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# Artificial Neural Network Based Particle Swarm Optimization for Microgrid Optimal Energy Scheduling

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***Abstract*- This paper proposes an enhancement for artificial neural network (ANN) using particle swarm optimization (PSO) to manage renewable energy resources (RESs) in a virtual power plant (VPP) system. This study highlights on the comparison of the ANN-BPSO algorithm with the original BPSO algorithm. The comparison has been made upon searching the optimal value of the number of nodes in hidden layers (N) and the learning rate (LR). These parameter values are used in ANN training for microgrid optimal energy scheduling. The proposed approach has been tested on the VPP system covering microgrids (MGs) involving RESs to minimize the power and giving priority to sustainable resources to participate instead of buying power from the utility grid. This model is tested using real load demand recorded for 24 hours in Perlis state, the northern part of Malaysia. Besides, real weather condition data are recorded by Tenaga Nasional Berhad Research (TNBR) solar energy meteorology for a 1-hour average (e.g., solar irradiation, wind speed, battery status data, and fuel level). Results show that ANN-PSO gives precise decision compared to BPSO algorithm which in turn prove that the enhancement for the Neural Net reaches the optimum level of energy scheduling.**

***Index Terms*—**ANN, optimization algorithm, microgrid, scheduling, energy management.

## I. Introduction

In the past, the integration of renewable energy resources (RESs) to utility grids, besides their impacts on power system operation, was low. However, year by year, the DESs, especially renewable energy resources (RESs) start to lead the power industry, and many countries invest a high budget in this direction [1]. As these power units are small, aggregation in the MG system has become a trend. However, RESs would cause problems in operations and distribution systems due to the intermittency and uncertainty natures. Thus, to improve their operation, energy management (EM) or scheduling is a very important feature [2].

With the existing scheduling controller advancement, many optimization techniques have been used, such as evolutionary algorithms, genetic algorithm, and ant colony algorithm as in [3-5]. But, in order to get the optimal fitness function, the algorithms may struggle by its complexities and coding difficulties of their parameters [6]. The gravitational search algorithm [7], lightning search algorithm [8], and artificial bee colony search algorithm [9] are dealing with EM in MG enhancement to resolve significant associated problems. These algorithms got complex parameter calculation, limitations, coding difficulties, formulation, and extensive computational time for the best fitness satisfaction. The PSO is also used for MG scheduling as in [10].

Moreover, based on the literature, there are still limitations related to the fuzzy logic controller and adaptive neuro-fuzzy inference system for scheduling controllers [11]. Thus, ANN-based optimization techniques are a good alternative in the simulation tools to generate incomparable solution predictions and controller enhancement. Therefore, an improved artificial neural network-based binary particle swarm optimization (ANN-BPSO) controller is proposed in this study to overcome the limitation of the aforementioned algorithms.

In this study, the proposed algorithm is to develop an ANN-BPSO schedule controller as an upgrading step for the optimal schedule controller by ANN to manage RESs in a virtual power plant (VPP) system by binary particle swarm optimization (BPSO) algorithm. The proposed approach has been tested on the VPP system covering microgrids (MGs) involving RESs to minimize the power and giving priority to sustainable resources to participate instead of buying power from the utility grid refer to [12] whereas, Fig.1 shows a sample of load data hourly active and reactive power load of bus 2 represent an industrial load and Fig.2 shows the Simulink model. In addition, the real weather conditions data recorded by Tenaga Nasional Berhad Research (TNBR) solar energy meteorology 1-hour average, for example, solar irradiation, wind speed, battery status data, and fuel level refer to [12] Table I, represent controller inputs data. This study contributes further improvement of the BPSO algorithm by enhancing ANN parameters using PSO optimization and training ANN on the optimal schedule as output data and controller input similar to the BPSO algorithm.

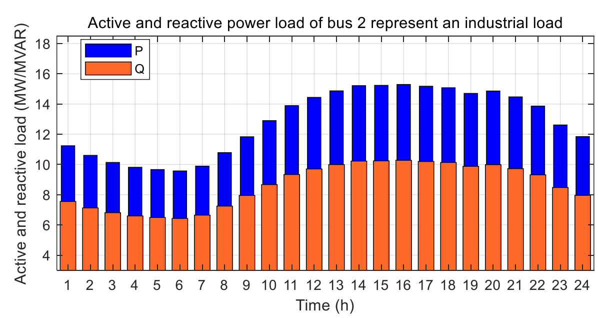


Fig. 1. The hourly active and reactive power load of bus 2 represent an industrial load.

## II. PSO based ANN algorithm

The PSO algorithm is adopted to search for the optimal number of neurons in each hidden layer of the ANN to enhance its performance. The proposed ANN-based PSO is utilizing the BPSO optimal schedule controller refer to [12]. PSO picks the optimal value of nodes in each hidden layer as well as the learning rate (LR) value. Table I representing controller constrains inputs for 24 hours. The implementation begins with setting the PSO parameters, namely, maximum iterations, number of particles, social rate, and cognitive rate.

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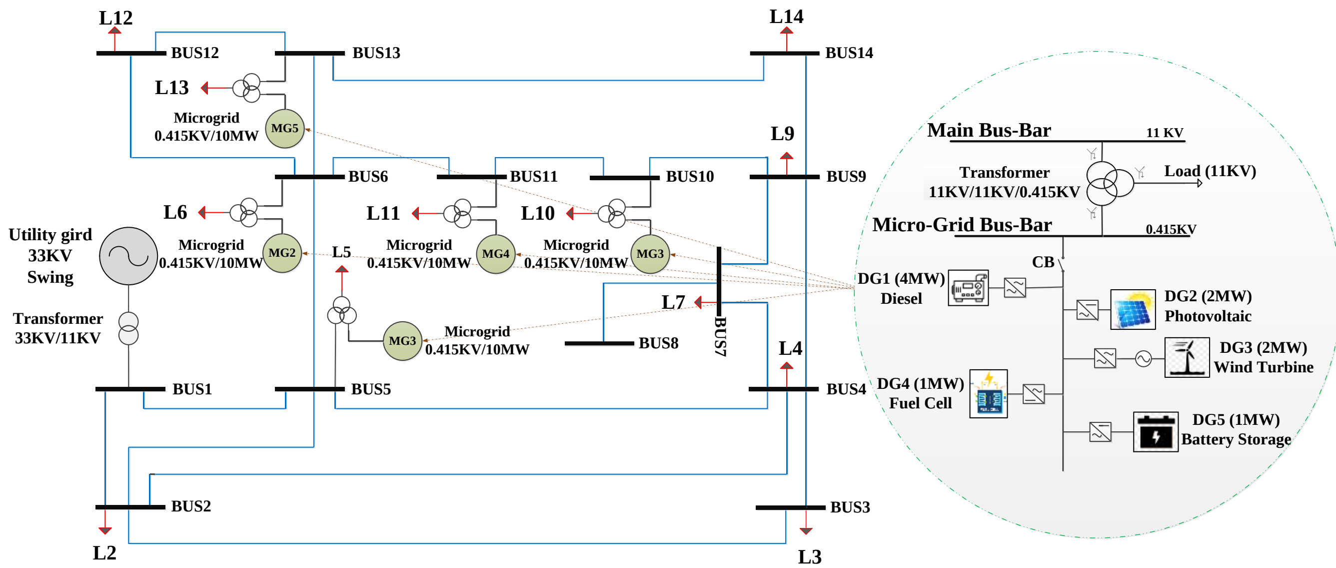


Fig. 2. Simulink model of modified 14-Bus IEEE test system in form of Virtual Power plant involving five MGs and distributed generators

TABLE I
WEATHER CONDTIONS, ELECTRCITY PRICE AND BATTERY STAT-OF-CHARGE FOR 24 HOURS

| Time (h) | Solar Irr ($W/m^2$) | Wind Speed (m/s) | Gird hourly Prices (KWh/RM) | State-of-Charge (%) |
|---|---|---|---|---|
| 1 | 0 | 1.2 | 0.218 | 100% |
| 2 | 0 | 1.4 | 0.218 | 100% |
| 3 | 0 | 0.9 | 0.218 | 75% |
| 4 | 0 | 0.5 | 0.218 | 75% |
| 5 | 0 | 0.6 | 0.218 | 70% |
| 6 | 0 | 0.6 | 0.218 | 50% |
| 7 | 0 | 0.7 | 0.218 | 50% |
| 8 | 0 | 0.6 | 0.218 | 25% |
| 9 | 128 | 1.3 | 0.516 | 25% |
| 10 | 311 | 1.5 | 0.516 | 50% |
| 11 | 430 | 1.6 | 0.516 | 50% |
| 12 | 486 | 1.6 | 0.334 | 25% |
| 13 | 610 | 1.6 | 0.334 | 25% |
| 14 | 486 | 1.5 | 0.516 | 50% |
| 15 | 345 | 1.6 | 0.516 | 50% |
| 16 | 112 | 1.3 | 0.516 | 25% |
| 17 | 99 | 1.4 | 0.516 | 25% |
| 18 | 65 | 1.4 | 0.516 | 25% |
| 19 | 35 | 1.4 | 0.334 | 25% |
| 20 | 0 | 1.6 | 0.334 | 50% |
| 21 | 0 | 1.9 | 0.334 | 50% |
| 22 | 0 | 2 | 0.218 | 50% |
| 23 | 0 | 2.2 | 0.218 | 75% |
| 24 | 0 | 1.7 | 0.218 | 100% |

After the search for the targeted objective function based-mean absolute error (MEA) can be founded by the sum of all error and dividing by a number of samples. Determine the minimum value of evaluation (fbest) along with its location (best) to find the new value of LR, N1, N2 based on the speed. Subsequently, check LR, N1, N2 if it is greater or smaller than predefined limits. The objective function is formulated based on the mean absolute error (MAE). The optimum values of LR and the number of neurons in the hidden layers are utilized in the ANN training to minimize the MAE. After updating all the values, the procedure is repeated for calculating the objective function by computing the error [13]. Finally, finding MEA by the sum of all errors and dividing on number of samples to get the best value number of the learning rate, number of nodes of layer 2. Table II shows algorithm limitations and data parameters.

TABLE II
ANN-BPSO CONTROLLER DATA AND LIMITATION

| | Symbol | Description |
|---|---|---|
| Algorithm Limitation Controller data | $p$ | controller input data |
| | t | controller output data |
| | C1 and C2 =1.5<br>W=0.5 | problem dimension |
| | $iteration_{ANN} = 100$ | maximum iterations for ANN |
| | $swarm = 20$ | swarm-size |
| | $Lower_{LR} = 0$ | min value of learning rate |
| | $Upper_{LR} = 1$ | max value of learning rate |
| | $Lower_{N1} = 1$ | min value of nodes in hidden layer1 |
| | $Upper_{N1} = 30$ | max value of nodes in hidden layer1 |
| | $Lower_{N2} = 1$ | min value of nodes in hidden layer2 |
| | $Upper_{N2} = 30$ | max value of nodes in hidden layer2 |

*A. Initialization*

The initialization stage is to set algorithm limitations, swarm-size, and iterations. Creating a matrix of 20x3 as in (1) and then determine initializes swarm position in search space.

$$swarm = zeros_{(swarm-size,3)} \tag{1}$$

*B. Run ANN in PSO optimization iteration*

Applying feed-forward neural network and levenberg-Marquardt to the initial PSO as in (2) after that the error can be obtained from ANN equations as in (3). Moreover, MAE is achieved by equation (4).

$$net = newff\,(minmax_{(p)}, [N1, N2, 25], \{'tansig', 'tansig', 'purelin'\}, 'trainlm') \tag{2}$$

$$error = abs\,(t - y) \tag{3}$$

$$MAE = \sum_{i=1}^{25} Sum(errori) \,/\, (4800 \times 25) \tag{4}$$

*C. Internal Loop*

Every iteration (*fbest*) is carrying the minimum value of evaluation, and (*best*) is the location of the minimum values of evaluation. PSO main equation is developed to calculate the best swarm and location in the search space. The finding of the new value of LR, N1, N2 based on speed are obtained based on (5) and (6), as follows:

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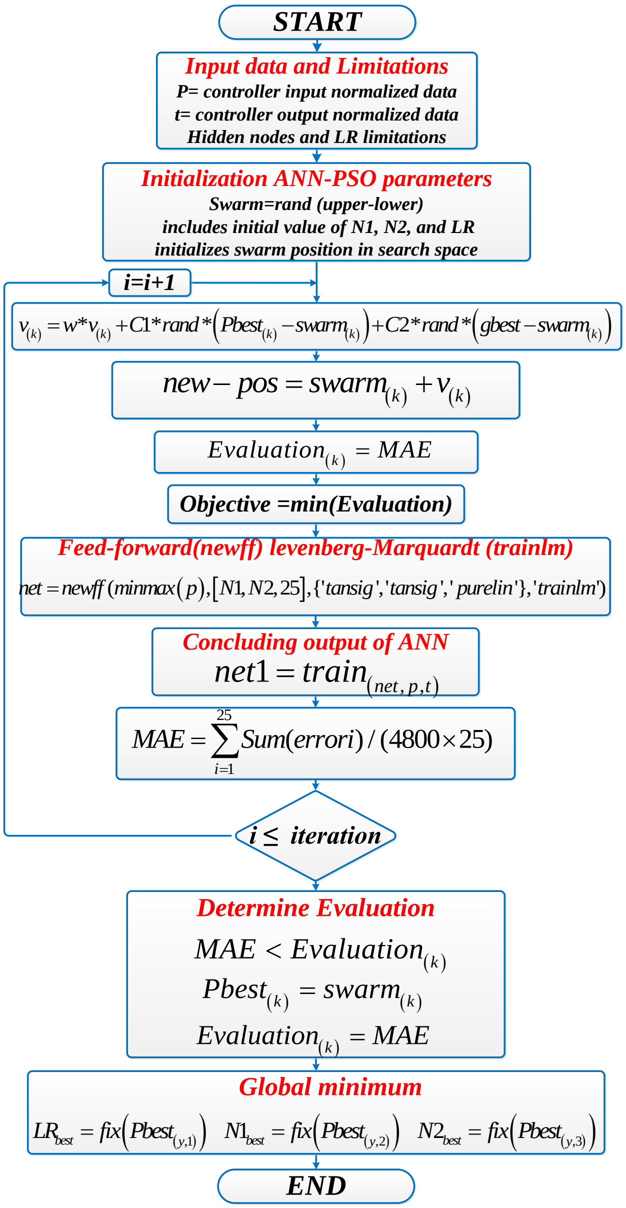


Fig. 3. ANN-BPSO algorithm Flow chart.

$$v_{(k)} = w * v_{(k)} + C1 * rand * \left(Pbest_{(k)} - swarm_{(k)}\right) + C2 * rand * \left(gbest - swarm_{(k)}\right) \tag{5}$$

$$new - pos = swarm_{(k)} + v_{(k)} \tag{6}$$

The obtained values of N1, N2, and LR are expected on Feedforward neural network (*newff*) and levenberg-Marquardt (*tainlm*) again, then evaluate the MAE as in ANN stage last is evaluation the minimum target values of ANN parameters as in (7)(8)(9).

$$Evaluation_{(k)} = MAE \tag{7}$$

$$\text{objective}_{(i)} = \min(\text{Evaluation}) \tag{8}$$

$$[x, y] = min(Evaluation) \tag{9}$$

Finally, from the above equations, the best value number of the learning rate, the number of nodes of layer1, and the number of nodes of layer2 can be obtained. The ANN-based PSO is achieved fully and illustrated in the flow chart as shown in Fig.3. the objective function considered in the optimization is minimizing the MAE. So, in every iteration, it will be compared with the minimal error held, and at the end of optimization, the minimalist MAE error swarm includes the best values for (N1, N2, and LR).

## III. ANN ALGORITHM TRAINING

Sigmoid function has been adopted for the proposed ANN as an activation function [14]. However, in this study, the ANN structure established consists of an input layer, two hidden layers, and an output layer. The input layer has six inputs, and the output layer has twenty-five outputs. The two hidden layers are used the number of neurons in the first hidden layer and the second hidden layer as well. Explains the strategy of ANN training based on the optimal schedule controller. Execute ANN training using the optimal parameters obtained from Hybrid ANN-PSO. The training process includes 100% of the data of the VPP system inputs and output on the same loading conditions obtained as in [12]. The final intelligent masterpiece is created according to (10). It is an ANN net for BPO, which can consider as an intelligent controller without any human interruption. The proposed ANN training based on optimal schedule controller steps is illustrated Pseudo-code in Table III. Using the Feed-forward neural network, which biologically inspired classification algorithm involves multilayer to train neural networks with the two layers selected and the Levenberg- Marquardt algorithm is specifically designed to minimize the sum of square error functions.

$$gen\,si\,m(Net1, -1) \tag{10}$$

TABLE III
PSEUDO-CODE OF THE PROPOSED ANN TRAINING BASED OPTIMUM SCHEDULE CONTROLLER

*Input:* *(controller input optimum schedule), t (controller output based optimum schedule).*
*Output: ANN-Net*

*N1=26*
*N2= 29*
*LR= 0.1021*
**// ANN**
Applying Feed-forward neural network ( $newff$ ) and levenberg-Marquardt ( *trainlm* )
$net = newff(minmax_{(p)},[N1,N2,25],\{'tansig','tansig','purelin'\},'trainlm')$
$net * trainParam * epochs = 4000$
$net * trainParam * lr = LR$
$net * trainParam * goal = 0$
$net1 = train_{(net,p,t)}$
$gen\,sin(Net1, -1)$
Output is a ANN-Net with 6 signals input data and 25 signals outputs

## IV. ANN BASED BPSO RESULTS

By using the ANN training data, the PSO searches the optimal values of learning rate and the number of nodes in each hidden layer to enhance the ANN performance in predicting the optimal ON/OFF status of each DG. Several populations are executed to permit the PSO to select the population size that can give minimum error and consumption time. Therefore, the minimum objective function value can be achieved by selecting the best number of population sizes to improve the ANN's performance during training and testing. The objective function is formulated in terms of MAE of ANN population sizes are obtained, as shown in Fig 4. Neural Network Training in MATLAB is shown in Fig 5. In this study, the actual measured data were allocated such that 100%

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of the data were used for training and testing of ANN as compare to the original BPSO algorithm in [12]. Fig. 6 shows the regression (R) of the hybrid ANN-BPSO using the training and testing data. Moreover, the performance of the hybrid ANN-BPSO training is shown in Fig. 6. The regression coefficient (R) is a good indicator for evaluating the prediction performance of the hybrid ANN-BPSO. From Fig. 7, the epochs 4000 iterations were done in a good time frame which was 8h:57min:12sec. The best training performance of mean squre error (MSE) reached 7.33e-7 to satisfy the hybrid ANN-BPSO performance's optimal prediction. Overall, the regression coefficient results are perfectly and successfully reach unity; hence validate the accuracy of the algorithm.

The results of the hybrid ANN-BPSO for predicting the optimal ON/OFF status of the energy management components is shown in Fig. 8. The best schedule is obtained by the hybrid ANN-BPSO optimization in order to explain the performance of every DG inside the MGs. It can be seen that there is a unique behavior for each source which in turn tested in the IEEE 14-bus system with MGs by selecting to represent the performance in MG1 at bus5 in the VPP system compare to the original BPSO. Similarly, Fig. 9 shows the load management of MG5 at bus13 using optimization algorithms.

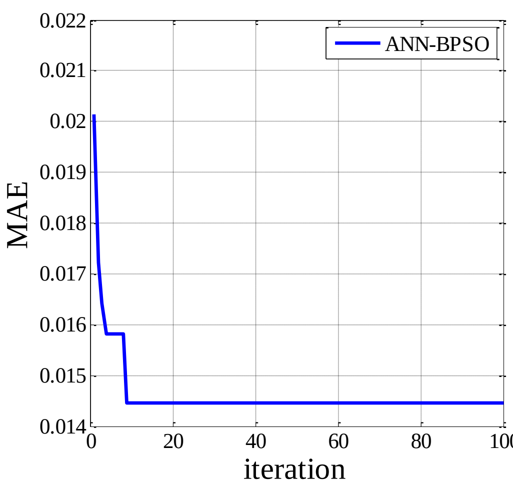


Fig. 4. MAE of the hybrid ANN-BPSO objective.

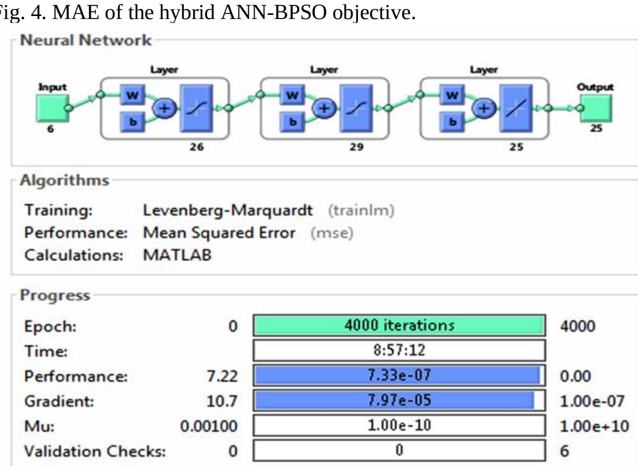


Fig. 5. Neural Network training in MATLAB.

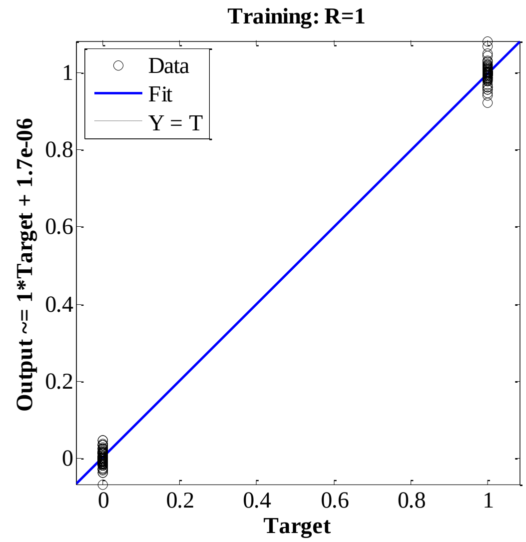


Fig. 6. Neural Network training Regression;

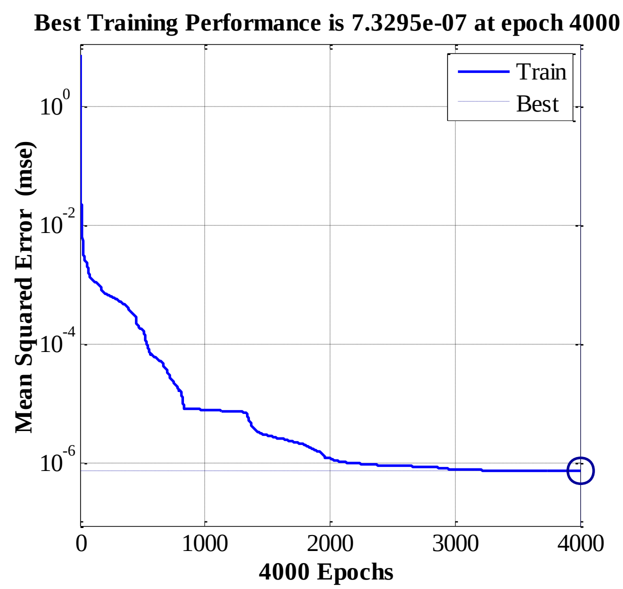


Fig. 7. Neural Network training Performance.

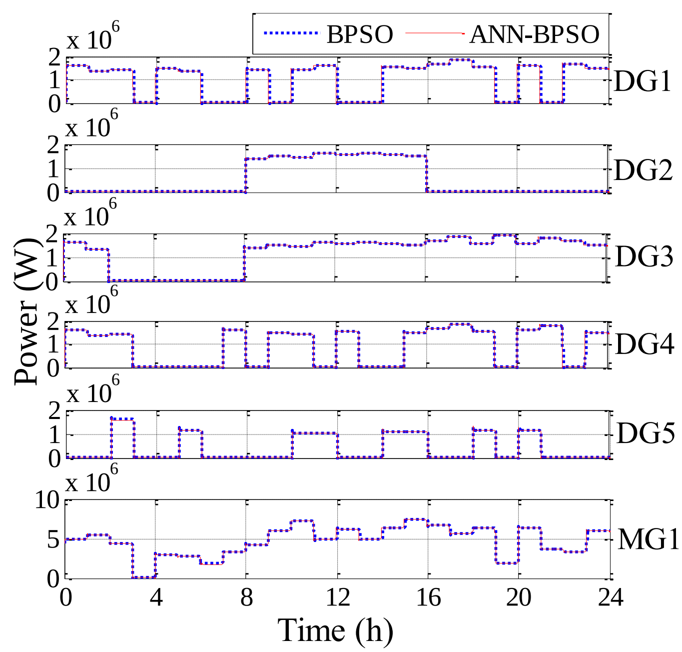


Fig. 8. DGs and MG real and predicted power for MG1 at bus 5 using the hybrid ANN-BPSO.

In Fig. 10, a comparative study has been conducted to show the effectiveness of the developed ANN-BPSO algorithm in which the main grid power at bus 1 is compared with no grid connection, random schedule, and BPSO optimized schedule, respectively. It is seen that the power drawing from the main grid is extremely reduced when optimized algorithms are used, which in turn is an energy-saving concern. Table IV compares the proposed technique with other techniques of enhancing neural networks. The excellent results obtained compares to the other techniques considering the enormous number of inputs and output and the performance time, which required more complexity in the ANN Net. Generally, all the techniques used in this table enhance the ANN by optimizing its parameters. It helps save the wasted time on trial and error and focus on training and testing with confidence on chosen parameters.

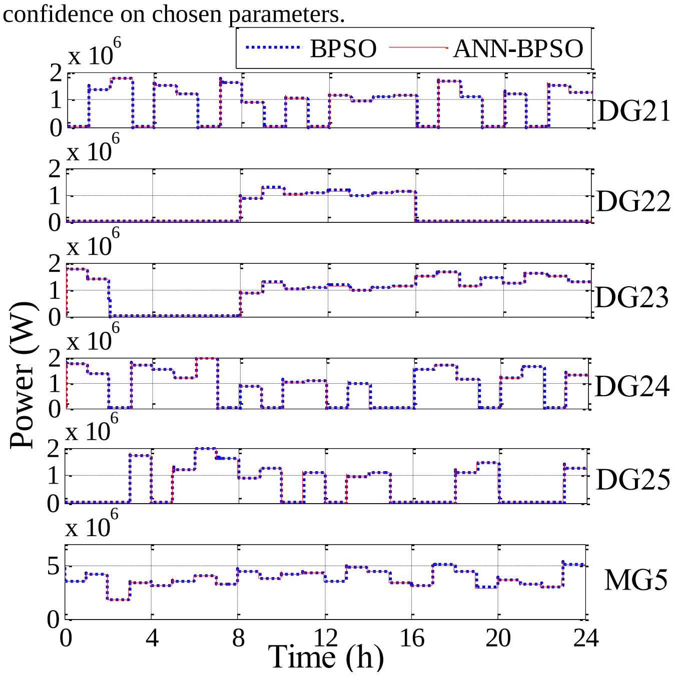


Fig. 9. DGs and MG real and predicted power for MG5 at bus 13

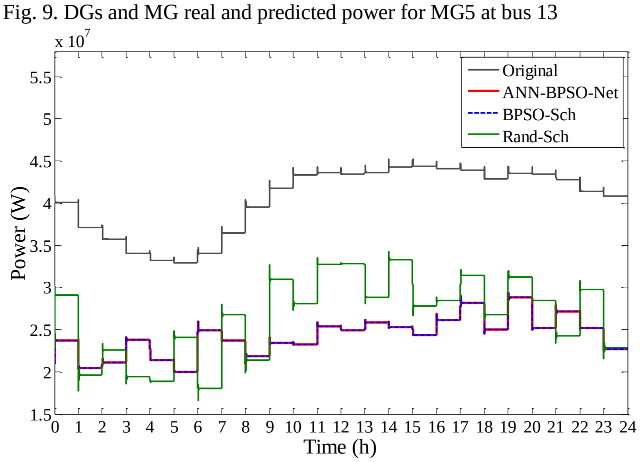


Fig. 10. MG with Random Schedule controller, BPSO schedule controller, and Neural Net obtained by ANN-BPSO and original main power.

TABLE IV

COMPARISON OF THE PROPOSED TECHNIQUE TO WITH OTHER TECHNIQUES OF ENHANCING NEURAL NETWORKS

| Ref. | MAE | N1 | N2 | LR | No. of input & output | R | MSE |
|---|---|---|---|---|---|---|---|
| hybrid LSA-ANN [15] | 9.128 e-9 | 6 | 4 | 0.6175 | 5 and 4 | 1 | - |
| PSO-DNN [16] | - | 20 | 60 | 0.1 | 12 and 6 | - | - |
| Hybrid ANN-PSO [17] | 0.1742 | 18 | 16 | 0.071 | 3 and 1 | 0.99991 | - |
| BPNN-PSO [18] | 0.1911 e-02, 0.20 e-02 | 14, 9 | 9,1 1 | 0.7373, 0.6481 | 7 and 1 | 0.99993, 0.99999 | 4.3 e-05 |
| **ANN-PSO Proposed** | 0.0144 | 26 | 29 | 0.1021 | 6 and 25 | 1 | 7.32 e-07 |

## V. Conclusion and Future Work

The results of the ANN-based BPSO for predicting the optimal ON/OFF status of the energy management components is considered as a new technique for improving the ANN performance by selecting the optimum learning rate and the optimum number of neurons in the hidden layers and then get a more accurate prediction. The performance of MAE reduced to a significant amount which shows the perfectly of optimizing ANN parameters. This may open the door for optimizing other parameters such as the number of hiding layers or using the optimal schedule data to other deep learning techniques such as the support vector machine.

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