APPLICATION OF SHORT TERM LOAD FORECASTING TECHNIQUES TO INDIAN POWER SYSTEM AND CASE STUDY FOR WESTERN REGION

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Abstract

The importance of accurate load forecasts for the power utilities as basic inputs for unit commitment, generation scheduling and EMS functions is well known and have economic implications. With the introduction of Availability Based Tariff(ABT) and Indian Electricity Grid Code (IEGC) in the country, the power utilities need to forecast their loads in 15-minute time blocks a day in advance (STLF) with high accuracy and accordingly work out their Central Sector requisitions to avoid payments for unscheduled interchanges. The paper discusses various STLF models with particular emphasis on ANN based STLF models as the later out perform other models and simple to build. A case study concerning Western region was considered and the STLF system is described in detail with typical results. The paper also discusses the constraints in demand forecasting in the Indian context and suggests suitable models, especially the generation dependency algorithm.

1. INTRODUCTION

In order to supply high quality electric energy to the customer in a secure and economic manner, electric utilities face many economical and technical problems in planning, operation and control of large electric energy systems. Load forecasting with lead times, from a few minutes to several days, helps the system operator to schedule spinning reserve allocation effectively. The long and medium term forecasts are used to plan the capacity of generation, transmission or distribution system additions and the type of facilities required in transmission expansion planning, annual hydro-thermal maintenance scheduling etc. The short-term forecast (STLF) is needed for control and scheduling functions and also as inputs to EMS functions. The STLF can also provide wide information regarding vulnerable situations that may take place, in advance, if the output of STLF is applied to the system security assessment problem. Thus STLF plays a key role in the formulation of economic, reliable and secure operating strategies for the power system.

The significant effect of STLF on power system operations and production costs depends upon its accuracy. System despatchers must anticipate the system load patterns so as to have sufficient generation. The errors in load forecasts could affect in planning reserve requirements. Under-prediction of load results in a failure to provide the necessary reserves, which in turn, translates to higher costs due to the use of the expensive peaking units. Over-prediction of load, on the other hand, involves the start-up of too many units resulting in unnecessary increase in reserves and hence operating costs.

In the Indian context, demand forecasting is needed in the following time horizons (as envisaged in IEGC).

Time Horizon	Functional requirement
Long Term	
5 to 20 years	Prospective planning of the power system
1 to 5 years	Power system planning, system strengthening, tariff planning, sale/purchase of generation capacity
Medium Term	
One year	Annual plans for maintenance scheduling of generating units and transmission lines, scheduling of fuel supplies, financial planning. Bilateral agreements for capacity trading
Quarterly	Outage planning, hydro generation schedules, planning of scheduled load shedding, study of generation and transmission constraints
Monthly	Evolving operating plans, hydro generation schedules, outage planning
Short Term	
Weekly	Unit commitment, operational planning, resource planning, outage clearance, fuel allocations, bilateral agreements for energy trading
Daily	Scheduling of generation, trading of energy, despatch of generation, EMS functions
Very Short Term	
Four minutes to few hours	Security assessment, economic despatch, other MIS functions

2. IMPORTANCE OF ACCURATE LOAD FORECASTS FOR INDIAN UTILITIES

The implementation of Availability Based Tariff (ABT) in India following CERC's order dated 4th January, 2000 is likely to revolutionize power system operations of the Indian power utilities. One part of the ABT is about pricing of Unscheduled Exchanges among utilities.. The Unscheduled Interchanges (UI) are priced as per frequency linked rates. Thus, the schedule becomes an important consideration in system operation and is considered as a contract. The States within a region are having Central Sector entitlements, for which, fixed charges are paid by the States as per their entitlements. However, the States are free to make their station-wise requisitions subject to an upper ceiling i.e. entitlement. RLDCs advise the States a day in advance on the declared capability of the Central Sector stations and entitlements of the States in each of the stations. The States are expected to furnish to RLDCs their station-wise requisitions for each 15-minute block for the following day. Based on the requisitions from all the States and any bilateral commitments among the States within or outside the region, the station-wise schedules and drawal schedules of the States are prepared by RLDCs. These schedules become a datum from which the deviations in drawal of the States are measured and deviations priced linking to frequency. Adhering to schedules becomes an important consideration to save from financial loss due to penalties. IEGC stipulates the responsibility to forecast demands to the States. Each state prepares the requisitions for the following day based on availability from their own sources and forecasted demand for the following day. The difference in forecasted demand and own availability becomes their requisitions. Thus, forecasting demand accurately for each 15-minutes block of the day has a major effect on the tariff. As an example, consider the requisition of a State as 1500 MW against an entitlement of 2000 MW from Central Sector. If the State draws 1800 MW in a particular hour due to forecasting error and if the frequency in all the four 15-minute blocks during the hour is 49 Hz, the UI payment to be made by the State would correspond to 300 MWH at an UI price of 420 paise per unit which works out to Rs.12.6 lacs in just one hour. 1% error in demand forecast for a State like Maharashtra meeting a demand of 11000 MW would mean Rs.4.62 lacs in just one hour if frequency during the hour is 49 Hz or below. Other means to handle forecasting error (under estimation) could be through distress load shedding, use of expensive peaking generation and real time trading leading to increased operating cost due to scheduling of higher cost generation (for e.g. liquid fuel) or depletion of hydro reservoirs which have other implications. Similarly, over estimation of demand by 1% may lead to high frequency operation with lower UI prices and may necessitate backing down of generation and thereby increased operating costs.

3. REVIEW OF STLF METHODS

Various algorithms have been suggested in the literature for STLF. They are mainly classified into:

- Time series models
- Regression models
- Expert Systems
- State Space & Kalman Filtering
- Artificial Neural Networks

Time series models employ the historical load data for extrapolation to predict future load. These models assure that the load trend is stationary and treat any abnormal data point as bad data. General problems with the time series approach include the inaccuracy of prediction and numerical instability. Since these models do not utilize weather information, they often give inaccurate results as there is a strong correlation between the behaviour of power consumption and weather variables such as temperature, humidity, cloud cover and wind speed.

Regression models determine dependent variables using the future evaluations of the independent variables. Regression models analyse the relationship between weather variables and loads. The conventional regression approaches use linear or piece-wise linear representations, the regression approach finds the functional relationships between selected weather variables and load demands. Linearisation of weather terms may not be justified also. These methods are computationally intensive and has less generalisation capability.

The objective of knowledge based approach is to use the knowledge, experience and logical thinking of experienced system operators through a set of rules. Further the rules can be modified or new rules can be incorporated at a later stage. Rules facilitate continuous revising mechanism based on heuristics. It is often difficult to convert rules or logic of the experienced operators into mathematical equations.

State Space & Kalman Filtering: These model periodic component of load of a random process and require large historical data base of one year or more to enable modelling of periodic load variations and to estimate the required initial as well as system dependent variables.

The models based on Artificial Neural Networks can effectively model the nonlinear relationships between various parameters through training. ANNs can represent complex non linear interdependencies in the raw data not explicitly known to human experts. Because of inherent non linearity, ANNs can effectively deal with the complex interacting between variables that affect loads. No complex mathematical equations need to be defined relating the input variables and the load. The models can follow sudden and random effects. Thus non-linear modelling and adaptation give edge to these models over other models. The other major advantages of the Artificial Neural Networks are robustness, fault tolerance and hardware implementation through VLSI, ability to perform reasonably well using incomplete data bases due to which the ANNs perform better than the other models.

4. FACTORS INFLUENCING SYSTEM LOAD [1]

Economic Factors

The economic environment in which the utility operates has a clear effect on the electric demand consumption patterns. Typically, these economic factors operate with considerably longer time constants than one week and hence need not be considered for STLF. However, these factors should be taken into consideration for long, medium-term forecasting models.

Time Factors

The principal time factors viz., seasonal effects, weekly-daily cycle, legal and religious holidays play an important role in influencing load patterns.

Weather Factors

Significant changes in load patterns are due to meteorological factors as most of the utilities have large components of weather sensitive load such as space heating, air conditioning and agricultural irrigation. The load level fluctuates with the climatic conditions and has high correlation with area temperature, rainfall, snowfall, etc. Temperature and precipitation are the main meteorological factor considered in load forecasting. Their influence on the system load varies not only between winter and summer, but also between peak and valley of the same day.

Random Disturbances

These include loads such as steel mills, synchrotrons, wind tunnels whose operation can cause large variations in electricity usage. Wide spread strikes, bandhs, special TV programmes whose effect on the load is not known a-priori could cause sudden and unpredictable variations in load.

5. CONSTRINTS IN DEVELOPING ACCURATE MODELS FOR UTILITIES IN THE INDIAN CONTEXT.

The following constraints have been described in relation to Western region. However, these remarks are applicable to most of the Indian power utilities

5.1 Generation Dependency.

The Western Region suffers from peaking shortages. The shortages are at times in the order of 4000 MW especially during evening peak. Due to inadequate generation within the region and due to non availability of assistance from the neighbouring regions, the load is curtailed through planned load shedding, power cuts, holiday and recess staggering and other restrictions. Even after imposing several restrictions, system frequency remains just above 48 Hz. However, during off-peak hours, the load reduces significantly and thermal generation backing down is implemented to control high frequency. During the off-peak hours, the load exhibits its natural behaviour while during the peak hours the load behaviour is suppressed due to imposition of manual load management measures and the load behaviour is by and large influenced by the generation availability. This generation dependency aspect throws the greatest challenge in developing a load forecasting model.

5.2 Demand Data

The historical data for the last few years has been preserved at WRLDC. The demand data is categorised into registered demand, computed demand and unrestricted demand. Registered demand is the demand actually met by an utility. The computed demand is the sum of the load met, load shedding and frequency correction (applied to refer the loads at 50 Hz and calculated from the power number). The unrestricted demand is the sum of the computed demand, power cuts, restrictions and effect due to recess and holiday staggering of loads. In case of generation constraints and lack of inter utility assistance, the load actually met could be different from the actual load. Thus a part of the load is shed through various load management measures described above or shed through defence mechanisms such as automatic under frequency load shedding schemes. Thus registered demand does not actually reflect the load demand of the utility but is a function of generation availability. The computed demand data is unreliable due to non availability of precise data on load shedding and errors introduced by the frequency correction. Further, due to non availability of precise data on power cuts, restrictions and staggering of loads, the unrestricted demand data cannot be totally relied upon. The above problems can introduce appreciable errors in the STLF models as well as make it difficult to validate the model parameters.

5.3 Weather Data

The importance of building up a weather model with variables such as temperature, humidity, cloud cover, wind speed, precipitation etc., needs no emphasis. In the Western Region, the temperature and humidity play a significant impact during the summer months especially in the urban areas where air conditioning is widely used. About 28% of the demand in Western Region is agricultural load which is sensitive to precipitation as pumping load comes into operation during hot weather and becomes negligible when it rains. Onset of darkness influences to some extent, the time of occurrence of evening peak load. Due to vastness of geographical area and wide variations in the climate, it is difficult to build up an accurate weather model. However, it is possible to build up weather models for forecasting bus loads/substation loads or city loads independently. Another dimension is the difficulty in interpretation of weather forecasts supplied by the weather bureau for the Regional forecasts. Further, errors in weather forecasts could also be reflected in the model errors. The load weather model can work properly only if the data used for its building or tuning represents the behaviour of the variables to be modelled [2]. As the weather variables are not built into our STLF model, the residual contain the weather effects which cannot be deciphered.

5.4 Accuracy of the Recorded Data

The quality of the data used is a factor of paramount importance in building an accurate STLF model [2]. The essential pre-requisites are:

- Data should be highly reliable
- The amount of data must be sufficient for the purpose of the study

The data in Western Region is gathered both through the SCADA system and manually from the constituent systems over the last 12 years. Bad data in the data set could be due to errors in measurement, errors in data transmission communication problems and human errors in data entry. The bad data could also be due to system disturbances, industrial strikes, bandhs, local festivals and holidays which affect the part of the load only. The model to be built will be as good as the data used and the use of the more sophisticated mathematical models (in order to capture the effect of various variables on load sensitivity) increases the necessity for more accurate and reliable data [2].

5.5 Interpretation of the Forecasted Demand

Due to the various peculiarities explained above, it is difficult to forecast a demand that can be easily interpreted by the load despatchers. The restricted demand is difficult to interpret due to generation dependency and the system frequency at which the forecasted demand occurs. The unrestricted demand is the most difficult to interpret. The computed demand can be interpreted to some extent as the forecasted demand and is given at 50 Hz and the load despatcher can apply the corrections in respect of load shedding and frequency. However, the hourly forecasted loads could only serve as an important tool to pre despatch functions as the despatcher would be more concerned about the instantaneous system parameters.

6. A CASE STUDY FOR WESTERN REGIONAL GRID

The Western Regional Grid comprises power systems of Maharashtra, Gujarat, Madhya Pradesh, Goa, Union Territories of Daman & Diu and Dadra & Nagar Haveli, power stations owned by the Central Sector organizations viz., NTPC & NPC and private sector organizations such as TEC, BSES, AE.Co and GIPCL. The EHV transmission is owned by the SEBs and POWERGRID. The 400kV transmission network of POWERGRID forms the backbone of the grid and evacuate power generated at the Central Sector power stations. POWERGRID also owns and operate HVDC links for bulk power transfer among the regions. The region caters to a peak demand of 23600 MW and daily energy consumption of the region is around 500Gwh. The load despatching operations in Western Region are coordinated by WRLDC through a hierarchial SCADA based load despatch centres with RLDC at Mumbai on the top of the hierarchy followed by State Load Despatch Centres (SLDCs) and Area Load Despatch Centres (ALDCs) of the constituent systems at the lower levels.

The operational strategies are made by the operating committee of the region constituted from the representatives of all the constituent systems. The implementation of these strategies is coordinated by WRLDC under POWERGRID.

7. STLF SYSTEM AT WRLDC

7.1 Pre-filtering

The purpose of pre-filtering is to check the validity of data and incorporate corrections. Pre-filtering is required to maintain consistency and acceptable level of signal to noise ratios. The bad data correction routine checks the bad data through various plausibility checks which are rule based analytical techniques such as [9] limit checking by comparison with normalised loads and similar morning peak or evening peak days using, short term trending index, load inertial index and clustering analysis.

7.2 Mathematical Models

7.2.1 The software Package

A software package consisting of various ANN based algorithms has been developed with several power system applications in mind. The algorithms tried for the STLF application include simple back propagation algorithm, cumulative back propagation algorithm variants of BP algorithm with cauchery training, adaptive BP, combination of the above, simulated annealing, random optimisation(Matyas), random optimisation (soils & wets), Kohonen's self organising feature map etc. All these algorithms have been tested for the STLF application. These algorithms have been tested with various system models which are described in the ensuing paragraphs. The performance of various models are compared with reference to: (i) training time (ii) maximum error at any particular hour (iii) Mean absolute percentage error (MAPE) (iv) RMSE (Root mean square error) and (v) Adaptability.

It has been found that the simple BP algorithm with one hidden layer was found to be adequate. Other variants of BP including the adaptive BP algorithm gave similar performance. As the back propagation algorithm has been widely discussed in the available literature, no attempt has been made to explain it further.

7.2.2 Parameter Optimisation

The optimal values of the learning rate (η) and the momentum constant (α) are generally problem dependant. A combination of η = 0.25 and α = 0.85 gave the best results for WRLDC application. Higher value of 'η' may cause non convergence even though faster learning rate is achieved. To begin with 'η' may be chosen as 0.2 but this may lead to increased training time. To cut down the training time, progressively higher values to be considered or adjusted adoptively. The software package allows for selection of wide range of non linearities such as sigmoidal function, hyperbolic function, hardlimiter, threshold logic etc., and random basic function. However, the sigmoidal function was chosen for the particular application after several trials with other nonlinearities. Different scaling methods have been tried to normalise the data in the range of 0.1 to 0.9. These include division by the maximum value, taking of logarithms, normalisation of vectors, normalisation using mean and variance. The scaling equation found to be most useful is as follows[6]

$x = 0.1 + (0.8) (xi- x min) / (xmax-xmin)$

Where x = scaled value xi = original value, xmax & xmin area the maximum and minimum elements of all patterns.

7.2.3 Training Variations

The frequency of presentation of patterns can be selected based on clustering and the days with generation availability close to the forecasted day's generation availability etc. Noisy data has been used for obtaining proper generalisation. Old data is continuously replaced by the new data. The network weights area updated by training with the latest data for few iterations in order to obtain better adaptability.

7.2.4 Data Set

The minimum required data to give better results was found to be 90 days data (one quarter) even though it was found that historical data base for one or two years were giving marginally better results. . Further this suits most of the utilities as it is difficult to get historical data for required number of years to give consistently good forecasts irrespective of seasonal effects. It is also seen that if more data is used, the size of the errors increase in case the forecasted day falls in the days interspersed between seasons. Selection of data set for 3 months also suits the system model described under 7.2.7. For the results displayed, data set of one year has been used.

7.2.5 Error Analysis

The errors are used to decide the presentation of patterns in the adaptive training stage. In case of large errors, the latest data is used with increased frequency of presentation for two more days to account for the load inertia effect.

7.2.6 Pre-processing and Smooth Methods

The data is analysed based on average load of the week, day of the week effect, load inertia, short term trend etc. and a new data set is prepared using one week initial data. The rest of the data in the data set is replaced with new data. The new data is infact, forecasts based on heuristics such as the methods presently employed by the utilities in Western Region. Due to heuristic forecasts replacing the original data, the random effects are smoothed out. Further, pre-processing helps in bad data correction, filtering out noise and use of the new data set helps in faster training.

7.2.7 System Models

A major part of the forecasting task is concerned with that of identifying the best possible model for the past load behaviour. The system modelling involves identification of factors that influence prediction of the future load. The load at hour 'h' on day 'd' i.e L(d,h) can be expressed as a function of various factors that influence the load.

L(d,h) = f (various factors that influence load)

On the basis of experience, features of the load curve and the patterns in historical load and weather data, the inputs could be selected. The accuracy in identifying all the factors influences model accuracy. The advantage of the ANN based STLF is that the relationship of the various factors to the load need not be defined precisely as the network learns these relationships even if they are non linear in nature. Thus ANN based STLF scores over Time Series and Statistical Methods in the simplicity of modelling. At WRLDC, five system models have been developed for STLF application. However, model #2 was found to be giving consistent results and as such only this model is explained here.

The load curve can be broken up into 5 to 6 parts, depending, upon gradient (+/-) in load curve [9]. Here, the crests and troughs of the load curve are considered to break the load curve into linear parts from 1st hour to the hour where a crest/trough arises in the load curve and considered as one part and from that point to next crest/trough as another part and so on. The hours falling in a particular part of the load curve are forecasted at a time. Say, for hours h1 to h2 the inputs used for training ANN are,

L(d-1, h1-e) to L(d-1, h2+e) to
L(d-7n, h1-e) to L(d-7n, h2+e)

Where 'n' varies from 1 to the number of weeks to be considered and 'e' is the number of extra hours considered to smoothen the curve to eliminate the edging effect. The values of 'n' & 'e' chosen decide the number of neurons in the input layer. Generation dependency algorithm to be described later determines the number of patterns. In this work, the load curve is broken up into 5 parts i.e. hours 1-4, 5-10, 11-15, 16-20 and 21-24. (for the quarter January-March). This method gave best results for forecasting of restricted demand and computed demand.

8. APPLICATION OF THE SYSTEM MODELS FOR FORECASTING RESTRICTED DEMAND

8.1 In WRLDC, various combinations of mathematical models and system models were tried with the restricted demand data. Model #2 was found to give satisfactory results using a neural network with one hidden layer. In order to model generation dependency, first the generation availability for the forecasted day (day #1) is to be computed from the plant availability on day # 0. The days with generation availability within +/-0.5% of day #1 are given a priority of #7, the days with +/- 1% of that of day #1 are given a priority #5 etc and these day's data is repeated based on the priority. The last two weeks data is used with a priority of #2 while same day loads in the previous weeks and latest two previous working days (only for working day nets) are given a priority of #4. Around 90 patterns can be chosen from the previous years data if available with a priority of #1. Similar data set is also used for adaptive training for about 100 iterations.

8.2 In case of large errors in forecast in the recent one or two days and if the errors are found to be due to weather effects, the data for the previous two days is given a priority of 10 to 7 based on the time lag, higher the weightage for recent effects.

8.3 As the restricted demand is difficult to interpret, the forecasts are updated using the last three hours forecasted demand, actual demand and the actual availabilities. For forecasting load at hour #0, loads and availabilities at hour #1, -2, & -3 can be used. This would enable consideration of recent plant outages. One hour-ahead forecast could be used for despatching needs whereas for the purpose of generation scheduling the day-ahead forecasts are used. Due to generation dependency, system frequency is highly correlated with restricted demand. This can also be gainfully employed to forecast frequency with a time horizon of five minutes.

8.4 A total of 10 networks viz., five for working day and five for Sundays/holidays/ national holidays are used. However, when preprocessed data is used the same network is used for all working days (two networks; one for working days and one for holidays) and we are not recommending the use of preprocessed data for holiday forecasting as errors as large as 10% were observed at certain hours despite training for several thousand iterations. In case of the network for forecasting holiday (other than Sunday loads, the last years' data on the same holiday and the load drop from the previous two days and from same day last week have been used as important factors. Thus holiday forecasts need data of previous years. This becomes a limitation for certain utilities.

9. PERFORMANCE EVALUATION AND RECOMMENDATIONS

9.1 The system model #2 using additional data for modelling generation dependency gave consistent results. The STLF model is being tested for number of months for ascertaining accuracy in modelling.

9.2 It is required to apply availability correction factors to compare the higher/increased availability on the current months' data with the previous months' data as some of the new generating units available in the current month were not available in the previous months. The efforts, however, would be worthwhile.

9.3 The ANN based model is also compared with another statistical model based on Generalized adaptive Filtering and the ANN based STLF model performed better.

9.4 The performance of the forecasts are compared using MAPE (Mean Absolute Percentage Error) and maximum error at a particular hour (ME). The indices can be computed day-wise/week-wise/month-wise for analysis of the model.

9.5 The results of the ANN based STLF system for a typical working day and holiday in the January-March quarter of the year 2001 are given with the performance indicators.

9.6 From the point of view of the accuracy of forecasts, it is prudent to devise the networks for the four seasons as indicated below:

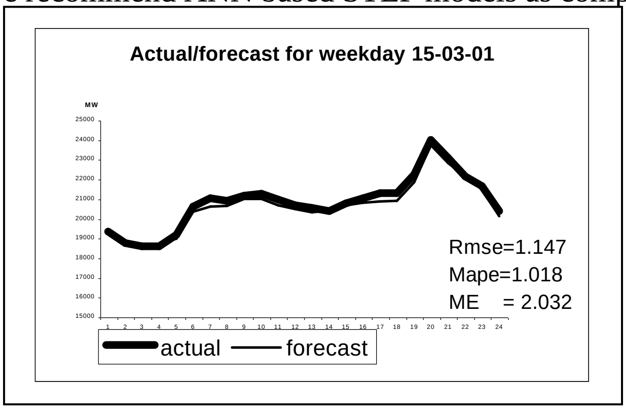
Season #1	::	January to March
Season #2	::	April to June 15th
Season #3	::	June 16th to September 15th
Season #4	::	September 16th to December

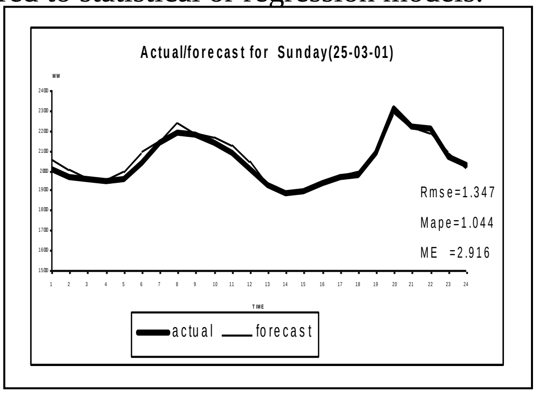
However, we have designed a system in which quarters of the year – January to March, April to June, July to September and October to December have been considered.

9.7 Neural Nets could also be built with a specific purpose of reducing forecast errors during certain hours of the day when marginal cost of power is higher. This would suit the present operating scenario in India. This can be simply achieved by selection of weights for each hour/time block in proportion to the marginal costs for that hour. In case of non availability of data on marginal costs, a typical expected frequency profile could be used or for simplicity frequency profile of the weeks with hourly average frequencies could be used and weights determined. This is possible since the UI rates which reflect marginal costs (avoided costs) are linked to frequency under the ABT regime.

CONCLUSIONS:

IEGC stipulates the responsibility to forecast demand for the following day to the states. A suitable forecasting system for the Indian power utilities has been described using the ANN based STLF in Western region is developed by WRLDC. Modelling of generation dependency, adaptive training of the network with the latest data is recommended. The model explained can also be utilised for 15-minute block-wise forecasts instead of hourly forecasts. However, data base of demands with 15-minute intervals need to be prepared. The same or another network can be used to fine tune the network as data for a part of the day becomes available. This would help in more accurate forecasts for the remaining part of the day and if required, the states can ask the RLDCs for revision of schedules. The ANN based STLF model suggested can also be used for building a weather model if the data base can be built up and weather forecasts for the following day are available. These changes are easy to implement in the ANN based STLF system. Due to these advantages and higher accuracy, we recommend ANN based STLF models as compared to statistical or regression models.





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