



# An Application of Artificial Neural Networks in Power Systems

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## Abstract

The power system is a perplexed 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 such a perplexed interconnected network it is crucial to meet the load demand with the power generation, otherwise, issues like voltage instability, voltage collapse, or blackout might take place. Here comes the role of demand-side management which holds a crucial position for managing the load demand and power generation to ensure the power system stability, security, and reliability. In demand-side management, there are certain strategies like load shifting, peak clipping, strategic growth valley filling, flexible load shape, and strategic conservation which can aid the electric utility in matching the power generation and load demand. However, load shifting proves to be one of the best strategies to fulfil the above-mentioned criteria satisfactorily. It is essential to revise the structure for generation, transmission, and distribution so that the additional load demand can be fulfilled but by using the DSM strategy we can eradicate the need of erecting the revised structure. Currently, The DSM algorithm is supposed to be applied by the human operator only on the forecasted load curve to obtain the load shifted curve which is a lengthy and very time-consuming process. This paper proposes a model which is based on artificial neural networks and has the potential to automatize the demand-side management process which in turn reduces human interference and hence mitigates the involved human error. The proposed model aids the electric utility in forecasting the load-shifted curve in the hourly pattern with the help of artificial neural networks and by using an autoregressive moving average model with exogenous inputs. This model will greatly help the electric utility in automatizing the demand-side management process and hence minimizes the human interference which in turn removes the involved human error.

**Keywords:** Artificial Neural Networks, Autoregressive moving average model with exogenous inputs, Demand-side Management, Load Shifting.

## Introduction

Protection of the transmission system is crucial for the secured and stable operation of a power system. Under stress conditions, the operating parameters of the power system violate their limits. From the past anatomy reports of several blackouts, it is clear that equipment, control, and protective relay failures are the major causes behind large power system failures. From the study, it is also revealed that failure of backup protection is more prone during system stressed conditions.

The power system is a perplexed 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). Generally, the electric power system comprises electrical components that are equipped to supply, transmit and distribute the electric power for utilization. Generators supply the power by the utilization of natural resources. The transmission system transmits power from generating stations to distribution substations, where the electric power is distributed among the connected utilities. Hence, the power flow is unidirectional. As compared with the last two decades the demand for the utilization of electricity increased due to the rapid population growth.

Even though the expansion of the existing interconnected power system network is restricted due to economic constraints. The adoption of distributed generating units such as solar power and wind power makes the direction of power flow bidirectional which requires advanced power flow controlling devices. During a short period, there has been a great implementation in hardware and software technology which has changed the power system control from simple process control to a system of distributed processing. Moreover, modern online monitoring system such as supervisory control and data acquisition has made it possible to use energy management system satisfactorily. Interconnections between the areas provide reliable operations of the system during emerging conditions but the number of parallel lines is increased which causes congestion. A planned or forced outage of generating units causes unbalancing between generation and load demand. As the consequences of all these make the operation of the power system very closer to its security limits [3].

Whenever a fault or abnormal conditions occur and that persists for a long time on such a system, then it will damage a certain portion of the system. Thus, causes an imbalance between the electric power supply and load demand. Consequently, it may lead to the initiation of cascaded events which make failure or collapse of the power system i.e., blackout. In such a perplexed interconnected network it is crucial to meet the load demand with the power generation, otherwise, issues like voltage instability, voltage collapse, or blackout might take place. In a power system, the power generation and load must balance at all times [5]. To some extent, it is self-regulating. If an unbalance between power generation and load occurs, then it results in a variation in the voltage and the frequency. If voltage is propped up with reactive power support, then the load increases with a consequent drop in frequency, which may result in system collapse. Alternatively, if there is inadequate reactive power, the system's voltage may collapse. To mitigate the above-mentioned problems certain strategies must be implemented. One of the strategies that can aid to mitigate the problems which lead to blackout is demand-side management (DMS) [9]. The DMS is an essential concept that can benefit the electric utilities in managing 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

## Electrical load Forecasting

Economic development, throughout the world, depends directly on the availability of electric energy, especially because most industries depend almost entirely on its use. The availability of a source of continuous, cheap, and reliable energy is of foremost economic importance. Electrical load forecasting is an important tool used to ensure that the energy supplied by utilities meets the load plus the energy lost in the system. To this end, a staff of trained personnel is needed to carry out this specialized function [11]. Load forecasting is always defined as basically the science or art of predicting the future load on a given system, for a specified period of time ahead. These predictions maybe just for a fraction of an hour ahead for operation purposes, or as much as 20 years into the future for planning purposes.

Load forecasting can be categorized into three subject areas—namely,

1. Long-range forecasting:

It is used to predict loads as distant as 50 years ahead so that expansion planning can be facilitated.

2. Medium-range forecasting:

It is used to predict weekly, monthly, and yearly peak loads up to 10 years ahead so that efficient operational planning can be carried out.

3. Short-range forecasting:

It is used to predict loads up to a week ahead so that daily running and dispatching costs can be minimized. Moreover, it can help to estimate the additional generation, transmission, and distribution requirements.

## Demand-Side Management

The term Demand Side Management refers to a group of actions designed to manage and optimize a site's energy consumption and to cut costs, from grid charges to general system charges, including taxes. Usually, the goal of demand-side management is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as night time and weekends. Peak demand management does not necessarily decrease total energy consumption but could be expected to reduce the need for investments in networks and/or power plants for meeting peak demands. An example is the use of energy storage units to store energy during off-peak hours and discharge them during peak hours [13].

Artificial intelligence can play a pivotal role in making the DSM process automatic as the human operator does not have to apply various DSM algorithms on the forecasted load curve to obtain the load-shifted curve. The artificial neural networks (ANN) 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. Has the potential to predict the load shifted curve by applying a mathematical model on the forecasted load curve and hence mitigates the human efforts required to apply certain DSM algorithms every time.

The following figure shows various demand-side management techniques:

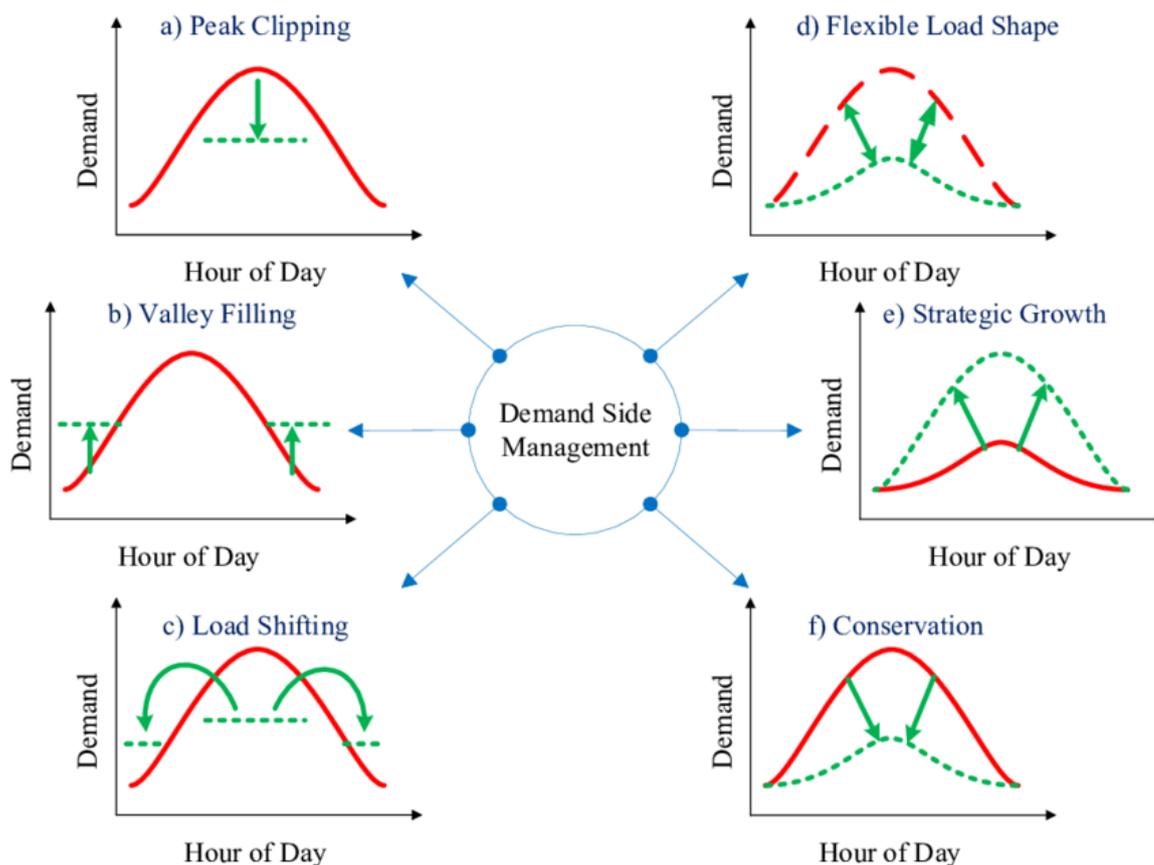


Fig. Several DSM techniques et al. [14]

## Stability of a Power System

Power system stability is defined as the property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance. In the power system voltage stability plays a vital role in maintaining the overall stability of the interconnected network. The voltage stability is highly dependent on the reactive power and the balance between the power generation and the load demand [16].

If the above-mentioned criteria are not taken into account, then it may lead to voltage collapse and the subsequent blackout. Therefore, it is essential to match the power generation and load demand to maintain the voltage under specified limits and demand-side management can do this task very satisfactorily. Several research papers have suggested models and solutions for forecasting the load demand but thereafter the human has to carry out the demand side management process by applying various strategies and observations which can be a lengthy process. It makes the overall demand-side management process very time-consuming due to lack of automation and this reason has motivated us to develop a model which can automate the demand-side management process [17].

## Proposed ANN Model

For the problem of load forecasting, ANN is proved to be one of the best solutions. However, ANN has some disadvantages like it demands training to operate efficiently which consists of a lot of historical data. On the contrary, ANN has the advantage of fast evolution of the learned target function. On a day-to-day basis, various DSM algorithms are carried out on the forecasted load curve in order to obtain the load curve which is called as load shifted curve.

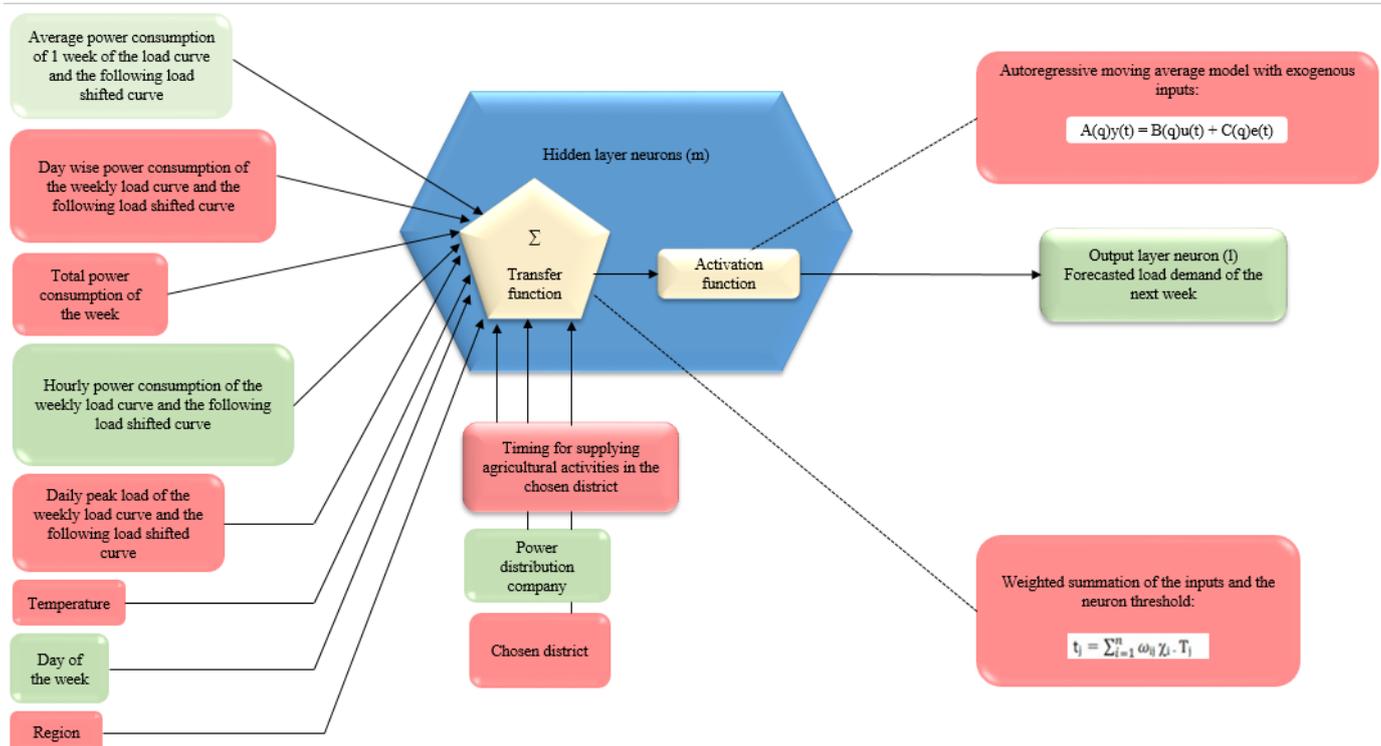


Fig. Proposed model based on artificial neural networks

In the proposed model we are going to predict the load shifted curve for the next week with the help of artificial intelligence which will eradicate the human involvement factor. The proposed model will forecast the load-shifted curve for the next week by taking the help of artificial neural networks. This will automate the DSM process which in turn saves a lot of time and mitigates the human involvement factor. The model as shown in the above figure is a two-layer feed-forward neural network version. It consists of two layers that are hidden layer and the output layer respectively. The hidden layer comprises neurons that obtain the input data and then the data is processed by each neuron whose output is given to the output layer neuron with the aid of the activation function.

The input parameters play a crucial role in training the model satisfactorily. Total power consumption of the week, temperature, average power consumption, day of the week, daily peak load, hourly power consumption, and day-wise power consumption are the input parameters that we have considered to train the model both accurately and satisfactorily. In this as per the chosen state, the input parameters like region, chosen district and power distribution network, and the time at which the supply is fed for the agriculture activities can be estimated. The determination of the seasonality component in the load shifted curve and the load curve can be done by taking temperature into consideration. In agriculture applications, the power supply is fed to the agricultural load in the time period 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 model with exogenous inputs is the combination of the autoregressive model (AR) and moving average (MA) model with an exogenous input  $x$ . An ARMAX is a model of lagged dependent variable and lagged independent variables. ARMAX models are time series models and are estimated using time series approaches. Here, at first, we will bifurcate the total number of Mondays, Tuesdays, Wednesdays, Thursdays, Fridays, Saturdays, and Sundays that are present in the load curve. Now, we will apply the mathematical model ARMAX on both the curves that are the load curve and the load shifted curve. This will eliminate the noise present in the time series and will result in a smooth time series. Moreover, it will provide us the information about the seasonal trend and irregular movements. This model can be simulated and trained in python with the specific input parameters in order to forecast the load-shifted curve of the next week. The proposed model will aid the electric utility in automizing the DSM process which in turn will minimize the required human efforts and hence mitigates the human error in the process.

The simple form of the ARMAX model can be represented as:

$$\mathbf{A}(q)\mathbf{y}(t) = \mathbf{B}(q)\mathbf{u}(t) + \mathbf{C}(q) \mathbf{e}(t)$$

Where  $y(t)$  = load at time 't'

$u(t)$  = exogenous temperature input at time 't'

$e(t)$  = noise at time 't'

$q^{-1}$  = back-shift operator

$A(q)$ ,  $B(q)$ , and  $C(q)$  are parameters of the Auto-Regressive (AR), Exogenous (X), and Moving Average (MA) parts respectively.

## Conclusion

Demand-side management with the help of artificial neural networks has the potential of providing several benefits to the electric utility. It will help in running the perplexed interconnected system smoothly by managing the generation, transmission, and distribution satisfactorily. This paper presents a model based on artificial neural networks which can automate the demand-side management process and hence helps to reduce human involvement. The proposed model can be used to forecast the load-shifted curve of the next week in the hourly format by using an auto-regressive moving average model with exogenous inputs. This model will aid the electric utility in automizing the demand side management process, minimizing human involvement, and eradicating human error.

## 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.

## References

1. Wang, Y.; Chen, Q.; Hong, T.; Kang, C. Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges. *IEEE Trans. Smart Grid* 2018, in press. [CrossRef]
2. Quilumba, F.L.; Lee, W.-J.; Huang, H.; Wang, D.Y.; Szabados, R.L. Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities. *IEEE Trans. Smart Grid* 2015, 6, 911–918. [CrossRef]
3. Alasserri, R.; Tripathi, A.; Rao, T.J.; Sreekanth, K. A review on implementation strategies for demand side management (DSM) in Kuwait through incentive-based demand response programs. *Renew. Sustain. Energy Rev.* 2017, 77, 617–635.
4. Zehir, M.A.; Batman, A.; Bagriyanik, M. Review and comparison of demand response options for more effective use of renewable energy at consumer level. *Renew. Sustain. Energy Rev.* 2016, 56, 631–642.
5. V. Cherkassky, S.R. Chowdhury, V. Landenberger, S. Tewari, and P. Bursch, "Prediction of electric power consumption for commercial buildings," in *Neural Networks (IJCNN), The 20th International Joint Conference on*, 2011, pp. 666–672.
6. A. Deoras, "Electricity Load and Price Forecasting Webinar Case Study," 2011.
7. L. Suganthi and A.A. Samuel, "Energy models for demand forecasting-A review," *Renewable and Sustainable Energy Reviews*, vol. 16, pp. 1223-1240, 2//2012.
8. J. D. Hollan et al., "STEAMER: An interactive inspectable simulation-based training system," *A/ Mag.*, vol. 5, no. 2, pp. 15- 27, Summer 1984.
9. B. Woolf et al., "Teaching a complex industrial process," in *Proc. AAAI Conf. (Philadelphia, PA, Aug. 1986)*.
10. R. D. Masiello et al., "Review of the EPRI project on operator training simulator implementation," presented at the 1984 EEI Engineering Computer Forum, Atlanta, GA.
11. R. S. Michalski, J. G. Carbonell, and T. M. Mitchell, Ed. *Machine Learning*. Palo Alto, CA: Tioga Publ. Co., 1983.
12. Panasetskii, D.A., *Improving the Structure and Algorithms for Failure Protection Control of an Electric Power Station to Prevent Voltage Avalanche and Cascade Outing of Lines*, Cand. Sci. Dissertation, Irkutsk: ISEM SB RAS, 2015.
13. Sheth, D., Sheth, C., & Patel, B. (2021). Artificial Intelligence for Automatic Load Management. *Journal of Artificial Intelligence Research & Advances*, 8(3). <https://doi.org/10.37591/joaira.v8i3.92>
14. Ain, Qurat-UI & Iqbal, Sohail & Javaid, Nadeem. (2019). User Comfort Enhancement in Home Energy Management Systems using Fuzzy Logic.
15. Hatalis, Kostas & Zhao, Chengbo & Venkitasubramaniam, Parv & Snyder, Larry & Kishore, Shalinee & Blum, Rick. (2020). Modeling and Detection of Future Cyber-Enabled DSM Data Attacks. *Energies*. 13. 4331. 10.3390/en13174331.
16. "Artificial Intelligence for Demand Side Management", *International Journal of Emerging Technologies and Innovative Research* (www.jetir.org), ISSN:2349-5162, Vol.9, Issue 1, page no.b647-b653, January-2022, Available :<http://www.jetir.org/papers/JETIR2201186.pdf>
17. Negenborn, R.R., De Schutter, B., and Hellendoorn, J., *Multi-agent Model Predictive Control for Transportation Networks: Serial Versus Parallel Schemes*, *Eng. Appl. Artif. Intelligence*, 2008, vol.21, pp. 353–366.