Chapter 1
Introduction

For an export-oriented economy or an energy-limited economy, like Taiwan, economic development mainly depends on the supply level of electric energy; particularly, most production activities for each industry also depend on its available level. As the economic development is proceeding vigorously, the electric energy demand in industries, in commerce, and in people's residential uses has also significantly increased. To ensure that electric energy is usable for all electricity users (i.e., meeting users' demands) will be an important challenge for the electric energy industry. The availability and reliability of electric energy become the most premier issue in energy policy making. Therefore, accurate electric load forecasting is quite an important guide for effective implementations/actions of energy policies. The policy makers desire to look for founded forecasts to well plan the new electric power facilities investments and to determine the import and export amounts.

In the meanwhile, along with the recent privatization and deregulation of the electricity industry, the reliance and accuracy of future electricity demand forecasting have received growing attention, particularly in the areas of electricity load planning, energy expenditure/cost economy, and secure operation fields, in regional and/or national systems. For electricity load reliance, electricity providers face increasing competition in the demand market and must pay increased attention to electricity quality, including unit commitment, hydrothermal coordination, short-term maintenance, interchange and transaction evaluation, network power flow dispatched optimization, and security strategies. On the other hand, inaccurate electricity load forecasting may increase operating costs [1–5]. Bunn and Farmer [4] point out that a 1 % increase in forecasting error implied a £10 million increase in operating costs. Hence, overestimation of future load results in unnecessary spinning reserve and, furthermore, is not accepted by international energy networks owing to excess supply. In contrast, underestimation of load causes failure in providing sufficient reserve and implies high costs in the peaking unit. Because buying at the last minute from other suppliers is expensive, it is necessary for international electricity production cooperation that every member is able to forecast its demands accurately. However, it is complex to predict the electric load, primarily due to the various influencing factors, such as climate factors, social activities, and seasonal factors [6]. Climate factors depend on the temperature and humidity; social

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factors imply human social activities including work, school, and entertainment affecting the electric load; seasonal factors then include seasonal climate change and load growth year after year.

1.1 Traditional Approaches for Electric Load Forecasting

In the last few decades, there are widespread investigations with regard to the efforts proposed to improve the accuracy of electricity load forecasting. One such method is a weather insensitive approach that uses historical load data to infer the future electricity load. Generally, it is famously known as the Box–Jenkins autoregressive integrated moving average (ARIMA) [7–13], which is theoretically based on univariate time sequences. Christianse [14] and Park et al. [11] design exponential smoothing models by Fourier series transformation for electricity load forecasting. Hence, many researchers consider related factors, such as seasonal temperature and day type, in load forecasting models. Mbamalu and El-Hawary [15] propose multiplicative autoregressive (AR) models that considered seasonal factors in load forecasting. The analytical results show that the forecasting accuracy of the proposed models outperformed the univariate AR model. Douglas et al. [16] consider verifying the impacts of temperature on the forecasting model. The authors combine Bayesian estimation with a dynamic linear model for load forecasting. The experimental results demonstrated that the presented model is suitable for forecasting load under imperfect weather information. Sadownik and Barbosa [17] propose dynamic nonlinear models for load forecasting. The main disadvantage of these methods is that they become time-consuming to compute as the number of variables increases. Azadeh et al. [18] employ fuzzy system to provide an ideal rule base to determine which type of ARMA models should be used; the results also indicate that the integrated approach outperforms those novel intelligent computing models. Wang et al. [19] propose hybrid ARMAX (autoregressive and moving average with exogenous variables) model with particle swarm optimization to efficiently solve the problem of trapping into local minimum which is caused by exogenous variable (e.g., weather condition). Their results also reveal that the proposed approach has superior forecasting accuracy.

To achieve the accuracy of load forecasting, state space and Kalman filtering technologies, developed to reduce the difference between actual loads and prediction loads (random error), are employed in load forecasting model. This approach introduces the periodic component of load as a random process. It requires historical data more than 3–10 years to construct the periodic load variation and to estimate the dependent variables (load or temperature) of power system [20–22]. Moghram and Rahman [23] proposed a model based on this technique and verified that the proposed model outperforms another four forecasting methods (multiple linear regression, time series, exponential smoothing, and knowledge-based approach). Similarly, Park et al. [11] proposed a load forecasting model based on the state space and Kalman filtering technology and also showed that their model outperformed other methods. The disadvantage of these methods is that they are difficult to avoid the observation noise in the forecasting process, especially multivariable considered. Recently, Al-Hamadi and Soliman [24] employ fuzzy rule-based logic, by utilizing a moving window of current values of weather data as well as the recent past history of load and weather data, to recursively estimate the optimal fuzzy parameters for each hour load of the day. Amjady [25] proposes hybrid model of the forecast-aided state estimator (FASE) and the multilayer perceptron (MLP) neural network to forecast short-term bus load of power systems. The proposed hybrid model has been examined on a real power system, and the results show that the hybrid method has better prediction accuracy than the other models, such as MLP, FASE, and the periodic autoregression (PAR) model.

The regression approach is another popular model for forecasting electricity load. Regression models construct the cause–effect relationships between electricity load and the independent variables. The most popular model is linear regression model, proposed by Asbury [26]; he considers the "weather" variable to explain the electric load. Meanwhile, Papalexopoulos and Hesterberg [27] add the factors of "holiday" and "temperature" into their proposed model. The proposed model uses the weighted least square method to obtain robust parameter estimation encountering with the heteroskedasticity. Furthermore, Soliman et al. [28] propose a multivariate linear regression model for load forecasting, which includes temperature and wind cooling/humidity factors. The empirical results indicate that the proposed model outperforms the harmonic model as well as the hybrid model. Similarly, Mirasgedis et al. [29] also incorporate weather meteorological variables, such as relative humidity, heating, and cooling degree days to forecast electricity demand in Greece. In contrast, Mohamed and Bodger [30] employ economic and geographic variables (such as GDP, electricity price, and population) to forecast electricity consumption in New Zealand. In these models, the dependent variables are generally decomposed into weather insensitive and weather sensitive components [4, 11, 31]. However, these models are all based on linear assumption, that is, these independent variables cannot be well justified due to nonlinear relationships among variables. Therefore, in the recent years, Tsekouras et al. [32] introduce a nonlinear multivariable regression approach to forecast annual load, which considers correlation analysis with weighting factors to select appropriate input variables. Asber et al. [33] employ kernel regression model to establish a relationship among past, current, and future temperatures and the system loads to forecast the load in the Hydro-Quebec distribution network. A set of past load history comprising of weather information and load consumption is used. The paper proposes a class of flexible conditional probability models and techniques for classification and regression problems. A group of regression models is used, each one focusing on consumer classes characterizing specific load behavior. Numerical investigations show that the suggested technique is an efficient way of computing forecast statistics.

1.2 Artificial Intelligent Technology for Electric Load Forecasting

Recently, lots of researches have attempted to apply artificial intelligence techniques to improve the accuracy of electric load forecasting models. Knowledge-based expert system (KBES) and artificial neural networks (ANNs) are the popular representatives. Rahman and Bhatnagar [34] present a KBES model for electricity load forecasting. They construct new rules based on received information, including daily temperature, day type, and load from the previous day. The characteristic feature of this approach is rule based, which implied that the system transformed new rule from received information. In other words, this approach is derived from training rules and transformed the information into mathematical equations; the so-called expert capability is training by the existence presuming and will significantly increase the forecasting accuracy [34–36]. Recently, applying fuzzy inference system and fuzzy theory in load forecasting has also received attentions; Ying and Pan [37] introduce adaptive network fuzzy inference system (ANFIS), by looking for the mapping relation between the input and output data to determine the optimal distribution of membership functions, to forecast regional load. Pai [38] and Pandian et al. [39] all employ fuzzy approaches to get superior performance in terms of load forecasting.

Meanwhile, many researches also have tried to apply ANNs to improve the load forecasting accuracy level. Dillon et al. [40] use adaptive pattern recognition and self-organizing techniques for short-term load forecasting. Dillon et al. [41] present a three-layered feedforward adaptive neural network to forecast short-term load. Their proposed model is trained by back-propagation neural network. The proposed model is applied to real data from a power system and is distinguished providing superior comparative results with other methods are given. In the meanwhile, Park et al. [42] propose a 3-layer back-propagation neural network to daily load forecasting problems. The inputs include three indices of temperature: average, peak, and lowest loads. The outputs are peak loads. The proposed model outperforms the regression model and the time series model in terms of forecasting accuracy index and mean absolute percent error (MAPE). Moreover, Ho et al. [43] develop an adaptive learning algorithm for forecasting the electricity load in Taiwan. The numerical results demonstrate that the proposed algorithm converges faster than the traditional back-propagation learning method. Novak [44] applies radial basis function (RBF) neural networks to forecast electricity load. The analytical results indicate that the RBF network is at least 11 times faster and more reliable than the back-propagation neural networks. Darbellay and Slama [45] apply ANNs to predict the Czech electricity load. The experimental results show that the proposed ANN model outperforms the ARIMA model in terms of normalized mean square error. Abdel-Aal [46] proposes an abductive network to conduct 1 h ahead load forecasts for a 5-year period. The proposed model achieves extremely promising results based on the measurement of mean absolute percent error. Hsu and Chen [47] employ back-propagation neural networks to forecast the regional load in Taiwan. The experiment results show that the artificial neural network approach outperforms the regression models. Recently, Kandil et al. [48] apply

ANNs for short-term load forecasting using real load and weather data from the Hydro-Quebec databases where three types of variables are used as inputs to the neural network. Their proposed model demonstrates ANNs capabilities in load forecasting without the use of load history as an input. In addition, only temperature (from weather variables) is used, in this application, where results show that other variables like sky condition (cloud cover) and wind velocity have no serious effect and may not be considered in the load forecasting procedure. Applications of hybrid ANNs model with statistical methods or other intelligent approaches have received a lot of attention, such as hybrid with Bayesian inference [49, 50], self-organizing map [51, 52], wavelet transform [53, 54], particle swarm optimization [55], and dynamic mechanism [56].

1.3 Support Vector Regression for Electric Load Forecasting

Proposed by Vapnik [57], support vector machines (SVMs) are one of the significant developments in overcoming shortcomings of ANNs mentioned above. Rather than most of the traditional neural network models by implementing the empirical risk minimization (ERM) principle to minimize the training error, SVMs apply the structural risk minimization (SRM) principle to minimize an upper bound on the generalization error. SVMs can theoretically guarantee to achieve the global optimum, instead of trapping local optimum like ANN models. Thus, the solution of a nonlinear problem in the original lower dimensional input space could be equivalent to solving a linear-constrained quadratic programming problem and find its linear solution in the higher dimensional feature space. Originally, SVMs have found wide application in the field of pattern recognition, bioinformatics, and other artificial intelligence relevant applications. In addition, with introduction of Vapnik's ε-insensitive loss function, SVMs have been extended to solve nonlinear regression estimation problems, which are so-called support vector regression (SVR). SVR has been successfully employed to solve forecasting problems in many fields, such as financial time series forecasting [58–65], production value forecasting of machinery industry [66, 67], software reliability forecasting [68], atmospheric science forecasting [69–72], tourism forecasting [73, 74], and so on. Meanwhile, SVR model has also been successfully applied to forecast electric load [75–81]. Cao [58] uses the SVMs experts for time series forecasting. The generalized SVMs experts contain a two-stage neural network architecture. The numerical results indicate that the SVMs experts are capable of outperforming the single SVM models in terms of generalization comparison. Cao and Gu [59] propose a dynamic SVMs model to deal with nonstationary time series problems. Experimental results show that the dynamic SVM model outperforms standard SVMs in forecasting nonstationary time series. Meanwhile, Tay and Cao [60] present C-ascending SVMs to model nonstationary financial time series. Experimental results show that the C-ascending SVMs with actually ordered sample data consistently perform better than standard SVMs. Tay and Cao [61] use SVMs in forecasting financial time series. The numerical results indicate that the SVMs are superior to the multilayer back-propagation neural network in financial time series forecasting. Hong and Pai [68] apply SVR in forecasting rainfall during the period while typhoon attacks Taiwan. The experimental results indicate that SVR outperforms other alternative forecasting models, such as Holt–Winters (HW) model, seasonal Holt and Winters' linear exponential smoothing (SHW) model, and recurrent neural network (RNN) model. Hong and Pai [67] apply SVMs to predict engine reliability. Their experimental results indicate that SVMs outperform Duane model, ARIMA model, and general regression neural networks model. Hong et al. [73] propose a multifactor support vector regression model to forecast Taiwanese demand for travel to Hong Kong from 1967 to 1996. They indicate that the proposed SVRCGA model outperforms BP model, FF model, Holt's model, MA model, naïve model, and multiple regression model. For electric load forecasting, Chen et al. [75] are the pioneers for proposing a SVM model, which is the winning entry of a competition aiming at midterm load forecasting (predicting daily maximum load of the next 31 days) organized by EUNITE network in 2001, to solve the problem. They discuss in detail how the SVM, a new learning technique, is successfully applied to load forecasting. Pai and Hong [80] employ the concepts of Jordan recurrent neural networks to construct recurrent SVR model in Taiwan regional long-term load forecasting. In addition, they use genetic algorithms to determine approximate optimal parameters in the proposed RSVMG model. They conclude that RSVMG outperforms other models, such as SVMG, ANN, and regression models. Similarly, Pai and Hong [81] also propose a hybrid model of SVR and simulated annealing (SA) algorithms to forecast Taiwan's long-term electric load, in which SA is employed to select approximate optimal parameters in the proposed SVMSA model. Conclusively, they indicate that SVMSA is superior to ARIMA and GRNN models in terms of MAPE, MAD, and NRMSE.

The empirical results indicated that selection of the three parameters, C (to trade off the training errors and large weights), ε (the width of the insensitive loss function), and σ (the parameter of Gaussian kernel function), in an SVR model influences the forecasting accuracy significantly. Although numerous publications in the literature have given some recommendations on appropriate setting of SVR parameters [82], however, those approaches do not simultaneously consider the interaction effects among the three parameters. There is no general consensus and many contradictory opinions. It is feasible to employ optimization solving procedure to obtain suitable parameters combination, such as minimizing the objective function describing the structural risk mentioned above. Evolutionary algorithms, such as genetic algorithm, simulated annealing algorithms, immune algorithms, particle swarm optimization, and tabu search, are the very candidates to be employed to determine appropriate parameter values. However, evolutionary algorithms almost lack knowledge memory or storage functions which would be either time-consuming or inefficient in searching the suitable parameters (i.e., being premature convergent or being trapped in local optimum). Therefore, it is necessary to consider some feasible approaches, such as hybridizing or combining other potential technologies, to overcome the premature convergent problems.

1.4 Feasible Approaches to Improve the Forecasting Accuracy Performance

As mentioned, evolutionary algorithms almost have their theoretical drawbacks, such as lack of knowledge memory or storage functions, time-consuming in training, trapped in local optimum, and so on. Therefore, hybridizing some novel search technique to adjust their internal parameters (e.g., mutation rate, crossover rate, and annealing temperature) to overcome the embedded shortcomings is the feasible improving approach. There are three feasible considerations.

1.4.1 Hybridization of Complementary Evolutionary Algorithms

Firstly, for example, in genetic algorithm (GA), new individuals are generated by the following operators: selection, crossover, and mutation. For all types of objective functions, the generation begins with a binary coding for the parameter set. Based on this special binary coding process, GA is able to solve some specified problems which are not easily solved by traditional algorithms. GA can empirically provide a few best-fitted offsprings from the whole population; however, after some generations, due to low diversity of the population, it might lead to a premature convergence. Similarly, simulated annealing (SA) is a generic probabilistic search technique that simulates the material physical process of heating and controlled cooling. Each step of SA attempts to replace the current state by a random move. The new state may then be accepted with a probability that depends both on the difference between the corresponding function values and also on a global parameter, temperature. Thus, SA has some institution to reach more ideal solutions. However, SA costs lots of computation time in annealing process. To improve premature convergence and to receive more suitable objective function values, it is necessary to find some effective approach to overcome these drawbacks from GA to SA. Hybridization of genetic algorithm with simulated annealing (GA–SA) algorithm is an innovative trial by applying the superior capability of SA algorithm to reach more ideal solutions and by employing the mutation process of GA to enhance searching process. GA–SA algorithm has been applied to the fields of system design [83], system and network optimization [84], continuous-time production planning [85], and electrical power districting problem [86]. Furthermore, due to easy implementation process and special mechanism to escape from local optimum [87], chaos and chaos-based searching algorithms have received intense attentions [88, 89]. Applications of chaotic sequence to carefully expand variable searching space, that is, let variable travel ergodically over the searching space, are more and more popular to be employed in evolutionary computation fields.

1.4.2 Hybridization of Chaos/Cloud Theories with Evolutionary Algorithms

Secondly, several disadvantages embedded in these evolutionary algorithms are required to be improved to get more satisfied performance. For example, based on the operation procedure of SA, subtle and skillful adjustment in the annealing schedule is required, such as the size of the temperature steps during annealing. Particularly, the temperature of each state is discrete and unchangeable, which does not meet the requirement of continuous decrease in temperature in actual physical annealing processes. In addition, SA is easy to accept deteriorate solution with high temperature, and it is hard to escape from local minimum trap with low temperature [90]. To overcome these drawbacks of SA, the cloud theory is considered. Cloud theory is a model of the uncertainty transformation between quantitative representation and qualitative concept using language value [91]. It is successfully used in intelligence control [92, 93], data mining [94], spatial analysis [95], intelligent algorithm improvement [96], and so on. Based on the operation procedure of SA, subtle and skillful adjustments in the annealing schedule are required, such as the size of the temperature steps during annealing, the temperature range, and the number of restarts and redirection of the search. The annealing process is like a fuzzy system in which the molecules move from large scale to small scale randomly as the temperature decreases. In addition, due to its Monte Carlo scheme and lack of knowledge memory functions, time-consuming is also an another boring problem. Author has tried to employ chaotic simulated annealing (CSA) algorithm, to overcome these shortcomings, in which the transiently chaotic dynamics are temporarily generated for foraging and self-organizing, then gradually vanished with autonomous decreasing of the temperature, and are accompanied by successive bifurcations and converged to a stable equilibrium. Therefore, CSA has significantly improved the randomization of Monte Carlo scheme, has controlled the convergent process by bifurcation structures instead of stochastic "thermal" fluctuations, and eventually performed efficient searching including a global optimum state. However, as mentioned that the temperature of each state is discrete and unchangeable, which does not meet the requirement of temperature continuously decrease in actual physical annealing processes. Even some temperature annealing function is exponential in general, the temperature is gradually fallen with a fixed value in every annealing step, and the changing process of temperature between two neighbor steps is not continuous. This phenomenon also appears while other types of temperature update functions are implemented, such as arithmetical, geometrical, or logarithmic one. In the cloud theory, by introducing the *Y* condition normal cloud generator to the temperature generation process, it can randomly generate a group of new values that distribute around the given value like "cloud." Let the fixed temperature point of each step become a changeable temperature zone, the temperature of each state generation in every annealing step is chosen randomly, the course of temperature changing in the whole annealing process is nearly continuous and fits the physical annealing process better. Therefore, based on chaotic sequence and cloud theory, the CCSA is employed to replace the stochastic "thermal" fluctuations control from traditional SA, to enhance the continuously physical temperature annealing process from CSA. The cloud theory can realize the transformation between a qualitative concept in words and its numerical representation. It is able to be employed to avoid problems mentioned above.

1.4.3 Combination of Recurrent/Seasonal Mechanisms with Evolutionary Algorithms

Thirdly, the concepts of combined or hybrid models also deserve to be considered. Please notice that the so-called hybrid model means that some process of the former model is integrated into the process of the latter one, for example, hybridizing A and B implies that some processes of A are controlled by A and some are by B. On the other hand, for the so-called combined model, it only indicated that the output of the former model is then the input of the latter one; therefore, the classification results from combined models will be superior to single model. The combined models are employed to further capture more data pattern information from the analyzed data series. For example, inspired by the concept of recurrent neural networks (RNNs) that every unit is considered as an output of the network and the provision of adjusted information as input in a training process [97], the recurrent learning mechanism framework is also combined into the original analyzed model. For a feedforward neural network, links may be established within layers of a neural network. These types of networks are called recurrent neural networks. RNNs are extensively applied in time series forecasting. Jordan [98] proposes a recurrent neural network model (Fig. 1.1) for controlling robots. Elman [99] develops a recurrent neural network model (Fig. 1.2) to solve linguistics problems. Williams and Zipser [100] present a recurrent network model (Fig. 1.3) to solve nonlinear adaptive filtering and pattern recognition problems. These three models mentioned all consist of multilayer perceptron (MLP) with a hidden layer. Jordan networks have a feedback loop from the output layer with past values to an additional input, namely, "context layer." Then, output values from the context layer are fed back into the hidden layer. Elman networks have a feedback loop from the hidden layer to the context layer. In Williams and Zipser networks, nodes in the hidden layer are fully connected to each other. Both Jordan and Elman networks include an additional information source from the output layer or the hidden layer. Hence, these models use mainly past information to capture detailed information. Williams and Zipser networks take much more information from the hidden layer and back into themselves. Therefore, Williams and Zipser networks are sensitive when models are implemented [101]. For another combined model, on the other hand, some data series sometimes reveals a seasonal tendency due to cyclic economic activities or seasonal nature hour to hour, day to day, week to week, month to month, and season to season, such as hourly peak in a working day, weekly peak in a business week, and monthly peak in a demand planned year. In order to excellently deal with cyclic/seasonal trend data series, some useful trial, for example, seasonal mechanism [102, 103], also received some intentions.

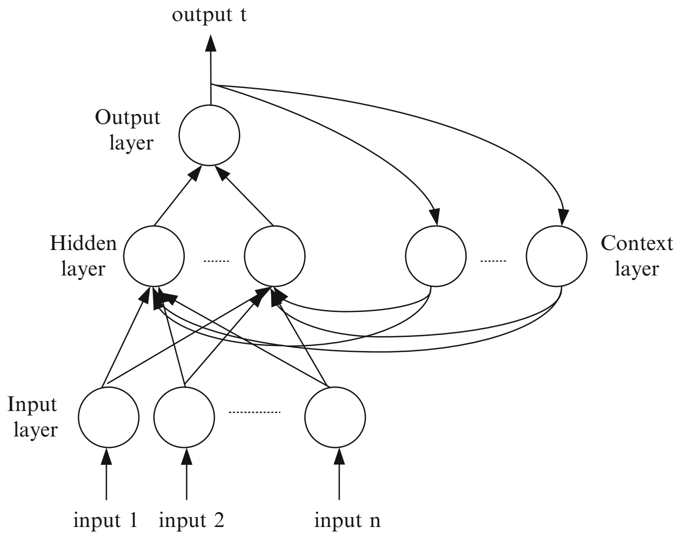

Fig. 1.1 Network diagram created from Jordan's definition

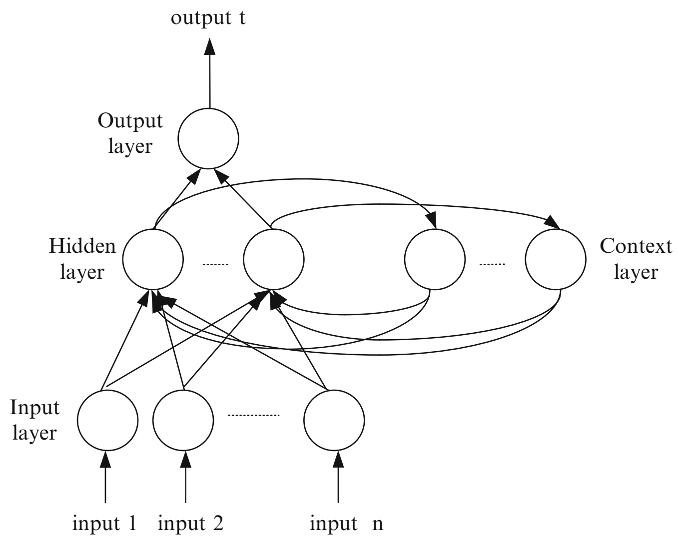

Fig. 1.2 Network diagram created from Elman's definition

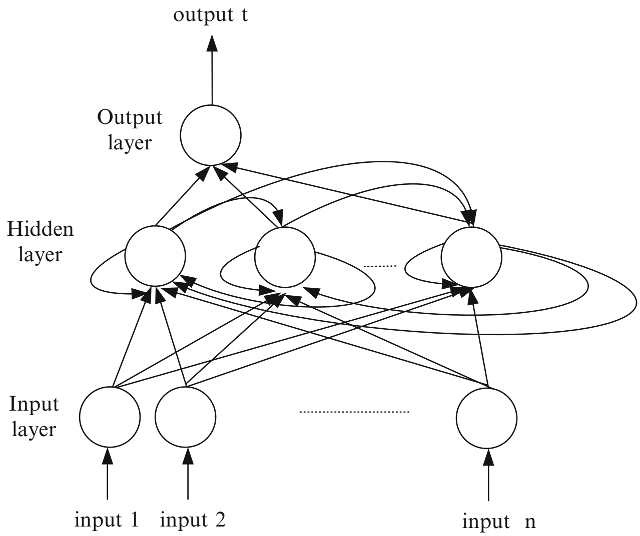

Fig. 1.3 Network diagram created from Williams and Zipser's definition

1.4.4 Summary: Electric Load Forecasting Support System (ELFSS)

Based on the discussions above, it will also become the research mainstream in SVR-based electric load forecasting, which is also the principal purpose of this book, to guide researchers how to employ alternative ways (proper evolutionary algorithms) in parameter determination while new electric load forecasting model is constructing, that is, the importance and necessity of the electric load forecasting support systems. This is because that for any forecasting model, the most important problem is how to catch the data pattern and apply the learned patterns or rules to forecast, that is, the key successful factor is how to suitably look for data pattern. The data patterns could be classified into three categories: (1) fluctuation, changing violently according to policy or herding behaviors of investors; (2) regular pattern, trends (electric load increasing or decreasing annually) or seasonality/cyclic (peak electric load in summer and winter); and (3) noise, accidental events (e.g., 9/11 event, SARS event) or man-made events (e.g., product promotion event). However, each model itself has excelled ability to catch specific data pattern. For example, exponential smoothing and ARIMA models focus on strict increasing (or decreasing) time series data, that is, linear pattern, even though they have seasonal modification mechanism to analyze seasonal (cyclic) change; due to artificial learning function being able to adjust the suitable training rules, ANN model is excelled only if historical data pattern has been learned, it is lacks of systematic explanation how the accurate forecasting results are obtained; SVR model could acquire superior performance only if proper parameter determination search algorithms.

Therefore, it is essential to construct an inference system to collect the characteristic rules to determine the data pattern category. Then, it should assign appropriate approach to implement forecasting: for (1) ARIMA or exponential smoothing approaches, the only work is to adjust their differential or seasonal parameters, and (2) for ANN or SVR models, the forthcoming problem is how to determine best parameter combination (numbers of hidden layer, units of each layer, learning rate or Gaussian σ, model flatness C, ε-insensitive) to acquire superior forecasting performance. Particularly, for the focus of this book, in order to determine the most proper parameter combination (σ, C, and ε), a series of evolutionary algorithms should be employed to test which data pattern is familiar with, such as genetic algorithms (GA), simulated annealing algorithms (SA), ant colony optimization (ACO), tabu search (TA), immune algorithm (IA), and particle swarm optimization algorithm (PSO). Based on experimental findings, those evolutionary algorithms themselves also have merits and drawbacks, for example, GA and IA could handle excellently in regular trend data pattern (real number) [80], SA excelled in fluctuation or noise data pattern (real number) [68, 81], TA is good in regular cyclic data pattern (real number) [104], and ACO is well done in integer number searching.

As aforementioned, it is possible to propose an intelligent forecasting support system to improve the usage efficiency of evolutionary algorithms, chaos/cloud theories, and recurrent/seasonal mechanisms hybridized in an SVR load forecasting model, namely, electric load forecasting support system (ELFSS). The main flowchart of the ELFSS suggested in this conclusion is given in Fig. 1.4. Firstly, employ fuzzy logic to construct the inference system to preprocess the time series data and find out or define the characteristic rules set of data pattern, such as linear, logarithmic, inverse, quadratic, cubic, compound, power, growth, and exponential. Secondly, filter the original electric load data by those data pattern rules set and then recognize the appropriate data pattern (fluctuation, regular, or noise). The recognition decision rules should include two principles (1) the change rate of two continuous electric load data and (2) the decreasing or increasing trend of the change rate, that is, behavior of the approached curve. Finally, decide appropriate evolutionary algorithm (including hybrid evolutionary algorithms) to be hybridized into an SVR model; in addition, to avoid trapping in local optimum, suitable chaos or cloud theory and appropriate (recurrent or seasonal) mechanism could be further hybridized or combined with associated evolutionary algorithms into these SVR-based forecasting models (such as CGA, CSA, CTA, CIA, CACO, and CPSO in Fig. 1.4).

1.5 Structure of This Book

In this book, different techniques used in the past decades are employed to construct the electric load forecasting models, including ARIMA, SARIMA, HW, SHW, GRNN, and BPNN models; chaos/cloud theories; and recurrent/seasonal mechanisms. The book contains six chapters:

Chapter 1, “Introduction.” This chapter introduces the background of electric load forecasting, traditional approaches, artificial intelligent technology, SVR for electric

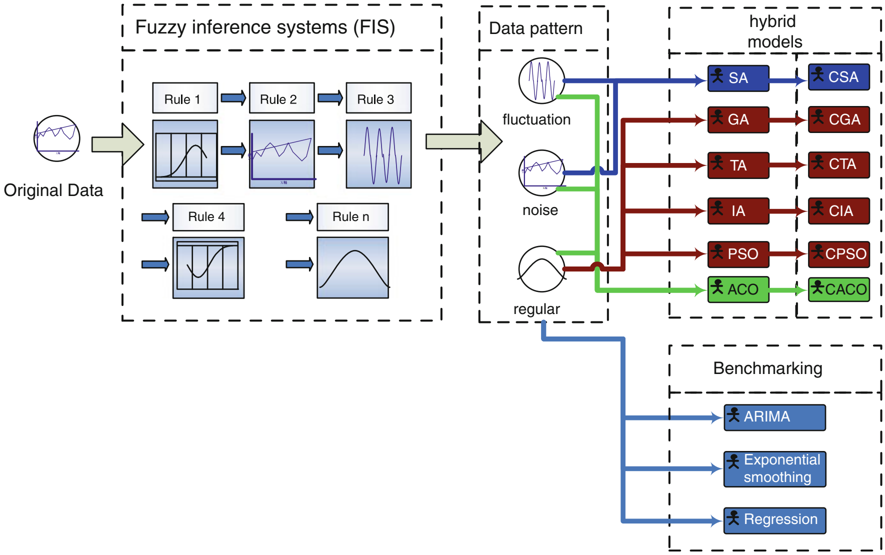

Fig. 1.4 The electric load forecasting support system (ELFSS)

load forecasting, and some feasible improvements of forecasting accuracy, to help the reader understand the very issue of electric load forecasting in this book and the current development tendency and shortcomings; in addition, some critical arrangements to improve the forecasting accuracy level are also discussed. In this chapter, readers will study the basic concepts of the electric load forecasting and associate forecasting technologies, including ARIMA, exponential smoothing, state space/Kalman filtering, regression, knowledge-based expert system (KBES), artificial neural networks (ANNs), fuzzy theory, support vector regression, and so on. The reader will also review these technologies proposed during the past decades for electric load forecasting. A brief discussion for each model is given in this chapter. Superiorities and shortcomings of each model are also taken into account and discussed.

Chapter 2, "Modeling for Energy Demand Forecasting." This chapter introduces different basic energy demand forecasting models, which will be employed in Chaps. 3–5. Electric load forecasting methods can be classified in three categories (1) traditional approaches, including Box–Jenkins autoregressive integrated moving average (ARIMA) model, autoregressive and moving average with exogenous variables (ARMAX) model, seasonal ARIMA (SARIMA) model, exponential smoothing models (including Holt–Winters model (HW) and seasonal Holt and Winters' linear exponential smoothing (SHW)), state space/Kalman filtering model, and linear regression model; (2) artificial intelligent approaches, including knowledge-based expert system (KBES) model, artificial neural networks (ANNs) model, and fuzzy inference system model; and (3) support vector regression (SVR) model and its related hybrid/combined models. These models are classified according to the basis of the forecasting technological development tendency, evolved from mathematical relationship model (e.g., statistics-based model) to application of artificial intelligent model (e.g., ANNs model) and eventually to hybridization of statistical model and artificial intelligent model (e.g., SVR model). Of course, the classifications are not unique, and the classification based on the technological evolution is not always suitable for another. Based on this classification, interested readers can be inspired to propose another new model to receive more accurate electric load forecasting performance. Each model has its outstanding advantages compared with other models due to its theoretical innovation and also has its embedded theoretical limitations; thus, it always has the potential to be improved by hybridizing or combining with other novel approaches. Seven representative models are introduced, namely, ARIMA, SARIMA, Holt–Winters (HW), seasonal HW (SHW), general regression neural network (GRNN), back-propagation neural networks (BPNN), and SVR models.

Chapter 3, "Evolutionary Algorithms in SVR's Parameters Determination." As mentioned, the traditional determination of three parameters does not guarantee to improve forecasting accuracy level, because it is unable to set up more suitable initial values of parameters in the initial step and unable to simultaneously consider the interaction effects among three parameters to efficiently find out the near-optimal solution for large-scale data set. Therefore, evolutionary algorithms are employed to conduct intelligent searching around the solution range to determine suitable parameter combination by minimizing the objective function describing the structural risk of an SVR model. This chapter introduces several representative evolutionary algorithms, such as genetic algorithm (GA), simulated annealing (SA) algorithm, hybrid GA with SA (GA–SA) algorithm, particle swarm optimization (PSO) algorithm, ant colony optimization (ACO) algorithm, artificial bee colony (ABC) algorithm, and immune algorithm (IA), used in an SVR forecasting model to determine suitable parameter combination to receive improved forecasting accuracy level.

Chapter 4, "Chaos/Cloud Theories to Avoid Trapping into Local Optimum." As demonstrated in Chap. 3, these different evolutionary algorithms, including genetic algorithm (GA), simulated annealing (SA) algorithm, hybrid GASA algorithm, particle swarm optimization (PSO) algorithm, continuous ant colony optimization (CACO) algorithm, artificial bee colony (ABC) algorithm, and immune algorithm (IA), are employed to determine suitable parameter combination of an SVR-based electric load forecasting model. These forecasting results indicate that almost all SVR-based models with different evolutionary algorithms are superior to other competitive forecasting models (including ARIMA, HW, GRNN, and BPNN models); however, these algorithms almost lack knowledge memory or storage mechanisms which would be either time-consuming or inefficient in searching the suitable parameters, that is, premature convergence (being trapped in local optimum). This chapter introduces that hybrid chaos theory with evolutionary algorithms can overcome the shortcomings of trapping local optimum to improve forecasting performance.

Chapter 5, "Recurrent/Seasonal Mechanism to Improve the Accurate Level of Forecasting." As demonstrated in Chap. 4, these different hybrid chaotic evolutionary algorithms, including chaotic genetic algorithm (CGA), chaotic simulated annealing (CSA) algorithm, chaotic cloud simulated annealing (CCSA) algorithm, chaotic GASA (CGASA) algorithm, chaotic particle swarm optimization (CPSO) algorithm, chaotic ant swarm (CAS) algorithm, chaotic artificial bee colony (CABC) algorithm, and chaotic immune algorithm (CIA), employed to determine suitable parameter combination of an SVR-based electric load forecasting model. These forecasting results indicate that almost all SVR-based models with different hybrid chaotic-evolutionary algorithms are superior to other competitive forecasting models (including ARIMA, GRNN, and TF-ε-SVR-SA models). However, these hybrid chaotic-evolutionary algorithms do not provide satisfactory forecasting performance (well fitting the actual fluctuation tendency), even though their forecasting accuracy receives significant level. To improve the fitting effects for each SVR-chaotic/cloud-evolutionary algorithm-based model, this chapter introduces two combined mechanisms (recurrent mechanism or seasonal mechanism) to significantly improve the fitting effects with the actual fluctuation tendency.

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