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Development of New Algorithms for Power System Short-Term Load Forecasting

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Abstract— **Load forecasting allows for the utilities to plan their operations to serve their customers with more reliable and economical electric power. With the developments in computer and information technology new techniques to accurately forecast power system loading are emerging. This research culminates in development of modified algorithms for short-term load forecasting (STLF) of a utility grade power system. The three proposed methods include: Modified Recursive Least Squares parameter estimation for online load foresting, Modified Kalman Filter based parameter estimation for online load forecast, and Artificial Neural Fuzzy Interference System approach. The load forecast performance of each new algorithm is validated with past utility data. The method performance is compared, and conclusions are drawn.**

Keywords-component; Short-Term Load Forecast, Least Squares, Kalman Filter, Parameter Estimation, Artificial Neural Fuzzy Interference System, ANFIS

I. INTRODUCTION

Load forecasts allow utilities to plan their operations such as unit commitment and generator maintenance beforehand, and thus, serve their customers with more reliable and more economically efficient electric power. The geographical location, population, social factors, and weather factors have different effects on the systems and therefore these systems have different types of load patterns [1]. The financial consequences for forecast errors are so significant that even a small fraction reduction in the forecast error can cause major financial benefits for the utility [2].

Load forecasting remains a difficult task to master. The difficulty comes initially because the system loads often display periodicity and seasonality at multiple time scales. Another reason is that there are many outside variables, such as weather conditions that should be considered in a load model. Research to this point has concluded that there is not a single forecasting model superior for all power systems [2-3]. The service areas have different geographic, climatic, social, economic, and customer characteristics, thus they are different in terms of loading.

The methods used for Short Term Load Forecasting (STLF) can be broadly classified into two main categories: statistical and artificial intelligence (AI) approaches. The statistical methods are often seen as attractive alternatives because some physical interpretation can be attached to their components. Most of the criticisms have been directed toward their limited abilities to handle non-linearity [1]. Some of the existing and statistical based STLF methods include: The Similar-Day approach [4], Exponential smoothing [5], Autoregressive (AR) model and Autoregressive moving average [6-7].

AI methods are generally flexible and can handle non-linearities and complexities within the system. Along with their promising performance, their popularity seems to be greatly due to the fact that no prior load modeling experience is necessary to obtain reasonably accurate forecasts [1-3]. These methods automatically organize the input data to find the relationship between it and the output data, without any human input; this can be both the advantage and the weakness of these systems. Some of the existing AI- based methods for STLF include Artificial Neural Networks (ANNs) [2,8,9], Fuzzy logic [10,11], Expert systems [12], and Support Vector Machines [13,14].

The motivation for this research is to use existing utility data and weather data to create new load forecasting algorithms for STLF of a large scale utility power system. The assumption for the research is that one can create fairly accurate models without in-depth knowledge of the power system. This paper describes evaluation of three modified techniques for STLF. The proposed techniques are validated using historical load and weather data for a large power system in the southeastern United States. The method outcomes are compared to the actual values on 24-h and 5-day time spans to evaluate their performance in terms of error during all four seasons.

This paper is organized as follows: Section II describes the proposed new methods for STLF. The proposed new methods on A and B utilize linear load model and moving averages of load and temperature data for creating load forecasts. The proposed method in C uses an ANFIS-network with moving average load and temperature values to forecast the system loading. Section III presents the information about the case study used to evaluate the three proposed new methods. Section IV draws results from the case study and compares the method performances against each other, this section is followed by the conclus11ions in Section IV.

II. Proposed New Techniques for Power System STLF

A. *Modified Recursive Least Squares Method*

In a linear load model, the system load is represented as a function of explanatory weather and non-weather related variables, where the load forecast is simply a summation of the explanatory variables multiplied by their estimated coefficients [1]. Mathematically, the system load at time t can be written in

$$y(t) = a_0 + \sum_{i=1}^{n} a_i x_i(t) + r(t), \tag{1}$$

where y(t) represents the load at time t, $[x_1(t)\ldots x_n(t)]$ are weather and non-weather related-variables determined in the load forecast model. The parameter r(t) is the unknown portion of the load at time t. The variables $[a_0\ldots a_n]$ are regression parameters relating the load to the explanatory variables. In the proposed model, the residual load will not be considered; therefore, the output y(t) can be written as a vector multiplication

$$y(t) = \begin{bmatrix} 1 & x_1(t) & \ldots & x_n(t) \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}. \tag{2}$$

If a load model is accurate, mathematical estimation tools can be used to find the regression parameters. In this research, Recursive Least Squares (RLS) method is proposed to be used for online load forecasts.

According to Gauss' principle, the unknown parameters should be chosen in a way that: "the sum of the squares of the differences between the observed values and the computed values multiplied by the numbers that measure the degree of precision, is a minimum" [15]. The Least Squares (LS) parameter estimation method can be written in a fairly simple mathematical form for systems. With the observed variable y(t), along with the parameters $[a_0\ldots a_n]$ and the known functions and variables $[x_1(t)\ldots x_n(t)]$, regressor and the parameter vectors are:

$$\varphi^T(t) = [\varphi_1(t) \ldots \varphi_n(t)] = [1 \;\; x_1(t) \ldots \, x_n(t)]$$

$$\theta = (\theta_1 \ldots \theta_n)^T = (a_0 \; \ldots a_n)^T$$

The regressors and the observations are derived from the existing data for load forecast, for each time t. The parameter values are determined in a way that the LS cost function V is minimized. The LS cost function becomes

$$V = \tfrac{1}{2}\sum_{t=1}^{t_f} (y(t) - \varphi^T(t)\theta)^2. \tag{3}$$

Since there are t_f number of measurements, one can write the observations, Y, errors, E, and regressors, Φ, in vector and matrix form

$$Y = [y(1) \ldots y(t_f)]^T$$

$$E = [\varepsilon(1) \ldots \varepsilon(t_f)]^T$$

$$\Phi = \begin{pmatrix} \varphi^T(t) \\ \vdots \\ \varphi^T(t_f) \end{pmatrix},$$

where the residual ε(t) and the cost function V are defined by

$$\varepsilon(t) = y(t) - \hat{y}(t) = y(t) - \varphi^T(t)\theta, \tag{4}$$

and

$$V = \tfrac{1}{2}\sum_{t=1}^{t_f} \varepsilon^2(t) = \tfrac{1}{2} E^T E = \tfrac{1}{2}\|E\|^2. \tag{5}$$

Reference [15] suggests that loss function V is minimum for parameters of θ when

$$\Phi^T \Phi \theta = \Phi^T Y. \tag{6}$$

A unique and minimum solution for the parameters can be found when the matrix ΦTΦ is nonsingular; therefore the parameter vector becomes

$$\theta = (\Phi^T \Phi)^{-1} \Phi^T Y = P \Phi^T Y. \tag{7}$$

The standard multiple linear regression method utilizing LS has found its greatest application in off-line forecasting [1]. However, the observations for the load profile and other external values are obtained sequentially in real time; therefore it is necessary for one to also consider the latest information in parameter computations. In order to save computational time and effort, it is desirable to make computations recursive. Computations of the LS estimate can be organized in a way that the results found at previous time step t-1, can be used to obtain the estimates at current time t [15]. According to [15] one can rearrange the $P^{-1}(t)$ matrix to form Recursive Least Squares (RLS) Algorithm. The RLS is used for the proposed algorithm.

The proposed new method also takes in account the fact that power system parameters are time-variant. To account for the non-linearity, a modification to the RLS algorithm was made in the proposed model. The modifications accounts for the possible changes in system dynamics by weighing recent values more heavily when calculating the parameter updates [15]. The parameter λ is introduced into the cost function (3), and the updated cost function becomes

$$V = \tfrac{1}{2}\sum_{t=1}^{t_f} \lambda^{t_f - t}(y(t) - \varphi^T(t)\theta)^2. \tag{8}$$

where λ is defined such that 0<λ≤1, and is called the forgetting factor. The proposed modified RLS SLTF algorithm assumes that the forgetting factor would be close to unity (λ =0.99), as the changes in power system dynamics are often fairly slow. Based on the updated cost function, the most recent data is weighted by unity, and n number of time steps old data is weighted by the factor of λ^n. The RLS algorithm can, therefore, be updated in such a way that exponential forgetting is taken into account

$$\theta(t) = \theta(t-1) + K(t)(y(t) - \varphi^T(t)\theta(t-1)), \quad (9)$$

$$K(t) = P(t-1)\varphi(t)(\lambda + \varphi^T(t)P(t-1)\varphi(t))^{-1}, (10)$$

$$P(t) = (P(t-1) - P(t-1)\varphi^T$$

$$\left(I + \varphi^T(t)P(t-1)\varphi(t)\right)^{-1}\varphi^T P(t-1))/\lambda. \quad (11)$$

The proposed RLS STLF model uses the past load data along with weather data as its inputs to forecast the load at a given time. The RLS algorithm is applied and the past loads, along with past and current weather data represent the linear combination of the load at a given time t. In the proposed model, the values for parameters are different for each hour of the day. Along with the actual past values for the load data, the proposed model utilized moving average vectors for past loads and temperatures. In the proposed model, the moving average calculates the average load and temperature values on the same hour as the forecast on past five days; these are used as model inputs. The model also considers the deviation of that actual temperature value from the moving average value, and uses the deviation values as one of its inputs.

The proposed new method also takes into account the fact that the temperature relationship with the load may not be simply linear or quadratic. A combination of both was used in the model to better estimate the relationship; the parameter multiplier was estimated for the temperature deviation and for its square. Different numbers of total inputs and the portion for each three types of inputs were considered for the RLS algorithm and their performance was evaluated, the best performance model was then selected to be compared against the other proposed STLF models. The best performance model utilizes load data moving average, base load, past load from one hour ago, past load from a day ago, actual temperature, the temperature deviation, the square of temperature deviation, temperature from one day ago, and humidity index as some of its inputs. The proposed new RLS approach differs from the existing regression based approaches by the fact that it is geared toward on-line load forecasts because of the continuous parameter updating. The introduction of the forgetting factor is also an important step towards the direction of on-line load forecasting. The proposed new algorithm also differs by using the moving averages of load and weather as its inputs.

B. *Modified Kalman Filter Method*

In most processes, as measurements are taken over time, they tend to have some imperfections, such as noise and other measurement errors. Kalman Filters are used to produce estimates that neglect the noise and yield better accuracy. In the case of load-forecasting, the residual load along with measurement errors can be thought of as the system noise that the Kalman Filter (KF) attempts to neglect. The recursive form of a KF is easy to implement in software [16]. The proposed KF model uses a time-varying state-space model to describe the load demand on an hourly basis. The KF is used to estimate and update the optimal load forecast parameters for each hour of the day. The proposed STLF model assigns each hour of a day with its own parameter model, and the parameters are updated daily.

To derive the KF model for STLF, we have to assume a state-space model

$$x(k+1) = A(k)x(k) + w(k), \quad (12)$$

$$z(k) = C(k)x(k) + v(k). \quad (13)$$

The parameters and the variables of (12) and (13) are presented in Table 1.

TABLE I. VARIABLES FOR STATE-SPACE SYSTEM MODEL

KF Parameter Variables and Explanations		
Variable	***Size***	***Description***
x(k)	nx1	State Vector
A(k)	nxn	State-Transition Matrix
z(k)	1x1	Measurement Scalar
C(k)	1xn	Time-varying Output Vector
w(k)	nx1	System Error Vector
v(k)	1xn	Measurement Error Vector

The proposed model assumes that w(k) and v(k) are white noise vectors, which have zero mean and no time correlation, along with known covariance matrices Q1 and Q2. In the model Q_1 is set to a positive semi-definite matrix, and Q_2 is set to a positive definite matrix as suggested by [1,17,18]. The matrices are in the following form

$$E[w(k)w^T(k)] = Q_1,$$

$$E[v(k)v^T(k)] = Q_2.$$

KF-model for parameter estimation is given in [1] in a form of three recursive update equations (14), (15), and (16). In the KF model, the initial values for the parameters of vector $x(k)|_{k=0}$, as well as for its error covariance matrix $P(k)|_{k=0}$, are defined for the recursive algorithm. With data from the system, the proposed model first uses the LS method with past system data to find initial values for the parameter vector x(0) and for the error covariance matrix P(0). After having obtained the initial estimates, the recursive KF-calculations can be performed by

$$K(k) = [A(k)P(k)C^T(k)][C(k)P(k)C^T(k) + Q_2]^{-1} (14)$$

$$\hat{x}(k+1) = A(k)\hat{x}(k) + K(k)[z(k) - C(k)\hat{x}(k)] \quad (15)$$

$$P(k+1) = [A(k) - K(k)C(k)]P(k)$$

$$[A(k) - K(k)C(k)]^T + K(k)Q_2K^T(k). \quad (16)$$

where K(k) is the Kalman gain matrix, x(k+1) is the vector for new state-estimates for the parameter vector, and P(k+1) is the updated error covariance matrix [1]. The proposed method uses this process to update the parameter estimates each time a set of new values becomes available.

The proposed new KF STLF model uses weather and load-related information to formulate the time-varying discrete-time (DT) dynamic system in state-space form, which is suitable for the KF-approach. In the proposed method, the state-transition matrix A(k) is assigned as a constant n x n identity matrix, whereas covariance matrices Q_1 and Q_2 are constant parameter matrices. In the proposed system, the matrices Q_1 and Q_2 are chosen scalars with values of unity. These covariance matrices are based on the actual characteristics of the system and measurement noises; they would be chosen differently if there were knowledge of the sensor accuracy of the load measurements obtained. Since we do not have this data, the covariance matrices were chosen to values of unity.

The parameter state vector x(k) estimates a finite, and the observation vector C(k) is the vector containing the load and weather data. The observation vector relates the data to the parameter state-vector and produces the observation scalar output z (k) for time becomes

$$z(k) = C(k)x(k) \tag{17}$$

The KF STLF input model is very similar to the one for the RLS system. Proposed KF method also uses the moving window method for the load and weather data to produce the load forecast for the given time**.** Past load and weather are modeled the same exact way, including moving average loads and temperature deviations. The total input number and number of each type of the inputs was varied to evaluate which one of the input arrangements produces the most accurate outputs. The proposed model has a different parameter set for each of hour of the day, just like the proposed RLS algorithm. The inputs of the best input model of the proposed KF algorithm include: Base load, moving average of the load, load one day ago, load two days ago, moving average temperature, temperature deviation and its square, current temperature, temperature one day ago, temperature two days ago, and various values of the humidity index.

C. Artificial Neural Fuzzy Interference System Method

AI-based methods provide perhaps the most interesting and promising approach to load forecasting problems. This is mainly because of their straightforward implementation and reasonably good performance, as suggested by [2]. The AI-based method proposed in this research utilizes Artificial Neural Fuzzy Interference System (ANFIS) for load forecasting. The ANFIS model combines features of an ANN and fuzzy system to create a model that can explain past load data and predict future loads.

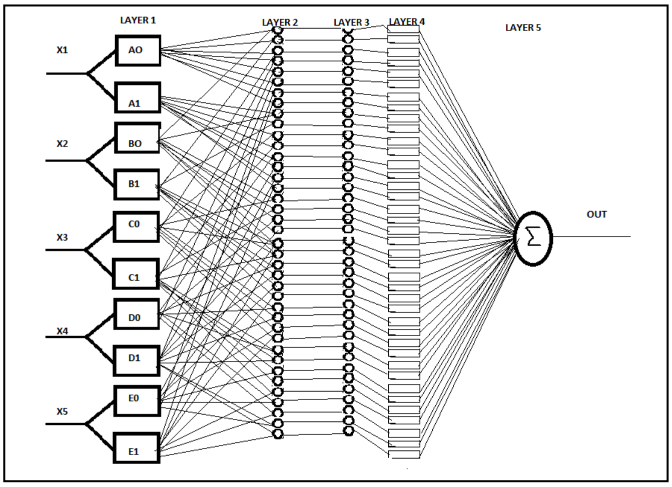

Figure 1. Five-layer ANFIS network with five inputs and one output.

The proposed ANFIS system uses past values of load and weather parameters inputs and outputs to generate the model. An ANFIS combines the low-level computation power of a neural network with the high-level reasoning capability of a fuzzy inference system. The architecture of the ANFIS model utilized for the proposed STLF model is shown in Fig. 1. The layout of the architecture of the ANFIS consists of five layers of calculations and decision-making between the input and the output.

The first layer consists of two nodes for each of the five inputs which represent the membership functions $\{A_i,B_i,C_i,D_i,E_i\}$ associated with those nodes. The forecast model uses two membership functions for each node, therefore i = 0, or i = 1. The membership function specifies the degree to which the given input satisfies the quantifier A_i [19]. In the proposed architecture, bell-shaped membership functions are utilized. The mathematical model for the membership functions can be describe as follows: the output of the layer (O^1_i) of the membership function is

$$O_i^1 = \mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]b_i}, \tag{18}$$

where x is the input and $\{a_i, b_i, c_i\}$ is a set of parameter to be estimated for each membership function.

The second layer of the architecture consists of nodes that multiply the incoming signals from the first layer outputs and send the products w_i out:

$$w_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2) \tag{19}$$

for i= [0,1…, n] where each node output w_i is multiplication of two membership functions, and represents the firing strength of the rule [19]. Since there are five inputs and each of the five inputs has two membership functions, there are total of 40 multiplication nodes in this layer.

The third layer nodes calculate the ratio of the rule's firing strength to the sum of all rules' firing strengths. The third layer's output is conveniently referred to as normalized firing strength [19]. The mathematical representation for each of the 40 normalized firing strengths can be written

$$\overline{w}_i = \frac{w_i}{\sum_{j=1}^{40} w_j} \tag{20}$$

The nodes on the fourth layer utilize parameter equations that correspond to the membership functions for each of the normalized firing strengths. The fourth node output function is

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x_n + q_i x_m + r_i) \tag{21}$$

where w_i is the firing strength associated with the i^{th} membership function of the inputs x_n and x_m. The parameter set $\{p_i, q_i, r_i\}$ is the parameter set for each of the 40 nodes of the proposed model on this layer.

The fifth and the final level of the ANFIS architecture has only one node; this node combines all the outputs of the fourth level and produces a single output, which is the overall output of the ANFIS. Mathematically the overall output O^5 is the summation of all the outputs of layer four:

$$O^5 = \sum_{i=1}^{40} O_i^4 \tag{22}$$

The architecture in Fig. 1 illustrates the connections between each level. The architecture as described can provide a platform suitable for STLF; however the ANFIS needs enough data and to be trained in order to produce accurate estimates for future loads.

The key to produce accurate estimates for future values with an ANFIS load-forecasting model requires past information, including load data and external parameters, such as weather, related to the past load values. The ANFIS network is then trained to use the input data to produce the related outputs. The training method that is utilized for the proposed forecasting model is a hybrid training algorithm; it uses forward and back propagation to estimate values for the parameters.

Training process uses a lot of computational power because of the number of parameters to be estimated and the utilization of the LS algorithm. In order to speed up the process, the number of inputs was kept low in the proposed model. The relationship between the inputs and the computational time for the model training depends on the parameters to be estimated. In a large system with many inputs, the computation time can be quite large. For this reason, proposed system model is not updated and trained hourly, unlike the other two models. The model can be still used in on-line forecasting, instead of being updated hourly, it is proposed that the parameters could be updated for example weekly, in which case the computational time will not be a problem.

The proposed new ANFIS algorithm uses the past load data along with past and current weather data to construct a network that is used for STLFs. The number of training repeats was kept low to reduce computational time and to avoid the over-fitting phenomenon. The ANFIS network was trained with the collected load and weather data between June 2004 – June 2005, and the forecasts were performed with the data for the following year. The proposed model uses the day of the week, and time of the day as its inputs. The other model inputs include the moving average for load, the moving mean for temperature, the previous day hourly load, load from two days ago, the current temperature, and humidity.

III. METHOD VALIDATION CASE STUDY

The data used in this research is the hourly load data of a large utility grade power system during a 24-month time span (June 1st, 2004 - June 1st, 2006). At first, a statistical load data study was performed with the corresponding weather parameters, mainly to get an idea of variations in loading. Table II describes the data values and their extremes throughout the time span.

TABLE II. STATISTICAL LOAD AND WEATHER DATA FOR THE STUDIED POWER SYSTEM

Power System Load and Weather Data Statistical Analysis				
DATA	***Average***	***Standard Deviation***	***Minimum***	***Maximum***
Load (MW)	19711.1	3228.5	12738.5	31531.1
Temperature (F)	61.49	16.21	16	98
Dew Point (F)	50.17	16.65	-5	77

The initial statistical load study was also performed to compare different average daily load patterns for the four seasons of a year. Only business days were included in the study, because loading patterns are quite a bit different on the weekend days. Fig. 2 shows the hourly load averages for working days (Monday through Friday) for the months of January, April, July, and October. Similarly, Fig. 3 was constructed to demonstrate the hourly temperature averages for working days during the same months.

Based on Fig. 2 and Fig. 3 we could see that the shapes of the temperature and load profiles for a summer day were somewhat similar. At night, when temperatures were the lower, the loads were also the lower, but during afternoon hours of high temperatures, the consumption was far greater. We observed also that the consumption and temperature curves for fall and spring were relatively similar. Since the weather is milder than in the summer, the consumption patterns differ from the shapes of the temperature profiles. On the other hand, the winter consumption profile is different from any of the other profiles: The peak temperatures in the afternoon actually seem to cause a sag in consumption. To explain this, the actual temperature values of the winter data were examined. The cold temperatures at night time would require use of more heating loads, whereas the mild temperatures during the afternoon would not require as much heating, therefore causing less loading to the system. Based on this information, we concluded that the weather effects were significantly different based on the season for the studied power system. The literature references [1,3,10,19] also reached the same conclusion.

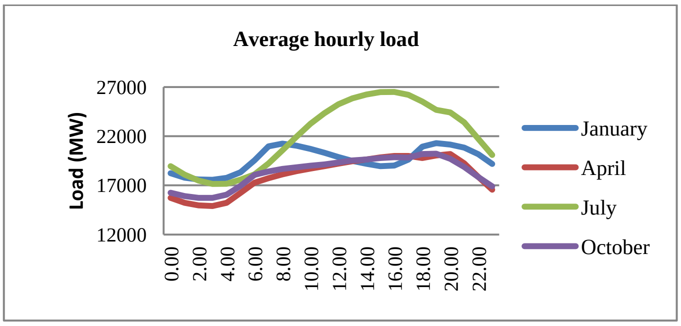

Figure 2. Average hourly loading.

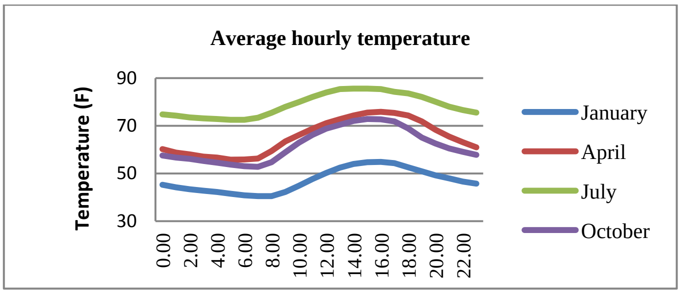

Figure 3. Average Hourly Temperature.

During the initial statistical analysis, the average hourly loading on each of the weekdays was examined. The loading patterns are shown in Fig 4. By examining the graph, we were able to draw conclusions that the hourly loading on the working days is quite consistent. On the other hand, weekend day loading patterns differ from the working days. Thus, decision was made to only consider the data from the working days in the forecast models at this initial stage of research due to the relatively small sample size of data.

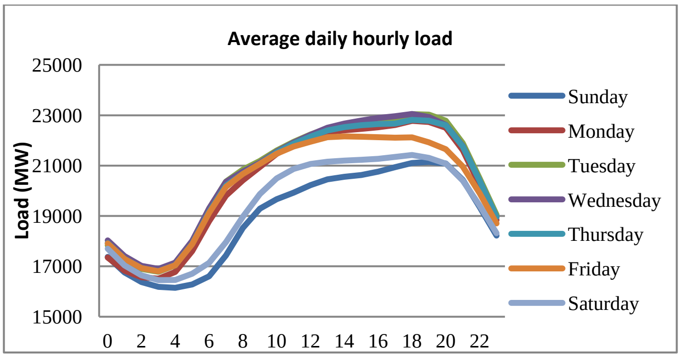

Figure 4. Average weekday hourly loading

The weather conditions, particularly the temperature, have a high effect for STLF, as shown previously. Humidity is also often considered in southern regions [1,2], and since the power system is at a relatively southern location, the humidity is included considered in the proposed forecast models. According to [1], a good method for taking humidity into account is using the humidity factor H (t), which is calculated from the dry bulb temperature and dew-point (DP) temperatures at time t

$$H(t) = 0.55 \times T_D(t) + 0.2 \times T_p(t) + 5.05\,, \qquad (23)$$

where T_D is the dry bulb temperature in ˚C and T_p is the DP temperature in ˚C, at time t. Also, according to [1], humidity effects become negligible at temperatures less than 25 ˚C; therefore, H(t) in the proposed forecast models is set to zero for temperatures lower than that.

The proposed STLF models are evaluated by their performance in forecasts for 24-hours-ahead, as well as for 5-days-ahead. The outputs of different models are compared to the actual recorded load, and the performance is evaluated by statistical Mean of Absolute Percentage Error (MAPE) and Standard Deviation of Absolute Percent Error (SDAPE). These methods are generally the statistical methods used in load forecasting studies to evaluate forecasting performance [2]. The presented solutions for the load models are not optimal; however the selected ones show relatively good forecasting performance. As the error becomes smaller, the load model becomes more acceptable for the purposes of load forecasting.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{l_{forecast}(i)-l_{actual}(i)}{l_{actual}(i)}\right| \qquad (24)$$

$$SDAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{l_{forecast}(i)-l_{actual}(i)}{l_{actual}(i)} - MAPE\right)^2\right| \qquad (25)$$

IV. Results and Analysis

Now that the theoretical background and information about the power system have been presented, it is important to validate of the performance of the each proposed STLF model, and compare their performances. The selected input models with the best tested performances for each algorithm were used, and MATLAB® is used to generate forecasts for all four seasons. The performance was evaluated statistically in terms of the MAPE and SDAPE for both 24-hour and five-day time-intervals. The results are described in Tables III, IV, and V.

TABLE III. Seasonal MAPE for Proposed STLF Algorithms

Seasonal MAPE for Proposed STLF Algorithms				
STLF Algorithm	***MAPE Summer***	***MAPE Fall***	***MAPE Winter***	***MAPE Spring***
RLS 24h	1.33%	2.86%	4.76%	2.09%
KF 24h	3.46%	2.64%	3.78%	2.60%

Seasonal MAPE for Proposed STLF Algorithms				
STLF Algorithm	***MAPE Summer***	***MAPE Fall***	***MAPE Winter***	***MAPE Spring***
ANFIS 24h	2.60%	2.43%	2.65%	2.13%
RLS 5-day	7.83%	7.62%	9.74%	5.01%
KF 5-day	2.85%	5.87%	4.23%	4.58%
ANFIS 5-day	2.98%	5.12%	4.08%	2.92%

TABLE IV. SEASONAL SDAPE FOR PROPOSED STLF ALGORITHMS

Seasonal SDAPE for Proposed STLF Algorithms				
STLF Algorithm	***SDAPE Summer***	***SDAPE Fall***	***SDAPE Winter***	***SDAPE Spring***
RLS 24h	1.87%	6.95%	6.97%	1.29%
KF 24h	5.06%	4.57%	10.58%	4.38%
ANFIS 24h	1.90%	3.32%	5.16%	3.61%
RLS 5-day	29.41%	36.76%	23.35%	15.74%
KF 5-day	21.29%	42.02%	13.46%	35.31%
ANFIS 5-day	6.50%	26.22%	13.08%	5.05%

TABLE V. AVERAGE MAPE FOR PROPOSED ALGORITHMS

Average MAPE for Proposed STLF Algorithms			
STLF Algorithm	***MAPE 24h Average***	***MAPE 5-day Average***	***Increase in MAPE from 24h to 5-day***
RLS 24h	1.33%	2.86%	4.76%
KF 24h	3.46%	2.64%	3.78%
ANFIS 24h	2.60%	2.43%	2.65%

By examining the tables for the two statistical methods: One can see that the RLS performs relatively well for the short 24-hour time-scale. The KF-approach becomes effective for the 5-day time-scale; the average error is less than 4.5% which is a total increase of only about 40.39% from the 24-hour average MAPE value. The error appears to accumulate on the RLS process, wherein the MAPE value worsens significantly, 173.62%, when the time-window is expanded to five days for the chosen input models. There are seasonal variations in the performance of the models as well; on average, all three methods seem to perform the best in summer and spring, but the performance in fall and winter does not appear to be optimal for any of the models.

The performance of the AI-based load forecasting method seems to be better than the performances of both statistical methods. The averages for the MAPE values in both the 24-hour and five-day timeframes are lower than the MAPE averages of the forecasts with the statistical methods. Also, by determining their seasonal variances in performance, the ANFIS approach seems to be the most consistent throughout the whole year. The average hourly error with ANFIS approach for the five-day forecast period is well under 4%. The forecasted load profiles are illustrated for all four seasons in comparison to each other in Fig. 5 through Fig.8.

The methods were also compared against existing moving average model. The moving average model calculates the average of five previous days load values to get a prediction of the load value, temperature is not considered. The average MAPE for whole year on a 24h prediction interval was 7.60%, to which all the proposed methods were able to provide improvements for. The error percentage for the moving average model is also expected to increase as the time interval increases.

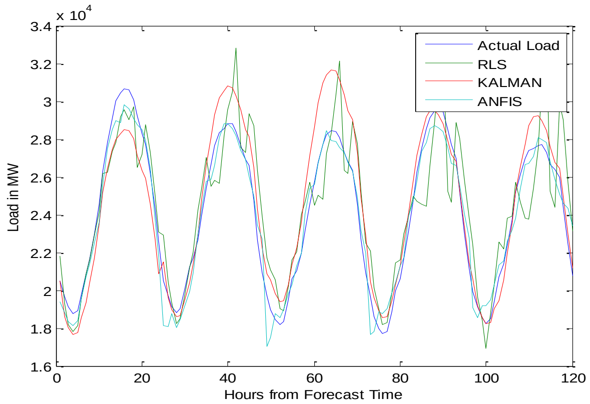

Figure 5. STLF Method Comparison in Summer

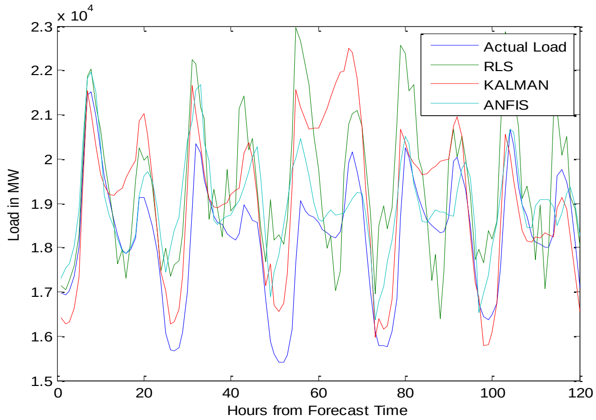

Figure 6. STLF Method Comparison in Fall

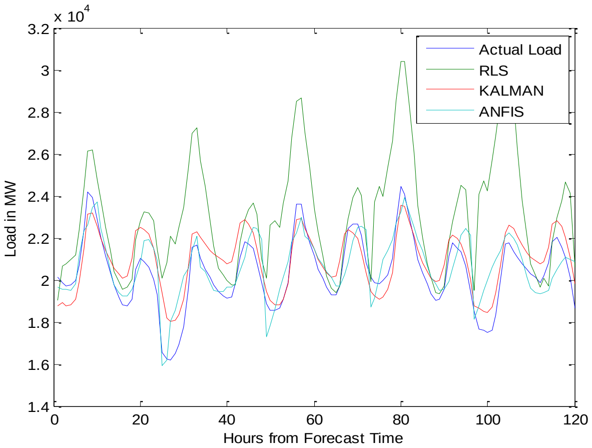

Figure 7. STLF Method Comparison in Winter

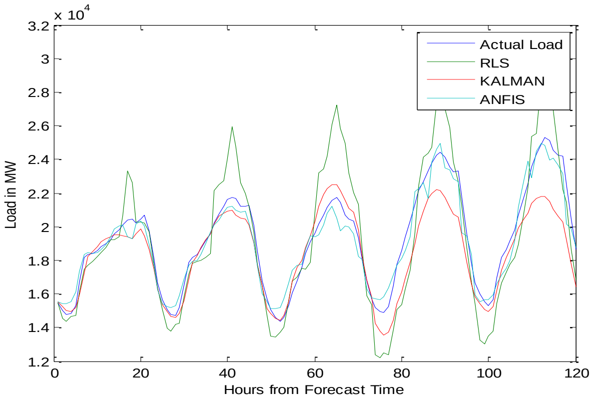

Figure 8. STLF Method Comparison in Spring

Overall, it appears the ANFIS-algorithm provides the most promise for accurate STLF in examined time-windows for the studied power system. The RLS appears to be good method for 24-hour forecasts, but the performance outside the 24-hour time-range worsens significantly. The KF-algorithm seems to perform relatively well for 24-hour forecasting, as well as well for the expanded time-range.

V. CONCLUSIONS

In this article, three methods for STLF were derived, and validated with real utility data. The performance of the forecasting algorithms varied to some degree. The proposed ANFIS algorithm yielded to most consistent results in the study. Proposed ANFIS method had also generally the lowest MAPE, while it also had the least amount of parameters. ANFIS seemed to be the method that also maintained its effectiveness over the longer time periods. The RLS algorithm performed the poorest. When the forecasting time span exceeded 24 hours, the error for the RLS started to accumulate. The proposed KF-approach performed relatively well. The statistical error associated with it was significantly lower than with RLS for most of the simulated cases. The KF appeared to handle the seasonality better than the RLS.

Although, the ANFIS approach performed relatively well compared to the other methods examined in the paper; there were still a significant amount of error associated with it. One reason for the error is that the system covers a large geographical area, and the weather information is only accurate for a small portion of it. By observing the data provided, the presence of some unpredictable load behavior is evident. The inputs of the forecast models lack the ability to account for large plant close-downs, major social events, and other occasions which could alter the system's load from time to time.

As a conclusion, the algorithms derived are capable predict and forecast the load for an electric power system. The algorithms however need further validation and development in order to be used in real life utility settings. The further development and validation with data from different power systems remains as the goal of future work.

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