Particle Swarm Optimization Based Demand Response Using Artificial Neural Network Based Load Prediction

Nasrin Bayat, Joon-Hyuk Park

Department of Electrical and Computer Engineering
University of Central Florida
Orlando, FL, USA
nasrinbayat@knights.ucf.edu, JoonPark@ucf.edu

Abstract—A new optimization method for Demand Response (DR) using Particle Swarm Optimization (PSO) is developed and validated where load prediction is done using Artificial Neural Network (ANN). The electrical load and climatological data of a residential area in Austin, Texas are used as the inputs of the ANN. Then, the outcomes with the day-ahead prices data are used to solve the load shifting and cost reduction problem. The results indicate that, the proposed model demonstrates the capability to optimize demand response and improve accuracy in load prediction, thereby reducing the cost and peak load.

Index Terms—demand response, differential evolution, artificial neural network, load forecasting, particle swarm optimization, smart grid.

I. INTRODUCTION

In the recent decades, we have been facing energy and environmental crisis, rapidly consuming natural resources and bringing global climate change. Smart grids are considered as a solution for these problems [1]. One of the most important goals in smart grid is energy efficiency [2]. Therefore, in order to enhance the efficiency, new approaches, such as demand response (DR), are incorporated into smart grid. The DR program can persuade end-user customers change their electricity usage pattern, by offering incentives to save their electric bills, save energy, and to help optimize the grid operation [3]. There are three types of consumers that the DR programs are applied: residential, commercial and industrial consumers. A residential DR is presented in [4], which is based on adaptive consumption pricing and enables customers to lower their energy consumption and utilities to manage total load. The proposed model encourages consumers to have an active participation in the DR program by fitting energy costs to consumers’ consumption levels. An incorporation of energy storage systems (ESS) that operate as loads, such as electric vehicle (EV) and uninterruptible power supply (UPS) with the help of DR for minimizing the costs is presented in [5]. Due to fast response and flexibility, electrically-driven water facilities, like pumps and desalination plants, can serve as virtual energy storage systems or virtual power plants in the DR program [6]. The loads are planned with the help of particle swarm optimization (PSO) algorithm. PSO is an effective way of solving large-scale non linear optimization problems [7]. PSO based DR methodology that contributes to making the load curve flatter is presented in [8]. Load shifting DR technique is used to modify the load curve of the system. A PSO based methodology, is proposed in [9] where the goal was to help a hypothetical power player that manages the resources in a distribution network and the network itself, in reducing operation costs. In the present work, PSO is suggested to solve load shifting DR management problem.

In addition, electrical load forecasting plays a vital role in achieving the concept of the next generation power system such as efficient energy management, smart grid and better power system planning. In general, load forecasting can be divided in three classes on the basis of time intervals, namely long, medium and short term load forecast. Short term load forecast plays a crucial role in efficient control of spinning reserve, unit commitment and evaluation of sales or purchase contracts between different companies [10]. Recently, soft computing methods has proven to be more effective in forecasting than traditional methods. Among soft computing methods, artificial neural network (ANN) is the most commonly used forecasting method [11]. ANN can be defined as an array of fundamental processors called neurons, that are highly inter-connected [12], and a perfect depiction of it is presented in [13], [14]. ANNs have been applied to a plethora of areas of statistics such as time series prediction [15], [16], and [17]. In this paper a time series prediction method and the multi layer feed forward ANN model that can learn complicated and non-linear relationships is employed to predict short-term load based on electric power consumption and climatological data of a residential area in Austin city. After this introduction section, section II explains the problem formulation and the detailed methodology. Simulation results are presented in section III, and conclusions are given in section IV.

II. PROBLEM FORMULATION AND METHODOLOGY

A. Detailed Methodology

First, the hourly electric power consumption data of a residential area in Austin is obtained from the Electric Reliability Council of Texas (ERCOT) [18], and the corresponding
local climatological data is extracted from National Centres for Environmental Information database [19]. Furthermore, day-ahead hourly prices are obtained from [20]. Data pre-processing and feature selection play an important role in machine learning. There are different methods for pre-processing and extracting features from data set [21], [22]. Bag-of-words feature representation method is used in [23] which demonstrates superior performance compared to statistical feature extraction methods. In bag-of-words method, the dataset is divided into sliding windows and similar sequences of data are given the same word. In this way we will have a combination of words which are then be used to classify different patterns of the data [23]. In this paper, pre-processing is done by normalizing ANN input data to [-1,1] range, to avoid convergence problems. ANN is represented as a set of layers, which are divided into three categories namely, input, hidden, and output. In terms of the number of hidden layers and neurons in each layer, we empirically optimized them by altering the number of neurons from 15 to 70, and best number of hidden layers is determined to be 4, with 25 neurons in the first layer, 20 in the second and 15 in the third layer and 1 in the output layer. If the number of neurons in the hidden layer is too big, the model can be overfitted with a small fluctuation in the data. On the other hand, if it is too small, the ANN can not predict properly. The type of training function is "TANSIG". The dataset during the first four months of 2010 is separated into two subsets. The first subset which starts from first of the January to April 6, is the training subset, and the second one which starts from April 7 to April 30, is the test subset. Second, an ANN model is used to predict day-ahead electric load. The inputs of ANN are hourly average wind speed, outside temperature, average heat index, average cold index, average dew point, and hourly power consumption of previous hours. The target is the 24 hour-ahead electrical demand. Third, to solve the load shifting problem, PSO algorithm is implemented and evaluated using MATLAB. The problem formulation of this part is based on the DR load shifting strategy given in [17]. The PSO method is based on the mathematical model proposed in subsection B. The goal is to minimize load shifting and energy operation costs. The objective function includes two normalized terms, load shifting and cost. In order to provide a give-and-take between load shifting and total operating costs, weighting coefficients are used. They provide a set of solutions and based on the preferences and energy management capabilities, the best solution will be achieved. There are several factors that can affect the preferences. For instant, during a specific period of time, the minimization of the load shifting can be more important than reduction of the costs. In this paper, Differential Evolution (DE) algorithm is also used to solve the DR program and the outcomes are compared with the PSO results. PSO and DE are meta-heuristic algorithms. They have a simple model with few parameters and have acceptable convergence. Additionally, they are population-based and derivative-free. PSO and DE algorithms are explained in subsection C and D, respectively. Moreover, the objective function for both of them is as stated in (1). The inputs of both algorithms are day-ahead hourly prices and ANN based hourly predicted load.

B. PSO-based DR methodology

The proposed day-ahead PSO scheme which uses ANN hourly load predictions, is formulated as the minimization problem below. Two criteria, namely normalized cost and load shifting, form the objective function, as shown in (1) [24]:

Minimize:

\[ OF = w_1 \times \frac{E_c}{E_{c_{max}}} + w_2 \times \frac{L_{sh}}{L_{sh_{max}}} + \alpha \times \text{violation} \] (1)

Where \( w_1 \) and \( w_2 \) are weighting coefficients, \( E_c \) is hourly energy operation cost (\$/h), \( E_{c_{max}} \) denotes the normalization index of cost criterion (\$/h), \( L_{sh} \) signifies total load shift in a day (KWh), and \( L_{sh_{max}} \) is the normalization index of load shift criterion (KWh). \( \alpha \) is violation coefficient. Violation is determined with (2).

\[ \text{violation} = \max \left( \left( \frac{L}{L_{h_{pre}}} \right) - 1, 0 \right) \] (2)

Where \( L \) is total load of a day (KWh), and \( L_{h_{pre}} \) is the predicted total load of that day (KWh). If violation is equal to zero, there will not be any deviation between the predicted and the optimized solution. \( E_c \) and \( L_{sh} \) are computed with (3) and (4), respectively.

\[ E_c = \sum_{h=1}^{24} L_h \times P_h \] (3)

\[ L_{sh} = \sum_{h=1}^{24} \left| L_h - L_{h_{pre}} \right| \] (4)

Where \( L_h \) is hourly load (KWh), \( P_h \) is day-ahead hourly price of energy \( \frac{\$}{\text{KWh}} \), and \( L_{h_{pre}} \) is predicted hourly load (KWh). Day-ahead hourly prices are obtained from [21].

C. Particle Swarm Optimization Algorithm

In the PSO algorithm, there are a number of candidate solutions that are called particles scattered in the search space. Each particle determines the value of the objective function using its position information. Then, it chooses a direction to move, using the information of its current position, the best position that it had experienced, and the information of one or more particles of the best particles available in the population. After a collective movement, one step of the algorithm is finished. This step will be reiterated several times until the desired solution is obtained. (5) and (6) describe the behavior of the particles.

\[ v_{t+1} = w \times v_t + c_1 \times r_1 \times (x_{t_{best}} - x_t) + c_2 \times r_2 \times (x_{t_{best}} - x_t) \] (5)

\[ x_{t+1} = x_t + v_{t+1} \] (6)

Where \( w \) is the inertial weight, \( v_t \) and \( v_{t+1} \) are velocity of the particle related to the current and the next iteration, respectively. \( c_1 \) and \( c_2 \) are local and global coefficients, respectively. \( r_1 \) and \( r_2 \) are random numbers between 0 and 1. \( x_{t_{best}} \) is the position of the best particle. \( x_t \) and \( x_{t_{best}} \) are the current position of the particle and the best position that it had experienced, respectively. Further, velocity has lower
and upper bounds. In our model, the maximum velocity is considered to be 10% of the difference between the upper and the lower bounds of the optimized load. \(c_1\) and \(c_2\) are set as 2 , and \(w\) is equal to 1. Here, the stopping criteria is the iteration number, which is equal to 100. The output will be load shifting pattern for residential customers of an area in Austin, Texas.

D. Differential Evolution Algorithm

DE algorithm uses a method to generate new solutions that are different from other evolutionary algorithms. It first generates an initial population, that all the members of this population are considered to be a solution. Next, a temporary solution using mutation operator is created, as shown in (7).

\[
y = \text{pop}_a + \beta \times (\text{pop}_b - \text{pop}_c)
\]  

(7)

Where \(y\) is the temporary solution; \(\text{pop}_a\), \(\text{pop}_b\), and \(\text{pop}_c\) are three random solutions, and \(\beta\) is a scale factor in the range of \([0.2, 0.8]\). Then a new solution with the help of the crossover operator will be created as presented in Eq. 8.

\[
z_j = \begin{cases} 
y_j & r_j \leq PCR \text{ or } j = j_0 \\
x_j & \text{otherwise} \
\end{cases}
\]

(8)

Where each \(x_j\) is a member of the initial population, and each \(z_j\) is a new solution. The steps of the DE algorithm are as follows:

1) Defining the parameters of the problem and algorithm such as population size, crossover probability, and objective function.
2) Creating an initial population and evaluating it.
3) Repeating below steps, until it reaches the maximum iteration (100).
   - Creating an initial population and evaluating it.
   - Using the crossover operator to create a new solution, then, evaluate it.
   - The new solution will be selected if it is better than the current solution.
4) The output will be the best solution found within these iterations, which is load shifting pattern and the favorable load curve.

III. Simulation Results

The model is implemented using Matlab and trained using Stochastic Gradient Descent (SGD) optimizer with a learning rate of 5e-4, a momentum value of 0.9, and 1e-4 weight decay. The model training is performed for 1000 epochs to minimize the predefined loss function. The predicted and real electrical demand for 24 hours on December 28, and September 20, are shown in Fig. 1. Fig. 2 presents the outputs of train and test data. The corresponding correlation coefficient of the training and test data, that shows the linear dependence of the predicted and the real load, is equal to 0.9983 and 0.9903, respectively. Fig. 3 depicts the training performance based on Mean Square Error (MSE). The best training performance is 0.00076 at epoch 1000. In addition, the value of MSE for the test data is 0.0043.
The results of PSO based DR load shifting for the selected days are provided in this section. Predicted load, optimized load, and corresponding costs are shown in Fig. 4 and 5. In regard to the results on December 28, peak load is reduced from 54844.932KW to 47000KW, and the daily cost is decreased from 24497.938$ to 23250.378$, leading to 5.09% cost reduction. The results of September 20 indicate that peak load is decreased from 50923.343KW to 45000KW, and the cost is reduced from 31431.06$ to 29976.657$, a 4.62% reduction. Table I shows the effect of altering $w_1$ and $w_2$, on the total cost of energy, using the predicted load of May 5. The cost of energy for the predicted load without using DR program is 31279.951$, which is more than the cost of all cases shown in Table I. As illustrated, the optimized cost varies between 28598.55$ to 30621.802$, leading to a percentage of cost reduction of up to 8.57%, and maximum percentage of peak load reduction equal to 17.9%.

Consequently, the best case is $w_1 = 0.4$ and $w_2 = 0.6$.

### TABLE I. PSO based cost results on May 5

| $W_1$ | $W_2$ | Cost ($) | Percentage of peak load reduction |
|-------|-------|----------|-----------------------------------|
| 0     | 1     | 29917.812 | 17.73                             |
| 0.1   | 0.9   | 29975.347 | 17.9                              |
| 0.2   | 0.8   | 30621.802 | 17.75                             |
| 0.3   | 0.7   | 29737.152 | 17.73                             |
| 0.4   | 0.6   | 28598.55  | 17.9                              |
| 0.5   | 0.5   | 30482.678 | 17.73                             |
| 0.6   | 0.4   | 29818.165 | 17.73                             |
| 0.7   | 0.3   | 30350.973 | 17.75                             |
| 0.8   | 0.2   | 29270.375 | 17.73                             |
| 0.9   | 0.1   | 29855.073 | 17.73                             |
| 1     | 0     | 30494.192 | 17.73                             |

In order to assess the efficiency of the proposed model, the results of the PSO algorithm corresponding to July 10, are compared with the results of the DE algorithm using the same data. Table II provides the results of these two algorithms for operating cost reduction and percentage of peak load reduction. Peak load of the predicted load is 60511.469KW and the corresponding cost of energy is 31389.529$. Both algorithms reduce cost and peak load. However, PSO shows better results in cost and peak load reduction.

### TABLE II. Peak load and cost reduction results on July 10,2010

| Algorithm | Total cost ($) | Percentage of cost reduction | Percentage of peak load reduction |
|-----------|---------------|------------------------------|----------------------------------|
| PSO       | 28929.995     | 7.83                         | 22.32                            |
| DE        | 30723.182     | 2.12                         | 15.75                            |
IV. CONCLUSION

In this paper, a multilayer feed-forward ANN model is employed for prediction of the day-ahead load and the outcomes show a near correlation with the real load with a low value of MSE. Then, PSO algorithm is used to solve the problem of day-ahead load shifting and cost saving with DR program. The proposed model, as it is illustrated with the simulation results, is effective in improving the load curve and reducing the operating costs. The percentage of cost reduction is between 4.62% to 8.57%. Moreover, peak load is decreased up to 17.9%. Finally, to evaluate the performance of the PSO algorithm the results related to a specified day, are compared with the DE algorithm results, which shows the superiority of PSO.

REFERENCES

[1] Thongchart Kerdphol, Yaser Qudaih, and Yasunori Mitani. Optimum battery energy storage system using pso considering dynamic demand response for microgrids. International Journal of Electrical Power & Energy Systems, 83:58–66, 2016.

[2] John S. Vardakas, Nizar Zorba, and Christos V. Verikoukis. A survey on demand response programs in smart grids: Pricing methods and optimization algorithms. IEEE Communications Surveys Tutorials, 17(1):152–178, 2015.

[3] Renzhi Lu, Seung Ho Hong, and Mengmeng Yu. Demand response for home energy management using reinforcement learning and artificial neural network. IEEE Transactions on Smart Grid, 10(6):6629–6639, 2019.

[4] Haider Tarish Haider, Ong Hang See, and Wilfried Elmenreich. Residential demand response scheme based on adaptive consumption level pricing. Energy, 113:301–308, 2016.

[5] Sukhlal Sisodiya, G. B. Kumbhar, and M. N. Alam. A home energy management incorporating energy storage systems with utility under demand response using pso. In 2018 IEEMA Engineer Infinite Conference (eTechNxT), pages 1–6, 2018.

[6] Mostafa Goodarzi and Qifeng Li. Evaluate the capacity of electricity-driven water facilities in small communities as virtual energy storage. Applied Energy, 309:118349, 2022.

[7] Yarnelle Del Valle, Ganesh Kumar Venayagamoorthy, Salman Mohagheghi, Jean-Carlos Hernandez, and Ronald G Harley. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Transactions on evolutionary computation, 12(2):171–195, 2008.

[8] Nandkishor Kinhekar, Narayana Prasad Padhy, and Hari Om Gupta. Particle swarm optimization based demand response for residential consumers. In 2015 IEEE power & energy society general meeting, pages 1–5. IEEE, 2015.

[9] Pedro Faria, Joao Soares, Zita Vale, Hugo Morais, and Tiago Sousa. Modified particle swarm optimization applied to integrated demand response and dg resources scheduling. IEEE Transactions on smart grid, 4(4):606–616, 2013.

[10] Muhammad Qamar Raza and Abbas Khosravi. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renewable and Sustainable Energy Reviews, 50:1352–1372, 2015.

[11] Pei-Chann Chang, Chin-Yuan Fan, and Juin-Jie Lin. Monthly electricity demand forecasting based on a weighted evolving fuzzy neural network approach. International Journal of Electrical Power & Energy Systems, 33(1):17–27, 2011.

[12] Arjun Baliyan, Kumar Gaurav, and Sudhansu Kumar Mishra. A review of short term load forecasting using artificial neural network models. Procedia Computer Science, 48:121–125, 2015.

[13] Haykin Simon. A comprehensive foundation. Neural networks, 2(2004), 2004.

[14] Yu-Jun He, You-Chan Zhu, Jian-Cheng Gu, and Cheng-Qun Yin. Similar day selecting based neural network model and its application in short-term load forecasting. In 2005 International Conference on Machine Learning and Cybernetics, volume 8, pages 4760–4763 Vol. 8, 2005.

[15] Cheng-Ming Lee and Chia-Nan Ko. Time series prediction using rbf neural networks with a nonlinear time-varying evolution pso algorithm. Neurocomputing, 73(1-3):449–460, 2009.

[16] Sven F Crone, Michele Hibon, and Konstantinos Nikolopoulos. Advantages in forecasting with neural networks? empirical evidence from the nn3 competition on time series prediction. International Journal of forecasting, 27(3):635–660, 2011.

[17] Ifat A Gheyas and Leslie S Smith. A novel neural network ensemble architecture for time series forecasting. Neurocomputing, 74(18):3855–3864, 2011.

[18] Electric Reliability Council of Texas. 2010.

[19] National Centre for Environmental Information. 2010.

[20] ComEd’s Hourly Pricing Program. 2010.

[21] Varun Gupta, Monika Mittal, Vikas Mittal, and Nitin Kumar Saxena. A critical review of feature extraction techniques for ecg signal analysis. Journal of The Institution of Engineers (India): Series B, 102(5):1049–1060, 2021.

[22] Saqib Hakak, Mamoun Alazab, Suleman Khan, Thippa Reddy Gadekallu, Praveen Kumar Reddy Maddikunta, and Wazir Zada Khan. An ensemble machine learning approach through effective feature extraction to classify fake news. Future Generation Computer Systems, 117:47–58, 2021.

[23] Nasrin Bayat, Elham Rastegari, and Qifeng Li. Human gait recognition using bag of words feature representation method. arXiv preprint arXiv:2203.13317, 2022.

[24] Nikos Kampelis, Elisavet Tsekeri, Dionysia Kolokotsa, Kostas Kalaitzakis, Daniela Isidori, and Cristina Cristalli. Development of demand response energy management optimization at building and district levels using genetic algorithm and artificial neural network modelling power predictions. Energies, 11(11):3012, 2018.