Preface to "Intelligent Optimization Modelling in Energy Forecasting"

Accurate energy forecasting is important to facilitate the decision-making process to achieve higher efficiency and reliability in power system operation and security, economic energy usages, contingency scheduling, planning, and maintenance of energy supply systems, and so on. In recent decades, many energy forecasting models have been continuously proposed to improve the forecasting accuracy, including traditional statistical models (such as ARIMA, SARIMA, ARMAX, multi-variate regression, exponential smoothing models, Kalman filtering, Bayesian estimation models, and so on) and artificial intelligent models (such as artificial neural networks (ANNs), knowledge-based expert systems, evolutionary computation models, support-vector regression, and so on). Particularly, in the Big Data era, forecasting models are always based on a complex function combination, and energy data are always complicated, such as seasonality, cyclicity, fluctuation, dynamic nonlinearity, and so on. Comprehensively addressing this issue not only involves concentrating on hybridizing evolutionary algorithms with each other, or hybridizing chaotic mapping mechanism, quantum computing mechanism, recurrent mechanism, seasonal mechanism, and fuzzy inference theory with evolutionary algorithms to determine suitable parameters for an existed model, but also on hybridizing or combining two or above existed models. These novel hybrid advanced techniques can provide better energy forecasting performances.

Recently, due to the great development of optimization modeling methods (quadratic programming method, differential empirical mode method, evolutionary algorithms, meta-heuristic algorithms, and so on) and intelligent computing mechanisms (e.g., quantum computing mechanism, chaotic mapping mechanism, cloud mapping mechanism, seasonal mechanism, and so on), many novel hybrid or combined with the mentioned intelligent-optimization-based models are also proposed to achieve satisfactory forecasting accuracy. It is deserved to explore the tendency and development of intelligent-optimization-based modeling methodology and to enrich the practical performances, particularly for marine renewable energy forecasting.

This book contains articles from the Special Issue "Intelligent Optimization Modeling in Energy Forecasting", which published articles from researchers with an interest in the research areas described. As Zhang and Hong [1] indicate that the research direction of energy forecasting in the recent years is concentrated on proposing hybrid or combined models: (1) hybridizing or combining these artificial intelligent models with each other; (2) hybridizing or combining with traditional statistical tools; and (3) hybridizing or combining with those superior evolutionary algorithms. Therefore, the Special Issue contains contributions that address recent developments, i.e., hybridizing or combining any advanced techniques in energy forecasting. The hybrid forecasting models should have superior capabilities over the traditional forecasting approaches, and are able to overcome some embedded drawbacks, and, eventually, to significantly improve forecasting accuracy.

The 11 articles in this compendium all display a broad range of cutting-edge topics in the hybrid advanced technologies. The preface author believes that the applications of hybrid technologies will play a more important role in energy forecasting accuracy improvements, such as hybrid different evolutionary algorithms/models to overcome some critical shortcomings of a single evolutionary algorithm/model or directly improve the shortcoming by theoretical innovative arrangements.

Based on these collected articles, an interesting (future research tendency) issue is how to guide researchers to employ proper hybrid technology for different data sets. This is because, in any analysis models (including classification model, forecasting model, and so on), the most important problem is how to catch the data pattern, and applied the learned patterns or rules to achieve satisfactory performance, i.e., the key to success is how to suitably look for data patterns. However, each model has an excellent ability to catch a specific data pattern. For example, exponential smoothing and ARIMA models focus on strict increasing (or decreasing) time-series data, i.e., linear pattern, even they have seasonal modification mechanism to analyze seasonal (cyclic) change; due to artificial learning function to adjust the suitable training rules, the ANN model excels only if historical data pattern has been learned, it lacks the systematic explanation of how the accurate forecasting results are obtained; the support-vector regression (SVR) model can acquire superior performance only if the proper parameters determination search algorithms. Therefore, it is essential to construct an inference system to collect the characteristic rules to determine the data pattern category.

Secondly, 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; (2) ANN or SVR models, the forthcoming problem is how to determine the best parameters combination (e.g., numbers of hidden layer, units of each layer, learning rate; or hyper-parameters) to acquire superior forecasting performance. Particularly, for the focus of this discussion, in order to determine the most proper parameter combination, a series of evolutionary algorithms should be employed to test which data pattern the model is familiar with. Based on experimental findings, those evolutionary algorithms themselves also have merits and drawbacks, for example, GA and IA could handle excellently in a regular trend data pattern (real number) [2–5], SA excelled in fluctuation, or noise data pattern (real number) [6], and ACO is well done in integer number searching [7].

It is possible to build an intelligent support system to improve the efficiency of hybrid evolutionary algorithms/models or improving by theoretical innovative arrangements (chaotization and cloud theory) in all forecasting/prediction/classification applications. Firstly, filter the original data by the database with a well-defined characteristic rule set of data patterns, such as linear, logarithmic, inverse, quadratic, cubic, compound, power, growth, exponential, etc., to recognize the appropriate data pattern (fluctuation, regular, or noise). The recognition decision rules should include two principles: (1) the change rate of two continuous data; and (2) the decreasing or increasing trend of the change rate, i.e., the behavior of the approached curve. Secondly, adequate improvement tools (hybrid evolutionary algorithms, hybrid seasonal mechanism, chaotization of decision variables, cloud theory, and any combination of all tolls) should be selected to avoid getting trapped in local optimum, improvement tools could be employed in these optimization problems to obtain an improved, satisfactory solution.

This discussion of the work by the author of this preface highlights work in an emerging area of hybrid advanced techniques that have come to the forefront over the past decade. The collected articles in this text span a great deal more cutting edge areas that are truly interdisciplinary in nature.

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