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Modeling of district load forecasting for distributed energy system

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HIGHLIGHTS

- Available DLF methods for DES are reviewed comprehensively (attributes, applications and merits).
- Impact factors of DES district load should be selectively considered in DLF modeling.
- The existing DLF methods are restricted to accuracy and workload.
- A framework of DLF is proposed for DES planning, design and service.

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ABSTRACT

Distributed energy system (DES) has successfully aroused increasing interests among energy policy makers and system designers, as its potential of replacing conventional energy system. The optimal modeling of district load forecasting is essential to guarantee the best design and operation of DES. This paper presents a comprehensive review of district load forecasting (DLF) models to support the application of DES. The main factors affecting district load are discussed from inside to outside, including building indoor condition, building design characteristics, district layout, local microclimate, and social & economic factors. Through classifying and comparing top-down and bottom-up methods in terms of their key features and applications, it is found that the existing methods are either lack of forecasting accuracy or burdened with forecasting workload. Previous literatures reviewed in this paper show that the hybrid forecasting models including scenario analysis, physical-statistical numerical simulation and least square support vector machine based intelligent approaches have a superior ability to balance these two contradictions under different conditions. Based on the comparison results and current trend, a framework of district load forecasting, as well as corresponding future research work, is proposed for DES planning, design and service.

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Nomenclature

ABC	artificial bee colony
ACO	ant colony optimization
ANNs	artificial neural networks
AR	autoregressive model
ARMA	autoregressive moving average model
ARMAX	autoregressive moving average with exogenous model
ARIMA	autoregressive integrated moving average model
ARX	autoregressive with exogenous model
BPNN	back propagation neural networks
CDA	conditional demand analysis
CDD/HDD/GDD	cooling degree-day/heating degree-day/growing degree-day
CHREM	Canadian Hybrid Residential End-use Energy and Emission Model
CSA	cuckoo search algorithm
DEDS	district energy design stage
DEPS	district energy planning stage
DESS	district energy service stage
DES	distributed energy system
DLF	district load forecasting
EcM/TM	econometric model/technological model
ELM	extreme learning machine
EMD	empirical mode decomposition
ES/EP	exponential smoothing/expert system
E-GIS	environment and geographical information system
FBTFS	knowledge-based feedback tunning fuzzy system
FL	fuzzy logic
GA	genetic algorithm
GABC	group method of data handing coupled with artificial bee colony
GDP/GNP	gross domestic product/gross national product
GLSSVM	least square support vector machine coupled with group method of data handing
GMDH	group method of data handing
GRA	gray relational analysis
GRNN	general regression neural network
HCLFM	hourly cooling load factor model
HLARM	hourly load apportionment ratio method
LSSVM	least square support vector machine
MAPE	mean absolute percentage error
MAE	mean absolute error
MIMO	multi-input multi-output model
MLPNN	multilayer perceptron neural network
(M) PSO	(modified) particle swarm optimization
(P) NARMAX	(periodic) nonlinear autoregressive moving average with exogenous model
PSR	phase space reconstruction
RBFNN	radial basis function neural networks
RMSE	root mean square error
SRWNN	self-recurrent wavelet neural network
SSA	singular spectral analysis
SVM/SVR	support vector machine/support vector regression
T2FLS	type-2 fuzzy logic system
WNN	wavelet neural network

1. Introduction

Distributed energy system is growing rapidly around the world, with a general trend of energy efficiency improvement and carbon emission reduction. Deployed DES involving distributed renewables and dispatchable distributed generation will play a key role on the future grid (Fig. 1), providing all electricity and thermal services at or near their points of use — district commercial, residential and small industrial customers [1]. The district[1] DES appears higher efficiency, lower carbon emissions and higher reliability than conventional thermal plants [2,3].

Although DES has tremendous market potential, there are still some significant barriers to promoting its development in terms of relevant policy, economy and technologies. Various efforts have been made in different system stages to overcome these barriers for DES sustainability, such as a feasibility assessment [4], system modeling [5], system optimization [6], operating strategies [7], exergy analysis [8,9], etc. It is obvious that most of them focus on how to solve the problems from supply-side; however, only very limited works [10–12] have their sight at accurate district load forecasting in consumer-side which is the key and foundation of DES development at any stage as shown in Fig. 1. Previous studies have proved that uncertainties of district load structure affect the DES capacity selection and operation performance greatly [13–15]. Thus, it is of great importance to investigate and select an appropriate load forecasting method at the planning, design and service stages of district DES.

To date, some researchers have analyzed the energy demand characteristics at building, urban and national levels [16,17], but these methodologies cannot be directly applied to total load forecasting of district buildings. DLF needs to consider the district morphology, building characteristics, surrounding environment, occupant behavior and other various factors [18]. In recent years, there have been several works to classify and review the previous methods of building energy-consumption/load forecasting, and the classifying standards differ from literature to literature. Swan and Ugursal [19] reviewed various modeling methods for evaluating residential sector energy consumption, including top-down models and bottom-up models. Raza and Khosravi [20] detailed artificial intelligence techniques for energy demand of smart grid and buildings with a classification of long term, medium term and short term. Reinhart and Davila [21] listed some emerging simulation tools and implementation workflows for bottom-up urban building energy models (UBEM) with regards to their input organization, model generation and execution, as well as result validation. All these reviews are very constructive and worth learning for load

[1] Generally, 'district' level is defined as a park, community, neighborhood, development zone or small town, whose floor area is below several square kilometers and building area is below millions of square meters.