CUCKOO SEARCH BASED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR SHORT-TERM LOAD FORECASTING

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Dedicated to

My parent for their support and prayers;
My wife and my children for their love, caring, sacrifice and prayers;
My friends and relatives for their support and encouragement;
and
My teachers, lecturers and supervisors for their guidance, support and encouragement.

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ABSTRACT

Short-Term Load Forecasting (STLF) is an essential input for power system operation computations to achieve proper system balancing. General economy and security of power system depend on accurate STLF. The accuracy of forecasting model depends on the number and types of the forecasting variables. Furthermore, a day-ahead hourly-load forecast has to reach the decision makers before the elapse of a pre-set time. Conventional methods used in determining future load demand were not able to explore all the available variables in a particular forecasting region. Moreover, artificial intelligence methods like Adaptive Neuro-Fuzzy Inference System (ANFIS), are associated with computational difficulties, thus influence the speed and accuracy of the model. Therefore, these variables need to be investigated so as to make the forecasting model simple and easy to use. Similarly, the forecasting speed needs to be improved. This thesis presents the development of short-term electric load demand forecasting algorithm, with the aim to improve the forecasting accuracy and speed. It starts with the development of data selection and data processing framework, through the use of correlation analysis, hypothesis test and wavelet transform. Variables of the four seasons in one year were investigated and were classified based on the available weather and historical load data in each season. To reduce the variability in the forecasting data, wavelet transform is used. The whole forecasting algorithm has been developed by integrating Cuckoo Search (CS) algorithm with ANFIS to produce CS-ANFIS model. CS was used to improve the forecasting capability and speed of the traditional ANFIS, by replacing the derivative-based gradient descent optimization algorithm with CS in backward pass. Its purpose is to update the antecedent parameters of the traditional ANFIS, through the determination of an optimal value of the error merging between the ANFIS output and targeted output. The whole system is validated by the comparison with an existing ANFIS model, and two other ANFIS models optimized with Particle Swarm Optimization (PSO-ANFIS) and Genetic Algorithm (GA-ANFIS). The developed CS-ANFIS model proved to be superior to these models in terms of accuracy and forecasting time. A reduction in average mean absolute percentage error of 84.48% for one year forecast is recorded using the developed CS-ANFIS, and 77.32% with the proposed data selection approach. The model was found to forecast the future load demand within an average period of 37 seconds, as compared to the traditional ANFIS which recorded an average forecasting time of 219 seconds. It can therefore, be accepted as a tool for forecasting future energy demand at utility level to improve the reliability and economic operation of the utility.

ABSTRAK

Ramalan beban jangka pendek (STLF) merupakan input penting untuk pengiraan operasi sistem kuasa bagi mencapai keseimbangan sistem yang betul. Ekonomi am dan keselamatan sistem kuasa bergantung kepada ketepatan STLF. Ketepatan model ramalan bergantung kepada bilangan dan jenis pembolehubah ramalan. Tambahan pula, ramalan beban yang dibuat sehari sebelumnya bagi setiap jam perlu mencapai sebuah keputusan sebelum masa yang telah ditetapkan berlalu. Kaedah konvensional yang digunakan dalam menentukan permintaan beban masa depan tidak dapat meneroka semua pembolehubah tersedia dalam kawasan ramalan tertentu. Selain itu, kaedah kecerdikan buatan, seperti sistem inferens neural kabur ubah suai (ANFIS), dikaitkan dengan masalah pengiraan, sekali gus mempengaruhi kelajuan dan ketepatan model. Oleh itu, pembolehubah ini perlu dikaji supaya model ramalan yang mudah dan senang digunakan dapat dibina. Begitu juga, kelajuan ramalan perlu diperbaiki. Tesis ini membentangkan pembangunan algoritma ramalan permintaan beban elektrik jangka masa pendek, dengan tujuan untuk meningkatkan ketepatan dan kelajuan ramalan. Ia bermula dengan pembangunan pemilihan data dan kerangka kerja pemprosesan data, melalui penggunaan analisis sekaitan, ujian hipotesis dan jelmaan wavelet. Pembolehubah daripada empat musim dalam setahun telah dikaji dan dikelaskan berdasarkan data cuaca yang ada dan sejarah beban dalam setiap musim. Untuk mengurangkan kebolehubahan dalam data ramalan, jelmaan wavelet digunakan. Keseluruhan algoritma ramalan telah dibangunkan daripada integrasi algoritma carian cuckoo (CS) dengan ANFIS bagi menghasilkan model CS-ANFIS. CS telah diguna untuk meningkatkan keupayaan ramalan dan kelajuan ANFIS tradisional, dengan menggantikan algoritma pengoptimuman terbitan berasaskan kecerunan keturunan dengan CS dalam laluan mengundur. Tujuannya adalah untuk mengemas kini parameter anteseden dari ANFIS tradisional, melalui penentuan nilai optimum gabungan ralat antara keluaran ANFIS dan keluaran yang disasarkan. Keseluruhan sistem disahkan oleh perbandingan dengan model ANFIS sedia ada, dan dua model ANFIS lain yang dioptimumkan dengan pengoptimunan kerumunan zarah (PSO-ANFIS) dan algoritma genetik (GA-ANFIS). Model CS-ANFIS yang dibangunkan terbukti lebih hebat berbanding model-model ini dari segi ketepatan dan masa ramalan. Pengurangan dalam purata min ralat peratus mutlak sebanyak 84.48% untuk unjuran setahun direkod menggunakan CS-ANFIS yang dibangunkan dan 77.32% dengan cadangan pendekatan pemilihan data. Model ini didapati meramal permintaan beban masa depan dalam tempoh purata 37 saat, berbanding ANFIS tradisional yang mencatatkan masa ramalan purata 219 saat. Oleh itu, ia boleh diterima sebagai alat untuk meramal permintaan tenaga masa depan pada tahap utiliti untuk meningkatkan kebolehpercayaan dan operasi ekonomi utiliti.

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LIST OF ABBREVIATIONS

ABC	-	Artificial Bee Colony
AD	-	Active Demand
AI	-	Artificial Intelligence
ANFIS	-	Adaptive-Neuro-Fuzzy Inference System
ANN	-	Artificial Neural Network
AR	-	Auto Regressive
ARIMA	-	Auto Regressive Integrated Moving Average
ARMA	-	Auto-Regressive Moving Average
ARMAX	-	Auto-Regressive Moving Average with Exogenous Variables
BNN	-	Bayesian Neural Network
BP	-	Back Propagation
BPNN	-	Back Propagation Neural Network
CART	-	Classification and Regression Tree
CGA	-	Chaotic mapping enhanced GA
CHW	-	Correlation analysis Hypothesis test and Wavelet
CO_2	-	Carbon Dioxide
CS	-	Cuckoo Search
CSANFIS	-	CS-Optimized-ANFIS
DB	-	Daubechies
DE	-	Differential Evolution
DER	-	Distributed Energy Resources
DSM	-	Demand Side Management
DWT	-	Discrete Wavelet Transform
EDNS	-	Expected Demand Not Served
EENS	-	Expected Energy Not Served

ELMABC	-	Extreme Learning Machine optimized with ABC
EM	-	Energy Management
EU	-	European Union
FCM	-	Fuzzy c-Means
FFNN	-	Feed Forward Neural Network
FIR	-	Fuzzy Inductive Reasoning
FIS	-	Fuzzy Inference System
FL	-	Fuzzy Logic
GA	-	Genetic Algorithm
GA-ANFIS	-	GA-Optimized-ANFIS
GD	-	Gradient Decent
GEFCom	-	Global Energy Forecasting Competition
GHG	-	Greenhouse Gasses
GM	-	Grey Model
HC-ANFIS	-	Huseyin-Cunkas ANFIS
HOGM	-	Hybrid Optimized Grey Model
IT2FL	-	Type-2 Takagi-Sugeno-Kang Fuzzy Logic
IWT	-	Inverse Wavelet Transform
LF	-	Load Forecasting
LF	-	Levy Flight
LSE	-	Least Square Estimation
LTLF	-	Long-Term Load Forecasting
LUBE	-	Lower-Upper Bound Estimate
MA	-	Moving Average
MAE	-	Mean Absolute Error
CS-ANFIS	-	Modified Adaptive-Neuro-Fuzzy Inference System
MAPE	-	Mean Absolute Percentage Error
MF(s)	-	Membership Function(s)
MFA	-	Modified Firefly Algorithm
MLR	-	Multiple Linear Regression
MSE	-	Mean Square Error
MTLF	-	Mid-Term or Median-Term Load Forecasting
NCNHNW	-	No Correlation analysis No Hypothesis test and No Wavelet

NCNHW	-	No Correlation analysis No Hypothesis test but with Wavelet
NN	-	Neural Network
NS	-	Nova Scotia
PIs	-	Predictive Intervals
PSO	-	Particle Swarm Optimization
PSO-ANFIS	-	PSO-Optimized-ANFIS
RBF	-	Radial Basis Function
RMSE	-	Root Mean Square Error
RW	-	Random Walk
SARIMA	-	Seasonal-ARIMA
SC	-	Subtractive Clustering
SRA	-	Simulated Rebounding Algorithm
SSA	-	Singular Spectrum Analysis/Analyser
STLF	-	Short-Term Load Forecasting
SVM	-	Support Vector Machine
TLSAR	-	Two-Level Seasonal Auto Regressive
WC	-	Wavelet Coefficients
WT	-	Wavelet Transform
WTANFIS	-	Wavelet Transform ANFIS

LIST OF SYMBOLS

A	-	Matrix of coefficients
a	-	Scale factor
A^T	-	Transpose of matrix of coefficients
A^{-1}	-	Inverse of matrix of coefficients
A_n	-	Approximate coefficient at *n*-level of decomposition
α	-	Scaling parameter
α_i	-	Premise parameter
α-value	-	Fixed/pre-set significance level
b	-	Time-shift parameter
b_k	-	Target output of data corresponds to raw k
β_i	-	Width/Spread of the membership function
β_n	-	Coefficient of linear regression equation
β_0	-	Constant of linear regression equation
c	-	Number of clusters
C	-	Cluster matrix
c_j	-	Initial cluster centre in FCM
c_i	-	Centre of the membership function
C_1, C_2	-	Cognitive and social parameters
$\mathrm{cov}(x, y)$	-	Covariance between *x* and *y*
D_n	-	Detail coefficient at *n*-level of decomposition
D_i	-	Density measure of data point x_i

D_{c1}	-	Density measure of cluster centre x_{c1}
Δc_{i+1}, $\Delta\beta_{i+1}$	-	New/updated premise parameters
Δc_i, $\Delta\beta_i$	-	Current premise parameters
ΔT	-	Temperature difference
δ_x	-	Standard deviation of *y* population
δ_y	-	Standard deviation of *x* population
δ_μ	-	Standard deviation of μ
δ_v	-	Standard deviation of v
ε_i	-	Residue/error estimate of linear regression equation
E_k	-	Error margin due to b_k and f_k
e_k	-	Error measure
$e_{\max}$	-	Maximum error
$e_{\min}$	-	Minimum error
e_k^{new}	-	New or updated error (value)
e_{kj}	-	Randomly generated population (error)
$\vec{e}_i(t-1)$	-	Previous error of particle i^{th}
e_m, e_n	-	Randomly newly selected different solutions
$\vec{e}_{pbest_i}$ or $\vec{e}_{best}$	-	Best error of particle i^{th}
$e^{optimum}$ or e_i	-	Optimal error of particle i^{th}
$\vec{e}_i(t)$, $\vec{x}_i(t)$	-	Current position (error) of particle i^{th}
f	-	Actual output/value
f_n	-	Output of ANFIS network
f_k	-	Estimated output of data corresponds to raw k
$F(.)$	-	Particle performance
H_0	-	Null hypothesis
H_1	-	Alternative hypothesis
$H(\bullet)$	-	Heaviside function

k	-	Current raw (data point)
K	-	Step-size
$Levy(\bullet)$	-	Levy flight function
λ	-	Penalty factor
m	-	Membership function weights adjusting parameter
N, K	-	Total number of data points
$P_p(h)$	-	Historical load
P_{F-1}	-	Last week, similar day load
P_{F-2}	-	Last two weeks, similar day load
P_{F-3}	-	Last three weeks, similar day load
P_m	-	Mutation probability
P_c	-	Crossover probability
P_a	-	Probability of discovery of cuckoo eggs
$P-value$	-	Smallest significance level
p_n, q_n, r_n	-	Consequent parameters
$\psi(t)$	-	Mother wavelet
R	-	Correlation Coefficient
R^2	-	Coefficient of Determination
r_a, r_b	-	Radius of determination of cluster neighbourhood
$rand$	-	Uniform random number generator
r_1, r_2	-	Positive acceleration constants
ρ_1, ρ_2	-	Random variables
$S(t)$	-	Time series signal
T_F	-	Forecasting day temperature
T_{F-1}	-	Last week, similar day temperature
T_{F-2}	-	Last two weeks, similar day temperature
T_{F-3}	-	Last three weeks, similar day temperature
U	-	Fuzzy partition matrix
μ_{ik}, μ_{A_i}	-	Membership function of input i^{th}
ν, μ	-	Levy flight uniformly distributed parameters

$\vec{v}_i(t)$	-	Current velocity of particle i^{th}
$\vec{v}_i(t-1)$	-	Previous velocity of particle i^{th}
w_i	-	Weight of i^{th} firing strength
$\overrightarrow{w_i}$	-	i^{th} firing strength
x	-	ANFIS input one
x_{in}	-	Independent variable of linear regression equation
x_j	-	Initial cluster centre in SC
x_i	-	Data point
x_{c1}	-	Cluster centre with density measure D_{c1}
X	-	Matrix of input variables
x^*	-	Estimate of the input variables
$x_i^{(t+1)}$	-	i^{th} pattern of previous generation
x_i^t	-	i^{th} pattern of current generation
$\vec{x}_i(t-1)$	-	Previous position (error) of particle i^{th}
$\vec{x}_{pbest_i}$	-	Best/Optimal position (error) of particle i^{th}
y	-	ANFIS input two
y_i	-	Output of firing strength
Y_i	-	Dependent variable of linear regression equation
z_i	-	Standardized value
$\oplus$	-	Entry-wise multiplication operator

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CHAPTER 1

INTRODUCTION

1.1 Background

This research is focussed on Short-Term Load forecasting using artificial intelligence approach. Load forecasting is very essential in the planning and operation of power systems, and its accuracy improves the reliability and economy of power systems [1]. Mao *et al* [2] reported that, unit commitment, economic dispatch, energy scheduling and real-time control benefitted more from Short-Term Load Forecasting (STLF). Thus, reduction in forecasting error can save the utility and co-generators notably [3], [4]. Other benefits of load forecasting are producing environmentally friendly energy that can enhance the use of renewable energy resources. One of the objectives outlined by European Union (EU) is to reduce greenhouse gases by 20%, and increasing renewable energy resources by 20% is believed to be realistic through load forecasting and distributed energy resources forecasting [5]. The idea presented is to introduce demand side management criteria so as to modify the load profile at specific nodes in the network, thereby potentially issuing economic benefits to the system operators [6]. This means that load forecasting can be classified as a way of enhancing energy management techniques [7] and improving environmental safety. An example of a typical load consumption pattern for one day is presented in Figure 1.1 [8]. It can be seen that consumption changes from low to high from early morning to afternoon and become peak in the late evening.

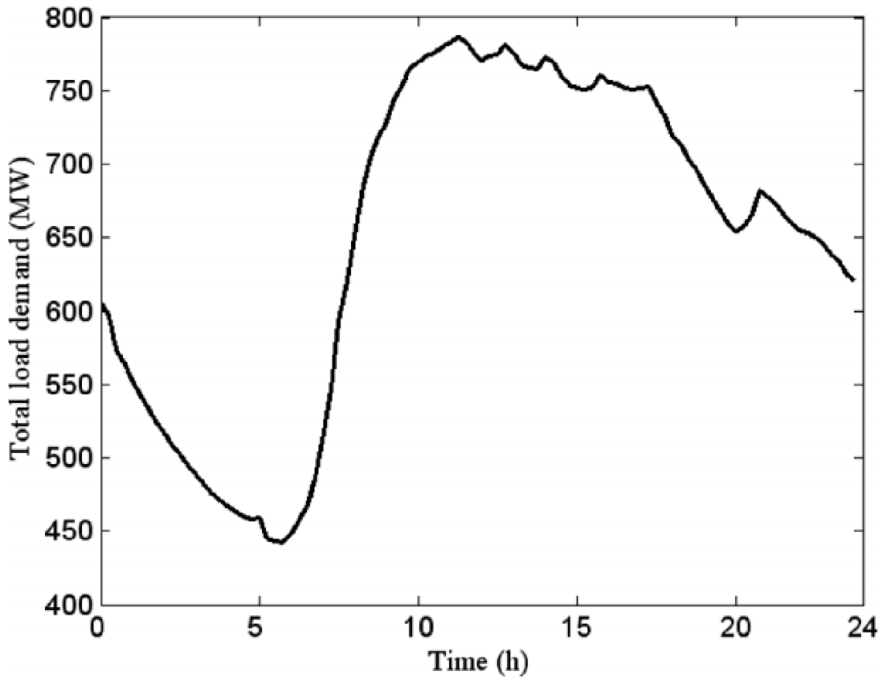

Figure 1.1: Example of One-day Load demand profile [8]

The importance of STLF in power system operation should never be overemphasized. It affects almost all the areas of power system operation. As reported by Qamar and Khosravi [9], accurate STLF can improve the generation scheduling through determination of generation resources, operational limitations and constraints associated with equipment usage and environment. Optimal control of reservoir and optimal generation scheduling in the case of hydropower generation system can be achieved through accurate STLF. Operations such as optimal production cost in unit commitment for thermal generation units can be obtained with good load forecasting algorithm [9]. Power system security depends on accurate STLF. Information on future energy demand can help the utility to arrange the system accordance with the subsequent demand state, and take corrective actions [9]. Also, accurate STLF can improve system reliability. Underestimating the demand may bring overloading and therefore affects the quality of the supply [9]. Potential benefits of load forecasting in electric utility operations are presented in Table 1.1 [1].

Table 1.1: Summarised STLF benefits to electric utility operations [1]

S/N	Function	Forecasting horizon	Forecasting intervals
1	Automatic Generation Control	Next 15 min	5 sec
2	Economic Dispatch	Next hour	30 sec
3	Power Flow	Next 2 days	5 min
4	Contingency Analysis	Next 2 days	10 min
5	Situational Awareness	Next hour	120 samples per sec
6	Voltage Stability	Next hour	120 samples per sec
7	Unit Commitment	Next 14 days	Hourly
8	Transaction Evaluation and Management	Next 14 days	Hourly
9	Wind Forecasting	Next 5 - 60 min	30 sec
10	Hydro forecasting	Next 14 days	Hourly
11	Fuel Scheduling	Next 1 – 6 months	Weekly

Consequently, these benefits brought about dedicating a discipline in determining what the demand might be for a prescribed future period, subject to previous demand, metrological factors and economic issues [10]. This is possible through developing a good forecasting algorithm.

On the other hand, forecasting accuracy depends on selecting the right variables (model inputs) in the forecasting activity [11]. Recent researches are attracted towards variables selection, because appropriate selection improves the forecasting accuracy significantly [12]. Also, the number and type of these variables improve the accuracy, or otherwise [13]. These pave a way for developing many data selection and processing approaches, that can improve the forecasting accuracy.

From the literature studies it is found that many researchers, including the utility companies, use traditional methods of Time Series (TS) and Regression Analysis (RA) [11], [14]–[18], Neural Networks (NN) [19]–[22] and Adaptive Neuro-Fuzzy Inference System (ANFIS) [23]–[28] to forecast the load in short-term time frame. Others [29]–[31] use a hybrid of these methods. But these methods are deficient in different ways. The well-known time series and regression methods cannot handle the non-linearity nature of the load series [27]. Because the load series is non-linear and complex due to time different cycles, and contains random features due to different customers' behaviours [32].

The Artificial Intelligence (AI) methods require tuning and finding many parameters and need to assign weights randomly to inputs and hidden biases, thus result in overtraining [33]. Among which Neural network methods are suffering from network topology, parameters identification and selection [2], [34]. It also uses gradient descent (GD) in the backward propagation, which is associated with the calculation of partial derivatives of weights and biases, making the training to be very slow [35]. Not only NN, ANFIS also suffers from such training complexity associated with GD [36], and therefore gives researchers the mandate to reduce the computational difficulties, and consequently improve the forecasting accuracy. This chapter summarises the existing problems within the STLF context, it also consists of the formulated research objectives, the scope of the research and the significance of the research.

1.2 Problem Statement

Recently developed methods used Artificial Intelligence (AI) methods, like Neural Network (NN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM) and Radial Basis Function (RBF), in forecasting the demand within the short-term time frame. On the other hand, only historical load data and temperature are used as model input parameters. Very few used relative humidity in addition to load and temperature. There might be other weather variables that affect the load consumption different from temperature and relative humidity, and the relationship between the load and these variables needs to be investigated.

Most of the developed forecasting methods used modelled equations of only temperature and historical load data. They did not justify using the equation or why only these variables are selected. The coefficients used in the equations are based on forecasting accuracy. This will delay the forecasting results. These equations are only applicable to a particular season, or forecasting region.

Moreover, some methods such as TS and RA lack the ability to trace the actual load pattern, which is nonlinear and complex. The use of AI methods is limited in operation due to dependence on initial parameters, choice and finding weights and biases, determination of appropriate activation function and its parameters, longer training time, choice of network structure and falling into local minima.

On the other hand, the hybrid learning in ANFIS requires determination of consequent parameters in forward pass using Least Squares Estimation (LSE), and premise parameters in backward pass using Gradient Descent (GD). The main problem of ANFIS is associated with training, in which the backward pass involves using GD in every step from layer-to-layer and from node-to-node. Thus, resulting to convergence of the network into local optima and slow convergence. Thus, it necessitates for development of a successful training approach that will get rid of these problems.

This research is aimed at providing an approach that can handle all the available forecasting data in any season and in any region or area. It is designed to formulate a data selection and analysis framework that can ease the computational difficulties of the forecasting algorithm, using Correlation Analysis, Hypothesis Test and Wavelet Transform. It also focused on developing an algorithm that will replace the GD in the conventional ANFIS with CS Algorithm. A Cuckoo Search based Adaptive Neuro-Fuzzy Inference System will be developed to forecast the future load, with maximum accuracy and within the shortest possible time.

Based on the problems highlighted above, the following are the summary of the problem statement:

i. The inability of the current researchers to investigate and incorporate all the available weather variables in the forecast. In addition, the data selection is based on modelled equations, which cannot be applied in all the available data, season and region. The coefficients used in the modelled equations are based on the forecasting accuracy after a number of trails. It is necessary to formulate an approach for selecting and analysing the forecasting variables without using modelled equations and tuning the equation coefficients.

ii. Presence of GD (a derivative based optimization technique) in ANFIS network is making the computation within the network to be complex, and has a tendency of being trapped in the local optima. There is need of replacing the GD in the ANFIS network with search-based optimization algorithm that has fewer parameters to be tuned, and has a very wide and deep search capability.

iii. The big data problem associated with load forecasting is beyond just incorporating calendar variables in the model inputs. This is because the load profile has taken care of seasonal effect in the load series. The proper way to handle overlapping of one timeframe (season, week, day or hour) over the other is to formulate the forecasting in such a way that each season is treated separately.

1.3 Motivation

The relation between power system operation and load forecasting explained in section 1.1 brought about three statistical challenges in power system. Firstly, the need to forecast future load demand so as to improve the security and reliability of the grid, and also make the financial commitments lower [37]. Secondly, the need of forecasting the energy price because it influences the decisions by energy companies in the energy market [38]. Lastly, the need to forecast energy production ability of renewable energy resources [37] for proper integration into the main grid, or planning and operations of microgrid and smart grid networks. These challenges are associated with the gathering of huge amount of data, processing the data and then formulating the forecasting algorithm in such a way that accuracy is assured.

Since the introduction of ANFIS network, a lot of researchers focus on its various applications. The reason behind this is the prospectus associated with ANFIS in modelling time series problems, and ability to match the non-linear relationship between input and output variables [39]. This makes it more reliable in forecasting future events than other forecasting methods [13]. Moreover, it has the ability to combine the advantages associated with fuzzy logic and neural network.

In the same vein, CS is a newly introduced meta-heuristic algorithm that has the capability of utilizing 75% of its search time in global search and 25% in local search [40]; thus it easily converges in the global minima when compared to other classical optimization methods, such as GA and PSO. This motivates the combination of ANFIS with Cuckoo Search (CS) algorithm; resulting to a Modified Adaptive-Network-based Fuzzy Inference System (CS-ANFIS) model. CS was used to improve the forecasting capability of conventional ANFIS, by replacing the GD algorithm in its backward pass. It is purpose is to find the minimum error between the actual and target output of the ANFIS, which can be used to update the antecedent parameters of the conventional ANFIS.

1.4 Objectives

The main aim of this research is to develop modified ANFIS with CS that will forecast electricity load within the allowable error. This can be achieved through the following objectives:

i. To develop data selection and analysis framework that can be applied in selecting the variables that influence the load demand in any region and season, using Correlation analysis, Hypothesis test, and Wavelet Transform.
ii. To develop a modified load forecasting model through combining the optimization capabilities of CS with ANFIS network.
iii. To develop a seasonal forecasting approach that can identify the effect of changes in the forecasting variables due to seasonal changes in each season, using the developed CS-ANFIS algorithm.

1.5 Scopes

Because of the fact that different data affect the load at different region, and the variety of the forecasting algorithms, the research is limited to the following items.

i. Historical load and weather data from Nova Scotia region for December 2010 to November, 2014 is going to be used in this study. This is because the data is available online for public use.
ii. Data selection and analysis approach using correlation analysis, hypothesis test and wavelet transform are incorporated to investigate the actual variables that enhance the load demand, and reduce the variability of the data.
iii. The focus of this research is the development of AI model by upgrading conventional ANFIS using CS, and simulate the whole system in Matlab® environment.
iv. The modified model will be applied in forecasting the hourly energy demand from November 2013 to December 2014.
v. Evaluation analysis will be applied to validate the results obtained using conventional ANFIS and two optimized ANFIS networks using GA and PSO.
vi. The approach is specified to forecast load at the utility level, which covers both domestic, commercial and industrial load demands.
vii. Only historical load and weather variables are considered, loads demand due to special occasions and calendar variables are not within the scope of this research, because the seasonal pattern of the load has taken care of calendar effect.

1.6 Significance of Study

The significance of this research is drawn from major aspects of power system operations that require forecasting future energy demand within the short-term time frame.

i. The power system operation must be ensured irrespective of any disturbance and load requirements. Demand responses should influence the generation and by extension, the available generation resources. Therefore, foreseeing the demand with required accuracy enables the system operators to allocate the corresponding generations and resources optimally.

ii. Power system performance depends on load forecasting methods that can produce minimum error, and promote economy within the energy market and at utility level. Therefore, producing models that can forecast the load with maximum accuracy is necessary.

iii. The inability of Electricity industry to device a means of storing its products in vast quantity like in other industries make it necessary to generate and deliver electricity according to consumption. Meaning that supply should be according to demand all the time. Complexity in the seasonal patterns and introduction of new technologies that can collect data across the grid at all time, and the need for highly accurate forecast are integral part of load forecasting. These characteristics together with social needs of electricity brought about the interesting features of demand forecasting.

iv. Introduction of energy management schemes such as Demand Side Management (DSM), in which customers are encouraged to modify their demand at certain period through monetary incentive, has tremendous impact on the daily load curve. These demand and supply sides issues challenge the system operators on grid maintenance. Thus, necessitate the determination of the future demand before generation, and allocation or purchase of electric energy in the case of deregulated system.

1.7 Thesis Outline

This thesis is categorized into five chapters, current chapter consists of general introduction of the thesis, problem statement, research objectives, scope of the research and significance of the research.

Chapter Two consists the general literature under the subject area. All the relevant components of Short-Term Load Forecasting are reviewed. It starts with load forecasting error and power system operation, followed by load feature selection and data analysis, load forecasting models and their applications.

Chapter Three covers the methodology of the research. A research framework is outlined in the beginning of the chapter, followed by preliminary study, and the main study. The developed forecasting models are also presented in this chapter, followed by assessment of the models.

Results obtained in this work are discussed in Chapter Four. The results include both preliminary experiment and main study results. Comparison was made using benchmark model and two other optimization algorithms.

Finally, Conclusion and Recommendation for Future Work are narrated in Chapter Five. Major research achievements are discussed and untouched areas within the context of Short-Term Load Forecasting using the proposed approach were recommended for futureresearch.

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