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Research Article

Efficient Load Forecasting Optimized by Fuzzy Programming and OFDM Transmission

Sandeep Sachdeva,[1] Maninder Singh,[2] U. P. Singh,[3] and Ajat Shatru Arora[4]

[1] *Nims University, Shobha Nagar, Jaipur, Rajasthan 303121, India*
[2] *Haryana Engineering College, Jagadhri, Yamuna Nagar, Haryana 135003, India*
[3] *Seth Jai Parkash Mukand Lal Institute of Engineering and Technology (JMIT), Radaur, Haryana 135133, India*
[4] *Sant Longowal Institute of Engineering and Technology (SLIET), Longowal, Sangrur, Punjab 148106, India*

Correspondence should be addressed to Sandeep Sachdeva, san_sach2000@yahoo.com

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Today, it is very important for developed and developing countries to consume electricity more efficiently. Though developed countries do not want to waste electricity and developing countries cannot waste electricity. This leads to the concept: load forecasting. This paper is written for the short-term load forecasting on daily basis, hourly, or half-hourly basis or real time load forecasting. But as we move from daily to hourly basis of load forecasting, the error of load forecasting increases. The analysis of this paper is done on previous year's load data records of an engineering college in India using the concept of fuzzy methods. The analysis has been done on Mamdani-type membership functions and OFDM (Orthogonal Frequency Division Multiplexing) transmission scheme. To reduce the error of load forecasting, fuzzy method has been used with Artificial Neural Network (ANN) and OFDM transmission is used to get data from outer world and send outputs to outer world accurately and quickly. The error has been reduced to a considerable level in the range of 2-3%. For further reducing the error, Orthogonal Frequency Division Multiplexing (OFDM) can be used with Reed-Solomon (RS) encoding. Further studies are going on with Fuzzy Regression methods to reduce the error more.

1. Introduction

Forecasting for future load demand requirement is the most important key for power system planning. The capacities of the generation, transmission, and distribution capacities are strictly dependant on the accurate energy and load forecasting for that system [1]. For transmission of data from outer world to load forecasting model and sending outputs from this model to outer world accurately, OFDM transmission can be used due to its less bit error rate [2]. The Energy Management System (EMS) demands accurate load forecasting and Short-Term Load Forecasting (STLF) gives better and accurate results [2, 3]. The short-term load forecasting is especially significant for economic load dispatch, load management scheduling, and optimum power flow with minimum transmission loss, fuel management, and contingency planning [3, 4]. The sources are limited and the costs for those are very high. Moreover, the advancements are going on in electrical and electronics technology, computer and control technology, which have led to a reasonable cause for the further development of techniques for load prediction for system operation. Load forecasting techniques can be divided into three categories: short-term forecasting—as hourly, daily, or weekly forecasting; mid-range forecasting—extends from a month to one year; and long-term forecasting—ranging from one year to ten years [5]. All these types of forecasting methods are useful for different types of systems and define the size of the system.

The method that has been stressed upon is short-term load forecasting. A number of methods and techniques have already been devised for prediction of load such as Artificial Neural Networks (ANNs), Fuzzy Logic, and Regression

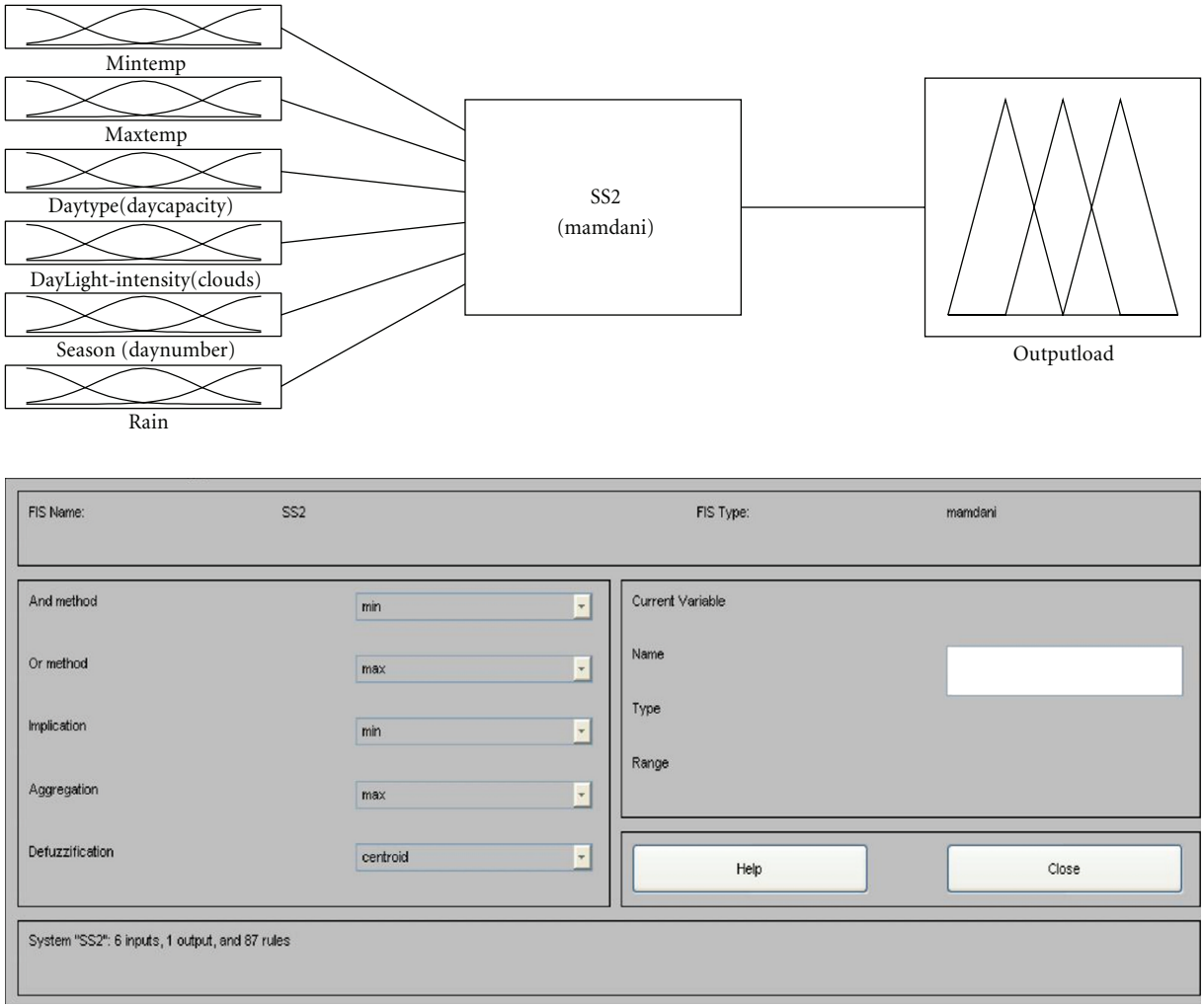

Figure 1: Flow and processing of data through fuzzy inference system.

Methods. Neural networks are having the properties of slow convergence time and poor ability to process a large number of variables at a time. Though, on other side, fuzzy logic gives a platform to represent and process data in linguistic terms, which makes the systems easily readable, understandable, and operateable [6, 7]. This is why the fuzzy logic has been used to deal with the input parameters information after detailed analysis of data and knowledge base (IF-THEN rules).

In fact, the load demand heavily depends on the number of factors such as weather, day type, and season. These factors actually decide the load to be forecasted depending on the conditions of these parameters on that day. The weather and seasons are factors which possess the nonlinear behavior with the load. One of the other important factors is day type. Day type generally means working day, week end, or a special day. It is important to extract a relation between electric load and the parameters affecting it. As accurate the parameters (weather, season, or day type) are judged, accurate will be the load forecasted for the day. For accuracy, OFDM and UWB systems can be used for calculating parameters.

2. The Work

In this study, a short-term load forecasting method using fuzzy logic has been developed, and a proposal to the advancement of the study with the use of artificial neural network (ANN) in different ways has been put up. A part of complete and generalized software using fuzzy logic has been tried to put into existence to forecast electrical load for domestic as well as commercial areas such as industries, institute, or residential colonies.

The system input parameters are day's minimum temperature, day's maximum temperature, season, day capacity, rain, and daylight intensity (Cloudy). Day's minimum temperature is a temperature when working hours start. All these parameters are put as input to fuzzy system, and the inputs are first of all scaled in the required value limits and fuzzified. Previous data (historical data or heuristic knowledge) which has already been stored in data base is used for inference. Rule base is designed to follow the heuristic knowledge according to the membership functions of various inputs. As in Figure 1, degree of membership for different input

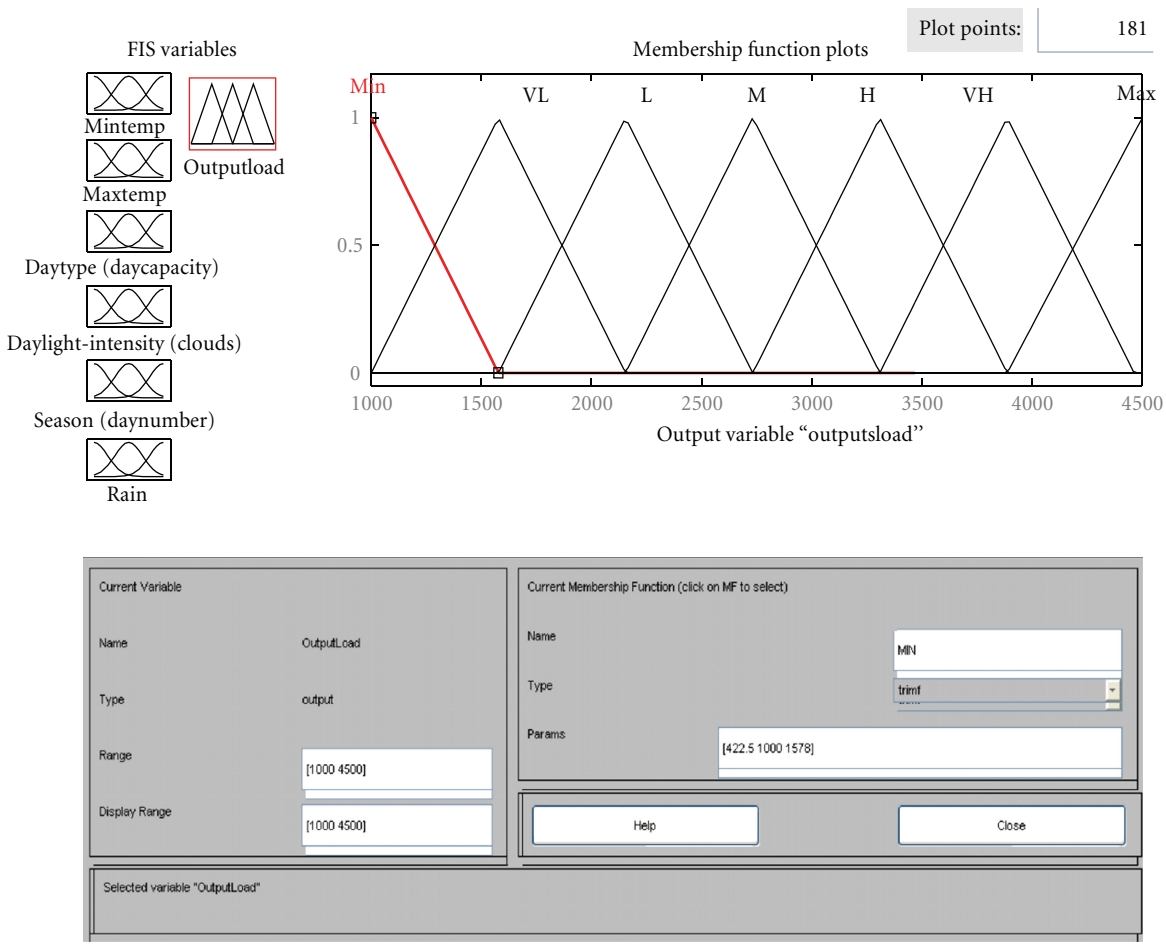

Figure 2: Membership functions of fuzzy inference system.

parameters is found out in the range of [0-1] and then defuzzified to get the crisp output which is then de-scaled to the required units and range [8, 9].

3. Historical Data and Key Factors

A good quality of historical data for input parameters for the last few years has been stored in data base management system (DBMS) for accurate load forecasting [6]. Short-term load forecasting mainly depends on the following conditions:

(i) day capacity,

(ii) weather conditions,

(iii) day temperature.

Though the day capacity can be defined as working day or non-working day (weekend or holiday). But as per this study, weekend and holiday are put in the same category when no work or negligible work is done. One more category as special day has been considered. This is the category when work is done after regular 8 working hours of the day (means if work is done for 9 Hrs. in a day shows one complete regular day and 1 Hr. of special day) or 9 Hrs. of special day depending on the type of work.

Overall working in an institute can be divided into two parts: Class (Theory and Tutorials) and Practical Labs and workshops. The day capacity is very much dependant on two factors:

(i) the type of work (either theory or practical),

(ii) day elongation.

So day capacity can be calculated as

$$\mathrm{DC} = \sum_{i}^{n} T_i \times D, \tag{1}$$

where n is number of jobs done simultaneously in the same campus and DC is day capacity, T_i is evaluation factor for the type of work, and D is elongation of the day in (1).

Two main factors have been defined to decide weather conditions: cloudy and/or rainy weather. Cloudy weather gives an important effect of the daylight intensity, meaning that, the more the clouds, the lesser will be the daylight intensity and the more will be the consumption of electricity. These factors somehow are related to days minimum temperature and days maximum temperature.

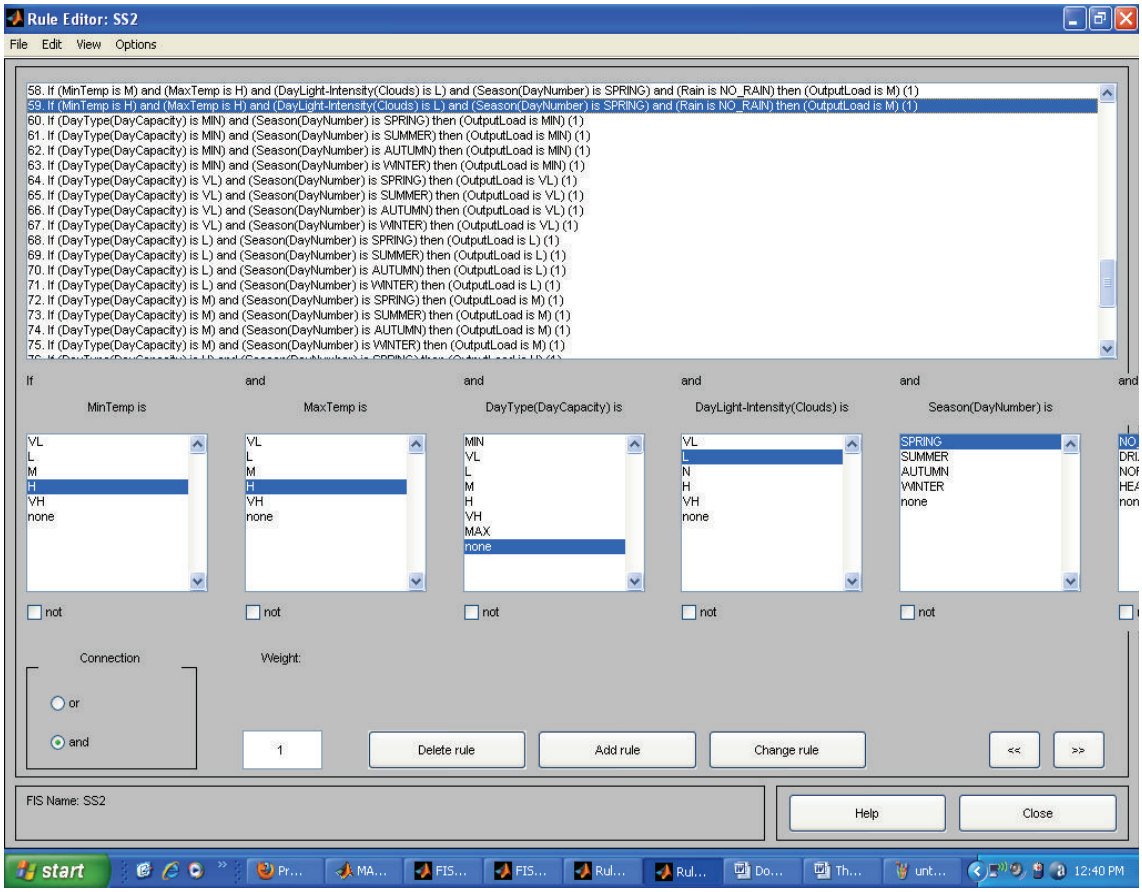

Figure 3: Rules of fuzzy system.

Actually, there can be a comparison between two working days with similar day capacity but different weather conditions; load consumed on both the days will be different. It can also happen that for two days, one is working and the other is nonworking with different weather conditions, the load consumed is the same [10, 11].

4. Load Forecasting

4.1. Fuzzification. Fuzzy linguistic variables are used to represent various inputs as well as output parameters as the member of fuzzy sets. A linguistic variable is used to define the value qualitatively by a linguistic term like any symbol serving its name and quantitatively by a corresponding membership function, that is, the meaning of a fuzzy set. In this work, we take example of temperature. We defined temperature as minimum temperature and maximum temperature which demonstrates the concept of linguistic variable. In order to express the fuzziness of information, this paper makes an arrangement of fuzzy subsets for different inputs and outputs in complete universe of discourse as membership functions [12, 13]. The relationship between several inputs and output may be nonlinear but linear membership functions have been used for simplicity and only the membership function for seasons is taken as ridge-shaped membership function such as gbell mf, gauss mf, and gauss2mf.

The day's minimum temperature and Maximum Temperature are represented as fuzzy subset [Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)].

The linguistic variables of day capacity are represented as [Minimum (min), Very Low (VL), Low (L), Medium (M), High (H), Very High (VH), Maximum (max)].

The fuzzy subset for day capacity is [Very Low (VL), Low (L), Normal (N), High (H), Very High (VH)].

The season's fuzzy subset is given with the names of seasons as [Spring, Summer, Autumn, Winter].

The rain forecast has been given by fuzzy subset [No Rain, Drizzling, Normal Rain, Heavy Rain].

Similarly, the output factor load also has been assigned as fuzzy subset with membership functions [Minimum (min), very low (VL), Low (L), medium (M), High (H), Very High (VH), Maximum (max)].

4.2. Fuzzy Rule Base. This is the part of fuzzy system where heuristic knowledge is stored in terms of "IF-THEN Type" Rules. The rule base is used to send information to fuzzy inference system (FIS) to process through inference mechanism to numerically evaluate the information embedded in

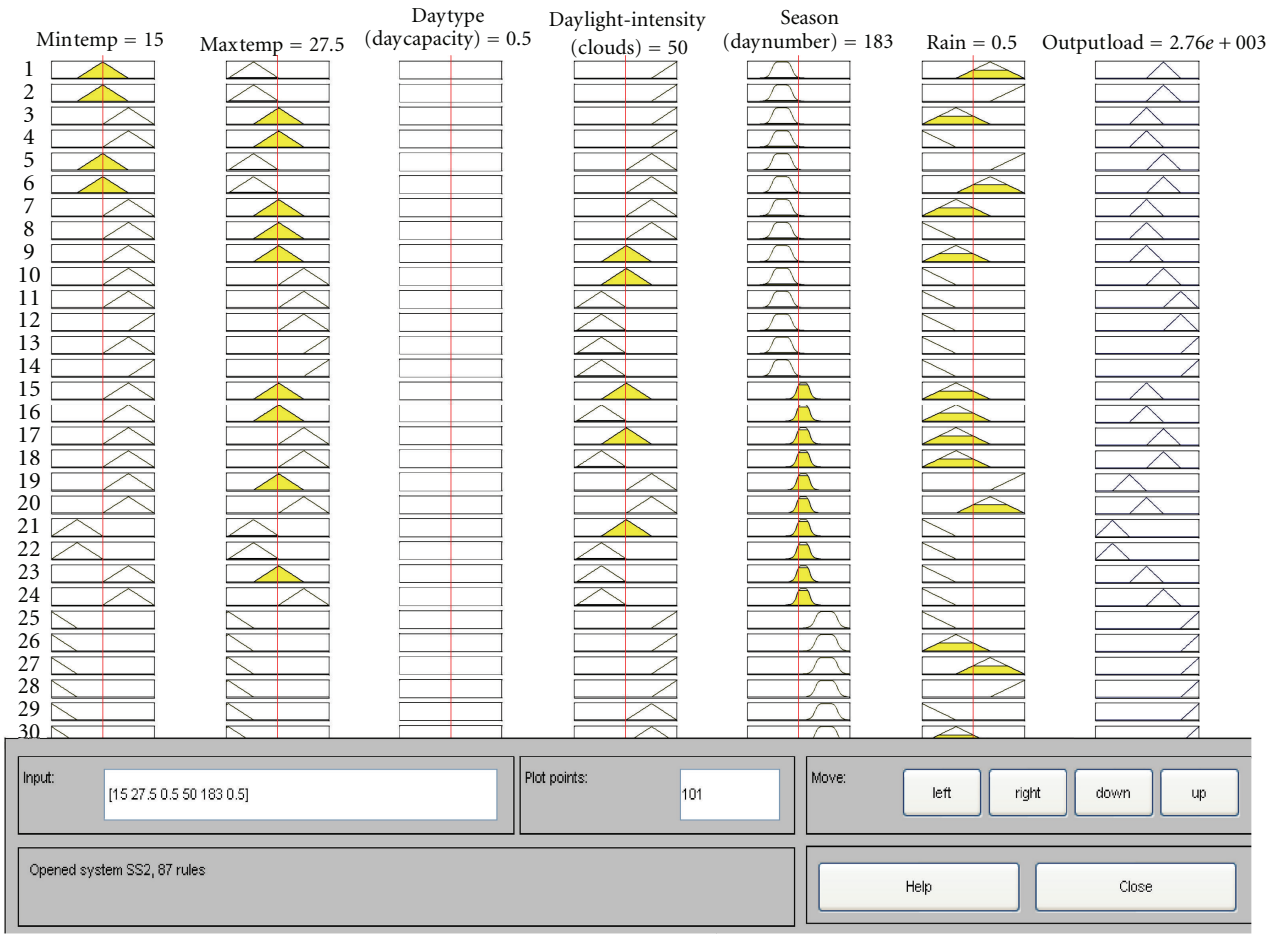

Figure 4: Rule Viewer of fuzzy system.

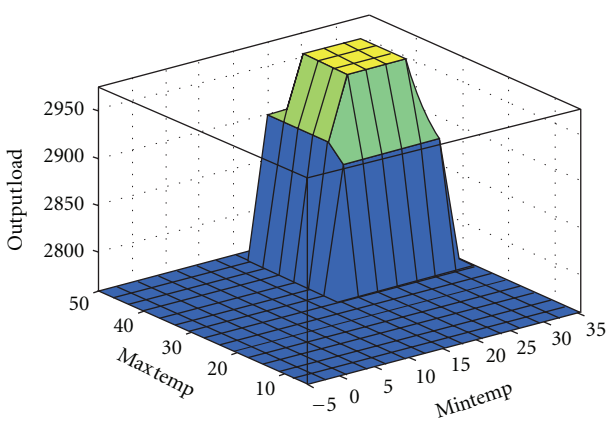

Figure 5: Surface viewer of fuzzy system.

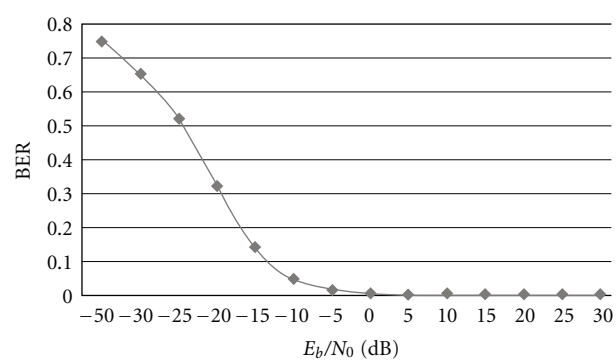

Figure 6: BER Plot of OFDM System with RS encoding and QPSK modulation scheme.

the fuzzy rule base to get the output. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned.

The different Rule Viewers of the Fuzzy Rule Base of the system is shown in Figure 4, though Figure 5 shows the Surface Viewer of the fuzzy optimized system.

5. Results

From the actual load, forecasted load and the % of error in the forecasted load for the data processed can be written as

$$\%\text{Error} = \frac{\text{AL} - \text{FL}}{\text{AL}} \times 100, \tag{2}$$

where AL is actual load and FL is forecasted load.

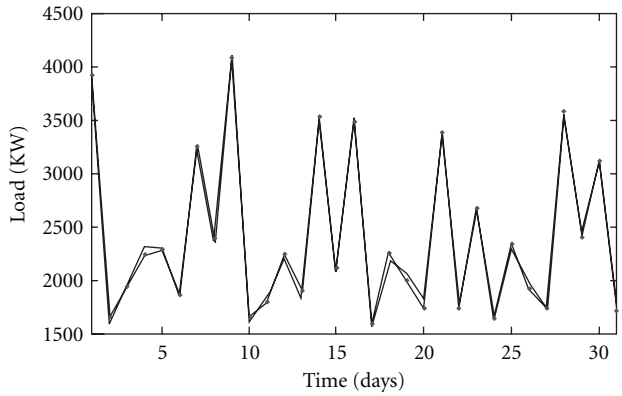

Figure 7: Comparison of actual load (–) and forecasted load.

The important factors for error are "inputs from outer world" and "output to outer world". Because if the transmission of data from outer world to fuzzy system is not accurate, the error rate of the system increases and the output data also comes with some error. So for transmission of data from outer world to fuzzy system for forecasting the load, OFDM can be used as a transmission scheme. Because OFDM system can handle number of users at same time with very less Bit Error Rate (BER) as shown in Figure 6.

So at overall the OFDM system minimizes the BER to 0.00436%, and it effects the overall load forecasting of a region. The forecasted load for the month of October has been shown for the reason that this is the mid time of a working session in an engineering college in India. Moreover, the change of season also takes place in this duration.

Both the results have been compared graphically, as in Figure 7, showing the minute variations in the actual and forecasted loads for the same session.

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