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Artificial Intelligence for Demand Side Management

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Abstract

The power system is a highly complex network due to the fact that it is a large interconnected system. The power demand is increasing exponentially with the increase in population and therefore it becomes necessary to control the power generation and load demand. If the voltage instability violates the predefined limits, then it can result in the total collapse of the power system that is a blackout. Demand-side management plays a very vital role in balancing the energy generation and power consumption to maintain the stability of the complex network which ensures a secured and healthy operation of the power system so that the operator does not have to face the condition of the black start of the generating stations due to blackout. There are various strategies for demand-side management and those are peak clipping, load shifting, valley filling, strategic growth, flexible load shape, and strategic conservation but load shifting is heavily performed by the electric utilities as it is a very reliable technique to fulfill the mentioned criteria. DSM proves to be extremely helpful as it mitigates the need of the electric utility to erect the structure for generation, transmission, and distribution in order to meet the additional power demand. In current practice, the human operator itself has to perform the DSM algorithm on the forecasted load curve which is very time-consuming. This paper proposes a model which is based on artificial intelligence which will automize the demand side management process in order to eliminate human error and to decrease the human involvement factor. This recommended model which uses artificial neural networks has the potential to forecast the load shifted curve in the hourly pattern with the help of an autoregression moving average model. The proposed model has the capacity to benefit the electric utility in automizing the demand side management process and thus will eradicate human error and decrease the human involvement factor.

Keywords: Artificial Neural Networks, Autoregression moving average model, Demand-side Management, Load Shifting.

Introduction

The power system is a highly complex interconnected network. The network is growing rapidly with the increase in the power demand with the increasing population which has made it compulsory to use modern energy management system (EMS).

In the past few decades, there has been a great shift in hardware and software technology which has transformed the power system control from simple process control to a system of distributed processing sufficient enough for supporting various levels of application functions. Moreover, advanced online monitoring system such as supervisory control and data acquisition has now given the way to full fledge use of energy management system.

These complex systems are located in the load dispatch center of a utility that performs continuous online monitoring, assessment, and analysis for a secured and economic operation of the power system network. In such a large complex interconnected network it is of utmost importance to manage the load demand with the power generation, otherwise, problems like voltage instability, voltage collapse, or blackout might take place.

As we know that there is a strong coupling between reactive power and voltage and real or active power and power angle, to avoid the above-mentioned problems we must be able to match the reactive power demand and reactive power generation through various strategies. Another important concept that can help to mitigate the problems which lead to blackout is demand-side management (DMS). The DMS is extremely useful to electric utilities in matching the load demand and power generation by applying various demand-side management strategies such as:

- load shifting,
- peak clipping,
- Strategic Growth,
- Valley Filling,
- Flexible Load Shape
- Strategic Conservation.

For the successful application of demand-side management, there is a need for accurate load forecasting which can predict future consumption of power so the utilities are well aware to take some important decisions like strategic load shedding, future expansion, and planning of generation, transmission, and distribution network.

Demand-side Management

Demand-side management is a technique by which the maximum demand during the duration of peak load is reduced by shifting some of the load in the time frame when the system does not experience peak load [1]. However due to this shifting, the total energy consumption is not affected and thus it helps the utilities to eradicate the need to develop new structures to increase their generation, transmission, and distribution capabilities. Additionally, it helps to decrease the power generation cost and effectively manage the supply and demand criteria in the electrical power network [5]. Artificial intelligence can play a great role in making the DSM process automatic as the human operator does not have to apply DSM algorithm on the load curve in order to obtain the load shifted curve. The artificial neural networks can be of great help to forecast the load shifted curve and thereby it eradicates the human efforts in applying various DSM algorithms every time.

The following figure shows various demand-side management techniques:

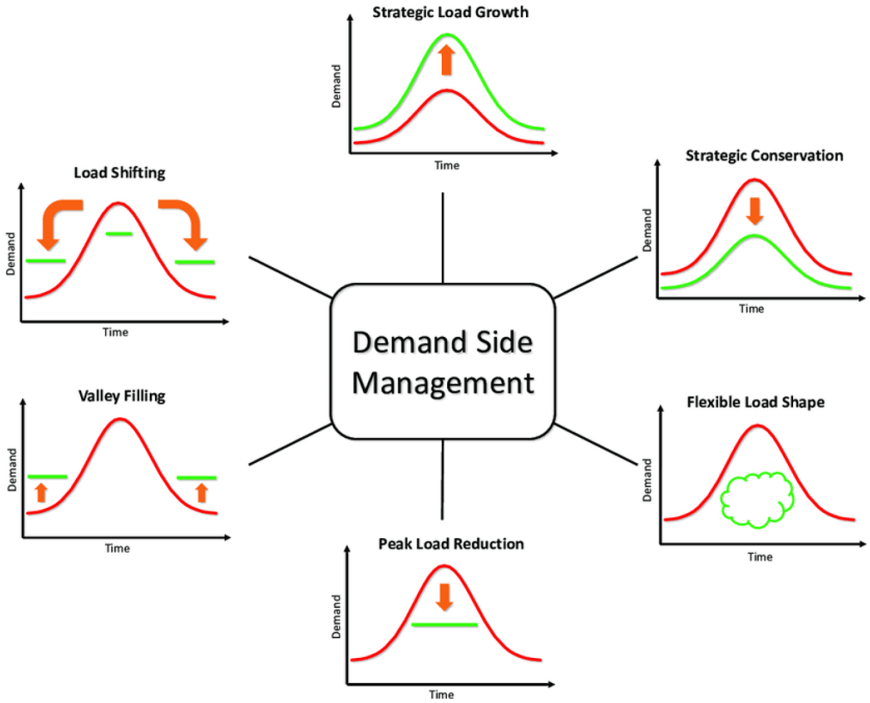

Fig. Several DSM techniques et al. [14]

Load Forecasting

Forecasting means estimating active load at various load buses ahead of actual load occurrence. Planning and operational applications of load forecasting require a certain lead time which is also commonly known as forecasting interval. The following are the various load forecasting methods:

1) Short term forecasting:
   Short-term forecasting consists of a lead time of half an hour to a few hours. It is used for framing or reviewing plans for the establishment of future points of supply for the point of view of their timings.

2) Medium-term forecasting:
   Medium-term forecasting consists of the lead time of a few days to a few weeks. Medium-term forecasting is used for formulating the immediate power development program.

3) Long term forecasting:
   Long-term forecasting consists of a lead time of a few months to a few years.

It is used to estimate the additional generation, transmission, and distribution required and helps the electric utilities to form future national power policies.

Voltage Instability

Voltage stability is the ability of a power system to maintain steady acceptable voltages at all the buses in the system under normal operating conditions and after being subjected to a disturbance [8]. The voltage stability depends greatly on the reactive power and the balance between the load demand and the power generation. The following are the causes of voltage instability:

- High reactive power consumption at heavy loads
- Generating stations are too far from load centers
- The difference in the transmission of reactive power under heavy loads
- Due to improper locations of FACTS controllers
- Poor coordination between multiple FACTS controller

Therefore, it is of utmost importance to manage the load demand and the power generation in order to keep the voltage under permissible limits and demand-side management can do this job very efficiently [11]. Many research papers are there which has provided models and solutions to predict the load demand but thereafter the human has to perform the demand side management process through certain strategies and observations which can be a time-consuming process. It slows down the overall demand-side management process due to the absence of automation and this reason has motivated us to develop a model which has the potential to automize the demand-side management process [13].

Proposed ANN model

For load forecasting, ANN is considered one of the best strategies. However, ANN has some disadvantages like it demands a lot of historical data for accurate modeling. On the contrary, ANN has the advantage of self-improving capabilities. On the regular basis, the DSM algorithm for load shifting is applied to the forecasted load curve by the human operator to achieve a load curve which is known as the load shifted curve. In the proposed model we are going to predict the load shifted curve of the next week with the help of artificial intelligence which will eradicate the human involvement factor. In practice, the human operator has to carry out certain DSM algorithms on the forecasted load curve in order to achieve a load shifted curve but using artificial intelligence we can make this process automatic and hence it saves a lot of time and human efforts.

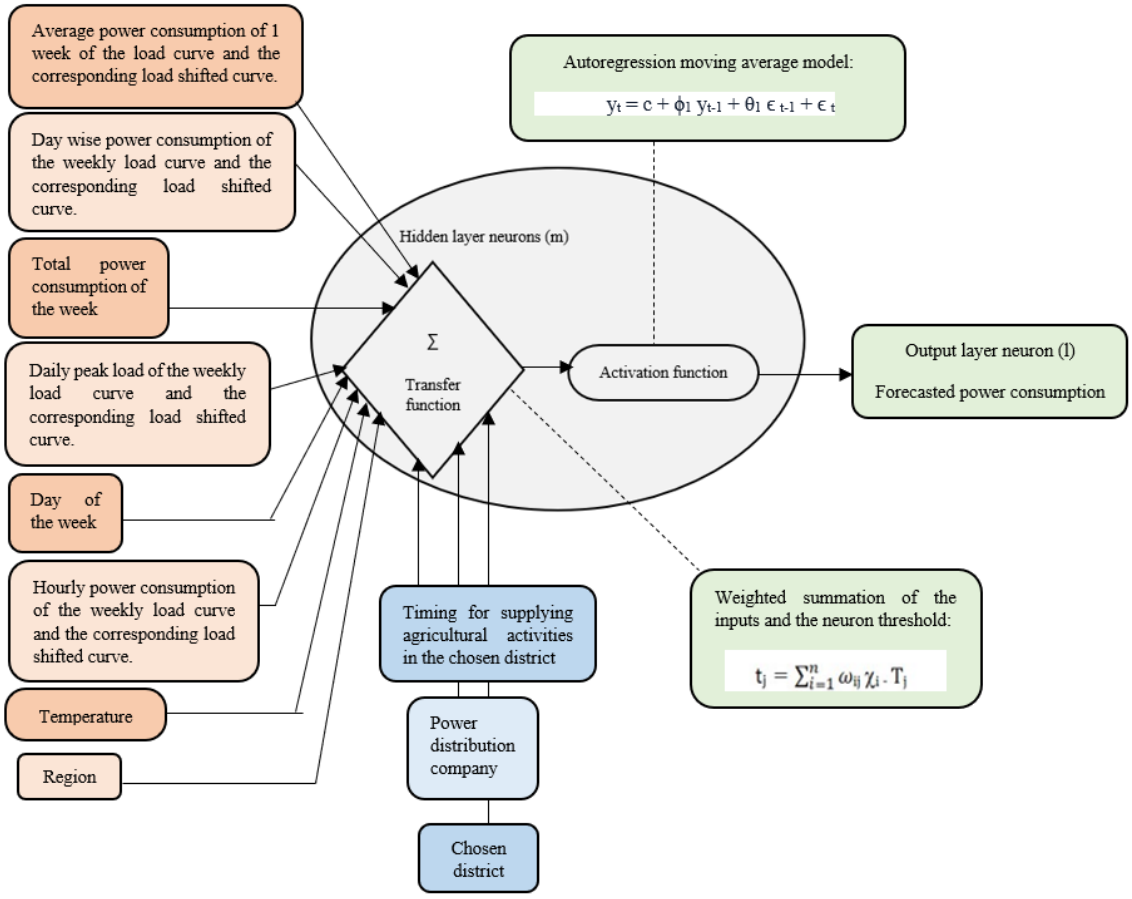

Fig. Proposed Model Based on Artificial Neutral Networks

The model as shown in the above figure is a two-layer feed-ahead neural community version. It consists of two layers namely the hidden layer and output layer respectively. The hidden layer consists of neurons that accept the input data and then the data is processed by each neuron whose output is given to the output layer neuron with the help of activation function. The input parameters play a pivotal role in training the model

accurately. Total power consumption of the week, average power consumption, temperature, Daily peak load, day of the week, day-wise power consumption, and hourly power consumption are the input parameters that we have taken to train the model both efficiently and accurately. In this as per the chosen state, the input parameters like chosen district, region, and power distribution network and the time at which the supply is fed for the agriculture activities can be estimated. The seasonality component present in the load shifted curve and the load curve can be determined by taking into consideration the temperature as an input parameter. In agriculture applications, the power supply is fed to the agricultural load in the time interval of 8 hours instead of 24 hours of the day and therefore the load curve of a single day consists of 8 hours instead of 24 hours.

Discussion

The auto-regressive moving average (ARMA) model is the combination of the autoregressive model (AR) and moving average (MA) model. It is used to represent a stationary stochastic time series corresponding to two polynomials, that is polynomial for autoregression and moving average. Here, at first, we will segregate the total number of Mondays, Tuesdays, Wednesdays, Thursdays, Fridays, Saturdays, and Sundays that are present in the load curve. Now, we will perform the autoregression on both the curves that are the load curve and the load shifted curve and then we will take out the moving averages so that we can have a better

understanding of the load curves and subsequently we will get the idea of the moving averages in the day-wise form. It will result in a smooth time series that is the noise present in the series can be eliminated by carrying out the mentioned process. Additionally, it will help to know the trend and seasonal factors more efficiently and accurately. This model can be simulated and trained in python with the given input parameters in order to forecast the load-shifted curve of the next week. This will surely benefit the electric utility to automate the DSM process which will decrease the human efforts and as a result, it will reduce the involved human error.

The simple form of the autoregressive moving average model can be represented as:

$$y_t = c + \phi_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

Where, y_t and y_{t-1} indicate the values in the existing period of time and ago one period of time. Here, ϵ_t and ϵ_{t-1} are identified as the error terms for the two identical periods. Moreover, ϕ_1 represents the parameters for the autoregressive model and θ_1 represents the parameters for the moving average model.

Conclusion

Demand-side management with the help of artificial intelligence has the capability of giving a number of benefits to the electric utility. It will help to manage the generation, transmission, and distribution efficiently and accurately and thus will help to run the power system smoothly. This paper presents a model that uses artificial intelligence for demand-side management which will help to mitigate human error and will also decrease human involvement. The proposed model works on the artificial neural networks which can forecast the load shifted curve of the next week in the hourly format by using an autoregression moving average model. This model will greatly help the electric utility to automize the demand side management process, removing the human error factor and decreasing human involvement.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Deep Sheth and Chetan Sheth proposed the main conceptual idea and conducted the research. Deep Sheth provided the direction for this research. Deep Sheth designed the proposed model. Deep Sheth and Chetan Sheth wrote the paper. All authors declare that this is the final version of the paper.

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