fixed layer was considered for generating power plant which causing the system to be limited.

New method proposed by[10] considered real time solution for unit commitment generator for plant. Neural network was used to arrange the constraints while managing the operating hours load with minimum down time. The main issue here was to optimize the balancing between cost and emission,[13]have produced new hyper neural network of feeding the forward neural network by annealing method in considering units commitment. Neural network could determine the variables constraint of each unit within interval time. They used variable hidden layers for multiple feedback to reduce time consuming.

BACKGROUND

Mathematical representation

For all thermal units that belong to power system minimization of fuel consumption, are represented by the cost function illustrated as [14]:

$$min_{Pi}\ j = \sum_{i=1}^{I_G} FC_i(P_i)$$

Where u_i is the binary parameter used to refer the status of all units. Binary units can be illustrated with ON unit =1 and OFF unit 0. In this study we assumed that units were identical.

Calculation for identical units

This section shows how the load distribution will be optimal over N power generating unit. When the demand D is provided by one or more unit u_i the operating units should be under the status =1 ON and the rest units should be =0 OFF such as :

$$if\ D \leq P_{max}\ then\ D = P_i\ \rightarrow (P_i = 1) for\ all\ operating\ i$$

In case of power demand is being less than generated power plane, another formula is needed. In designing of the power system, the units u_i are selected to satisfy P_min≤D≤P_max and the operation of units should satisfy the condition of minimum and maximum demand such as:

$$if\ D \leq P_{max}\ then\ [\ u_2 = \cdots = u_N = 0$$

$$if\ P_{max} < D \leq 2 * P_{max}\ then\ [u_2 = 1] and [u_N = \cdots = u_N = 0]$$

This will continue until it reaches the condition of :

$$(n-1)P_{max} < D \leq n * P_{max}\quad then\ u_i = 1\ for\ all\ i$$

In this case, all units are run in parallel to get maximum power. To estimate the units which one can ON at certain time and which one OFF, we have to find a method that can draw the plan for every change that happens in power demand. As mentioned above, the weight controls the power generator units according to the demand. Which means limitation of power generated is related to the demand which is varied all the time under need of the users. There is another important factor that should be calculated which is the cost of each unit.

We can consider $\text{þ}_{N,\ldots,N-1}$ as a binary indicator to represent the region as following:

$$if\ [D \leq (N-1)P_{max}]\quad then\ [\text{þ}_{N,\ldots,N-1} = 1]$$

In case of satisfying the condition $\text{þ}_1 = 1]\ for\ all\ set\ to\ 1\ (N - 1\ to\ sub\ rang\ of\ \text{þ})$.

Formulation of the problem

The main objective of UC is to reduce the total operation cost F_c which means the fuel summation shutdown and startup costs for all the time T should be as folowing:

$$F_c = SUM_{t=1}^{N} SUM_{i=1}^{N} \big(u_i^t Fc_i^t + u_i^t(1-u_i^{t-1})SU_i^t + u_i^{t-1}(1-u_i^t)SD_i\big)$$

Where N represents the total number of units, u_i^t is the commitment binary status represented by unit i with time t (when ON is 1 otherwise is OFF), and Fc_i^t is fuel cost of unit i in time t; SU_i^t is startup cost.

Every hour cost can be represented as $Fc_i^t = a + bp_i^t + c(p_i^t)$

a,b,c represent coefficients for the equation and p_i^t is power output for units at time t and the evaluation cost should be considered as :

$$SU_i^t = \begin{cases} SU_i^t \;\; h & if\ down - time \leq coldstarthours \\ SU_i^t \;\; c & othewr\ case \end{cases}$$

$SU_i^t \;\; h$ considers hot cost startup $SU_i^t \;\; c$ considers cold cost startup, where the shutdown cost is fixed amounts for each unit in shutdown.

System and generator constrains can cause problems for Unit Commitment which are:

- Constraint of the system : including the power demand pd^t should meet for each time interval such as:
-

$$pd^t = \sum_{i=1}^{N} u_i^t\, d^t \forall t$$

- Should reserve the guarantee Sr^t at each interval time t:
-

$$\sum_{i=1}^{N} u_i^t Pmax_i \geq pd^t + Sr^t\ for\ all\ t$$

- Limitation of unit generation.
- Keep the system stable when status will be changed by ON\OFF units before they change. [15].

Neural network

Neural Network is a machine learning concept, which is modeled after the human brain. The artificial equivalents of biological neurons are the nodes or units in our preliminary definition and a prototypical example is shown in Fig. 1(a). Synapses are modelled by a single number or weight so that each input is multiplied by a weight before being sent to the equivalent of the cell body. Here, the weighted signals are summed together by simple arithmetic addition to supply a node activation. In the type of node as shown in Figure 1(b), the so-called threshold logic unit (TLU)—the activation is then compared with a threshold; if the activation exceeds the threshold, the unit produces a high-valued output (conventionally "1"), otherwise it outputs zero. In the figure, the size of signals is represented by the width of their corresponding arrows, weights are shown by multiplication symbols in circles, and their values are supposed to be proportional to the symbol's size; only positive weights have been used.

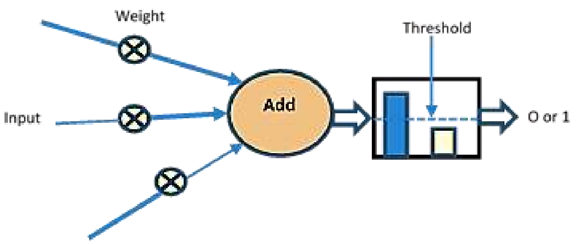

Fig. 1(a) Simple artificial neuron.

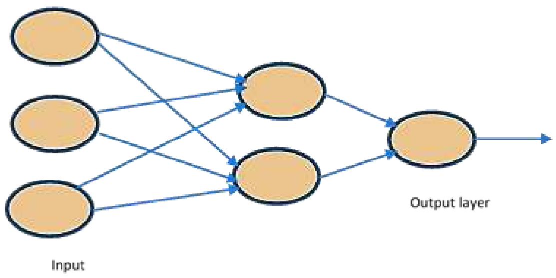

Fig. 1(b) Simple example of neuronal network.

Neural networks are simple, but robust, compelling and adjustable means for predicting, as long as there are sufficient information for training, decent choice of the input- output patterns, an apt number for hidden nodes and plenty computing resources that are accessible. Also, neural networks have the benefit of being capable to proximate any non-linear mathematical function and have ability to resolve complications where the input-output relationship is neither well specified nor estimable, this is due to the fact that neural networks are information driven. Generally, the neural networks can map input details to predict load demands. The input data for the neural networks is previous load patterns and parameters which have impacted the realistic load demand. During conditioning, characteristics from historical data are recorded into the network's input layer. The node actuation in input layer is fed ahead via the network and the results are analyzed with respect to the actual load values.

PROPOSED SOLUTION

Model flowchart

The main goal of unit commitment is to balance the load that generated with the demands which will be changed during the time the system is run, while considering constrains. The units will distribute over the virtual network and map these units to calculate the input and output of each one, each unit will operate according to the decision taken during training course of neural network. The main steps for our system were shown in the following flowchart:

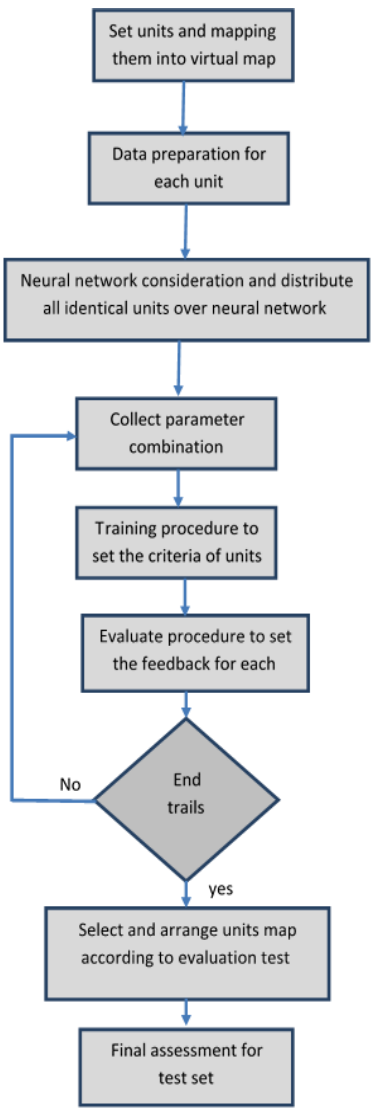

Fig. 2 Proposed Model Flowchart.

In employing a neural network to load estimating, one must select the configuration (e.g: feed forward or feedback of the units), the count and connectivity of layers and neurons, usage of bidirectional on unidirectional connection.

In this paper we suggested a neural network based solution, with back propagation algorithm for the following benefits:

1. They can achieve complicated input-output mapping without definitive programming and determining both linear and nonlinear relationship.
2. It is information driven system and it does not need restarting presumptions about the type of the key model.
3. It can anticipate the pattern which is not given during training.
4. It is effective at training huge scale of patterns because of its parallel processing ability.
5. It is enormously powerful computational tool.
6. It has the capability to discover all potential interactions between predictors and variables

However, complex design of such system may need more time for training, but the advantage is it can reduce the cost while the system supports the demanded power. Increasing training times over testing time may give the system more reliability under certain condition.

Proposed system has some components related to neural back propagation algorithm, such as:

- Processing element (artificial neuron).
  Representing the input, output and feedback input under the weight condition $O_{qj} = f(net_{qj})$ with weight (W_{ij})
- Weighting elements (which are the criteria of each unit)
  A neuron encounters many inputs concurrently. Each input processes its own weight which yields the input influence that it required on the processing components summation function.
- Summation (addition) function represented by the connection between the income and outcome calculation weight.
- Activation function.
  Which indicates as $\varphi(.)$ this function consists of two sub-actions 1) Unipolar sigmoidal function $f(x) = \frac{1}{1+e^{-x}}$ and 2) Bipolar sigmoidal function $f(x) = \frac{1-e^{-x}}{1+e^{-x}}$
- Output function (that gives sufficient power)
- Error and back propagated value (the wrong operating unit)
- Learning function (plays under condition of requirement).
  Weight on the inputs of each processing components as per some neural based algorithm, generally the weight updating is given as:

$$\Delta w_{ij} = \delta \Delta E$$

Δw_{ij}= change in the weight linking a_i and a_j neuron
δ =learning constant
$\Delta E = \frac{\partial E}{\partial E_{ij}}$that is derivative of energy function

Experimental setup

Data used in proposed method was collected from Al-Naseria thermal generated plants in Iraq, in which contains of 10 units (each identical of 45 M) and constraints for each units was the same, which were maximum load, minimum demand wind affected, water supported, and all physical and environmental criteria. These constraints were considered as nodes, for each layer some of them were constant for all procedure and some of them were varied during the process such as fuel, load demand and etc. Transformation of some constraints from one layer to another was reflected in the training process. When increasing the number of fixed constraint within the system, it gave the system more stability. Calculating the wait of each hidden layer was depended basically on this wait. Inputs to the system mainly are 16 and the outputs should be 5 for the output layer as shown in Table 2.

Table 2 structure of proposed system.

Input	stages	Number of hidden layer (with iteration)	Wait and constraints (nodes)	output
16	1	3	25	5
	2	8	21	
	3	6	15	
	4	5	19	
	5	4	9	

Experimental setup and results

Artificial intelligent system was aimed to run the system smartly by prediction of the variable inputs. For this reason, neural network was used in proposed system to control more on the units in the generators plants. Every system was needed to train in advance to become reliable and this training was based on how the system would response against different varying constraints, with our system the weight of each time of training was considered and the main issue with each process was weight calculation which was determined with other little constraints number of hidden layer used to specifywhich unit would be off and on. Table 3 shows the training and testing system from different layers.

Table 3 performance of the system within training and testing.

stages	layers	Training %	Testing %	MSE for training	MSE for testing
1	3	50.2	45.4	0.05	0.08
2	8	59	49	0.09	0.05
3	6	61.3	32	0.13	0.09
4	5	58.8	44.1	0.11	0.8
5	4	55	39.9	0.93	0.12

EXPERIMENT AND SIMULATION

Problem formulation

Firstly we started from problem formulation, which was focused on the analysis of the artificial neural network model performance to carry out demands and loads that were carried out in different stages:

1. Selection of optimal architecture
2. Training of patterns
3. Validation and testing.

Learning of neural network could be done in different ways. A network could be trained by carrying out structure learning or parameter learning or both simultaneously or separately. Structure learning involved varying the topology or the basic structure of the network. It was executed by either adding or eliminating existing connections. Varying number of processing elements by modifying connection type that was feed forward network with self-loops etc. parameter learning was carried out by controlling the set of weights or by modifying learning constants or type of activation function used. Here, the different topologies could undergo structure learning and then the optimal, selected network would undergo parameters learning using back propagation algorithm.

Secondly, selection of network configuration (structure learning)

Major factors which have an impact on load consumption were recognized. Number of input parameters that relayed on number of effective parameters were considered such as weather data, load data, and time factor. The impact of different combinations of multilayer networks, hidden layers and hidden nodes on the forecasting error were analyzed. The relative accuracy of different types of neural network architectural combinations was estimated.

With too many trainable units, the network was failed to learn the training data and performed poorly on the testing data. Whereas, if the number of neurons in hidden layers was not sufficient, it might difficult for the network to train according to historical data.

Some real time data such as:

- Weather data
    - Temperature of hour of the day
    - Humidity of the day
    - Wind speed of the day

- Calendar variable
    - Hour of the day
    - Day of the week
    - Month of the year
- Hourly load demand

Three categories of day type that were weekdays, weekend, and holidays have been considered in the study as the load consumption was not the same on working day as compared to the weekends, and holidays. Status of days was tabulated in Table 1.

Table 1 Status of days.

Day Type	Status
Weekday	1
Weekend	0.5
Holiday	0.1

Hours variable was referred to hour of the day as load was kept on varying during the day from one hour to another. Hit and trail method was used in order to estimate the size of hidden layer, besides the number of hidden neurons was the fraction off. These hidden neurons have variable number of nodes and depended on minimal error that would allow the addition and deletion of neurons at the hidden layer. The change in the number of neurons was increased and decreased, which reflected on the performance of network until it was settled for certain nodes. To transfer between sigmoidal function of two variables of -1 to +1 (bipolar) and 0 to 1 (unipolar), we used:

$$a(f) = \frac{2}{1 + e^{-\gamma f}} - 1$$

Where a(f) represents the activation function
f is value of additive
and γ is steepness of curve
Important criteria to evaluate the unit's performance was considered as Mean Square Error (MSE) which was squared prediction error and could be obtained by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(d_{i-}y_i)^2$$

Where d_i is the target output that covered the i^{th} inputs
y_i is actual output over i^{th} inputs
n= all count of inputs
The second important criterion was training time which was the time taken to train the network according to set of parameters for training and measuring by second.

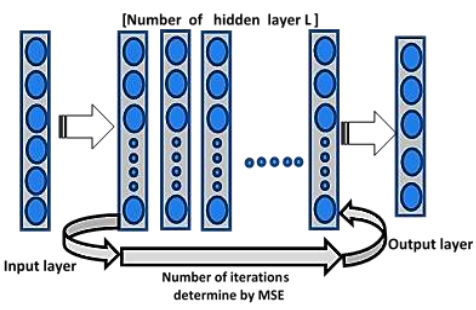

Fig. 3 Neural network representation.

Simulation results

During training, the system changes would fall in hidden layer, then number of nodes would be dynamic under condition of MSE until the system has been settled as shown in Fig. 3. The feedbacks could be considered as input from one hidden layer to another. This iteration could validate the system during training phase and determine when it was matched between training and the system. Validation of the system reflected the appropriate point that satisfied between trains and system test. In Fig. 4, there were four attempts to validate the system, however we only ran the system approximately 100 times to reach the best point of validation and the most important attempts were shown in Fig. 4.

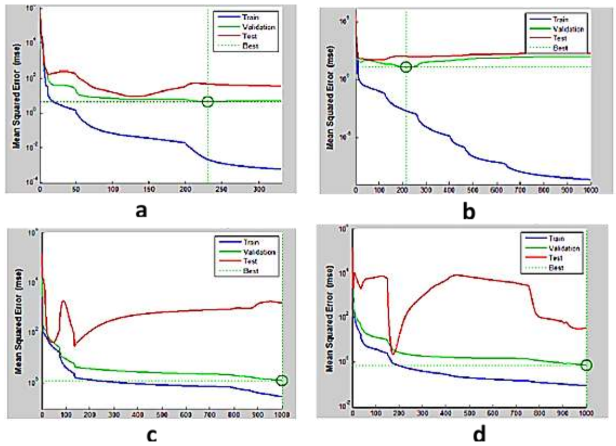

Fig. 4 Simulation results.

The network was generalized when its sensibility interpolated input patterns that were new to network. Network with too many trainable parameters for the given amount of training data set was learnt well but did not generalize well. This case was usually called over fitting. Training error was denoted in blue in the figure 4, where validation error was denoted in red.

It was observed that the system was started to over fit as the choosing number of hidden neuron was near to three times the number of input neuron. Different architectures of the network were analyzed and confined to 21 hidden neurons. The results were obtained from different networks of neural system and the performance was tested under the same criteria and environment.

In our case there were 100 runs of the system and MSE was attended to different number of hidden neuron as shown in table 4.

Table 4 MSE Obtained for 100 Times.

case	No. of neurons	MSE
1	15	0.006
2	18	0.0214
3	21	0.0181
4	23	0.004
5	25	0.015

The feedback for 15 hidden neurons in multilayer network was noted as the optimum hidden layer because of the least Mean Squared Error (MSE). As we could see in the table above, number of neurons, 23 was the best instance that resulted in minimum MSE. At this stage we tried to settle the network and keep the criteria under certain condition.

CONCLUSION

The most important issue with unit commitment is how to reduce the cost when the demand is considered normal and high. The cost in general is defined as fuel and time of supporting power. Existing methods might be costly due to no synchronization during the operation of the units. However, using intelligent methods such Artificial

Intelligent (AI) could allow the system to control the providing power with demand especially in peak demand (at night). For this reason, the neural network method was used to keep the units in such a way that was able to provide the power within minimum operating units. Neural system used feedback iteration to control the units and identify which one was ready to operate according to certain conditions (such as life time of unit, generating capacity of each, etc). This method was proved to be efficient when the demand was lower than provided units. In this paper, we recommended the usage of neural network when the units were identical and have the same general conditions from manufacture. Additionally, the number of units should not exceeded 25.

REFERENCES

[1] Lin, C. E., Chen, S. T., & Huang, C. L. (1992). A direct Newton-Raphson economic dispatch. *IEEE Transactions on Power Systems*, 7(3), 1149-1154.

[2] Guan, X., Luh, P. B., & Zhang, L. (1995). Nonlinear approximation method in Lagrangian relaxation-based algorithms for hydrothermal scheduling. *IEEE Transactions on Power Systems*, 10(2), 772-778.

[3] Hindi, K. S., & Ab Ghani, M. R. (1991). Dynamic economic dispatch for large scale power systems: a Lagrangian relaxation approach. *International Journal of Electrical Power & Energy Systems*, 13(1), 51-56.

[4] Granelli, G. P., Marannino, P., Montagna, M., & Silvestri, A. (1989, September). Fast and efficient gradient projection algorithm for dynamic generation dispatching. *IEE Proceedings C (Generation, Transmission and Distribution),* 136(5), 295-302.

[5] Wang, K. P., & Yuryevich, J. (1998). Evolutionary-programming-based algorithm for environmentally-constrained economic dispatch. *IEEE Transactions on Power Systems*, 13(2), 301-306.

[6] Zhuang, F. & Galiana, F.D. (1990).Unit Commitment by Simulated Annealing," *IEEE Transactions. on Power Systems*, 5(1), 311-318

[7] Khamsawang, S., Booseng, C. & Pothiya, S., (2002). Solving the economic dispatch problem with Tabu search algorithm. *IEEE International Conference on Industrial Technology*, 1, 108-112.

[8] Roa-Sepulveda C. A., Herrera M., Pavez-Lazo B., Knight U. G., & Coonick A.H. (2003). Economic dispatch using fuzzy decision trees. *Electric Power Systems Research,* 66(2), 115-122.

[9] Tung, N. S., Kaur, G., Kaur, G., & Bhardwaj, A. (2012). Optimization techniques in unit commitment. A review. *International Journal of Engineering Science and Technology (IJEST)*, 4(4), 1623-1627.

[10]Nemati, M., Braun, M., &Tenbohlen, S. (2018). Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming. *Applied Energy*, 210, 944-963.

[11]Li, W., Peng, H. Y., Zhu, W. H., Sheng, D. R., & Chen, J. H. (2009). An immune-tabu hybrid algorithm for thermal unit commitment of electric power systems. *Journal of Zhejiang University-SCIENCE A*, 10(6), 877-889.

[12] Bello, S. A., Akorede, M. F., Pouresmaeil, E., & Ibrahim, O. (2016). Unit commitment optimisation of hydro-thermal power systems in the day-ahead electricity market. *Cogent Engineering*, 3(1), 1251009.

[13] Morales-España, G., Latorre, J. M., & Ramos, A. (2013). Tight and compact MILP formulation for the thermal unit commitment problem. *IEEE Transactions on Power Systems*, 28(4), 4897-4908.

[14] M. Tuffaha, and J. T. Gravdahl. (2013). *Mixed-Integer Formulation of Unit Commitment problem for power systems: Focus on start-up cost*. To be published in *Proceedings of the 39th Annual Conference of the IEEE Industrial Electronics (IECON'13)*, Nov. 2013.

[15] Shao, C., Wang, X., Shahidehpour, M., Wang, X., & Wang, B. (2017). Security-constrained unit commitment with flexible uncertainty set for variable wind power. *IEEE Transactions on Sustainable Energy*, 8(3), 1237-1246.

[16] Luh, P. B., Wang, Y., & Zhao, X. (1999). *Lagrangian relaxation neural network for unit commitment.* In Power Engineering Society 1999 Winter Meeting, *IEEE*, 1, 490-495.

[17] Alzaidi, A. I., Turki, B., Mlkt, S. M., Martin, A., Hashim, O., & Gupta, N. 2014. Neuron-MOSFET junction with sodium potassium voltage gate channel. equilibrium. 2014 The Long Island Systems, Applications and Technology Conference (LISAT 2014), 2 May. Farmingdale, NY, USA: IEEE, 1-7.

[18] al-Mutoki, S. M. M., Basha, A. D., Mnaathr, S. H., Atiyha, B. T. (2014). Integrating Wireless Communication and Broadband Powerline Communication: Applications of Networking of Depreciation Data Acquiring System. *International Journal of Scientific & Engineering Research*, *5*(3), 825-828.

[19] Kumar, S. S., & Palanisamy, V. (2007). A dynamic programming based fast computation Hopfield neural network for unit commitment and economic dispatch. *Electric power systems research*, 77(8), 917-925.

[20] Ouyang, Z., & Shahidehpour, S. M. (1992). A hybrid artificial neural network-dynamic programming approach to unit commitment. *IEEE Transactions on Power Systems*, 7(1), 236-242.

[21] Ronne-Hansen, P., & Ronne-Hansen, J. (1991). Neural networks as a tool for unit commitment. In *Proceedings of the First International Forum on Applications of Neural Networks to Power System. IEEE, pp. 266-270, International Forum on Applications of Neural Networks to Power System, Seattle, USA: IEEE.*

[22] Jahromi, M. Z., Bioki, M. M. H., Nejad, M. R., & Fadaeinedjad, R. (2013). Solution to the unit commitment problem using an artificial neural network. *Turkish Journal of Electrical Engineering & Computer Sciences*, 21(1), 198-212.

[23]Nayak, R., & Sharma, J. D. (2000). A hybrid neural network and simulated annealing approach to the unit commitment problem. *Computers & Electrical Engineering*, 26(6), 461-477.