Preface to “Short-Term Load Forecasting by Artificial Intelligent Technologies”

In the last few decades, short-term load forecasting (STLF) has been one of the most important research issues for achieving higher efficiency and reliability in power system operation, to facilitate the minimization of its operation cost by providing accurate input to day-ahead scheduling, contingency analysis, load flow analysis, planning, and maintenance of power system. There are lots of forecasting models proposed for STLF, including traditional statistical models (such as ARIMA, SARIMA, ARMAX, multi-variate regression, Kalman filter, exponential smoothing, and so on) and artificial-intelligence-based models (such as artificial neural networks (ANNs), knowledge-based expert systems, fuzzy theory and fuzzy inference systems, evolutionary computation models, support vector regression, and so on). Recently, due to the great development of evolutionary algorithms (EA), meta-heuristic algorithms (MTA), and novel computing concepts (e.g., quantum computing concepts, chaotic mapping functions, and cloud mapping process, and so on), many advanced hybridizations with those artificial-intelligence-based models are also proposed to achieve satisfactory forecasting accuracy levels. In addition, combining some superior mechanisms with an existing model could empower that model to solve problems it could not deal with before; for example, the seasonal mechanism from ARIMA model is a good component to be combined with any forecasting models to help them to deal with seasonal problems.

This book contains articles from the Special Issue titled “Short-Term Load Forecasting by Artificial Intelligent Technologies”, which aims to attract researchers with an interest in the research areas described above. As Fan et al. [1] highlighted, the research trends of forecasting models in the energy sector in recent decades could be divided into three kinds of hybrid or combined models: (1) hybridizing or combining the artificial intelligent approaches with each other; (2) hybridizing or combining with traditional statistical approaches; and (3) hybridizing or combining with the novel evolutionary (or meta-heuristic) algorithms. Thus, the Special Issue, in methodological applications, was also based on these three categories, i.e., hybridizing or combining any advanced/novel techniques in energy forecasting. The hybrid forecasting models should have superior capabilities over the traditional forecasting approaches, and be able to overcome some inherent drawbacks, and, eventually, to achieve significant improvements in forecasting accuracy.

The 22 articles in this compendium all display a broad range of cutting-edge topics of the hybrid advanced technologies in STLF fields. The preface authors believe that the applications of hybrid technologies will play a more important role in STLF accuracy improvements, such as hybrid different evolutionary algorithms/models to overcome some critical shortcoming of a single evolutionary algorithm/model or to directly improve the shortcomings by theoretical innovative arrangements.

Based on these collected articles, an interesting (future research area) issue is how to guide researchers to employ proper hybrid technology for different datasets. This is because for any analysis models (including classification models, forecasting models, and so on), the most important problem is how to catch the data pattern, and to apply the learned patterns or rules to achieve satisfactory performance, i.e., the key success factor is how to successfully look for data patterns. However, each model excels in catching different specific data patterns. For example, exponential smoothing and ARIMA models focus on strict increasing (or decreasing) time series data, i.e., linear pattern, though they have a 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 the historical data
pattern has been learned, there is a lack of systematic explanation on how the accurate forecasting results are obtained; support vector regression (SVR) model could acquire superior performance only with 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 an appropriate approach to implement forecasting for (1) ARIMA or exponential smoothing approaches, the only option is to adjust their differential or seasonal parameters; (2) ANN or SVR models, the forthcoming problem is how to determine the best parameter 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 best parameter combination, a series of evolutionary algorithms should be employed to test which data pattern is most familiar. Based on experimental findings, those evolutionary algorithms themselves also have merits and drawbacks, for example, GA and IA are excellent for regular trend data patterns (real number) [2,3], SA excelled for fluctuation or noise data patterns (real number) [4], TA is good for regular cyclic data patterns (real number) [5], and ACO is good for integer number searching [6].

It is possible to build an intelligent support system to improve the efficiency of hybrid evolutionary algorithms/models or to improve them 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 set of rules for the data pattern, 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, select adequate improvement tools (hybrid evolutionary algorithms, hybrid seasonal mechanism, chaotization of decision variables, cloud theory, and any combination of all tools) to avoid being trapped in a local optimum, improvement tools could be employed into these optimization problems to obtain an improved, satisfied 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. These collected articles in this text span a great deal more of cutting edge areas that are truly interdisciplinary in nature.

References


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