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A Multi-agent Approach To Short Term Load Forecasting Problem

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Abstract - **Artificial Neural Network (ANN) based solutions of Short Term Load Forecasting (STLF) have gained great popularity in time-series prediction and classification tasks because of their simplicity and robustness. However, the approach of using ANN methodology alone is limited which has generated interest to explore hybrid solutions for a better alternative. This paper presents a brief review of the recent work focusing on the STLF solution based on combining ANN approach with other techniques. An intelligent multi-agent based solution of STLF is proposed that provides a better framework for building a more realistic solution**

Index Terms---**Agent technology, Short term load forecasting neural network, and power systems**

1. INTRODUCTION

Load forecasting is one of the central functions in power system operations. The ability to predict loads from hours to several days in the future can help utility operator to efficiently schedule and utilize power generation. Short term load forecasting (STLF) plays a pivotal role in the formulation of economic, reliable and secure operating strategies for the power system. The main objective of the STLF function is to provide the load prediction for the basic generation scheduling function.

According to the conventional techniques employed, these approaches can be classified into two categories. In one approach the load pattern is treated as a time series signal and predicts the future load by using various time series analysis techniques. The second approach recognizes that the load pattern is dependent on weather variables and finds a functional relationship between the weather variables and the system load. The future load is then predicted by inserting the predicted weather information into the predetermined relationship. [1][2]. In real practice the relationship between load and its exogenous factors is complex and non-linear, making it quite difficult to model through conventional techniques, such as time series and linear regression approaches. They fail to give accurate forecast when quick weather changes occur. Besides not giving the required precision, most of the traditional techniques are not robust enough. Since time series and regression techniques use many complex relationships, so a long computational time is required.

Another perspective of solving STLF problem emerged with the growing popularity of intelligent techniques including Artificial Neural Network, Expert System, Fuzzy Logic and Genetic Algorithm. These techniques have been experimented by several researchers and have proposed innovative solutions. Among these, ANN technique attracted lot of attention and a variety of solutions have been reported in the literature [3,4].

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The ANN is more advantageous than statistical models, because it is able to model a multivariate problem without making complex dependency assumptions among input variables. By learning from training data, the ANN
the implicit nonlinear relationship among input variables. As in expert system approach, neural networks do not rely on human experience, but attempt to draw links between sets of input data and observed outputs. Neural networks offer the potential to overcome the reliance on a function form of the forecasting model and large historical bases. Since ANN based solutions involve training cases, the problem of the application of a neural network reduces to two fundamental parts. Appropriate training cases must be selected and the structure of the network must accommodate the size and complexity of patterns.[4]

ANNs have gained great popularity in time-series prediction and other pattern recognition tasks because of their simplicity and robustness. However, there are several issues in the STLF problem that can not be addressed by ANN alone through its pattern recognition feature which limits its scope to offer a complete solution to the STLF. Some of these include: (i) modeling load deviations caused by effects of weather, (ii) prediction of special days such as Mondays, Fridays and holidays, and (iii) incorporation of operator knowledge in the forecasting model.

There are technical issues relating to ANN architecture and its learning features that create problems while making an ANN-based STLF model. The learning process is time-consuming involving risk of local minima and there is no exact rule for setting the number of hidden neurons to avoid over fitting or under fitting for making the learning phase convergent. Also, the standalone approaches of ANN have exposed limitations associated with lack of structured knowledge representation and processing the linguistic information. The ANNs show inability to generate explanations for their results which limit their applicability in various applications. Another major limitation associated with ANNs is the problem of scalability thus restricting their abilities to generalize. To overcome the shortcomings in stand alone ANN based models, the recent trend is growing towards using other techniques combined with the ANN to form a hybrid model of STLF. The area has received great attention in the research community with some notable success in recent years. This paper reviews some of the more recent work in this regard. Based on modularized structure of STLF process, a conceptual model of STLF is also proposed that can fit into the intelligent multi-agent framework. Such a model can potentially offer autonomy and adaptiveness by knitting together the functionalities and behavior of various emerging techniques.

The rest of the paper is organized as follows: Section 2 gives an overview of the reported work involving hybridization of ANN approach with the other techniques for solution of STLF. These include both conventional as well intelligent techniques. Section 3 presents the proposed scheme based on modularized structure of ANN in conjunction with other intelligent techniques that can best fit into the multi-agent framework. The solution of Short term load forecasting is modeled in a multi-agent environment and a conceptual model is described in section 4. Finally, the paper is concluded in section 5.

2. THE HYBRID APPROACH

Hybridization has been exploited in a variety of ways and solutions have been proposed in the recent years for different applications involving emerging field of intelligent systems using neuro-symbolic, neuro-fuzzy, and neuro-genetic models [5-8]. The STLF solution has not been exception to this. The synergy of ANN with the intelligent techniques as well as other conventional approaches such as time series and regression techniques etc. have been tried by several researchers to show its promise for a better solution of STLF. Some of the important models proposed recently in the literature are reviewed in this section.

2.1 ANN and Fuzzy Logic

This approach deals with a combination of neural networks and fuzzy logic to overcome the deficiencies each technology when working standalone.

Karman et al. [9] present a model using a small fraction of the training time required by the back propagation model. Forecasts were made one day ahead of time for 24 hours of Wednesdays. Every hour is predicted with one and ten separate networks, using the parameter values that yielded the best performance during the network parameter evaluation phase. The Fuzzy ARTMAP neural network architecture applies incremental supervised learning of recognition categories and multidimensional maps in response to arbitrary sequence of analog or binary input vectors, which may represent fuzzy or crisp set of features. The proposed model offers better logical explanation for the architecture used in predicting certain days.

Srinivasan et al. [10] suggest a neural fuzzy approach that incorporates the effect of yearly load growth due to economic expansion. The hybrid fuzzy model based on one-day ahead load forecast involves three main stages. In the first stage, historical load was updated to the current load demand by studying the growth trend and making the necessary compensation. The second stage attempts to map the load profile through Kohonen’s Self Organizing Feature Map. Load forecast of the current day is then obtained using the auto associative memory of neural network. Post-processing of the neural network output is performed with a fuzzy expert system which successfully corrects the load deviations caused by the effects of the weather and holiday activity. A fuzzy parallel processor takes variables such as day type, weather and holiday proximity into considerations when making the required hourly load accommodations for each day. The results indicate that accurate forecasting of the load curves can be achieved by the purposed Fuzzy-Neural approach. The capability of hybrid network for online prediction, robustness, learning ability and interpolation ability are confirmed by simulation results. The average mean average percentage error is calculated to be 0.83%, 0.75% and 0.84% for weekdays, Sundays and public holidays respectively as compared to the multiple linear regression model having 2.20%, 2.51% and 6.42% errors respectively.

Kim et al. [11] also uses fuzzy neural approach to improve the STLF for special days in anomalous load conditions. In their method, an ANN provides the forecast scaled load curve (normalized with respect to the maximum and minimum values) and a fuzzy inference model gives the forecast of maximum and minimum loads of the special days. Special days are marked with binary codes during an ANN training process. The 24-hourly forecast load of special days is predicted by combining the results of the ANN and fuzzy inference method. The benefit of the proposed hybrid structure is to utilize the advantages of both, i.e., the generalizing capability of ANN and the ability of fuzzy inference for handling and formalizing the experience and knowledge of the forecasters. The average percentage error for special days ranges from 1.23% to 3.14% and maximum percentage error ranges from 3.18% to 9.31%. The results show that the proposed forecasting model provides a considerable improvement in the forecasting accuracy for special days.

WenXiao et al. [12] propose a hybrid model, which divides the electrical load into two parts. The load scaled curve and the day maximal load and minimal load. The scaled curve load is forecasted using five ANNs. Based on the historical load, weather conditions and holiday information, the day maximum and minimum load are forecasted using a fuzzy logic strategy. The average forecasting errors for the test ranges from 1.86% for Monday, 1.34% for weekday, 1.98% for Saturday, 1.70% for Sunday and 2.73% for holidays. The proposed model performs better than the Linear extrapolation model and an ANN model.

2.2 ANN and Genetic Algorithm

Genetic Algorithms (GA) are powerful searching algorithms and are popular for handling optimization problems. This feature has been utilized in conjunction with ANN and Fuzzy logic techniques in modeling STLF as described below:

Ling et' al [13] proposes a GA based neural network in which the GA tunes the neural network with arithmetic crossover and uniform mutation. The model utilizes seven multi-input multi-output neural networks, one for each day in a week. Each network has 24 outputs representing the expected hourly load. The proposed model outperforms the traditional feed forward neural network and fewer hidden nodes are needed. The forecasting error are 1.9365% and 2.8316% for Wednesday and Sunday respectively. Compared with traditional neural network, it has 31.6% and 30.9% improvement.

2.3 ANN, Fuzzy and Genetic Algorithm

Ling et al. [14] propose a hybrid_approach for daily load forecasting realized by Neural Fuzzy network (NFN) with an improved Genetic Algorithm. The GA is used to find the optimal number of fuzzy rules by introducing switches in the links of the neural fuzzy network.

The data for the ANN are selected using fuzzy rules. Fuzzy logic technique helps in dealing with variable linguistic information in load forecasting and thus overcomes the common problems of convergence to local minima and sensitivity to initial values to some extent. The forecasting error for Sunday by this approach turns out to be 1.5034%.

2.4 ANN, Fuzzy, Expert System and Regression

Hwang [15] describe the development of STLF expert system named LoFy. It has three models i.e. daily, weekly and special day forecasting models. The LoFy contains several kinds of forecasting models and selects an appropriate model which seems to be more desirable method for the case. It contains expert's knowledge base in the form of fuzzy rules which utilizes trending model for weekdays, multiple regression and ANN model for weather sensitive days and fuzzy rule base model for special days. The average error of daily forecasting is 1.86% for an ordinary day, 1.54% for special days and 2.00% for weekly forecasting.

2.5 ANN and Regression

Mori et al. [16] propose a hybrid method of globally optimal regression tree and Multi Layer Pereceptron (MLP) for STLF. The paper presents a data mining technique to discover rules in short-term load forecasting. The optimal regression tree allows clarifying the relationship between input and output variables through the systematic rules. It also classifies input data into clusters as a pre-filtering technique for MLP. The proposed method is applied to model maximum daily load forecasting on weekdays during the summer. The simulation results have shown that the proposed method is better than CART-MLP and MLP in terms of the average and maximum errors. Comparing with the MLP, the proposed method reduces the maximum error from 7.17% to 5.20%.

Sfetsos [17] develops a hybrid approach using ANN and linear regression in which, the patterns are assigned to each cluster based on their distance from the hyper-plane that is defined from the governing equation of each cluster. The hybrid model groups data with similar characteristics and a function approximation to capture the underlying characteristics of each cluster of data to form a special class. The analysis of the results indicates that the Hybrid Clustering Algorithm (HCA) with the preprocessing of the data is able to consistently return forecasting errors that are lower than those of ANN. With California data, this scheme returns the overall forecasting error to 0.5546% when 12 clusters are initialized for the preprocessed HCA. This corresponds to 7.54% improvement over the respective ANN. On the NY system load, using eight clusters, the overall minimum error is found to be 9.88% lower than the respective ANN model.

2.6 ANN and Wavelet

Tao et al. [18] present wavelet-neural-network hybrid model in which, the load serial is firstly decomposed to several sub-serials using wavelet multi-resolution analysis. To forecast each sub-serial, twenty four models of neural networks are constructed and the final forecasting result is obtained by summing up all the sub-serial forecasting results representing a 24-hour ahead forecast. This approach accelerates the training of neural networks and improves the stability of the convergence. The average error per month for peak load ranges from 1.90% to 2.24% and for per day from 1.65% to 2.17%.

2.7 ANN and Time Series

Magd et al. [19] presents a hybrid approach using ANN and time series model for forecasting hourly loads of weekdays as well as weekends and public holidays. Two methods are proposed in this approach. The first one is based on correlation/auto-correlation coefficient to select the input variables and to devise a measure for selecting training sets for ANNs. The second method develops two algorithms for adjusting the forecast of holidays, weekends and Mondays. The model gives the mean percent relative error of 2.066% for all days including holidays.

Table 1 gives the summary of various intelligent techniques used in conjunction with the ANN methodology and highlights different STLF targets that have been associated with each technique for processing.

3. THE PROPOSED SCHEME

In the light of the literature review, and our experiences in building ANN models [20-22], we can view STLF problem as one which can be improved by: (i) reducing the complexity of ANN through modularized structure and (ii) using ANN with other techniques to form a multi-paradigm based solution of STLF. These are explained as follows:

3.1 Modularized structure

The most unique feature of the ANN performance is its ability to form its own working model for a given problem through learning by training examples based on domain data. However, the notion that a single ANN model can perform the generalization tasks for all purposes is not supported through experience [22]. Modeling all features through a single ANN and fitting the model by "brute force" to the available data leads to more complex systems which are difficult to train and hard to understand. The ANNs are sensitive to domain training sets upon which they are trained: e.g an ANN trained on a summer training set performed poorly when applied to a January day. Similarly, a weekday trained ANN cannot be expected to perform well over weekends. Even, to be more selective, ANN trained over Thursday data produced high errors when tested for Mondays and Fridays. These observations therefore suggest a revised framework of load forecasting problem involving decomposition of the application tasks into sub-tasks that can be trained separately on carefully selected data. This will keep the network small thus reducing its complexity as well as less data will be required for training.

One of the major benefits of the decomposition approach is the possibility of evaluating the success of each sub-task independently. For each sub-task, a partial success criterion and verification procedure can be defined. If the entire application fails to operate correctly, the search for the cause of the failure can, in turn be decomposed with respect to the partial tasks. In this way, we can reconfigure the whole forecasting problem into a decomposed structure.

In our proposed strategy, the key concept in arriving at the modular ANN-based solution for STLF is a step-wise refinement consisting of repeatedly decomposing the problem into smaller forecast models. Eventually, one has a collection of small tasks/models each of which are trained using historical data selected for hourly period, daily, weekly and seasonal time varying windows. It is expected that such a modular based STLF model will be able to encompass a more realistic picture of load profile over variety of situations in time frame that can help to make a better forecast.

3.2 Multi-paradigm based Solution

It is evident from the literature survey that a range of techniques of both conventional as well as intelligent techniques are available to be exploited for a better solution of STLF. For example, neural network can be utilized to perform pattern recognition from the load and weather data, Fuzzy logic can deal with high level reasoning involving linguistic information obtained from the operator in the control center, KBS can fine tune load prediction using heuristics used by human forecasters dealing anomalous conditions of weather and load type, Genetic algorithm can optimize neural network based solution involving weight adjustments and also search for best possible solution among the trained ANNs representing forecasting models over time varying window. By data mining and knowledge discovery process, one can reach to new rules and hypothesis from the available data and information which can be used to update our model. Thus a multi-paradigm structure involving intelligent techniques can be used to cover the weakness of each techniques by the strength of the others. The above tasks based on intelligent techniques and conventional approaches can be best fit in into the framework of a multi-agent environment that can offer a more need based and realistic solution of STLF. Such a multi-agent structure offers characteristics namely autonomy, collaboration, adaptation, learning and complex communication.

4. MULTIAGENT BASED STLF MODEL

Intelligent agents and multi-agent systems are one of the most important emerging technologies in computer science today. In an agent based system, for a given set of percepts or inputs a particular action is performed. Multi-agent systems are concerned with a coordinating problem solving behavior amongst collection of agents. Each agent in a multi-agent system represents a specific set of problem solving skills and experience. The intention is to coordinate the skills, knowledge, plans and experience of different agents to pursue a common high level goal system.

4.1 The Proposed STLF Model

Here we propose a solution based on a modularized STLF model working within the framework of an intelligent multi agent system. We address the STLF problem from: (i) behavioral perspective and (ii) knowledge base perspective. The behavioral based approach deals with the unknown relationships and can utilize approaches such as ANNs, regression, time series etc. to map the data and extract relationships among different parameters that affect the STLF such as load, weather and social habits. From the Knowledge based perspective, we can determine known relationships through techniques such as expert system, fuzzy logic etc. to capture the heuristics and intuition of human operators implicit in the forecasting model. The agent maintains several problem solving plans and can do it concurrently. The four ingredients Percepts, Action, Goal and Environment (PAGE) of an agent has been derived from Russell and Norvig [23] that can be used to describe systems modeled as agent types.

The proposed STLF problem solving strategy is defined in multi-agent framework which features the amalgamation of various types of intelligent agents, each is anticipated to do the following tasks:

4.1.1 Data Mining Agent

The data mining agent communicates with Data Resource as well as with the Interface Agent. It has mainly two tasks namely Knowledge Discovery and Pre/Post processing. Based on the data retrieval specification obtained from the user through Interface Agent, the Data Mining agent will maintain its interaction with the sources to collect all the in-house data relating to historic load and weather information. It will also be able to acquire weather forecasts from external sources and format it for the given requirements. It will be responsible to preprocess and post-process the most relevant data for the training and testing of ANNs, Fuzzy inferencing and expert system. The Decomposition provides a frame work for STLF capable of providing the most relevant load and weather data selected from historical window to train variety of ANNs. This agent will also serve to extract rules and relationships from the given data and to from the linguistic information obtained from the experts.

Through Knowledge Discovery, it will be able to extract the most effective information that helps in forming rules to be used for the knowledge based systems as a part of Intelligent Agent.

4.1.2 Intelligent Agent

This agent will incorporate ANNs, Knowledge Base Systems (KBS) and Fuzzy Logic techniques to do the following tasks including:

(i) to generate library of ANNs trained over time hourly period, daily, weekly and seasonal time varying windows ,

(ii) To select the most appropriate ANN from the available library of trained ANNs using expert system and

(iii) to fine tune the selected ANN for end user by utilizing the high level reasoning for context validation using both the Expert System and Fuzzy Logic approach for handling degrees of truth that fall in between being completely true or completely false.

The expert system will do the analogical reasoning that provides intuitive forecasting of electrical load and thus reducing it into formal logical steps. Thus, a variety of fine tuned ANNs would be available in the form of ANN library and be accessed by the expert system to make the most relevant forecast through heuristic rules. Such an agent orientation can result in improving forecast in the correct and more realistic context.

4.1.3 Interface Agent

Our proposed model requires an interface agent communicating with the other agents as well as users. It allows activities such as altering resultant forecast output or reporting discrepancies between forecasts and weather observations etc. The interface agent will serve to collect user-specification for forecasting and autonomously translates it to various follow-up task-specification namely (i) the target forecast, (ii) the data that need to be retrieved and (iii) the results.

During this phase, an interface agent will communicate and cooperate with other agents and will try to find a good match between the requirements and the type of agent which handle the given task. The final answer will be synthesized based on integrating the resultant outputs acquired from various agents for an overall solution of STLF problem. The sharing of information among different intelligent agents allows the system to produce a consistent answer. The conceptual diagram is shown in Figure 1. Table 2 shows the PAGE description of multi-agent based STLF model detailing percepts, actions, goal and environment associated with each agent tasks.

5. CONCLUSION

This paper examined the recent published work to highlight the potentials of using ANNs in combination with the other techniques. The hybrid neuro-fuzzy and neuro-symbolic approaches have been used to forecast loads with better accuracy than the conventional ANN approaches when used in a stand-alone mode. It reveals that the knowledge base can be easily developed and modified to reflect changes in weather load relationship during different seasons. Neuro-fuzzy provides a general method for combining available numerical information and human linguistic information in a common framework. Similarly, the neuro-genetic approach is also another potential application of hybrid approach which offers its optimization feature to be used for the convergence of ANN weights. Conventional techniques such as regression and time series have been used with their proven abilities to select and condition the pattern examples to improve training features of ANNs.

We have also examined opportunities for revising STLF model, focusing specifically on incorporating intelligent agent (IA) technology. A conceptual model of STLF has been proposed based on the framework of multi-agents which can potentially offer autonomy and adaptiveness by knitting together the powerful functionalities and behavior of various emerging and conventional techniques.. IA technology appears to offer considerable promise across the gamut of STLF problem where multiple intelligent techniques can play important role to satisfy various requirements of STLF problem.

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Table 1: Summary of Short Term Load Forecasting Targets Modeled by various intelligent Techniques

Citation	STLF Targets	Hybrid Approach	Description
[9]	Load deviations caused by weather and holiday activity on daily load	FL	Post processing of ANN output conducted to correct load deviations
		ANN	Load profile mapped using Kohonen model
[10]	(ii) Maximum and minimum load prediction (iii) 24 hour load prediction for special days	FL	Fuzzy inference used for maximum and minimum load
		ANN	Standard ANN approach used for daily load prediction with special days marked with binary codes.
[11]	(i) Max and min load prediction (ii) 24 hour load prediction for special days	FL	Fuzzy inference used for maximum and minimum load
		ANN	ANN trained on scaled load
[12]	(i) Daily load profile prediction (ii) Max and Min load prediction	FL	Max. and min. load prediction based on historical load, weather and holidays information
		ANN	Scaled load data used in predicting daily load
[13]	Daily load profile prediction	GA	Tunes the ANN
		ANN	Standard prediction approach used for daily load
[14]	Daily load profile prediction	FL	Fuzzy rules used to model linguistic information
		GA	To find optimal number of fuzzy rules
		ANN	Uses training data selected through fuzzy rules
[15]	Daily, weekly, and special day load forecasting	FL	Fuzzy rules derived for special days modeling
		KBS	Knowledge of special days utilized
		ANN	Standard models of weather sensitive days
[16]	Daily peak load forecasting	Regression	(i) To cluster data through filtering (ii) To do data mining to discover rules (relationships)
		ANN	MLP was used to do training
[17]	Hourly load data	Regression	Groups data of similar characteristics to form special class
		ANN	The clustered data is used to train in standard way
[18]	(i) Hourly load forecast (ii) 24 load profile	Wavelet	Hourly load analyzed using multi resolution analysis
		ANN	Wavelet based data used for training
[19]	Hourly load of weekdays, weekends and holidays	Time series	Training examples are selected using correlation/autocorrelation coefficient
		ANN	Training is done based on times series based selected data

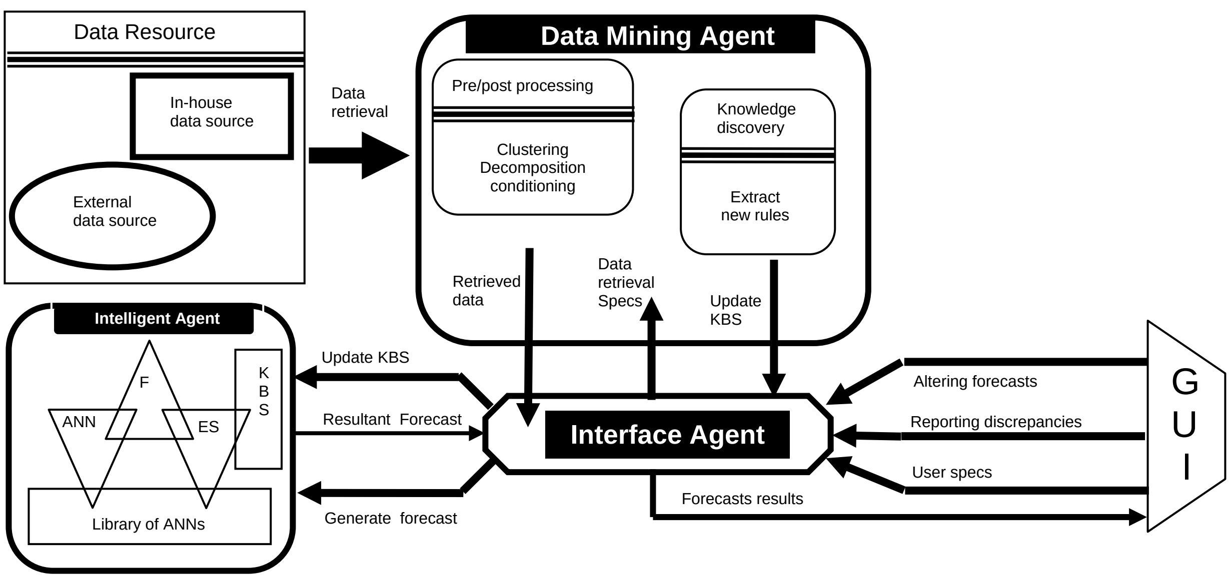

Fig. 1: A Conceptual Multi-Agent based STLF Model

Table: 2: A PAGE Description of Multi-Agent Model of Short Term Load Forecasting

Data Mining Agent				
Agent Tasks	**Percepts**	**Actions**	**Goals**	**Environment**
Preprocessing	Discrete load and weather Data, Fuzzy data	To Transform, normalize, Fuzzyfy, Filter, cluster, decompose, or to sort	Conditioning the inputs for ANNs and fuzzy Logic	Non-deterministic and fuzzy
Post processing	Discrete Data, Fuzzy data,	To De-normalize resultant output data, To Defuzzify data	Reinstating and conditioning data for meaningful results	Continuous, non deterministic
Clustering	Conditioned data,	Apply feature extraction and nearest neighbor liklyhood approach	Grouping and classifying load and weather data based on common Features	Non-deterministic
Decomposition	Data sets, decomposition framework	To identify and separate load and weather training data into seasonal and time windows. Make ANN Library based on decomposed structure	Specifying the particular data in a decomposed structure to form relevant data for training ANNs	Hierarchical and relational
Knowledge discovery	Raw data,	Find relations and correlations	Discovering relational data, rule formation	ANN, Regression,
Intelligent Agent				
Fuzzy Logic	Discrete load and weather data, rule propositions, linguistic variables	Make fuzzy sets, fuzzy inferencing, defuzzify data	Quantifying fuzzy variables	Non deterministic
Expert System	Symbols, Rule propositions,	Load knowledge, Infrencing,	High level reasoning	Deterministic
Artificial neural Network	Load and weather data	Make network configuration, train, test and verify, update existing ANN	Pattern recognition, classification, prediction, rule extraction	Non-deterministic and dynamic environment.
Interface Agent				
Interfacing	Output of DM agent: retrieved relevant and conditioned data, new rules, decomposed structure, Resultant forecast, User specific information	To coordinate and mobilize Intelligent agent for producing ANN, Fuzzy logic or Expert system based forecasts, Customizing the output to user specifics	Coordinating, with Data resource through data mining agent, intelligent agent and graphical user interface	Dynamic

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