Preface to "Hybrid Advanced Optimization Methods with Evolutionary Computation Techniques in Energy Forecasting"

More accurate and precise energy demand forecasts are required when energy decisions are made in a competitive environment. Particularly in the Big Data era, forecasting models are always based on a complex function combination, and energy data are always complicated. Examples include seasonality, cyclicity, fluctuation, dynamic nonlinearity, and so on. These forecasting models have resulted in an over-reliance on the use of informal judgment and higher expenses when lacking the ability to determine data characteristics and patterns. The hybridization of optimization methods and superior evolutionary algorithms can provide important improvements via good parameter determinations in the optimization process, which is of great assistance to actions taken by energy decision-makers.

This book contains articles from the Special Issue titled "Hybrid Advanced Optimization Methods with Evolutionary Computation Techniques in Energy Forecasting", which aimed to attract researchers with an interest in the research areas described above. As Fan et al. [1] indicate, the research direction of energy forecasting in recent years has concentrated on proposing hybrid or combined models: (1) hybridizing or combining these artificial intelligence models with each other; (2) hybridizing or combining with traditional statistical tools; and (3) hybridizing or combining with those superior evolutionary algorithms. Therefore, this Special Issue sought contributions towards the development of any hybrid optimization methods (e.g., quadratic programming techniques, chaotic mapping, fuzzy inference theory, quantum computing, etc.) with superior evolutionary algorithms (e.g., genetic algorithms, ant colony optimization, particle swarm optimization algorithm, and so on) that have superior capabilities over the traditional optimization approaches to overcome some embedded drawbacks, and the application of these advanced hybrid approaches to significantly improve forecasting accuracy.

The 11 articles in this compendium all display a broad range of cutting-edge topics in hybrid optimization methods and superior hybrid evolutionary algorithms. The preface author believes that the hybridization of the advanced optimization methods and evolutionary computation techniques will play an important role in energy forecasting accuracy improvements, such as hybrid different evolutionary algorithms/models to overcome some critical shortcomings of single evolutionary algorithms/models or direct improvement of the shortcomings by innovative theoretical arrangements.

For Hybridizing Different Evolutionary Algorithms/Models

(1) Hybrid different evolutionary algorithms: It is known that the evolutionary algorithms have their theoretical drawbacks, such as a lack of knowledge, memory, or storage functions; they are time consuming in training; and become trapped in local optima. Therefore, the goal of hybridizing optimization methods to adjust their internal parameters (e.g., mutation rate, crossover rate, annealing temperature, etc.) is to overcome these shortcomings. For example, 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 can then be accepted with a probability that depends both on the difference between the corresponding function values and on a global parameter (temperature). Thus, SA can reach more ideal solutions. However, SA costs a great deal of computation time in the annealing process. To improve premature convergence and to receive more suitable objective function values, it is necessary to find an effective approach to

overcome these drawbacks of genetic algorithm (GA) and SA. The hybridization of a genetic algorithm with a simulated annealing (GA-SA) algorithm [2] is an innovative trial applying the superior capability of the SA algorithm to reach more ideal solutions, employing the mutation process of GA to enhance the search process.

(2) Different hybrid models: Each single model has its own drawbacks. For example, in Box–Jenkins' ARIMA model, the worst disadvantage is the inability to predict changes that are not clear in historical data, particularly for the nonlinearity of data patterns. The support vector regression (SVR) model cannot provide accurate forecasting performance when the data set reveals a cyclical (seasonal) tendency (e.g., caused by cyclic economic activities or seasonal nature hour to hour, day to day, week to week, month to month, and season to season), such as an hourly peak in a working day, a weekly peak in a business week, and a monthly peak in a demand-planned year. Therefore, the concepts of combined or hybrid models deserve consideration. Note that the term "hybrid" means that some process of the former model is integrated into the process of the later one. For example, hybrid A and B implies some processes of A are controlled by A, and some are controlled by B. On the other hand, for the so-called combined models, the output of the former model becomes the input of the latter one. Therefore, the classification results from combined models will be superior to a single model. Combined models are employed to further capture more data pattern information from the analyzed data series. For the mentioned shortcoming of the original SVR model, it is necessary to estimate this seasonal component (i.e., applying the seasonal mechanism to accomplish the goal of highly accurate forecasting performance). The preface author proposed a seasonal mechanism [3–5] with two steps for convenience in implementation: the first step is calculating the seasonal index (SI) for each cyclic point in a cycle length peak period; the second step is computing the forecasting value by multiplying the seasonal index (SI).

Another model hybridization example can be found in artificial neural network models. Inspired by the concept of recurrent neural networks (RNNs) where every unit is considered as an output of the network and the provision of adjusted information as input in a training process [6], the recurrent learning mechanism framework is also combined into the original analyzed model. For a feed-forward neural network, links can be established within layers of a neural network. These types of networks are called recurrent neural networks. RNNs include an additional information source from the output layer or the hidden layer. Therefore, they mainly use past information to capture detailed information, then improve their performances.

For Improvement by Innovative Theoretical Arrangements

Several disadvantages embedded in these evolutionary algorithms, such as their tendency to become trapped in local optima and evolutionary mechanism failure, can be improved by innovative theoretical arrangements to obtain more satisfactory performance.

(1) Chaotization of decision variables: Chaos is a ubiquitous phenomenon in nonlinear systems. Chaotic behaviors have characteristics such as high sensitivity to initial value, ergodicity, and randomness of motion trail, and can traverse each trail within a certain range according to its rule. Therefore, chaotic variables may be adopted by utilizing these characteristics of chaotic phenomena for global search and optimization to increase the particle diversity. Due to easy implementation process and a special mechanism to escape from local optima, chaos and chaos-based searching algorithms have received intense attention [7]. Any decision variable in an optimization problem can be chaotized by the chaotic sequence as a chaotic variable to carefully expand its search space (i.e., variables are allowed to travel ergodically over the search space). The critical factor influencing the performance improvement is the chaotic mapping function. There are several commonly adopted chaotic mapping functions for the chaotic sequence generator, such as the logistic mapping function, the tent mapping function, the An mapping function, and the cat mapping function.

(2) Adjustments by cloud theory: for example, based on the operation procedure of SA, subtle and skillful adjustment in the annealing schedule is required (e.g., 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 easily accepts deteriorated solutions with high temperature, and it is difficult to escape from local minimum traps at low temperature [3]. To overcome these drawbacks of SA, cloud theory is considered. Cloud theory is a model of the uncertainty transformation between quantitative representation and qualitative concept using language value [3]. Based on the SA operation procedure, subtle and skillful adjustment in the annealing schedule is required (e.g., the size of the temperature steps during annealing, the temperature range, the number of re-starts and re-direction 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, its time-consuming nature is another problem. It is deserved to employ a chaotic simulated annealing (CSA) algorithm [3] to overcome these shortcomings.

In this, the transiently chaotic dynamics are temporarily generated for foraging and self-organizing. They are then gradually vanished with autonomous decrease of the temperature, and are accompanied by successive bifurcations and converged to a stable equilibrium. Therefore, CSA significantly improves the randomization of the Monte Carlo scheme, and controls the convergent process by bifurcation structures instead of stochastic ‘‘thermal” fluctuations, eventually performing efficient searching including a global optimum state. However, as mentioned above, 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. Even if some temperature annealing functions are exponential in general, the temperature gradually falls 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 when other types of temperature update functions are implemented (e.g., arithmetical, geometrical, or logarithmic). In 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 a ‘‘cloud’’. The fixed temperature point of each step becomes a changeable temperature zone in which the temperature of each state generation in every annealing step is chosen randomly, the course of temperature change in the whole annealing process is nearly continuous, and fits the physical annealing process better. Therefore, based on chaotic sequence and cloud theory, the chaotic cloud simulated annealing algorithm (CCSA) is employed to replace the stochastic ‘‘thermal” fluctuations control from traditional SA to enhance the continuous physical temperature annealing process from CSA. Cloud theory can realize the transformation between a qualitative concept in words and its numerical representation. It can be employed to avoid the problems mentioned above.

This discussion of the work by the author of this preface highlights work in an emerging area of hybrid optimization methods with superior evolutionary algorithms that has come to the forefront over the past decade. The articles collected in this text span many cutting-edge areas that are truly interdisciplinary in nature.

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Guest Editor

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