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LOAD FORECASTING MODEL FOR ENERGY MANAGEMENT SYSTEM USING ELMAN NEURAL NETWORK

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ABSTRACT

Electric load forecasting is used for forecasting of future electric loads. Since the economy and reliability of operations of a power system are greatly affected by electric load, cost savings mainly depend on load forecasting accuracy. An accurate system load forecasting which is used to calculate short-term electric load forecasts, is an essential component of any Energy Management System (EMS). This can be improved by making use of Artificial Neural Networks (ANN). Existing Boosted Neural Networks (BooNN) technique helps in reduction of forecasting errors and variation in forecasting accuracy. However it is not flexible to rapid load changes.In the proposed work, Elman Neural Network technique is considered. This technique improves the load forecasting accuracy. The proposed method is implemented in IEEE 14 bus system. Simulation results showed that this method has increased the Voltage profile and also the active power losses have been reduced. Overall power transfer capability has been improved. Also the computational time has been minimized when compared to the existing techniques.

Keywords: Elman Neural Network,Energy Management System(EMS),Forecasting

1. INTRODUCTION

Energy management is the process of monitoring, controlling, and conserving energy in a building or an industry. Energy management involves efficient utilization of energy consumed on a daily basis and engineering innovative methods to conserve that energy for better utilization. EMS is designed to reduce energy consumption, improve the utilization of the system, increase reliability,predict electrical system performance and optimize energy usage to reduce cost.

The objectives of Energy Management are

- To achieve and maintain optimum energy procurement and utilization, throughout the organization
- To minimize energy costs / waste without affecting production & quality.
- To minimize environmental effects.
- Increase efficiency
- Find superior energy alternatives

The system architecture of energy management is shown in Figure 1.1

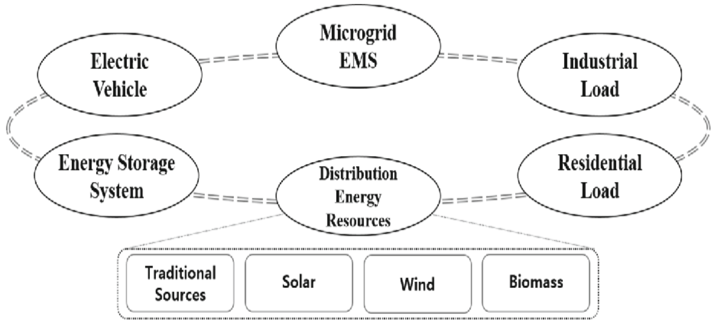

Fig 1.1 Energy Management System

2. LOAD FORECASTING

Load forecasting has been composed in several time scales, ranging from hourly to yearly. The forecasting model considers a number of hours and that includes load forecasting on an hourly time scale. This means that load forecasts in MW/h have been made for each hour according to updated information for individual future hours.According to different time horizons the classification of load forecasting are given in Table 1.

Table 1. Load Forecasting according to Different Time Horizons

S.NO	TYPE	DURATION	IMPORTANCE
1	Long Term	One year to ten months	Decisions on generation and transmission planning, used for determining the economical location, type, and size of the future power plants
2	Medium Term	Several months to one year	Generation, transmission maintenance and also for fuel scheduling
3	Short Term	One hour to one week	Unit commitment and economic dispatch
4	Real Time or Very Short Term	Minutes	Minutes ahead and is used for automatic

Load forecasting is a process to predict load for a future period. Application of load forecasting falls into different time horizons: long-term forecasting (from one year to ten years), medium-term forecasting (from several months to one year), short-term forecasting (from one-hour to one-week) and real-time or very short term forecasting (in minutes). Long-term forecasts influence the decisions on generation and transmission planning, which is used for determining the economical location, type, and size of the future power plants.

Medium-term load forecasts are necessary for generation and transmission maintenance, and also for fuel scheduling. Accurate short term load forecasts are necessary for unit commitment and economic dispatch. Very short-term load forecasting is for minutes ahead and is used for automatic generation control (AGC).

3. ELMAN NEURAL NETWORK

Elman neural network is generally divided into four layers: the input layer, the middle layer (hidden layer), the undertake layer and output layer, as shown in Figure 3.1.

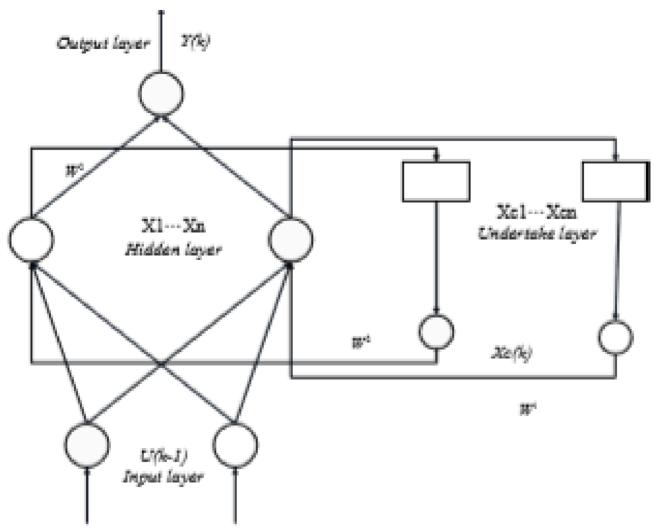

Figure.3.1 Elman Neural Network

The input layer, the hidden layer and the output layer are connected to the feed forward network. The input layer unit only acts as a signal transmission, and the output layer unit acts as a linear weighting mechanism. Elman neural network is characterized by the output of the hidden layer that through the structural unit of the delay, storage, self-linked to the hidden layer of the input.

Advantages:

- Lowers computational time.
- Improved loadcasting performance with respect to other techniques.
- Improves forecasting accuracy.

Elman neural network is used to forecast the short term load, and the Elman neural network with the demand response factor is improved the accuracy of the analysis. The flowchart of Elman Neural Network model is given in figure 3.2

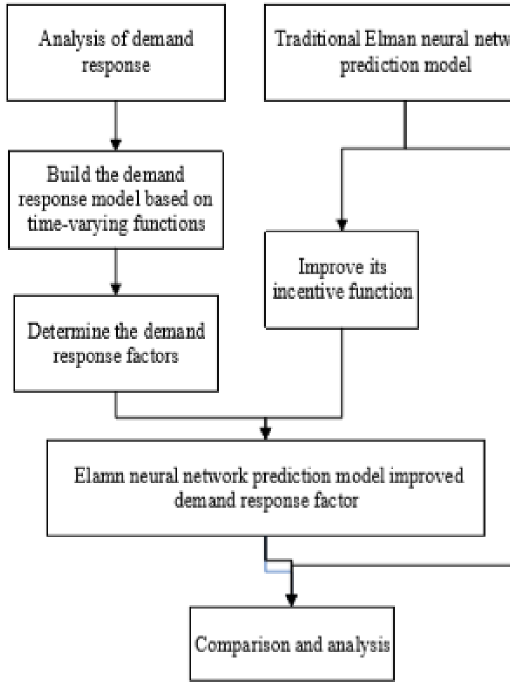

Fig 3.2 Flowchart of Elman Neural Network

4. WIND FARM EMBEDDED MULTI MACHINE POWER SYSTEM

The two generating stations (1500 MVA, 2500 MVA) each of which generates 11kV is transmitted to the load through transmission lines after it is stepped-up and stepped-down by a transformer which forms the primary distribution. The distribution to the load forms the secondary distribution.

The wind turbine is modeled using the equations. Then this model is coupled with Induction Generator (IG). The Wind Turbine Induction Generator embedded with the Multi-Machine Power System is shown in figure 4.1

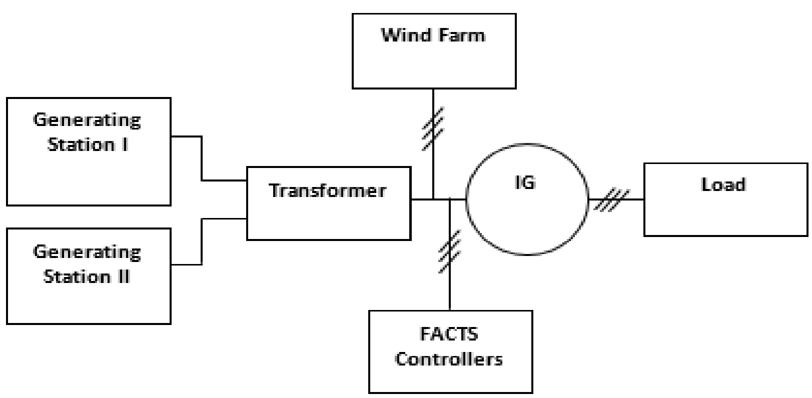

Fig 4.1 Wind Farm Embedded Multi Machine Power System

The Wind Turbine Induction Generator is embedded with the Multi-Machine Power System. The power prediction is introduced in the power system and the response is observed using simulation results for system connected with THREE CASES

1. CONNECTED TO GRID
2. OFF GRID
3. SUDDEN CHANGE IN DEMAND.

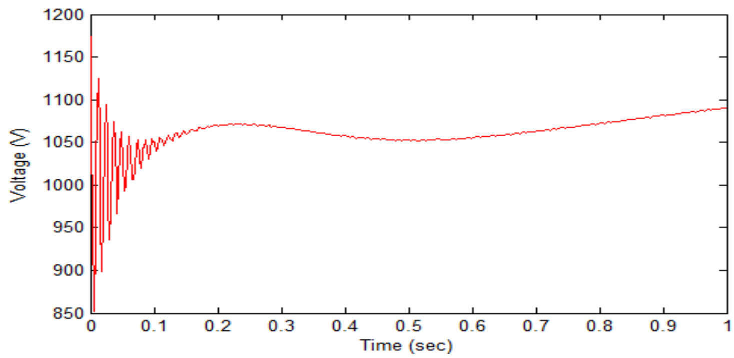

Fig 4.2 Voltage waveform of the wind farm embedded multi machine power system

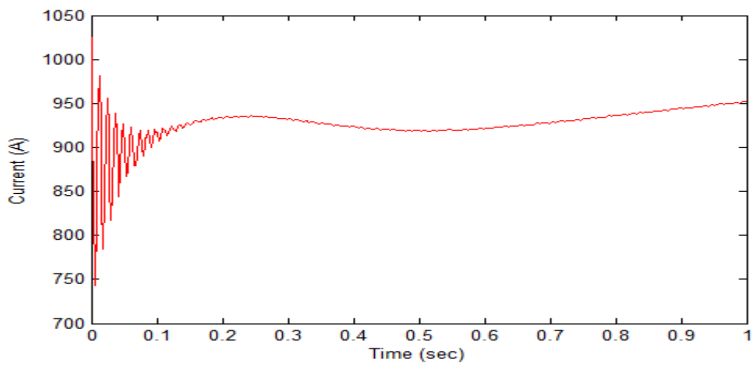

Fig 4.3 Current waveform of the wind farm embedded multi machine power system

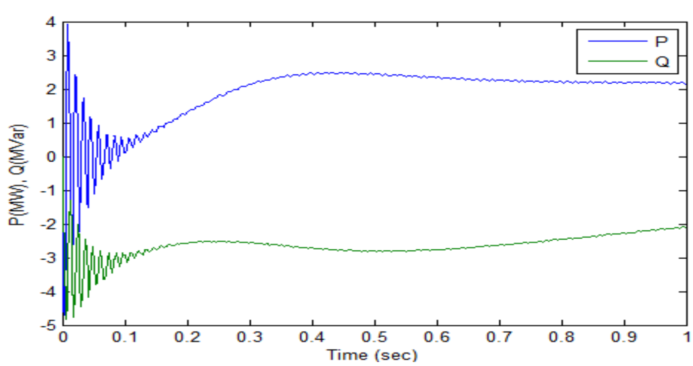

Fig 4.4 Real and Reactive Output power of the wind farm Embedded multi machine power system

5. SIMULATION RESULTS AND DISCUSSION

The modified IEEE 14 bus test system considered for implementing the proposed technique is shown in Figure 5.1. The simulated results of IEEE 14-bus system for proposed conditions with different cases are tabulated. A comparison between the voltage profile and active power losses at each bus are tabulated to prove the effectiveness using Elman Neural Network for different test cases.

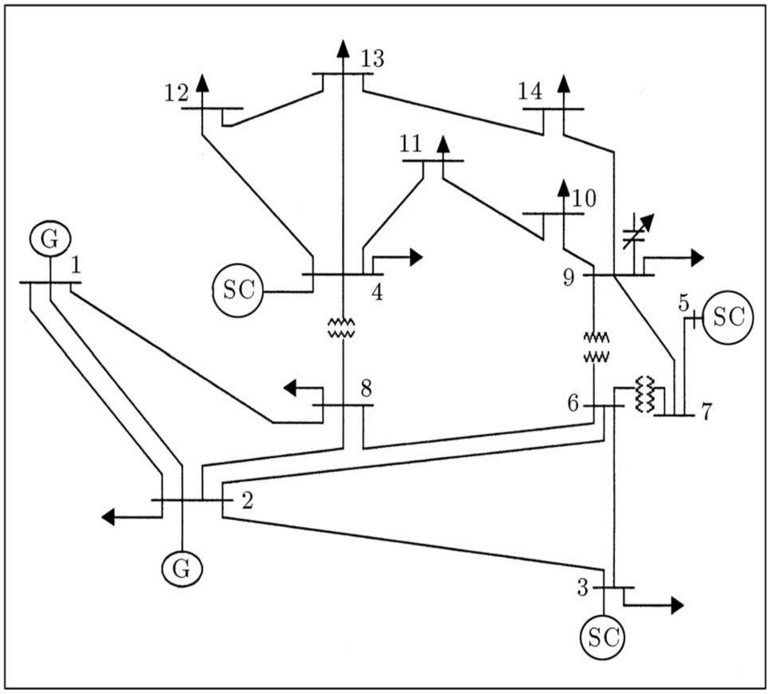

Fig 5.1 IEEE 14 bus test system

Case 1: Load flow analysis when system operates with 100% nominal load

Case-2: Load flow analysis when there is sudden increase of power at bus number 9 and 10

Case 3: Load flow analysis when there is sudden decrease of power in the system i.e system operates with 75% nominal load

Table 2 Comparative simulation results of voltage profile and active power losses for IEEE 14 Bus for case 1 with different preceding methods.

Bus number	Without controllers using conventional method Tso et al (1997)		Power flow with MGSA optimization of EMS control parameters		Power flow with optimization of EMS control parameters using proposed approach	
	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)
1	1.0600	13.59	1.0622	12.81	1.0634	11.63
2	1.0450	13.59	1.0401	12.81	1.0409	11.63
3	**1.0100**	**13.59**	**1.0215**	**12.81**	**1.0297**	**11.63**
4	1.0500	13.59	1.0589	12.81	1.0667	11.63
5	1.0800	13.59	1.0875	12.81	1.0919	11.63

Table 3 Simulation results of voltage profile and active power losses for IEEE 14 bus system for case 2 with different preceding methods.

Bus number	Without controllers using conventional method Tso et al (1997)		Power flow with MGSA optimization of EMS control parameters		Power flow with optimization of EMS control parameters using proposed approach	
	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)
1	1.0600	16.23	1.0600	15.07	1.0601	11.50
2	1.0310	16.75	1.0387	15.95	1.0398	11.50
3	1.0100	16.92	1.0120	15.97	1.0132	11.50
4	1.0413	16.46	1.0463	15.56	1.0593	11.50
5	1.0763	16.07	1.0793	14.96	1.0878	11.48

Table 4 Simulation results of voltage profile and active power losses for IEEE 14 bus system for case 3 with different preceding methods.

Bus number	Without controllers using conventional method Tso et al (1997)		Power flow with MGSA optimization of EMS control parameters		Power flow with optimization of EMS control parameters using proposed approach	
	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)	Voltage profile (p.u)	Active power losses (MW)
1	1.0705	10.56	1.0707	8.45	1.0715	7.29
2	1.0450	10.56	1.0451	8.45	1.0456	7.29
3	1.0100	10.56	1. 0201	8.45	1.0305	7.29
4	1.0705	10.56	1.0710	8.45	1.0720	7.29
5	1.0805	10.56	1.0807	8.45	1.0810	7.29
6	1.0082	10.56	1.0286	8.45	1.0390	7.29

The proposed method is studied and tested on IEEE 14 bus test system. The system is mainly studied for improvement of voltage profile and thereby decreasing the active power losses in the line with the EMS . To validate the effectiveness of the proposed methodology using the proposed MGSA, it is compared with earlier literature studies as given in Benabid et al (2009) with NPSO and Bagriyanik et al (2003) with GA. A comparative study of active power and voltage profile for the proposed method The results depict clearly the effect of hybridization with addition of modification factor in the proposed method helps the controllers to improve the voltage profile of the system there by reducing the active power losses in the line.

6. CONCLUSION

An EMS is formulated as an offline optimization problem in electricity forecasting in existing methodology. In existing methodology as per literature reviews the models proposed by different researches omit distribution network power flow and system operational constraints such as voltage stability and active power. Such approaches violate the control decisions which depict real time scenarios in the power system leading to miscalculation and an economical power transfers for preferred forecasting, hence a model which takes into account the power system constraints such as voltage constraints and active power flow will formulate an economical power transfer and a predictive EMS.

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Conflict of Interest

None of the authors have any conflicts of interest to declare.

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