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A Theoretical Approach To Forecasting Of Electric Power Of Distribution Transformers

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Abstract: *This paper is targeted at discussing the theory involved in addressing the problem of forecasting electric power at a substation transformer in a distribution network. Accurate power forecast is of great essence in power distribution planning, reactive power support control and intelligent power management. Due to the dynamics of the power system, an intelligent and adaptive forecast algorithm based on the Adaptive Neuro-fuzzy Inference System (ANFIS) is proposed for the power forecast. However the forecast model involves the use of five layer Adaptive neuro-fuzzy inference system (ANFIS) and its learning algorithm for the forecast of active and reactive power. For efficiency of the forecast model, training and validation, historical data for active and reactive power distribution network are utilized. Therefore the input voltage v(t) to the network is time varying series of vector patterns called sequence. Ultimately, this paper presents an algorithm for forecasting electric power of distribution transformers.*

Keywords: *Power system, Dynamic system, ANFIS forecast algorithm, Active and Reactive power, Intelligent power management*

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I. Introduction

Accurate active and reactive power forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydrothermal coordination, unit commitment, for solving optimal control problem required in minimizing power losses, enhancing voltage stability, raising general system reliability, and system security analysis among other functions [1, 2, 3]. Short-term active, reactive and load forecasts have become increasingly important since the rise of the competitive energy markets [4,5, 6, 7].

Forecasting is necessary in the provision of look-ahead information for effective reactive power management which has become important for distribution system operators (DSO). This is vital in keeping voltage limits, providing quality and system reliability[8]. For effective reactive support, accurate forecast is necessary in determining suitable reactive power to be injected into the system.

Furthermore, in certain countries, DSOs must make active and reactive power forecast to provide necessary information for national transmission and generation planning studies according to regulatory legislation. It is reported [2], that with the liberation of the electric sector, power forecasts started to play a key role with regard to investments in distribution, planning and energy management strategies at regional and national systems.

Power forecast is very important in providing the proactive, look-ahead data for effective coordination control required in distribution system for intelligent voltage regulation, especially in systems involving distributed generations [9]. Voltage regulation is very important in maintaining utility power quality and satisfactory voltage levels at customer terminals. Therefore, the utility usually controls the main transformer under load tap charger (ULTC) position and capacitor status to improve the voltage profile, reduce system losses and increase system efficiency [10]. Reactive power and voltage are efficiently controlled to improve the voltage quality and decrease power generation costs. However, reactive power and voltage control devices are operated independently by themselves, i.e, these devices are not coordinated. Switched shunt capacitors have some shortcomings that include delivering reactive power to the system without following load variations and the inability to absorb superfluous reactive power from the system. In the literature, there are many studies [11-13] that have been reported to solve the reactive power and voltage control problem in a distribution system. However it is strongly held [2, 14] that accurate power forecast is required to improve on these control techniques. A model for the real-time forecast of active and reactive power is necessary for the optimal coordination of control devices to achieve the objectives which minimize the total reactive power flow through the substation transformers, the total voltage deviation on the buses, and the total number of ULTC tap operation in the day.

System planners and operators need tools and methods to better forecast the dynamic changes of active, reactive power demands and resources[15]. They need to better recognize significant changes of network active and reactive power demand and supply based on loading (notice the ever increasing motor and power electronics loads and their nonlinearity), voltage profile, and topology changes due to maintenance, contingency, and consequent mitigation measures. It is also important to clearly understand the interplay and impact of switching operations of reactive power resources, load tap changes of transformers, and power electronics based reactive power compensators.

There are several methodologies for electric power and load forecasting reported in the references [3, 16, 17]. The most common models reported are the Autoregressive Moving Average (ARMA) models, possibly with exogenous inputs (ARMAX), the naïve forecast model, and statistical models. The main shortcoming of these forecast models, as reported [16, 17], is that they are based on the assumption that the dynamics of the power system is linear. It is found that these deterministic forecast models might not perform well under dynamically changing operating conditions of the power system, hence operational forecast using these models might not be reliable. Furthermore, as showed by reference [14], that the forecast of reactive power cannot be modeled by a simple regression of active power. Due to these shortcomings of these forecast algorithms, a more intelligent and adaptive algorithm is required for the real-time forecast of active and reactive powers in a power system.

II. Review Of Related Literature

2.1. Power Forecasting in the Presence of Active Demand

The research reports [23, 24, 25] addressed the problem of electric energy, electric load forecasting for distribution networks with active demand. It is argued [23] that advances of information technologies and the increased accessibility of renewable energy resources to end users have triggered new concepts in electricity power distribution and consumption. One of these new concepts is Active Demand (AD) which has been introduced in the context of the European project ADDRESS [25-28]. ADDRESS stands for Active Distribution network with full integration of demand and distribution energy resources and its target is to enable the active demand in the context of the smart grids of the future. The key idea is that domestic and small commercial consumers will play an active role in the electricity system, adjusting their consumption patterns depending on the forecasted dynamics of the electricity market.

It is reported [23] that with this scheme, a new intermediary function or entity called the aggregation function or aggregator, is needed to coordinate the consumer's behaviour with market based on forecasts. For instance, the Distribution System Operator (DSO) may ask an aggregator to enforce an energy reduction in a given Low Voltage (LV) load area, if an overload is forecasted in that area, in order to contract possible networks unbalancing.

The energy consumption in a given area of the distribution network is denoted by y, while the outdoor temperature is denoted by u. The requested Active Demand (AD) profile sent by aggregators to consumer's is denoted by ad, while the consumers' response to the signal ad is denoted by ad true. Indeed, ad^{and} ad^{true} may differ due to consumers not behaving according to the request.

Let T_s be the sampling time. It is assumed that n_n = 60/T_s is an integer number, representing the number of samples per hour. It follows that n_d = 24.n_n is the number of samples per day, while n_w = 7 - n_d is the number of samples per week. Typical value in ADDRESS are T_s = 15min, n_n = 4, n_d= 96 and n_w = 672.

Conventionally, some Monday at 00:00 is chosen as the time origin. Hence, if one lets k = 0, 1, 2, … be the discrete time index, a new day starts when k is a multiple of nd, a new weeks starts when k is a multiple of n_w, and so m the sample of a variable x at time kT_s from the time origin is denoted by x (k). The forecast of x (kth), with h a positive integer, computed using only the information available up to time k, is denoted by $\hat{x}$ (k + h/k).

Reference [23] formulated the power forecast problem as follows:

Problem 1: For fixed forecasting horizon
H > O, predict the electric power at time
k th based on the following information:

- load observation y up to time k;
- AD signal ad up to time k th;
- temperature observations up to time k, and
- forecasted temperature $\hat{u}$ from time k t 1 to k th.

For tackling the forecast problem 1, the reference [23] reported that the so-called black-box approach, a mathematical relationship of the following type is estimated using a batch record of data:

$$\mathrm{y\ (k\ th)} = \mathrm{f}\left(\mathrm{z(k)}\right) + \mathrm{e(k)} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

Where z(k) is a vector of fixed dimension (called regression vector) containing (a subset of) the information available at time k, and e(k) is the error process. Concerning the choice of the happening f(k), it may range from simple linear structures to non linear ones (neural networks, kernel methods and support vector machines, etc).

The choice is typically made by considering the mopping that makes the error e(k) "small" not only on estimation data, but also on validation data used for estimation. The "predictor" or "forecastor" is then given by:

$$\hat{y}\,(k\ th/k) = f\big(z(k)\big) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

The approach proposed in reference [23] to solve problem 1 is called grey-box, since as reported, it tries to exploit the characteristics of the variable to be forecasted and other available knowledge in order to enhance the prediction accuracy, but also to reduce the computational burden of the estimation algorithm, as is typically expected in model estimation when prior knowledge is used.

In the problem studied, two types of prior knowledge are available:

AD is expressed as power variation with respect to the expected power consumption profile if no AD request were sent. Therefore, assuming that m aggregate operates in the considered area, the power demand can be decomposed as follows:

$$y = y_b - \sum_{m=1}^{M} ad_m^{true} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3)$$

Where y is the actual power, y_b is the expected power if no AD request were sent, and each ad_m^{true} term represents the actual AD profile (including energy pay back effects) of the consumers enrolled with the mth aggregator in response to an AD request ad_m. Indeed, ad_m and ad_m^{true} may differ due to delayed and/or partial response of the consumers with respect to the request AD profile conventionally, positive (negative) value for ad_m and ad_m^{true} mean a decrease (increase) of the power consumption with respect to y_b classical load series (i.e. not including Ad effects) show a strong seasonal behaviour. Extracting known periodic (daily, weekly, yearly) patterns from time series helps the model estimation procedure to better capture the stochastic component of the underlying data generation mechanism. Based on this, y_b can in turn be decomposed as follows:

$$y_b = b + \gamma_b \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4)$$

Where b is the so-called base power (the periodic pattern) and r_b is the residual due to stochastic fluctuations.

By substituting (4) into (3), one obtains:

$$y = b + \gamma_b - \sum_{m=1}^{M} ad_m^{true} = b + \gamma \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (5)$$

Where the new residual

$$\gamma = \gamma_b + r_b - \sum_{m=1}^{M} ad_m^{true} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (6)$$

takes into account all perturbations to the base load b determined by both stochastic fluctuations and AD.

According to (5), the problem of forecasting y can be decomposed into two sub problems:

(1) estimation of b;

(2) forecasting of γ.

Then, the forecasted value of the power can be obtained as the sum of two contributions:

$$\hat{y}(k+h/k) = \hat{b}(k+h) + \hat{\gamma}\,(k+h/k) \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Estimation of the base power b

An estimate of the base power b can be obtained by applying an experimental smoothing to y_b. The adopted experimental smoothing estimates b as a smoother version of y_b through the following formula:

$$\hat{b}(k) = \propto y_b(k - n_w) + (1{-}\propto)\hat{b}(k - n_w) \ldots \ldots \ldots \ldots \ldots (8)$$

Where $\propto \epsilon(0.1)$ is called the smoothing parameter. Values of $\propto$ close to one give greater weight to recent changes in the data, while values of $\propto$ close to zero determine a stronger smoothing of the stochastic fluctuations.

When evaluating (8), the most important implementation issue is concerned with the fact that the consumer's response to AD roughest, namely the term $\sum_{m=1}^{M} ad_m^{true}$ in (3), may not be known, and therefore y_b cannot be reconstructed exactly from (3). The most straight forward way to overcome this problem is to roughly estimate y_b as follows:

$$\hat{y}_b = y + \sum_{m=1}^{M} adm \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

i.e. by adding the nominal AD profile to the actual power, and then to replace y_b with $\hat{y}_b$ in (8)

Forecasting of the residual γ

From (5), the residual γ is addressed by modeling γ on the basis of a record of data previously collected and then by using the estimated model to forecast the future residuals.

2.2. Economic Dispatch and Power Forecasting

Reference [29] reported that power/load forecasting is vital to the advancement of economic dispatch as a power engineering task. Economic dispatch is defined as the process of allocating generation levels to the generating units in the mix, so that the system load may be supplied entirely and most economically. Comprehensive surveys on the subject of economic dispatch have been done by Happ [30] and an IEEE working group [31, 32]. The impact of power forecasting on the function of economic dispatch has been studied and reported by a number of authors.

Isoda [33] recognizes the response limitations of generation units in the mix and assesses its impact as well as the impact of short term load forecasting on the economic dispatch scheme. The author claims that with short term load forecasts available, the manual operation (by operator) to regulate the power generations of the thermal units, when the load changes steeply for a long time, is reduced. According to the authors, the optimum forecast period is approximately one hour in which the load demand should be forecast for a total of 4 to 6 points. Application of the method is also possible in an on-line dispatching control in electric utilities. Innorta and Marannino [34] discussed a method of redefining the optimal and secure operation strategies (a very short period) in advance by exploiting the availability of the on-line state estimation and load forecasting.

Viviani and Heydt [35] presented an algorithm to incorporate the effects of uncertain system parameters into optimal power flow. The method employs the multivariate gram-charher series as a means of modeling the probability density function which characterize the uncertain parameters. The sources of uncertainty are identified as those emanating from long and short term forecast errors.

Economic dispatch may sometimes be classified as a static optimization problem in which costs associated with the act of changing the outputs of generators are not considered. On the other hand, a dynamic dispatch is one that considers change related costs with the use of steady-state operating costs in the static optimization, poor transient behaviour results when these solutions are incorporated in the feedback control of dynamic electric power networks. The dynamic dispatch methods uses forecast of system loads to develop optimal generator output trajectories.

Ranthel, et al [36] introduced a successive approximation dynamic programming to obtain the optimal unit generation trajectories that meet the forecasted area load. They use “dynamic” optimization as compared to the “static” case, as the dispatch program determine the economic allocation of generation for the entire future period of interest, using knowledge of both the present and the forecasted load. The forecasting capability provides the advantage of responding to sudden severe changes in load demand.

2.3. Forecasting and VAR Planning

The importance of forecasting for reactive power planning is reported [32]. Reactive power planning, or Volt-Ampere-Reactive (VAR) planning, is an effort to find the most economic investment plan for new reactive sources at selected load buses while ensuring proper voltage profile and satisfying operational constraints.

Resource and transmission planners focus on future active power demand through conventional load forecastings. In this regard there are arguments that system planners and operators need tools and methods to better forecast the dynamic changes of reactive power demands and resources. It is said that better reactive power forecasting model has to be developed. Reference [37] indicated that the task of forecasting should collect historical data and analyze the patterns correlated with seasonal weather changes and operating condition to design short or mid-term forecasting models. For long term forecasts, the general level of economic activity might provide useful information as a key driver for projections of energy consumption.

III. Methodology And System Design

3.1 Methodology

The primary methodology adopted for the development of the power prediction model is based on the use of Adaptive Neuro-fuzzy inference system (ANFIS) architecture and its learning algorithm for the Sugeno fuzzy model for the real-time prediction of active and reactive power at substation transformer in a distribution network. The ANFIS is a class of adaptive networks that act as a fundamental framework for adaptive fuzzy inference system [18]

Extensive research in the area of non-linear modeling has shown that neural network enhance complex systems forecasting, mainly because they perform advanced mathematical and statistical processes such as non-linear interpolation and function approximation [19]. Though the fuzzy technique only can be utilized to obtain learning rules for forecasting the power systems active and reactive power, this may not always yield the best forecast, and the choice of the fuzzy membership functions depends on trial and error [20]. Hence the methodology adopted in this work is to use the neural network learning ability to adjust and fine-tune the fuzzy membership function. This adopted modeling architecture combines the learning ability of neural networks and the expert systems strength of fuzzy logic. In this adopted neuro-fuzzy technique, the basic concept is the derivation of various parameters of a fuzzy inference system by means of adaptive training methods obtained from the neural networks. The technique is the use of the ANFIS for the configuration of the fuzzy membership functions, and the processing and optimization of the parameters of the membership function via neural network learning.

3.2 Design of the Active Power forecasting model

The reference [2] based its active power forecast methodology on the co-integration series theory, to obtain a regression function that allows mapping energy associated with the substation with its measured peak active power. In this case the forecast indicator variable is limited. However, it is reasoned in [19] that energy disaggregation (breakdown into number of classes) is effective as inputs for better forecast.

Hence the neuro-fuzzy forecast model developed in this study uses measured value of load (measured-load) (ML) peak energy demand (ED), consumed energy (CE) and measured peak active power (AP) as inputs for the forecast development of the neuro-fuzzy forecast model.

For the fuzzification of the model input variables, the fuzzy sets used is {LOW, HIGH}. The associated fuzzy inference rules are dynamically generated by the model. The five layer, feed forward neuro-fuzzy model for the forecasting of active power is shown in Figure 1. The output of layer 5 is the forecast of the active power.

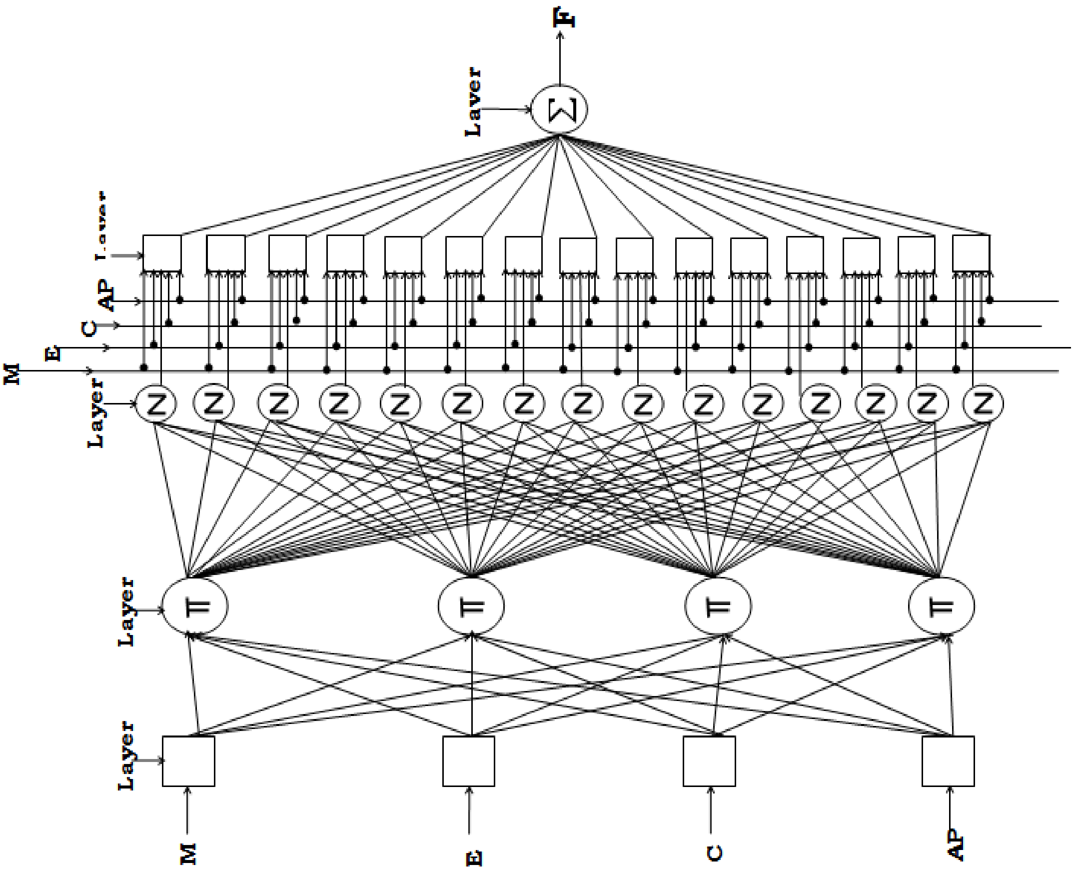

Figure 1: Neuro-fuzzy model for forecasting Active Power

The number of nodes in layer 1 and 2 is equal to the number of input variables, the number of nodes in layers 3 and 4 is equal to the number of dynamic fuzzy rules, being equal to 2^{n-1} where n is the number of the variables. For the description of the model of figure 3.1, O_1, i is used to denote the output values of node i in layer 1.

Layer 1

Each node in layer 1 is an input node in proportion to one input variable. Every node i in this layer is an adaptive node with a node output defined by

$$O_{1,i} = \mu_{Mi}(X_j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

where $O_{1,i}$ is the output value of the ith node in layer1, Xj is jth input variable (in this case measured – load (ML), or Peak Energy Demand (ED), or Consumed Energy (CE) or Measured Active Power AP), μ is the membership function operator, and M_i is the ith fuzzy set (in this cab LOW or HIGH) associated with ith node. Taken together, $\mu_{Mi}(X_j)$ is called the membership function of X_j in M_i.

Layer 2
Every node in this layer is a fixed node labeled Π. Fuzzification is done in layer 2 with each node corresponding to one linguistic term of the input variable via Gaussian function [18].

$$O_{2,i} = \exp\left[-\left(\frac{O_{1,i}-S_{2,i}}{\sigma_{2,i}}\right)^2\right] \quad \ldots\ldots\ldots\ldots\ldots.. \quad (11)$$

to calculate the membership value of the fuzzy sets, where $S_{2,i}$ and $\sigma_{2,i}$ are the center (mean) and width (variance) of the Gaussian membership function of the ith node in layer 2, respectively.

Layer 3
Every node in this layer is a fixed node labeled N. Each load in layer 3 represents its fuzzy rule and has the form,

R_i : If X_1 is M_{j1} and X_2 is M_{j2} ……… and X_p is M_{jp}
then

$$f_i = C_{io} + C_{i1}X_1 + \ldots\ldots.. + C_{ip}X_p \ldots\ldots\ldots\ldots\ldots \quad (12)$$

where R_i signifies the ith fuzzy rule, $X^T = [X_{i,} X_{2,} \ldots\ldots. X_P]$ is the input in the system {in this case ML, Ed, CE, AP}, f_i (a polynomial) is the output consequent of the fuzzy rule R_i. $M_{j1,}$ M_{j2}, ….. and M_{jp} are the variable parameters of the membership functions, and the weight of each firing rule $C_{io,}$ C_{i1}…., and C_{ip} are real parameters.
The weights $W_{2,i}$ in layer 2 express the association of the rule with the ith linguistic output variable.
Every node in this layer is a fixed node labeled N. the ith node calculates the ratio of the ith rule's firing strength to the sum of all rules firing strengths [18]:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2}, i = 1, 2 \ldots\ldots\ldots\ldots\ldots\ldots.. \quad (13)$$

That is, the output of layer 3 is calculated by taking the average of the individual rules contribution. Each node output represent the firing strength of a rule.

Layer 4
Every node i in this layer is an adaptive node with a node function [18]:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (C_nX_1 + d_nX_2 + K_nX_3 + h_n) \ldots\ldots\ldots \quad (14)$$

where w_i is the output of layer 3 and $\{C_{n,} d_{n,} k_{n,} h_n\}$ is the parameter set of the nth rule. Parameters in this layer is referred to as the consequent parameters. The neuro-fuzzy model comprises two parameter sets, namely the membership function parameters and the polynomial parameters (c, d, h, k), which are all time-varying in order to account for dynamic changes and persistence, and structural changes in the input variables and are adaptively updated.

Layer 5
The single node in this layer is a fixed node labeled ∑, which computes the overall output as the summation of all incoming signals:

$$O_{5,I} = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum iwifi}{\sum iwi} \quad \ldots\ldots\ldots\ldots.. \quad (15)$$

The proposed neuro-fuzzy forecast model is a self-organized, two-phase learning process with phase one to locate the initial membership function and phase two to fire the fuzzy rules. In phase 1, the center and the width of the initial membership function are determined by the feature-map algorithm [20]:

$$\| x(k) – S_c (k)\| = \min \{// x(k) - Si(k) // \} \ldots\ldots\ldots\ldots\ldots.. \quad (16)$$

where

$$S_c(k+1) = S_c (k) + \alpha(x(k) – S_c (k)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.… \quad (17)$$

and

$S_i(k+1) = S_i(k)$ for $S_i \neq S_c$ where x(k) and S_i (k) are the input and the center of membership function, respectively. The subscript c indicates the associative closest value. This adaptive formula runs independently for each input and linguistic output variables. Once $S_i(k)$ is calculated, the width $\sigma_i(k)$ can be determined by the first-nearest-neighbor heuristic,

$$\sigma_i = {(Si – Sc)}/{\gamma} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...... \quad (18),$$

where r the overlap parameter. After the membership functions have been calculated, the back propagation learning algorithm is to find the fuzzy rules in phase 2. The output of layer 2 is transmitted to layer 3 to find the firing strength of each rule node. Based on the firing strength and the node output in layer 4, the correct consequent-link for each node can be determined by using error propagation to minimize the error function

$$E = \left(d(k) - y(k)\right)^2 / 2 \ldots\ldots \quad (19)$$

where d(k) is the desired output and y(k) is the current output. The weight is tuned via the update rule [19],

$$W_{i,j}(k+1) = W_{i,j}(k) + \Delta w_{i,j}(k) \ldots\ldots \quad (20)$$

$$\Delta w_{i,j}(k) = \eta(d(k) - y(k))O_{3,j}\, W_{i,j}\, \sigma_{4,j} \frac{S_{4,j}\,(\Sigma\sigma_{4,j}\, O_{4,j}) - (\Sigma S_{4,j}\,\sigma_{4,j}\, O_{4,j})}{(\Sigma\sigma_{4,ji} + O_{4,j})^2_{,if\ j = \hat{r}}} \ldots \quad (21)$$

where $\hat{r}$ = Arg Max $(O_{3,j}(W_{i,j})^2)$ and η is the learning rate. By adjusting the weight, the correct consequent link of each rule node is determined. For every antecedent clause, the centroid of all the possible consequent is calculated. Only the dominant rule whose consequent has the highest membership value is selected.

By using equation (3.6) and the gradient of center $S_{4,i}$, the center is updated via: $S_{4,i}(k+1) = S_{4,i}(k) + \eta\big(d(k) - y(k)\big).\ \sigma_{4,i}\, O_{4,i} / \Sigma\sigma 4,i\, O4,i \ldots\ldots$ (22)

similarly, the width parameter is

$$\sigma_{4,i}(k+1) = \sigma_{4,i}(k) + \eta(d(k) - y(k)).O_{4,i} \frac{S_{4,i}\,(\Sigma\sigma_{4,i}\, O_{4,i}) - (\Sigma S_{4,i}\,\sigma_{4,i}\, O_{4,i})}{(\Sigma\sigma_{4,i} + O_{4,i})^2} \ldots\ldots (23)$$

The error signal in layer 4 is derived as [20]

$$\delta_{4,i}(k) = (d(k) - y(k).\ \sigma_{4,I} \frac{S_{4,i}\,(\Sigma\sigma_{4,i}\, O_{4,i}) - (\Sigma S_{4,i}\,\sigma_{4,i}\, O_{4,i})}{(\Sigma\sigma_{4,i} + O_{4,i})^2} \ldots\ldots (24)$$

In the same way, only the error signal $\delta_{3,i}$ is needed and it is identical to $\delta_{4,i}$. In layer 2, the center and width parameters are updated by

$$S_{2,i}(k+1) = S_{2,i}(k) - 2O_{2,i}\,\eta \frac{(O_{1,i} - S_{2,i})}{(\sigma_{2,i})^2} \sum_k 9_k \ldots \quad (25)$$

$$\sigma_{2,i}(k+1) = \sigma_{2,i}(k) - 2\, O_{2,i}\,\eta \frac{(O_{1,i} - S_{2,i})^2}{(\sigma_{2,i})^3} \sum_k 9_k \ldots \quad (26)$$

where q_k =1 when $O_{2,i}$ = min (input of the kth rule node) and
q_k = 0 for the others.

The weight vector of the firing rule is updated by

$$C_i(k+1) = C_i(k) + g_i\,\alpha_i\,(y_i(k) - y_d(k)\,[1, x^T(k)]^T \ldots\ldots \quad (27)$$

Where g_i is the decreasing rate, $0 \leq g_i < 1$, and α_i is the firing strength of the ith rule, $\alpha_i = \min\{M_{j,1}(X_1), M_{j,2}(X_2),.. M_{j,p}(X_p)\}$.

After adjusting the weight vector C_i, the correct consequent link of each rule node can be determined for every antecedent clause, the centroid of all the possible consequent is computed.

If W_{inj} is the relative width of the minor fuzzy rule [20],

$$w_{inj} = \frac{\min\{V\gamma_{m,j}, V\gamma_{n,j}\} - \max\{Vl_{mj}, Vl_{n,j}\}}{/C_{mj} - C_{nj}/} \ldots\ldots \quad (28)$$

Where C_{mj} and C_{nj} are the center of the winner rule and the first runner-up respectively. Similarly Vr_{mj} and Vl_{nj} are the right and left spreads of the winner fuzzy rule, Vr_{nj} and Vl_{nj} are those of the runner-up rules. The spread V_r is adapted by

$$V(k+1) = V_r(k) + \eta(k)\,(C_r(k) - V_r(k)) \ldots\ldots \quad (29)$$

When $Sg_n(y - y_i) = Sgn(y_r - y_l) \ldots\ldots$ (30)

Otherwise

$$V_r(k+1) = V_r(k) - \eta(k)(C_r(k) - V_r(k) \ldots\ldots \quad (31)$$

Where C_r is the center of winner rule, $\eta(k)$ is the learning rate, y_r and y_i are the output computed independently for each rule. The antecedent parameter with smallest relative width is tuned by

$$win_i = \min_j \{win_j\} \ldots\ldots \quad (32)$$

and the center of the fuzzy sets are updated when only a normal fuzzy rule fires. The center C_r is moved towards the input x(k)according to

$$C_r(k+1) = C_r(k) + \alpha_i\,\eta(k)\,(x(k) - C_r(k)) \ldots\ldots \quad (33)$$

The above learning algorithm shows the computational procedures in the design of adaptive neuro-fuzzy model. After training and validation by another set of input and output, the neuro-fuzzy model can be applied to forecast active power in a power system.

3.3 Design of the Reactive Power Forecasting Model

Power factor relates instantaneous active and reactive powers. Also it relates the peak active and peak reactive power, since the peak demand of reactive power should occur simultaneously with the peak demand of active power when there is no reactive support equipment on the power grid [2].

Therefore in order to accurately forecast the non-compensated peak active power, the power system operational data that is used as input in this design for the development of the 5-layer adaptive neuro-fuzzy prediction model are:

- Power Factor (PF)
- Reactive power (RP)
- Forecasted Peak Active Power (FAP) (this being the output of the active power forecast model of figure 3.1)
- Angular Coefficient (ACO) i.e angular coefficient between variation of active and reactive power

Using these input variables, the 5-layer feed forward adaptive neuro-fuzzy model for the forecast of the reactive power is shown in Figure 2

The steps of the learning algorithm specified previously, as in the case of the active power neuro-fuzzy forecast model apply in this case (i.e that of Figure 2).

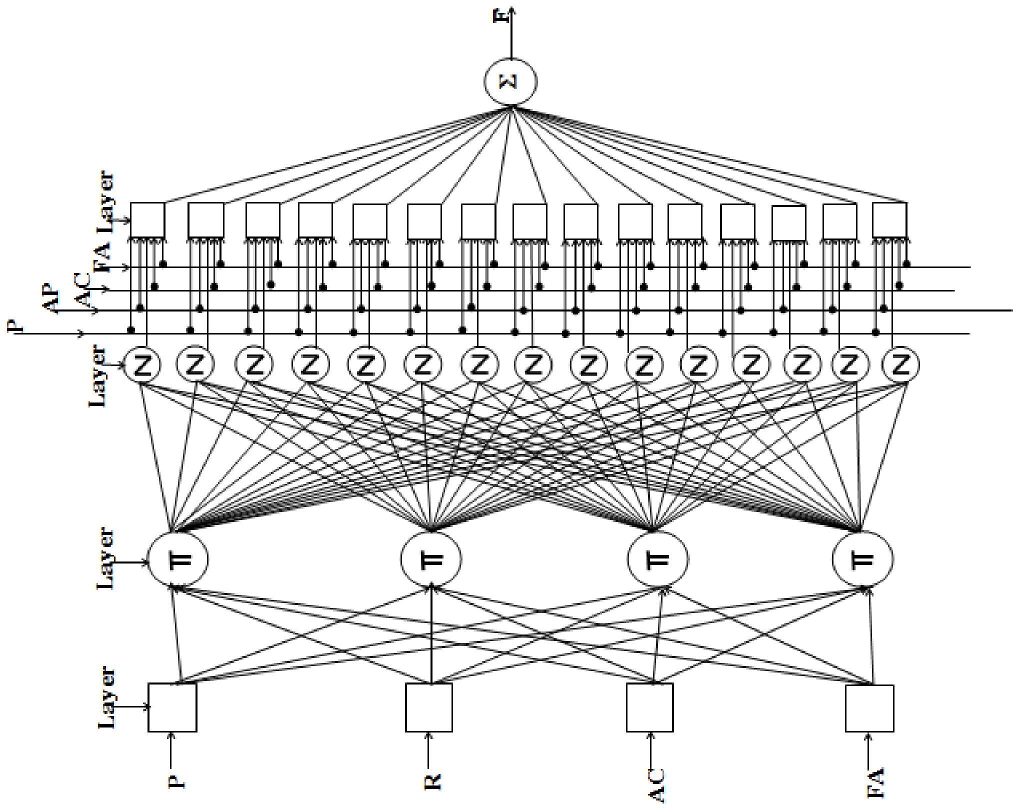

Figure 2: Neuro-fuzzy model for forecasting reactive

3.4 The Power Forecast Processing Flow

The data processing flow for forecasting the systems active and reactive power is depicted in the flow chart of Figure 3

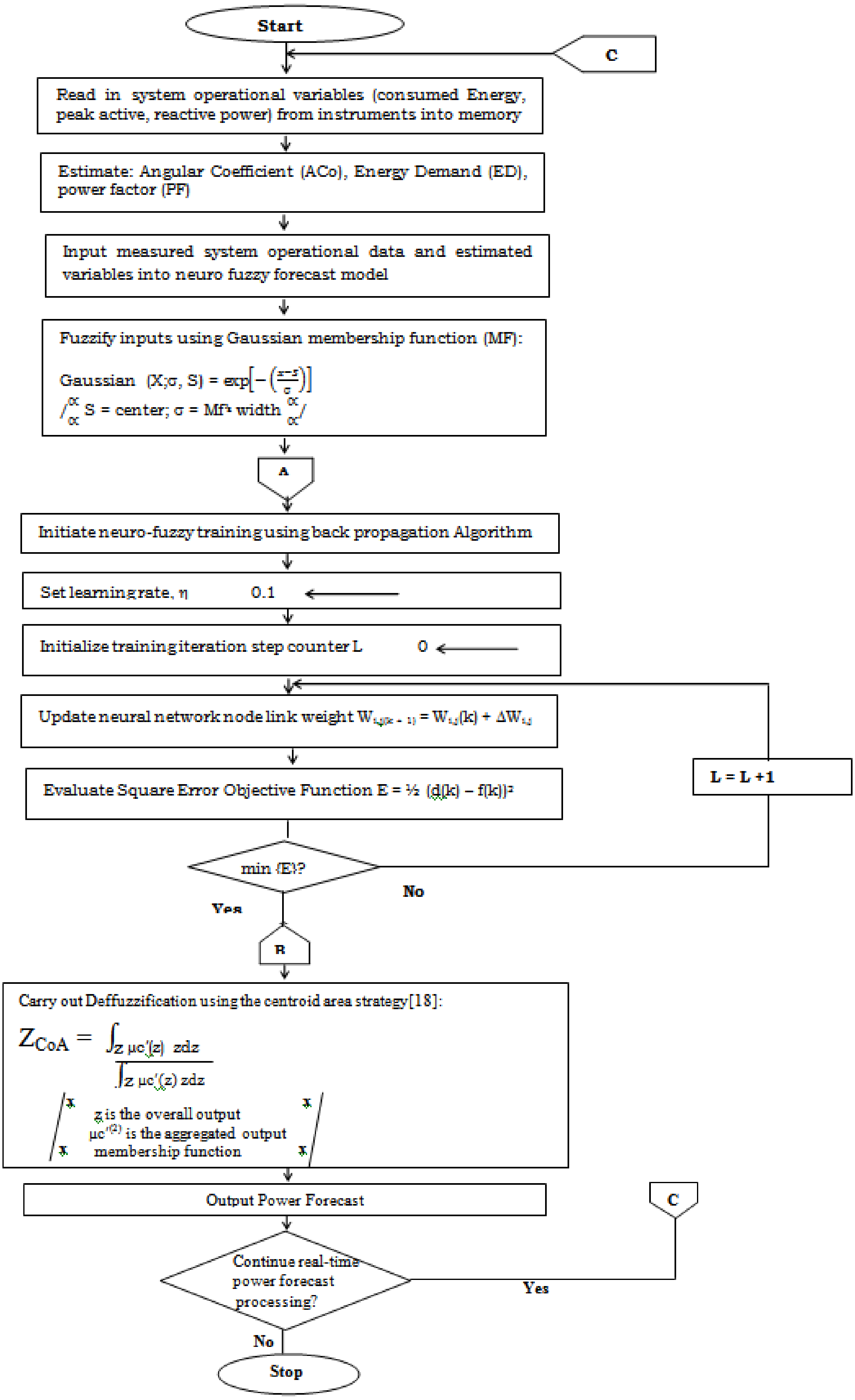

Figure 3 The Power Forecast Processing Flow

3.5. Neural Network for Long Term Non Real-time Forecast

To obtain long term (non real-time) forecast of active and reactive power, this work uses a special kind of Neural network: Time Lagged Recurrent Neural Network (TLRN). TLR is a neural network topology that includes memory elements, which allow it to identify patterns that occur over multiple samples (such as the 12 months data of active and reactive power given in appendix G and H). For forecast based upon past input, a time delay recurrent neural network model is more efficient [39].

The three layer focused time lag recurrent neural network used for one year ahead forecast of active and reactive power is shown on Figure 4. The model is designed with Gamma memory and conjugate gradient back propagation learning algorithm.

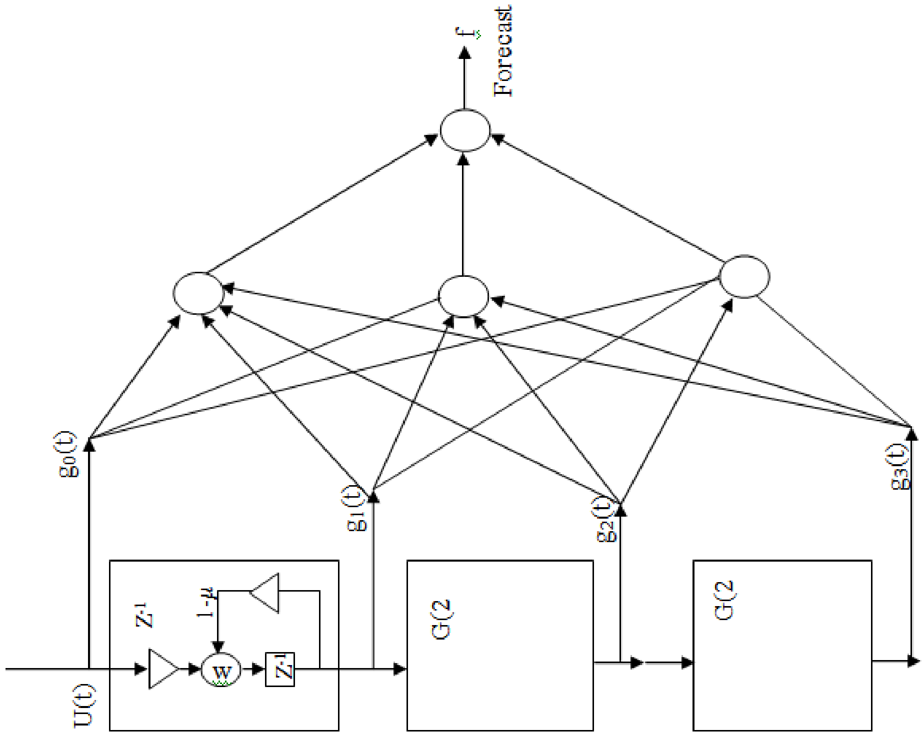

Figure 4: Time lag recurrent neural network with gamma memory

In this design, the short-term memory structure is implemented using gamma memory. The MATLAB programmer is to exercise control over the memory depth by building a feedback loop around each unit delay, as illustrated in figure 3.4 effectively, in the MATLAB code, the unit delay Z^{-2} of the standard TDL memory is replaced by the transfer function [40].

$$G(2) = \frac{\mu 2^{-1}}{1-(1-\mu)2^{-1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(34)$$

Where μ is an adjustable parameter in the range: $0 < \mu < 2$.

The overall impulse response of the gamma memory, consisting of p sections, is the inverse Z transform of the overall transfer function.

The input (V(t)) to the network is time-varying series of vector patterns called sequence. Therefore, the simulation carried out and presented in our second paper is achieved by using vectors in MATLAB code indexed by days to compose the input sequence.

IV. Conclusion

The main shortcoming of conventional forecast model (like the Autoregressive moving Average) system is the assumption that the dynamics of the power system is linear. This deterministic view of the power system makes the conventional forecast models unreliable. As a result, the conventional forecast Models do not perform well under dynamically changing system operating conditions, hence operational forecast using these models might not be reliable. Hence this work proposes neuro-fuzzy model for forecast of active and reactive power in a power system. This forecast model is more intelligent and adaptive. The adopted forecast model architecture combines the learning ability of neural networks and the expert systems capability of fuzzy logic. In this adopted neuro-fuzzy technique, the basic concept is the derivation of various parameters of a fuzzy inference system by means of adaptive training method obtained from the neural network. Hence the forecast model developed in this work involves the use of the five layer Adaptive neuro-fuzzy inference system (ANFIS) and its learning algorithm for the forecast of active and reactive Power. For the ANFIS forecast model, training and validation, historical data for active and reactive power distribution network is proposed.

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