Preface to "Hybrid Advanced Techniques for Forecasting in Energy Sector"

Accurate forecasting performance in the energy sector is a primary factor in the modern restructured power market, accomplished by any novel advanced hybrid techniques. Particularly in the Big Data era, forecasting models are always based on a complex function combination, and energy data are always complicated by factors such as seasonality, cyclicity, fluctuation, dynamic nonlinearity, and so on. To comprehensively address this issue, it is insufficient to concentrate only on simply hybridizing evolutionary algorithms with each other, or on hybridizing evolutionary algorithms with chaotic mapping, quantum computing, recurrent and seasonal mechanisms, and fuzzy inference theory in order to determine suitable parameters for an existing model. It is necessary to also consider hybridizing or combining two or more existing models (e.g., neuro-fuzzy model, BPNN-fuzzy model, seasonal support vector regression–chaotic quantum particle swarm optimization (SSVR-CQPSO), etc.). These advanced novel hybrid techniques can provide more satisfactory energy forecasting performances.

This book contains articles from the Special Issue titled "Hybrid Advanced Techniques for Forecasting in the Energy Sector", 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, such as: (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 superior evolutionary algorithms. Therefore, this Special Issue was interested in contributions to these recent developments (i.e., hybridizing or combining any advanced techniques in energy forecasting). The hybrid forecasting models should be with the superior capabilities over the traditional forecasting approaches, with the ability to overcome some embedded drawbacks, and with the very superiority to achieve significant improved forecasting accuracy.

The 14 articles collected 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 an important role in energy forecasting accuracy improvements, such as hybrid different evolutionary algorithms/models to overcome some critical shortcomings of single evolutionary algorithm/models or direct improvements of these shortcomings by innovative theoretical arrangements.

Based on these collected articles, an interesting emergent issue for future research is how to help researchers to employ the proper hybrid technology for different data sets. This is because the most important problem for any analytical model (e.g., classification, forecasting, etc.) is how to capture patterns in the data and apply the learned patterns or rules to achieve satisfactory performance (i.e., the key factor in success is determining how to suitably search for data patterns). However, each model has an excellent ability to capture a specific data pattern. For example, exponential smoothing and ARIMA models focus on strict increasing (or decreasing) time series data (i.e., linear patterns). They even have a seasonal modification mechanism to analyze seasonal (cyclic) change. Due to the use of an artificial learning function to adjust the training rules, artificial neural networks (ANNs) excel only if a historical data pattern has been learned. They lack a systematic explanation of how the accurate forecasting results are obtained. Support vector regression (SVR) can achieve superior performance only if there is a proper parameters determination for the search algorithms. Therefore, it is essential to construct an inference system to collect the characteristic rules to determine the data pattern category.

The next main problem in model development is assigning the appropriate approach to implement forecasting: For (1) ARIMA or exponential smoothing approaches, only their differential or seasonal parameters need to be adjusted. (2) In ANN or SVR models, the forthcoming problem is how to determine the best combination of parameters (e.g., number of hidden layers, units of each layer, learning rate—also called hyper-parameters) to achieve 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 their compatibility with the data pattern. Experimental findings demonstrated that those evolutionary algorithms also had merits and drawbacks. For example, genetic algorithm (GA) and immune algorithm (IA) performed excellently with regular trend data patterns (real numbers) [2,3], SA excelled with fluctuating or noisy data patterns (real numbers) [4], Tabu search algorithm (TA) performed well with regular cyclic data pattern (real numbers) [5], and ant colony optimization algorithm (ACO) did well in integer number searching [6].

As mentioned previously, it is possible to build an intelligent support system to improve the efficiency of hybrid evolutionary algorithms/models or to make improvements by innovative theoretical arrangements (chaotization and cloud theory) in all forecasting/prediction/classification applications. Firstly, the original data should be filtered by a data base with a well-defined characteristic data pattern rules set (e.g., linear, logarithmic, inverse, quadratic, cubic, compound, power, growth, exponential, etc.), in order to recognize the appropriate data pattern (fluctuating, regular, or noisy). 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., behavior of the approached curve). Secondly, adequate improvement tools should be selected (e.g., hybrid evolutionary algorithms, hybrid seasonal mechanism, chaotization of decision variables, cloud theory, and any combination of all tools). In order to avoid becoming trapped in local optima, improvement tools can be employed into 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 has come to the forefront over the past decade. The collected articles in this text span many cutting edge areas that are truly interdisciplinary in nature.

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Guest Editor

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