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A novel hybrid algorithm for electricity price and load forecasting in smart grids with demand-side management

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HIGHLIGHTS

- Proposes a novel hybrid algorithm for price/load forecasting.
- Proposes a new conditional feature selection with inherent uncertainties of input data.
- Propose a new nonlinear LSSVM technique for learning and wavelet packet for signal decomposing.
- Used three real markets and models demand side management on price/load forecasting.
- Proposed a new modification for standard artificial bee colony optimization.

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ABSTRACT

Smart grid is a platform that enables the participants of electricity market to adjust their bidding strategies based on Demand-Side Management (DSM) models. Responsiveness of the market participants can improve reliability of system operation as well as capital cost investments. In this regard, the accurate forecast of electricity price and demand in smart grids is an important challenge as their strong correlation makes a separate forecasting to be ineffective. Therefore, this paper proposes a novel hybrid algorithm for simultaneous forecast of price and demand that uses a set of effective tools in preprocessing part, forecast engine and tuned algorithm. To highlight our contributions, the proposed forecast algorithm classified into three main parts. The first part employs a new Flexible Wavelet Packet Transform (FWPT) to decompose a signal into multiple terms at different frequencies, and a new feature selection method that employs Conditional Mutual Information (CMI) and adjacent features in order to select valuable input data. The second part consists of a novel Multi-Input Multi-Output (MIMO) model based on Nonlinear Least Square Support Vector Machine (NLSSVM) and Autoregressive Integrated Moving Average (ARIMA) in order to model the linear and nonlinear correlation between price and load in two stages. The final part employs a modified version of Artificial Bee Colony (ABC) algorithm based on time-varying coefficients and stumble generation operator, called TV-SABC, in order to optimize NLSSVM parameters in a learning process. The proposed hybrid forecasting algorithm is evaluated on several real and well-known markets illustrating its high accuracy in simultaneous forecast of electricity

Abbreviations: DSM, Demand-Side Management; FWPT, Flexible Wavelet Packet Transform; CMI, Conditional Mutual Information; MIMO, Multi-Input Multi-Output; NLSSVM, Nonlinear Least Square Support Vector Machine; ARIMA, Autoregressive Integrated Moving Average; ABC, Artificial Bee Colony; GARCH, generalized autoregressive conditional heteroskedastic; DR, dynamic regression; TF, transfer function; MI, mutual information; WT, wavelet transform; LSSVM, Least Square Support Vector Machine; FNN, fuzzy neural network; RDFA, recursive dynamic factor analysis; NN, neural network; BNN, bayesian neural network; ANN, artificial neural networks; CNN, cascaded neural network; CS, cuckoo search; OP-ELM, optimally pruned extreme learning machine; ARMA, autoregressive moving average; PSO, particle swarm optimization; SVM, support vector machine; FASE, forecast-aided state estimator; RBF, radial basis function; WPT, wavelet packet transform; MLP, multi-layer perceptron; DAM, data association mining; ANFIS, adaptive neural fuzzy inference systems; KKT, Karush–Kuhn–Tucker; NSW, New South Wales; NYISO, New York independent system operator; MAPE, Mean Absolute Percentage Error; FMSE, Forecast Mean Square Error; MeE, Median Error; RMSE, Root Mean Square Error; ANEM, Australian national electricity market; QLD, Queensland; VIC, Victoria; AEMO, Australian energy market operator; NMIFS, normalized mutual information feature selection; MIFS, mutual information feature selector; mRMR, min-redundancy max-relevance; DLC, direct load control; PTR, peak-time rebate; CPP, critical-peak pricing; ToU, time-of-use; PDC, Price Duration Curve; ELM, extreme learning machine; EMD, empirical mode decomposition; EKF, extended Kalman filter; KELM, extreme learning machine with kernel.

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price and demand. Moreover, the interactive effects of demand-side management programs on load factor (load curve) and price signal are investigated by numerical indices.

1. Introduction

1.1. Aims and difficulties

Growing recognition of electricity grid modernization for enabling novel electricity consumption and generation models has found expression in the infrastructure of smart grid concept [1]. Smart grids provide energy more economically, sustainably, securely and efficiently as they combine novel concepts, models and ancillary services from generation, transmission and distribution all the way to customer devices with highly developed communication, sensing and control tools [2]. Smart grids enable the customers to manage their demand according to price variation based on DSM models. DSM is defined as the implementation of measures to set policies in order to regulate energy consumption [3]. Typically, DSM determines the various activities undertaken by an electric utility and the consumers, and uses such activity-related data to regulate the quantity and time of energy consumption. Ref. [4] surveys DSM in the smart grids in great details. Fig. 1 illustrates the relation between DSM and price/load forecast in smart grids. Different goals of DSM in some real markets are described in Table 1 [2–4]. The main goal for electricity market participants is to have a clear and cost-effective market without any external forces. Therefore, to maximize the profits, market participants need to have an exact and robust estimate of future electricity price to make their bidding policies for the real market. With the inherent correlation between electricity price and demand, prediction in smart grid environment is more complex than the conventional power systems [4].

Table 1
Different types and goals of DSM in real electricity markets [2–4].

Market	Objective	Share of DR%	DSM solution
PJM	Economic load response	4.50	DLC, direct feedback
France	Switch to sub-marginal plant	2.00	PTR, ToU, CPP
Germany	Switch to sub-marginal plant	3.45	PTR, ToU, CPP, direct feedback
Belgium	Load-balancing, reliability	5.00	DLC
Australian	Reliability pricing model	4.00	PTR, DLC, direct feedback

1.2. Literature review

There are many forecast methods such as ARIMA, GARCH model [5,6], EMD + EKF + KELM + PSO [7], MI + WT + LSSVM [8], MI + WT + FNN [9], RDFA [10], hybrid method based on modified NN [11], WT + ELM + partial least squares regression [12], WT + grey model [13], hybrid evolutionary fuzzy [14], multiple seasonal patterns and modified firefly algorithm [15], CS + OP-ELM [16], ANN [17],

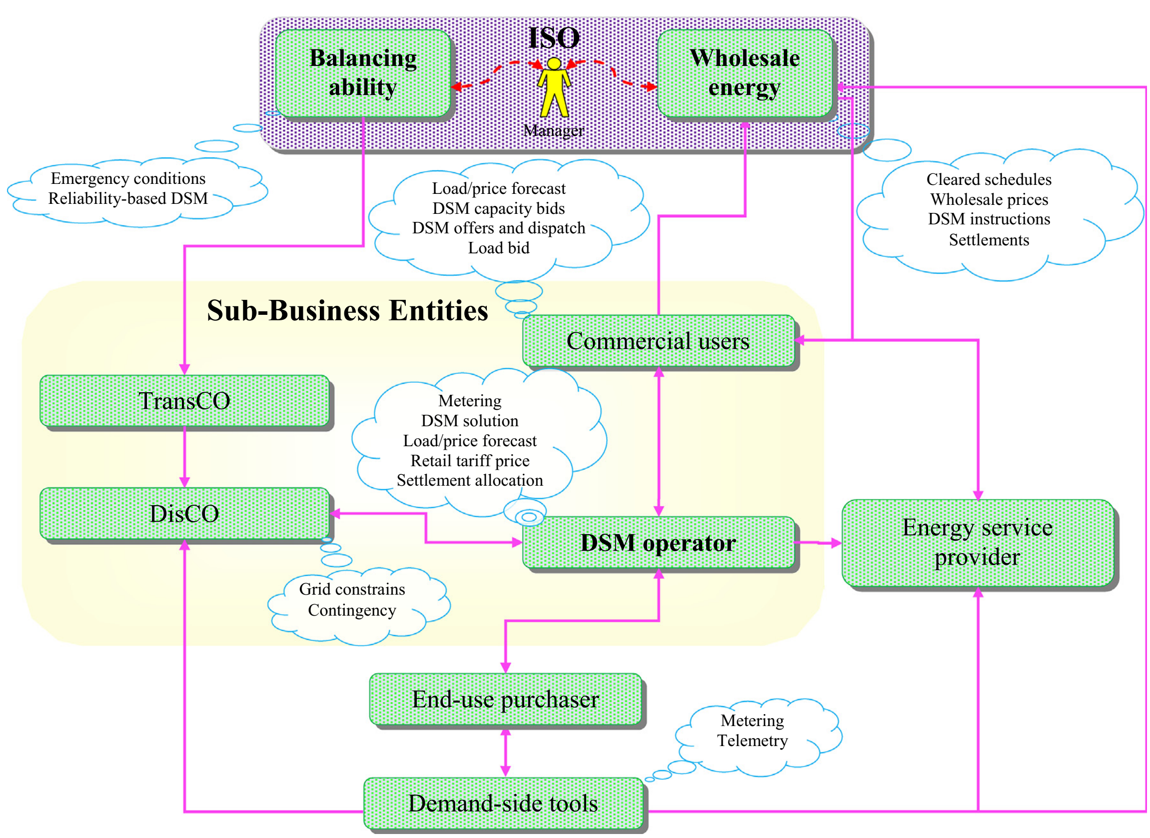

Fig. 1. Proposed concept of smart grids based on relation between DSM and price/load forecast.