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Research Article

A Hybrid Neural Network and Genetic Algorithm Based Model for Short Term Load Forecast

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Abstract: Aim of this research is to develop a hybrid prediction model based on Artificial Neural Network (ANN) and Genetic Algorithm (GA) that integrates the benefits of both techniques to increase the electrical load forecast accuracy. Precise Short Term Load Forecast (STLF) is of critical importance for the secure and reliable operation of power systems. ANNs are largely implemented in this domain due to their nonlinear mapping nature. The ANN architecture optimization, the initial weight values of the neurons, selection of training algorithm and critical analysis and selection of the most appropriate input parameters are some important consideration for STLF. Levenberg-Marquardt (LM) algorithm for the training of the neural network is implemented in the first stage. The second stage is based on a hybrid model which combines the ANN and GA.

Keywords: Artificial neural network, genetic algorithm, levenberg-marquardt, short term load forecast

INTRODUCTION

STLF has gone under constant improvements for the last few decades because of its great importance in economic growth of a country. Load forecasting can be divided into three classes as shown in Fig. 1 with respect to the lead time horizons, which are (Adepoju, 2007):

- Short term forecast with a lead time of up to a few hours or days ahead
- Medium term forecast with a lead time of few weeks to 1 year period
- Long term forecast with a lead time of up to 10 years

Accurate models for electric power load forecast are essential for the operation and planning of a utility company (Hippert *et al*., 2001; Rothe *et al*., 2009). Load forecast is extremely important for energy suppliers, ISOs, financial institutions and other participants in electric energy generation, transmission and distribution (Adepoju, 2007). However, load forecast is a complicated task because the consumption is influenced by many factors, such as day type, anomalous days, weather conditions, vacations, economy factors, status and distinctive habits of individual customers (Nahi *et al*., 2006). Inaccurate load forecasts also give rise to increase in operating costs (Eugene and Feinberg, 2006). A poor load forecast misleads planners and often results in wrong and expensive expansion plans (Gross and Galiana, 1987).

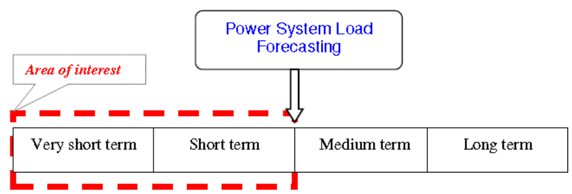

Fig. 1: The categories of load forecast and the area of interest

In the recent past years Artificial Neural Networks (ANN) and numerous searching algorithms are deployed in this domain to improve the accuracy of load forecast. ANNs are integrated with these intelligent search techniques to get the hybrid advantages of both by some of the researchers. Genetic algorithm has proven its effectiveness in the solutions of many optimization problems including STLF.

Over forecast may result in a redundant reserve of electric power and increase in operating cost. On the contrary, under forecast causes failure in providing sufficient electric power. For a planner to neither underestimate nor overestimate the load, convenient forecast techniques with reasonable degree of accuracy need to be developed (Gross and Galiana, 1987).

The focus of the research is mainly to integrate ANN and GA to search out the hybrid advantages of each technique. The performance of ANN not only

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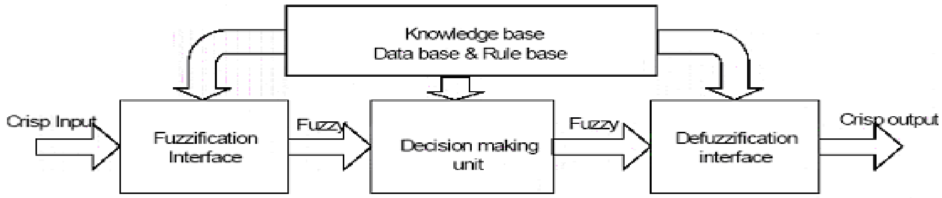

Fig. 2: Basic block diagram of fuzzy logic

depends on the input variable selections but also on the network architecture (Srinivasan, 1998). The network architecture optimization is related with the selection of exact number of input and hidden layer neurons which leads to enhanced accuracy in STLF. The selection of optimized initial network weights leads to fast and global convergence during the learning process of ANN. Due to the mentioned limitations of ANN an alternative ANN training approach based on genetic algorithm is investigated. The objective of the research is to minimize the electrical load forecast error using the computational intelligence technique combined with ANN.

STLF techniques: The applied techniques in STLF can be broadly segregated in two classes, parametric (Statistical) and non-parametric (Artificial Intelligent) techniques. The statistical models provide physical transparency in interpretation of data and reasonable accuracy in STLF but the associated problem, such as, limited modeling ability for nonlinear load behavior, complex mathematical modeling and heavy computational effort make them less preferable over computational and intelligent techniques (Srinivasan, 1998; Chen *et al*., 2001).

Artificial Neural Network (ANN) based models are most frequently deployed and has shown very promising results in STLF. This is because of their ability to achieve complicated input-output mappings without explicit programming and it can also extract relationships between data sets presented during learning process (Tzafestas and Tzafestas, 2001; Yalcinoz and Eminoglu, 2005). These massively parallel high speed networks do not require massive mathematical formulation or quantitative correlation between inputs and outputs (Hippert *et al*., 2001). The bulk amount of historical data is also not required for the training process of ANN (Srinivasan, 1998). Despite of all these benefits of ANN models, some drawbacks are also associated with them, such as, their dependence on initial parameters, long training time, improper choice of network topology, falling into the local minima and improper convergence (Liu and Li, 2011) and incomprehensive (black box) nature of ANN (Tzafestas and Tzafestas, 2001).

Some other important intelligent techniques used for STLF are summarized as the following.

Expert systems: Expert system can be deployed in the STLF domain to establish a set of relationships or rules between the changes in the system load and exogenous factors that affect the load. Some of the rules do not change over time, while others may have to be regularly updated (Rahman, 1990).

In general, the ES technique utilizes the knowledge of a human expert for load demand forecast that leads to a logical approach. However transformation of an expert's knowledge in to set of mathematical rules is very difficult (Srinivasan, 1998). A critical limitation associated with this technique is the frequent need to upgrade the rules makes it dependent upon domain experts. The lack of generalization is another problem, as the conditions and rules may differ.

Fuzzy logic: Fuzzy logic provides a mathematical approach based on Boolean algebraic principles. However its inputs can acquire multiple values in between 0 and 1 instead of having only two binary outcomes. The complete process of fuzzification and defuzzification is depicted below in Fig. 2.

Popławski (2008) proposed a technique based on fuzzy logic for load demand prediction. A linear membership functions is implemented in this model which yields a reasonably good mean absolute percentage error of 3.55%.

Support vector machines: Support Vector Machine (SVM) is a powerful and recent technique for the solution of classification and regression problems. SVM uses the nonlinear mapping of the data by implementing a kernel functions. Kernel function is a training algorithm that provides a way of mapping the inputs and outputs. The choice of a suitable kernel function to achieve satisfactory results is one of the major limitations in SVM. One of the SVM based techniques that had been reported in the literature is (Nagi *et al*., 2008). This technique applied a Gaussian kernel function to predict 24 h ahead load demand. The result of this approach shows a reasonable degree of forecast accuracy.

LITERATURE REVIEW

Literature comparison-findings: The viewed literature illustrates a variety of solutions for load forecast related problems using different methods for STLF. Some of the findings are illustrated as follows.

Adepoju (2007) used a supervised neural network based model to forecast the load in the Nigerian power system. LM algorithm along is used for the training of the network. The average mean absolute error is about 2.54% in this research.

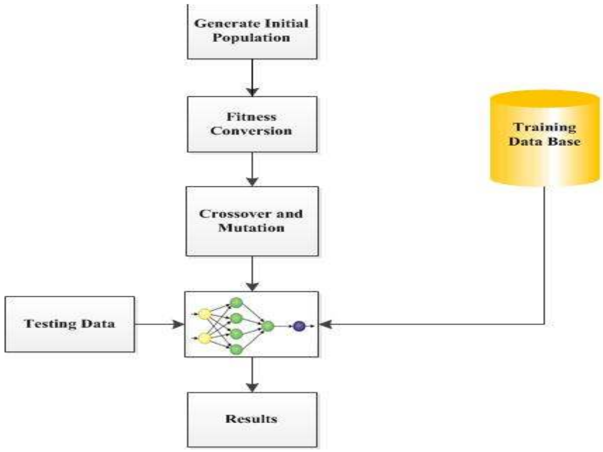

Fig. 3: General structure of hybrid (GA-ANN) model

Satish *et al*. (2004), presented the effect of the temperature on the load trend using ANN based method. The study concluded an average forecasting error of around 4%. Among other weather variables, only the temperature was incorporated in the model, thus a consideration of other factors would greatly improve the result.

Al-Saba and Amin (1999) implemented the application of the ANN for long-term load forecast. The model forecasted the annual peak demand of a Middle Eastern utility and repeated the process using a time-series approach. This comparative study established that the ANN-based model produces better forecast rather statistical methods.

Ganzalez and Zamarreno (2005), proposed a feedback ANN-based model to predict energy consumption in buildings with high precision. The optimal network structure was not evidently achieved.

Mandal *et al*. (2006) carried out a comparison of a classical load forecasting technique with an ANN-based model using actual load data. The models were used to forecast the load 1 to 6 h ahead and the results of MAPE showed that the ANN-based model provides reliable forecasts.

Topalli *et al*. (2006) used a recurrent neural network model to forecast Turkey's total load one day in advance. The study reported an average error of 1.6%.

Ningl *et al*. (2010) designed a Bayesian-BP Neural Network model for STLF. It shows a good generalization capacity to forecast the hourly load of weekdays and weekends. The proposed technique is found effective in overcoming the limitation of poor generalization in conventional Levenberg-Marquardt (LM) algorithms.

Morinigo-Sotelo *et al*. (2011) designed an ANN model for prediction of hourly load for a hospital. The statistical correlation analysis of data set is emphasized in this research. This customer based STLF model produced reasonable accuracy.

Related work: From the literatures it is found that varieties of techniques using GA to optimize the ANN have been implemented. The hybrid approach that combines the both techniques is found very useful in STLF. GA can be applied to provide optimized initial values of ANN weights or to completely train the ANN. The general structure of the GA-ANN hybrid model is shown in Fig. 3 and 4. The initial population of chromosomes represents different alternatives of number of neurons in the hidden layer and initial weight of ANN connections in the form of genes. A fitness function (small output error of ANN) is applied to complete the evolution. The best individual is selected after a certain number of iterations. The genes of this individual are decoded to provide the optimized network weights and architecture. The GA based training algorithm for the complete training of the ANN can help to overcome the limitations found in LM training algorithm.

Several research findings have been investigated and their outcomes are mentioned as follows.

Yaxi and Liu (2001) implemented GA to train connection weights of a feed forward ANN until the

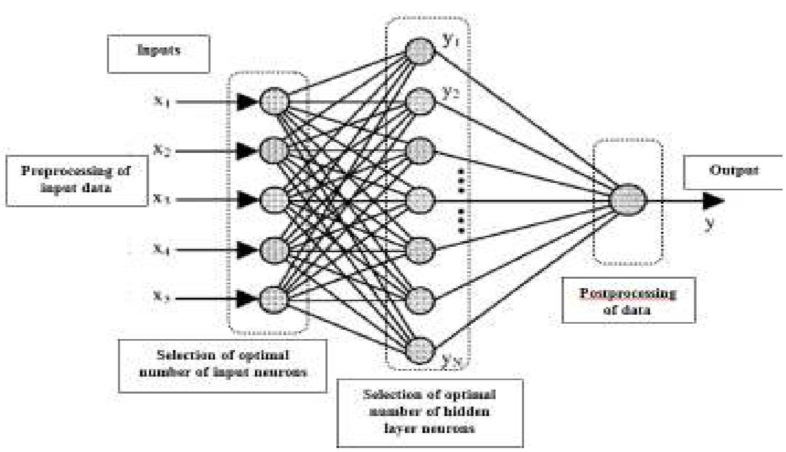

Fig. 4: Major addressable regions of research

learning error approached to stability. Once the optimal values of the initial weights are found rest of the training was accomplished using conventional technique.

Srinivasan (1998), employed back propagation ANN-based model and genetic algorithm to evolve the optimal neural network structure. This approach is powerful despites the fact that the model is unable to detect sudden load changes.

Yanxi *et al*. (2010) proposed a load forecast system based on Radial Base Function (RBF) neural network and GA. The focus of the research is on the optimization of hidden layer neurons. Other important factors like selection of input parameters and optimized initial weights were left unaddressed.

Edmund *et al*. (1998) presented an ANN model trained by a Genetic Algorithm (GA) for short term load forecast. The proposed model is a three layered feed forward back propagation network. The results of this model could be further improved by adding some technique for preprocessing and post processing of the data such as fuzzy logic. The scope of network architecture optimization is also unaddressed in this approach.

Satpathy (2003) explored the possibility of GA based optimization of the parameters of a Fuzzy Neural Network (FNN) for STLF. The adjustable parameters of the network such as connecting weights and rule sets of the network are optimized using GA to improve the learning process. The effectiveness of the proposed algorithm is demonstrated by comparison to a non-GA based forecasting approach. The results of GA based model were found more accurate in this research.

METHODOLOGY

In order to overcome the deficiencies found in the existing STLF models, a new approach is proposed which integrates the genetic algorithms and artificial neural networks for the development of STLF model. The phases involved in this research work are presented below.

The selection of proper techniques for preprocessing of the input data and post processing of the output data is also helpful to increase the forecast accuracy. Figure 4 highlights the main addressable regions, which are focused in the research work by implementing evolutionary programming techniques for ANN performance optimization.

Literature review: A variety of load forecast techniques are developed and implemented in the past few decades. A comprehensive literature review needs to be carried out for extensive analysis of proposed approaches and to establish the associated drawbacks. Preliminary study of the existing literature reveals the strength of the hybrid approach based on ANN and other evolutionary programming techniques. Previous section of this report covers the details of reviewed literature on these hybrid models and techniques.

Critical analysis: The existing methodologies used for STLF with an emphasize on hybrid techniques based on genetic algorithms and ANN will be critically analyzed. The research journal articles, conference papers, books, internet articles and databases will be thoroughly explored in this analysis phase.

Network topology optimization: Network architecture optimization is about the selection of exact number of neurons in the input and hidden layer that lead to the better performance of ANN. Following are the GA steps that select the optimum topology of ANN:

a) Set the size of initial population randomly. There are two sets of genes (bits) in each chromosome, first set represents number of input neuron and the second shows the number of hidden layer neuron. A reasonable number of input and hidden layer neurons should be represented in the mentioned population.
b) Evaluate the fitness function for each individual in the population.
c) Select the first two individuals with highest fitness value in the current generation and apply crossover and mutation genetic operations, to reproduce the individuals in the next generation. Standard one-

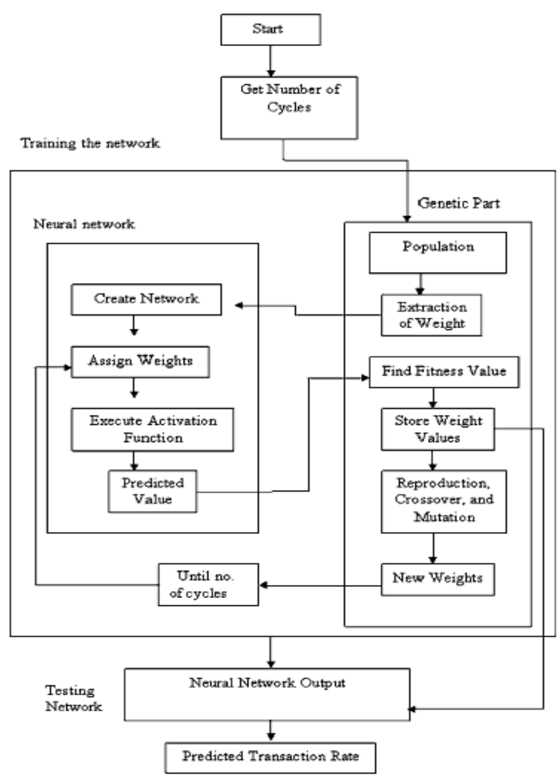

Fig. 5: Flow diagram for initial weight optimization

point or two point crossover can be used and the probability of crossover and mutation should be determined properly.

d) Repeat from Step b) until all individuals in population meet the convergence criteria or the number of generations approach to a preset number.

Decode the converged individuals in the final generation and obtain the optimized neural network architecture with optimal or near optimal number of input neurons and hidden layer neurons.

Initial weight optimization: Genetic algorithms can be used to provide good initial values for the weights of ANN. Once the exact network architecture is know the number of weighted connection can be determined. A generic scheme for GA ANN hybrid system is shown in the Fig. 5. Genetic algorithm works for the optimization of ANN initial weight set determination. After the generation of the initial populations, an individual with high fitness (i.e., small output error of the NN) is selected to compete for evolution. The best individual is kept in each generation. The genes of this individual are decoded to give the network weights. The complete training of NN with GA will be implemented in the next phase.

Development of GA for ANN training: The next step is to develop a GA for the complete training of optimized neural network. This algorithm will be used in place of LM and employ its own activation function. The proposed activation function will be based on GA search technique that updates the network weights in such a way that the network output error is minimized. The various steps of this algorithm are explained below:

[Start] Generate random population of n chromosomes.
[Fitness] Evaluate the fitness $f(x)$ of each chromosome x in the population.
[New population] Create a new population by repeating following steps.
[Selection] Select two parent chromosomes from a population according to their fitness.
[Crossover] Cross over the parents to form new offspring.
[Mutation] With a mutation probability mutate new offspring.
[Replace] Use new generated population for a further run of the algorithm.
[Test] If the end condition is satisfied, stop and return the best solution in current population.
[Loop] Go to fitness function evaluation step again.

RESULTS AND DISCUSSION

Although the artificial intelligent techniques, especially artificial neural networks have shown promising accuracy in STLF, but the associated problems, such as, their dependence on initial parameters, long training time, improper convergence and incomprehensive network topology are still in question and have not yet been successfully resolved.

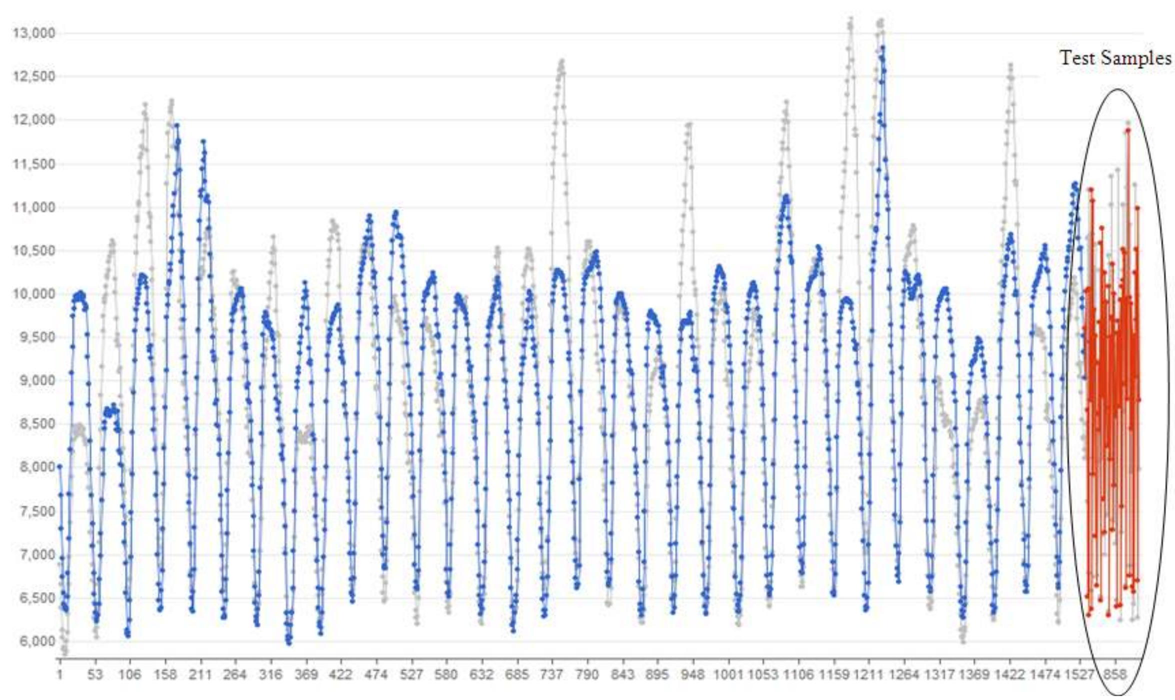

Fig. 6: LM based forecast result

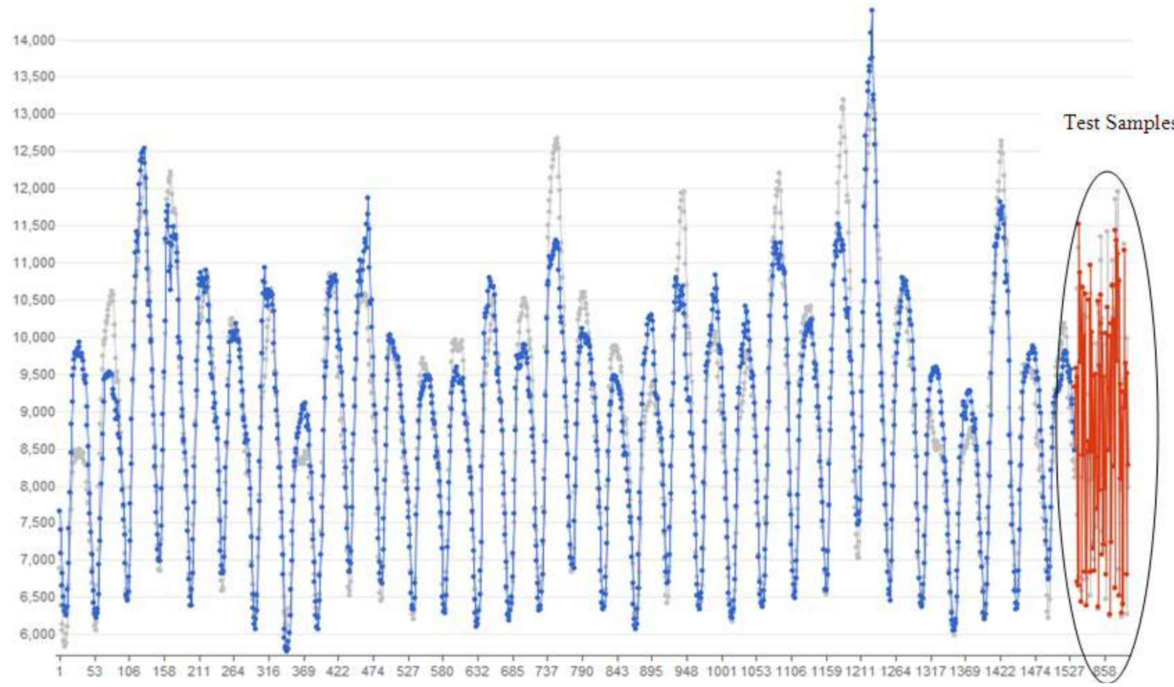

Fig. 7: GA based forecast results

The results obtained from training and testing the neural network on historical load data of one month period sampled at half hour frequency are presented below in graphical form (Fig. 6). The graph shows a plot of both actual and forecast load in MW on Y-axis against hour of the day for one month on X-axis. In total, 1527 number of samples of load data are used for the training of the NN and the network is tested against 858 number of data points, which are represented in an oval shape at the end of the following graph. The Mean Absolute Percentage Error (MAPE) of 3.95% is calculated in this technique.

In the second approach GA is used to forecast the load for 24 h of a day over one month period. The plot of both actual and forecast load in MW against hour of the day for 1 week is presented in Fig. 7. The Mean Absolute Percentage Error (MAPE) in this method is 2.14%.

The overall decrease in the MAPE of almost 2% reflects that the GA based approach is superior as compared to LM.

CONCLUSION

The system load forecast models are critically important for secure and economic operation of electric power companies. Different techniques have been applied to develop the load forecast models. After surveying multiple approaches, a trend towards intelligent and dynamic techniques is observed. Because of their input and output mapping ability, artificial neural networks are well suited for this type of applications. There is also a clear shift towards hybrid methods, which combine two or more of these techniques. In this study, the integrated approach based on artificial neural network and genetic algorithm is used to get the hybrid advantages of both techniques. Although the feed forward neural networks with Levenberg-marquardt training algorithm reported reasonably good results, yet improper convergence, choice of optimized architecture and dependence on initial parameters are the major limitations of LM training algorithm. A hybrid approach based on ANN and GA provide promising results for enhanced accuracy in STLF.

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