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Spinning Reserve Requirements Forecasting Using Local Linear Wavelet Neural Network In Wind Integrated Power System

Prasanta Kumar Pany
NIT, Durgapur, West Bengal, India.

S. P Ghoshal
NIT, Durgapur, West Bengal, India

Abstract: – Adequate spinning reserve is a basic requirement for maintaining reliable electrical power supply. As the wind power industry expands, it is important that these facilities are integrated in the existing generating capacity planning and operating protocols and procedures. An accurate short term prediction of spinning reserve requirements help the Independent System Operator (ISO) to make effective and timely decisions in managing the compliance and reliability of the power system. In addition, they play an important role in enabling operators to effectively schedule and sell power into the electricity markets, balance output on a regional or national scale. The work presented in this paper makes use of local linear wavelet neural network (LLWNN) to find the spinning reserve requirements for a given period, with a certain confidence level.

Index Terms:- Spinning reserve (SR) , Spinning reserve requirements (SRRs), Operating reserve (OR), Independent system operator (ISO), local linear wavelet neural network (LLWNN), Gradient descent, artificial neural network (ANN), Weekly mean absolute percentage error (WMAPE).

I. INTRODUCTION

WIND power has seen rapid growth in the past decade. Its zero-cost fuel and emissions-free output provide great benefits to consumers and society. The integration of large shares of wind generation requires an increase in the amount of reserves that are needed to balance generation and load. Studies described in [1] and [2] showed that large scale integration of wind generation does not create problems in terms primary reserve levels. So, the analysis should be considered in terms of the spinning reserve management only. The methods employed by the ISOs to define operating reserve requirements are generally deterministic, as can be seen in the survey presented in [3] about reserve categorization that reviews the criteria used across eight electrical systems.

If wind power generation is viewed as a negative load [4], the uncertainty on this generation increases the uncertainty on the net demand that must be met by traditional forms of generation. This increased uncertainty must be taken into account when the requirement of spinning reserve is determined, since SR is intended to protect the system against unforeseen events such as generation outages, sudden load changes or a combination of both. Therefore one might expect that the integration of wind power might require a significant increase in the requirement of spinning reserve. Several ISOs have adopted deterministic criteria to access SR requirements. According to their operating rules, the operating reserve should be equal to the capacity of the largest on line generator plus a fraction of the peak load [5]. The operating reserve is made up of the spinning reserve or synchronous reserve as well as non-spinning reserve or supplemental reserve. The spinning reserve is the extra generating capacity that is available by increasing the power output of generators that are already connected to the power system. The non-spinning reserve is the extra generating capacity connected to the system but can be brought on line after a short delay.

Determining the optimal amount of spinning reserve that must be provided as a function of the system conditions is thus an important and timely issue. The optimal amount of spinning reserve is such that the cost of providing an extra MW of reserve is equal to the benefit that this MW provides, where this benefit is measured in terms of the reduction in the expected cost of interruptions. Ideally the energy and SR amounts and repartitions should be optimized simultaneously. The main difficulties in solving such a problem are the stochastic nature of the net demand due to the demand and wind forecast errors, and the fact that there is no discrete capacity outage probability distribution in the optimization procedure. The stochastic and highly combinatorial nature of the problem led some researchers to find alternative solutions to the problem.

The determination of spinning reserve requirements has been analyzed using many different methodologies and can differ significantly from study to study. Most wind power integration studies run hourly simulations of bulk power system operations for a particular study area. Two important objectives that often form part of these studies are the cost or savings of integrating addition wind power [6],[7]. Many of the studies recommend the use of incremental operating reserves, which will also affect the total costs.

Several ISOs have adopted deterministic criteria to access the spinning reserve requirements. As per the deterministic criteria, the operating reserve requirement is equal to 5% of the load to be supplied by hydroelectric resources plus 7% of load to be supplied by generation from other sources, plus 100% of any interrupting imports or the single largest contingency [8]. The deterministic criteria, however, do not reflect the uncertainty in the forecast load. Probabilistic methods [9, 10] have therefore been proposed to evaluate the SR requirements in a more constant way. If SR requirements forecast are based on historical SR requirements time series data itself, forecast accuracy may improve. However, SR requirements time series data exhibits non-linear and non-stationary characteristics. Therefore stationary and non-stationary time series models, which are linear predictors, can not capture the behavior of SR requirement signal completely. To overcome this difficulty, artificial intelligence methods were proposed [11]. There are enormous numbers of statistical models available for this type of application. The most popular models for SR requirements forecasting are artificial-intelligence-based models such as Neural Networks (NNs), Fuzzy-neural networks, which are the advanced forecasting methods. However, to the best of the authors' knowledge, a Local Linear Wavelet Neural Network (LLWNN) has not yet been tested for SR requirements forecasting. In this paper an LLWNN model which smoothly maps the input-output space by adapting the shape of wavelet basis function of hidden layer neurons according to training data set is examined for SR requirements prediction of the Ontario electricity market [12]. The proposed model does not require external decomposer/composer. So risk of loosing high frequency components of SR signal is averted. It is found that prediction of SR requirements based on LLWNN model gives good performance because of its favorable property of modeling the non-stationary high frequency signals such as SR.

The rest of the paper is organized as follows: Section II describes main characteristics of the SR data. SR requirements forecasting using LLWNN model is described in section III. Training of LLWNN model by standard back propagation (BP) gradient descent algorithm is described in section IV. Section V describes the statistical measures used to evaluate the forecasting performance. Section VI presents results and discussions on SR requirements forecast of Ontario electricity market. Finally, section VII provides concluding remarks.

II. SPINNING RESERVE-DATA ANALYSIS

Traditionally the SR requirement is based on criteria that protect against the loss of the largest online in feed. Such deterministic criteria take into account neither the accuracy of the demand and wind power forecast, nor the probability of largest generator or interconnection outage. G. Danny [13] investigated and quantified the technical consequences of the penetration of wind power on the primary, secondary and tertiary reserves. He concluded that the SR requirements increase proportionally to the installed wind power capacity. S. Persaud et al [14] state that the SR requirements are inversely proportional to the net demand forecasting accuracy. As a consequence, when the wind-based power generation is integrated in the power system, larger amount of SR would be required to maintain the same level of security in the system. To develop an appropriate model for SR requirements forecasting, we examine the main characteristics of the hourly SR series in this Section. To illustrate the forecasting procedure, the spinning reserve (synchronous reserve) requirement of Ontario electricity market from 1st Jan. 2006 to 14th July 2006 is used for prediction.

The spinning reserve requirement presents high volatility and non constant mean. The abrupt changes and volatility of SR requirements can be reflected as a switch in the SRRs series dynamics owing to the discrete behaviors in competitors' strategies. .

If SR requirement at hour h (R_h) is to be forecasted, the SRRs information of previous hours up to 'm' hours is $R_{h-1,} R_{h-2,} ..... R_{h-m}$ should be taken as a part of the input of SRRs forecasting model. The auto co-relation function (ACF) can be used to identify the degree of association between data in the SRRs series separated by different time lags i.e. previous SRRs. The historical hourly data of 7 days prior to the day whose SRRs to be predicted have been considered to build the forecasting model. Hence the total data points are equal to 7 x 24 = 168. Since the proposed model uses SRRs data 7 hours ago to predict the SRRs $R_{h,}$ 168-7 =161 input vectors are used to develop the forecast model.

. The historical hourly SR data used to construct LLWNN model which would be employed to forecast the SR requirements for test weeks are shown in table 1.The MATLAB 7.6 high level language has been used to implement the LLWNN model.

III.SPINNING RESERVE REQUIREMENTS FORECASTING USING LLWNN

In stead of using multi layered neural networks and its several variants, a LLWNN is used for forecasting the next hour, next day and next week SRRs in a deregulated environment.

In order to take the advantage of the local capacity of the wavelet basis functions while not having too many hidden layer units, the architecture of the LLWNN is proposed. The structure of an LLWNN model is shown in Fig. 1.

The LLWNN model has very good prediction properties. It is discrete and logical in nature. It can map input-output relations by simply learning historical samples. Connection weights are viewed as locally accurate piece wise constant models. It has higher convergence rate, easy estimating and adjusting model parameters and localized activation of the hidden layer units.

The day-ahead hourly final SR requirements of Ontario grid for winter and summer seasons for the year 2006 are used in the case study. The historical data of day-ahead hourly SRR Ontario control grid of the 7 days previous to the day of the week whose SRRs are to be forecasted have been considered to build the forecasting model. After the one step ahead training, the next hour prediction is evaluated. Multiple steps ahead are reached via recursion i.e. by feeding input variables with model's outputs. The next hour forecasts are performed for every hour of the day. The model is retrained at the end of each day to incorporate the most recent information. The concatenation of 7 days training windows, for a particular day, is shifted one day-ahead and forecasts for the next 24 hours are computed. The performance of LLWNN model is demonstrated by using 2nd week of winter and summer as test weeks.

According to wavelet transformation theory, wavelet in the following form is a family of functions generated from one single function ψ(x) by the operation of dilation and translation. Ψ(x) which is localized in both time space and the frequency space is called a mother wavelet.

$$\psi = \psi_i = |a_i|^{-1/2}\psi\left(\frac{x-b_i}{a_i}\right) : a_i, b_i \in R^n, i \in z \qquad (1)$$

$$x = (x_1, x_2, \ldots x_n)$$
$$a_i = (a_{i1}, a_{i2}, \ldots\ldots a_{in})$$
$$b_i = (b_{i1}, b_{i2} \ldots\ldots b_{in})$$

The parameters a_i and b_i are the scale and translation parameters, respectively. According to the previous researches, the two parameters can either be predetermined based on wavelet transformation theory or be determined by a training algorithm.

In the standard form of wavelet neural network, the output of a WNN is given by

$$f(x) = \sum_{i=1}^{m} w_i \psi_i(x) = \sum_{i=1}^{m} w_i |a_i|^{-1/2} \psi\left(\frac{x-b_i}{a_i}\right) : a_i, b_i \in R, i \in z \qquad (2)$$

The above wavelet neural network is a kind of basis function neural network in the sense of that the wavelets consists of the basis function. An intrinsic feature of the basis function networks is the localized activation of the hidden layer units, so that the connection weights associated with the units can be viewed as locally accurate piecewise constant models whose validity for a given input is indicated by the activation functions. Compared to the multilayer perceptron neural network, this local capacity provides some advantages such as the learning efficiency and the structure transparency. However, the problem of basis function networks is also led by it. Due to the crudeness of the local approximation, a large number of basis function units have to be employed to approximate a given system. A shortcoming of the wavelet neural network is that for higher dimensional problems many hidden layer units are needed.

In order to take advantage of the local capacity of the wavelet basis functions while not having too many hidden units, LLWNN has been used as an alternative neural network.

The difference of a local linear wavelet neural network (LLWNN) with conventional wavelet neural network (WNN) is that the connection weights between the hidden layer and output layer of conventional WNN are replaced by a local linear model[15]. The output of LLWNN is given by

$$Y = \sum_{i=1}^{m} (w_{i0} + w_{i1}x_1 + \ldots\ldots + w_{in}x_n)\psi_i(x) \qquad (3)$$

Where, instead of the straight forward weight w_i (piecewise constant model), a linear model $v_i = w_{i0} + w_{i1}x_1 + \ldots\ldots\ldots + w_{in}x_n$ is introduced.

The activities of the linear models v_i (i=1,2,--------n) are determined by the associated locally active wavelet functions $\psi_i(x)$ (i= 1,2,-------,n), thus v_i is only locally significant.

The architecture of the proposed model is shown in Fig.-1.

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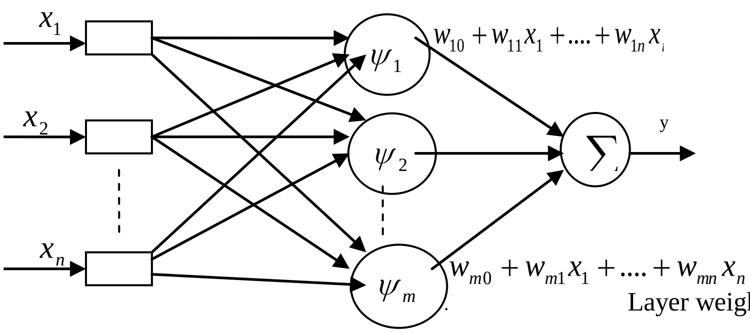

Fig.1. General Structure of a local linear wavelet neural network.

In this paper, the used mother wavelet is as follows:

i) $\psi(x) = \frac{-x^2}{2} e^{-x^2/\sigma^2}$ (3).

ii) $\psi(x) = e^{-\left(\frac{x-c}{\sigma}\right)^2}$ (4)

Where x = $\sqrt{R_1^2 + R_2^2 + ... + R_n^2}$

IV. TRAINING ALGORITHM

A neural learning algorithm to get all the unknown parameters of network i.e. translation and dilation coefficients, weights may be used for supervised training of an LLWNN. Since the function computed by the LLWNN model is differentiable with respect all the mentioned unknown parameters, a standard back propagation (BP) gradient descent training algorithm can be used for updating weights, dilation and translation parameters which are randomly initialized at beginning.

It is possible to over fit the training data if the training session is not stopped at the right point. The unset of the over fitting can be detected through cross validation in which the available data set are divided in to training, validation and testing subsets. The training set is used to compute the gradients and update all the unknown parameters of the networks. The error on the validation set is monitored during the training session. In this work, the standard BP gradient descent training algorithm has been adopted and training is based on minimization of the cost function (E), given as:

$$E = \frac{1}{2}\begin{bmatrix} D - w_{10}\psi_1(x) - w_{11}R_1\psi_1(x) - ...... - w_{20}\psi_2(x) - w_{21}R_2\psi_2(x) - .... \\ .... - w_{m0}\psi_m(x) - w_{m1}R_1\psi_m - .... - w_{mn}R_n\psi_m(x) \end{bmatrix}^2 \quad 2$$

(5)

Where D= desired output

The parameter learning based on BP gradient descent is performed as follows,

Layer weights (w) updation:

$$w(k+1) = w(k) - \eta e \frac{\partial E}{\partial w} \quad (6)$$

Such that $w_{10}(k+1) = w_{10}(k) + \eta e \psi_1(x)$

Where eta is the learning rate parameter and 'e'is the average error.

$w_{11}(k+1) = w_{11}(k) + \eta e R_1 \psi_1(x)$ and so on.

Dilation parameter (sigma) and translation parameter (c) updation:

$$\sigma(k+1) = \sigma(k) - \eta e \frac{\partial E}{\partial \sigma} \quad (7)$$

$$c(k+1) = c(k) - \eta e \frac{\partial E}{\partial c} \quad (8)$$

Such that

$$\sigma_1(k+1) = \sigma_1(k) + \eta e(w_{10} + w_{11}R_1 + ... + w_{1n}R_n)\frac{\partial \psi_1(x)}{\partial \sigma_1}$$

(9)

$$c_1(k+1) = c_1(k) + \eta e(w_{10} + w_{11}R_1 + ... + w_{1n}R_n)\frac{\partial(\psi_1(x))}{\partial c_1}$$

(10)

$$\frac{\partial(\psi_1(x))}{\partial \sigma_1} = \frac{-x^4}{\sigma^3} e^{-x^2/\sigma_1^2} \quad (11)$$

$$\frac{\partial \psi_1(x)}{\partial \sigma_1} = \frac{2(x-c_1)^2}{\sigma^3} e^{-\frac{(x-c_1)^2}{\sigma^2}} \quad (12)$$

$$\frac{\partial(\psi_1(x))}{\partial c_1} = \frac{4c_1(x)}{\sigma_1^2} e^{-\left(\frac{x-c_1}{\sigma_1}\right)^2} \quad . (13)$$

V. ACCURACY MEASURES

To asses the prediction capacity of the LLWNN model, in addition to root mean square error (RMSE), mean absolute percentage errors (MAPEs) are computed as follows.

$$RMSE = \sqrt{\sum_{t=1}^{N} \frac{(R_{a,t} - R_{f,t})^2}{N-1}} \quad (14)$$

The absolute error (AE) is defined as

$$AE_t = \frac{|Ra,t - R_{f,t}|}{R_{a,t}} \quad (15)$$

Where $R_{a,t}$ =Actual ORRs

$R_{f,t}$ =Forecasted ORRs

The daily mean absolute error (DMAE) can be computed as follows.

$$\text{DMAE} = \frac{1}{24}\sum_{t=1}^{24} AE_t \quad (16)$$

The daily mean absolute percentage error

$$\text{(DMAPE)} = \frac{100}{24}\sum_{t=1}^{24} AE_t \quad (17)$$

The weekly mean absolute error

$$\text{(WMAE)} = \frac{1}{168}\sum_{t=1}^{168} AE_t \quad (18)$$

And

The weekly mean absolute percentage error

$$\text{(WMAPE)} = \frac{100}{168}\sum_{t=1}^{168} AE_t \quad (19)$$

To avoid the adverse effect of hourly SRRs close/equal to zero, the mean absolute percentage error (MAPE) can be redefined as mean error (M.E). So the denominator of right hand side of (15) is replaced by average SRRs.

$$(ME)_t = \frac{|Ra,t - R_{f,t}|}{R_{a,av}} \quad (20)$$

VI. RESULTS & ANALYSIS

The effectiveness of the LLWNN model is demonstrated on SRRs prediction in Ontario electricity market for the year 2006. The forecasted SRRs obtained with proposed model during winter and summer test weeks with actual SRRs and errors are shown in Fig. 3.and Fig.5. respectively. It can be seen from Fig. 3 and Fig.5. that the predicted SRRs of the week are quite close to the actual one.

The relative errors for the test weeks are presented in table 2 and 3 respectively. These results in uneven accuracy distribution throughout the week that reflects reality.

It is observed that WMAPE values of LLWNN model for the winter test week and summer test week are 2.8134 and 2.0478 respectively. Therefore accuracy is reasonable enough with a weekly mean absolute percentage error of less than 3.

For comparison purposes, the weekly MAPEs of the spinning reserve forecast, using ANN approach which been included in MASCEM [16], ANN, Adaptive Wavelet Neural Network (AWNN) [17] are also presented in table-4. MASCEM is a multi-agent based electricity market simulator that uses sophisticated Artificial Intelligence based techniques for players modeling and decision support [16].

TABLE 1

HOURLY SRR DATA FOR FORECASTING MODEL CONSTRUCTION AND TESTING.

Sl.No.	season	Historical hourly SRRs data	Test weeks
01	Winter	Jan.1-Jan7	Jan 8-Jan14
02	Summer	July1-July7	July8-July 14

TABLE -2
RESULTS OBTAINED BY PROPOSED MODEL FOR 24 HOURS OF WINTER TRAINING AND TEST WEEKS.

FOR TRAINING DATA SET **FOR TEST DATA SET**

(1st day) **(1st day)**

Predicted hourly SRR	Hourly Error	Predicted hourly SRR	Hourly Error
0.7080	-0.0137	0.7119	-0.0232
0.6897	0.0077	0.7050	-0.0118
0.6989	0.0005	0.7026	-0.0051
0.7056	-0.0078	0.7148	-0.0127
0.6903	0.0028	0.7062	-0.0123
0.6909	-0.0011	0.6929	-0.0004
0.6726	0.0151	0.6891	-0.0004
0.6688	0.0192	0.6670	0.0262
0.6785	0.0137	0.6749	0.0326
0.6894	0.0051	0.6925	0.0157
0.6900	-0.0096	0.6739	0.0245
0.6649	0.0130	0.6708	0.0276

0.6854	0.0189	0.6815	0.0331
0.7292	-0.0247	0.6986	0.0124
0.6851	-0.0315	0.6782	-0.0195
0.6124	-0.0080	0.6101	-0.0032
0.5883	-0.0195	0.5862	-0.0212
0.5477	0.0013	0.5486	-0.0017
0.5391	-0.0013	0.5425	-0.0044
0.5297	0.0110	0.5345	- 0.0010
0.5248	0.0124	0.5261	0.0064
0.5472	0.0156	0.5455	0.0029
0.5991	0.0191	0.5821	0.0284
0.6718	-0.0206	0.6694	0.0113

TABLE -3
RESULTS OBTAINED BY PROPOSED MODEL FOR 24 HOURS OF SUMMER TRAINING AND TEST WEEKS.

FOR TRAINING DATA SET (1st day) | **FOR TEST DATA SET (1st day)**

Predicted hourly SRR	Hourly Error	Predicted hourly SRR	Hourly Error
0.7102	-0.0162	0.7007	0.0268
0.6951	0.0023	0.7520	-0.0061
0.6979	0.0015	0.7393	0.0144
0.7041	-0.0063	0.7559	0.0015
0.6909	0.0022	0.7603	0.0008
0.6824	0.0075	0.7609	-0.0034
0.6803	0.0074	0.7514	0.0054
0.6782	0.0098	0.7534	0.0030
0.6810	0.0112	0.7519	0.0117
0.6890	0.0055	0.7639	0.0253
0.6893	-0.0090	0.8015	0.0276
0.6624	0.0155	0.8457	-0.0199
0.6777	0.0267	0.8052	0.0005
0.7258	-0.0213	0.7929	-0.0068
0.6901	-0.0364	0.7854	-0.0290
0.6062	-0.0017	0.7438	-0.0332
0.5808	-0.0120	0.6872	-0.0306
0.5511	-0.0021	0.6276	-0.0014
0.5343	0.0034	0.6129	-0.0026
0.5300	0.0040	0.5947	-0.0064
0.5384	-0.0027	0.5614	0.0191
0.5513	-0.0120	0.5728	0.0050
0.5922	-0.0021	0.5757	0.0259
0.6604	0.0034	0.6185	0.0415

TABLE-4
WMAPE COMPARATIVE RESULTS

MODELS	ANN	AWNN	ANN (MASCEM) With load	ANN (MASCEM) Without load	Proposed model
WMAPE	4.106	3.710	3.674	3.729	2.0478

Table 2 &3 provide the predicated hourly SRRs in terms of maximum SRRs (2574MW) along with hourly error for 1st day of the test week and month. .We believe, these results are reasonably accurate for a study spanning of one week and month. Very less training time(less than 2seconds) shows the higher convergence rate of LLWNN model to predict the SRRs with higher accuracy. A LLWNN performs satisfactory, because both smooth global and sharp local variations of SRRs signal can be effectively represented by the wavelet basis activation function for hidden layer neurons without any external decomposer / composer and also not having too many hidden units.

VII. CONCLUSION

In this paper, SRRs forecasting by using a local linear wavelet neural Network (LLWNN) model is used. The characteristic of the network is that the straight forward weight is replaced by a local linear model and thereby it needs only smaller wavelets for a given problem than the common neural networks. It is also observed that reasonably accuracy is attained by LLWNN model with high convergence rate and out performed in the forecasting the SRRs compared to other models because of its favorable property for modeling the non-stationary and high frequency signal such as spinning reserve requirements.

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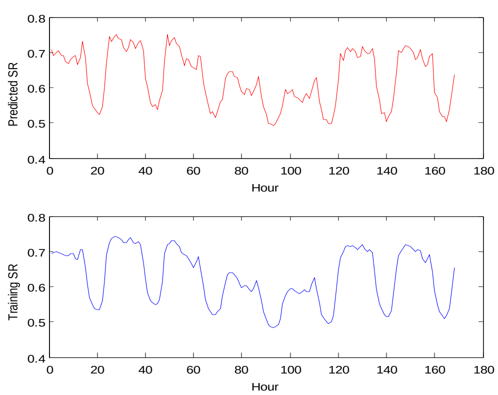

Fig-2.a. Dynamic system output and model output for winter training data set

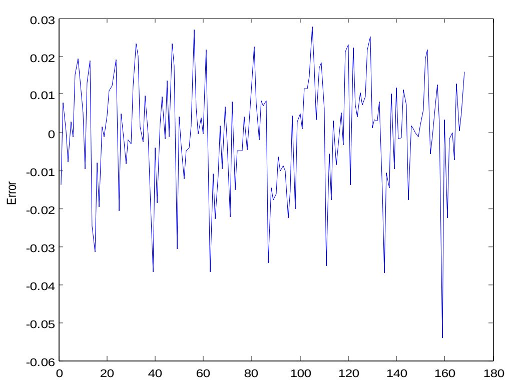

Fig-2.b. Hourly error for winter training data set

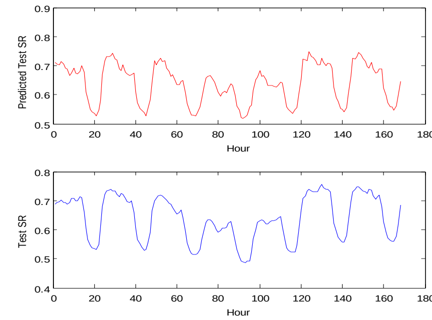

Fig-3.a. Dynamic system output and model output for winter test week data set.

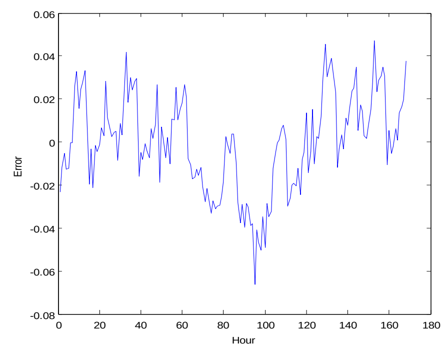

Fig-3.b Hourly error for winter test week data set

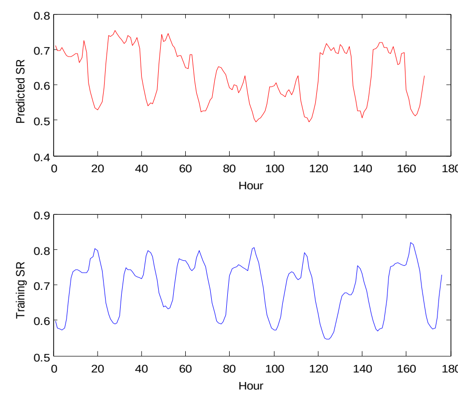

Fig.4. a. Dynamic system output and model output for summer training data set

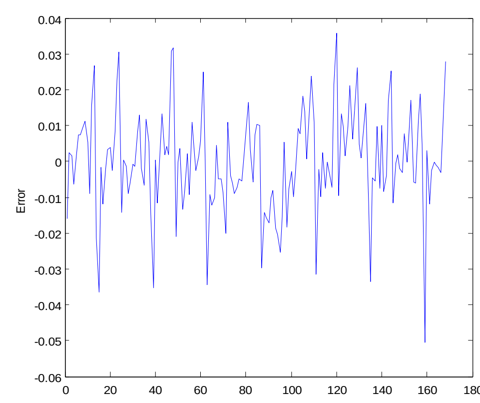

Fig.4.b. Hourly error for summer training data set.

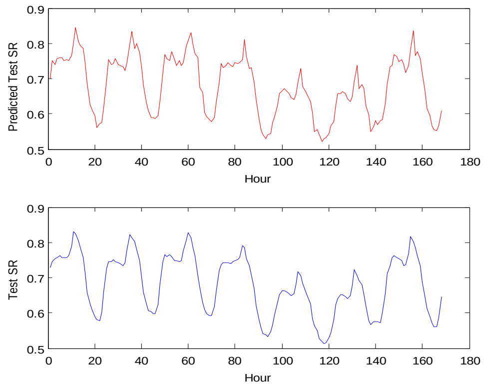

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Fig.5.a. Dynamic system output and model output for summer test data set..

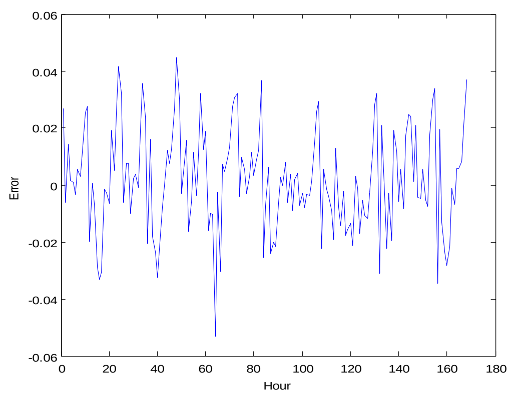

Fig.5.b.Hourly error for summer test data Set