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A review of forecasting algorithms and energy management strategies for microgrids

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History: received: 2018-02-28 accepted: 2018-05-22

Abstract

As an autonomous subsystem integrating with the utility, a microgrid system consists of distributed energy sources, power conversion circuits, storage units and adjustable loads. With the high penetration of distributed generators, it is challenging to provide a reliable, consistent power supply for local customers, because of the time-varying weather conditions and intermittent energy outputs in nature. Likewise, the electricity consumption changes due to the season effect and human behaviour in response to the changes in electricity tariff. Therefore, studies on accurate forecasting power generation and load demand are worthwhile in order to solve unit commitment and schedule the operation of energy storage devices. The paper firstly gives a brief introduction about microgrid and reviews forecasting algorithms for power supply side and load demand. Then, the mainstream energy management approaches applied to the microgrid, including centralized control, decentralized control and distributed control schemes are presented. A number of the optimal energy management algorithms are highlighted for centralized controllers based on short-term forecasting information and a generalized centralized control scheme is thus summarized. Consensus protocol is discussed in this paper to solve the cooperative problem under the multi-agent system-based distributed energy system. Finally, the future of energy forecasting approaches and energy management strategies are discussed.

KEYWORDS: Microgrid; power generation forecasting; load demand forecasting; optimal energy management; centralized controller; consensus protocol

1. Introduction

Conventional power station mainly depends on the non-renewable fossil fuels such as coal, oil and gas, which emits a large amount of greenhouse gases during the power generation. The traditional, centralized electricity grid also causes losses in the transmission system. Moreover, the potential large-scale power outages will bring huge risks for sensitive loads, when the mechanical or electrical faults occur at the over-centralized power station.

The deployment of the distributed energy resources (DER) plays a significant role in strengthening a reliable and stable power line for the local end-user, reducing the production task for the power station and lowering the environmental impacts. With the high penetration of DER devices, energy storage devices and local loads integrating into the electricity grid, an innovative concept called 'microgrid' has been proposed to group these participants as a whole to connect the utility via the Point of Common Coupling (PCC) (U.S. Department of Energy, 2011). Microgrids enable to disconnect with the utility regarding them as an autonomous subsystem. However, there are still a lot of inevitable issues to be addressed in microgrids. Wind and solar are uncontrollable and unstable resources, which is a big challenge to provide a consistent supply for microgrids (Ma, Wang, & Qin, 2013). Similarly, the load consumption is affected by many time-varying factors, such as weather and human behaviours. Furthermore, many advanced control strategies have been developed based on the short-term forecasting results of supply and demand sides, in order to balance the dispatch between the intermittent power generations and load demand under various situations and provide a stable and consistent power line for the endusers.

This paper is organized as follows. Section 2 presents a detailed microgrid system structure and distribution system. The current methodologies used for short-term power forecasting are reviewed in Section 3. Section 4 generalizes approaches to solving the short-term load forecasting problem. Section 5 classifies the current energy control schemes and emphasizes on discussion of centralized control strategies and distributed energy coordination based on multi-agent system (MAS) microgrid system. Finally, the future energy forecasting methods and energy management algorithm are given in the Section 6.

2. Microgrid system

Building a modern, localized, small-scale grid in a limited geographical area can maximize the local resources and reduce the economy and energy losses during the power transmission. In terms of the utility, the development of microgrids is beneficial for enhancing local main grid stability, shifting the peak load demand, providing better voltage support, thus leading to an innovative low carbon technology.

2.1. Microgrids structure & operation modes

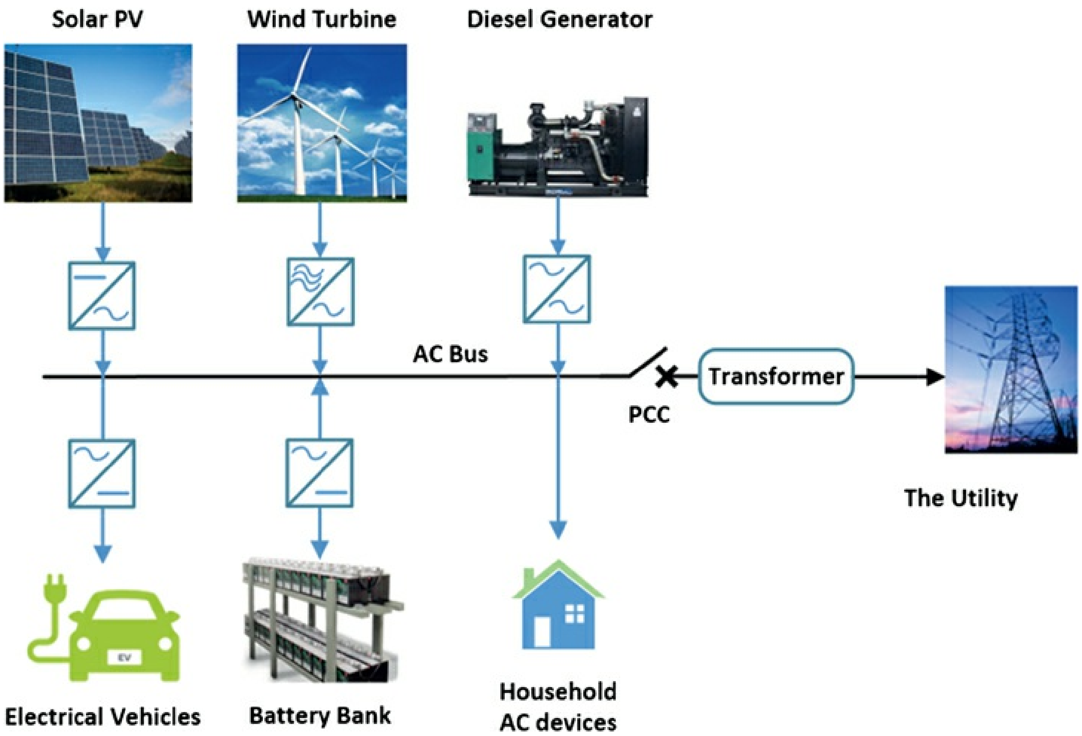
A microgrid system is a cluster of DER devices, storage devices and controllable AC and DC loads, providing heat and electricity for local users. A microgrid system typically comprises five components: DER devices, distribution systems (AC or DC bus), AC and DC loads, storage units and control and communication modules. The power generation in the microgrid system typically relies on the DER devices or/and conventional power generators, such as diesel generators. A DER system may include solar photovoltaic panels, wind turbines, combined heat and power (CHP), small hydro, biogas and fuel cells. On-site power generation aims to maximize benefits of the local resources, decrease the power loss and economic loss due to the long-distance high-voltage transmission. The storage system in microgrids not only stores the excess power generated by the DER, but also works as a power regulator to provide consistent power for the sensitive loads during the operation mode switching and reduce supply-demand mismatch. The commonly accepted storage devices involve flywheels, batteries and super-capacitors. Furthermore, an energy storage system is a cluster of a few storage devices, where storage units are coordinated and organized to complete energy scheduling task in a large-scale microgrid system. The control and communication modules can be a single centralized controller or many distributed controllers integrating with power electronic interfaces (PEIs), used for realizing plug-and-play functionality to convert the power from DER devices to the bus voltages. The operation point of PEI is controlled by its master controller, which is responsible for automatic state switching, reference signal supplement and state monitoring of physical devices (Mariam, Basu, & Conlon, 2016).

A microgrid system normally operates in two modes, namely the grid-connected mode and the island mode. Under the grid-connected mode, the microgrid system makes benefits from selling the electricity to the utility, if the on-site power generation totally satisfies the end user needs. Otherwise, it is required to purchase the electricity from the main grid in order to maintain its operation. If the power quality from the main grid is lower than an acceptable level, the microgrids should be seamlessly switched to island mode, for the sake of maintaining stability and avoiding the disturbance from the utility faults.

2.2. Distribution systems

The distribution system is referred as a common bus to interconnect all physical devices. Microgrid interconnects the main grid via the PCC, which is located on the primary side of the step-up main transformer. The microgrid system is generally classified into AC microgrid and DC microgrid, depending on the type of distribution system. Normally, operation indicators in AC-microgrids follow the standard in the conventional AC grid, which is the major reason for its popularity. Figure 1 shows the microgrid architecture with AC-line configuration, where all of the non-AC micro-generators and loads are converted to 50 Hz AC grid with the power converter. However, considerable power loss during the power conversion and harmonic voltage are inevitable. In reference (Su, Chang, Ranade, & Lu, 2012), a high-frequency AC-link microgrid is proposed, where a UPQC (Unified Power Quality Condition) is applied to achieve harmonic-free voltage and compensate for reactive power. The existing microgrid testbeds are mainly implemented on the AC grid, such as CERTS testbed in America and MICROGRIDS project in Europe. CERTS testbed is a leading practical project launched by American Electrical Power, aiming at implementing the seamless transition between grid-connected and island operation in terms of reconnected and resynchronized process and maintaining the stability of voltage and frequency in microgrids when working on island condition. The testbed consists of three feeders for sensitive loads and a feeder for non-sensitive loads. In each sensitive feeder, sub-controller, breaker and more than one DER device are set to ensure a consistent power supply for sensitive loads. Both sub-controller and central controller are introduced to realize ‘plug and play’ and ‘peer-to-peer’ functionality, respectively (Lasseter et al., 2011).

Figure 1. Vision of microgrid in AC-link configuration.[Q11]



~~M~~Meanwhile, the development of the DC-microgrid system has driven a larger number of researchers’ attentions in recent years, with high penetration of household DC devices and battery bank. On contrary, in a conventional AC grid system, the power output of DC-based DER is transmitted to DC load through DC–AC-DC power conversion, which causes considerable power losses. The power loss and financial cost are reduced substantially in DC-based microgrids due to no need of reactive power compensator and DC/AC inverter.

In microgrid, the objective of energy management system (EMS) is to provide operational reference signals for microgrid units, state monitoring and device communication technology to construct a bi-directional interaction framework between the power production to be properly dispatched and the user consumption. This has been made based on the forecasting results from the power side and load side. A number of the centralized MAS (multi-agent system) are implemented based on the short-term forecasting information. Alternatively, microgrid units can be regarded as agents in a MAS framework, where the interaction among the agents can be described with directed topology. An effective cooperative control strategy can be an optimal solution for a distributed network.

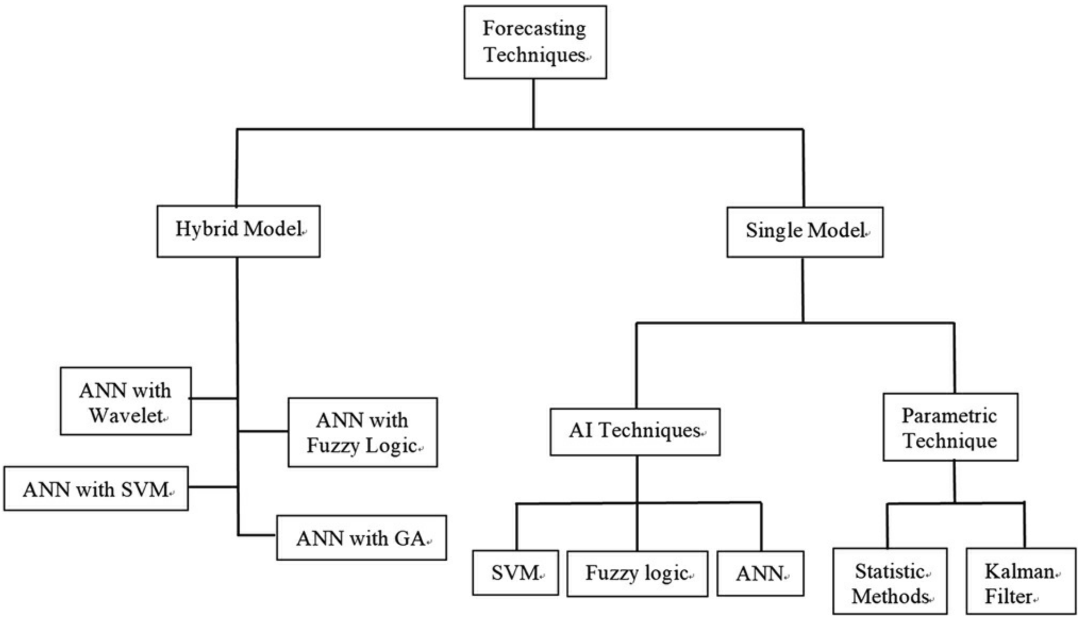
3. Power generation forecasting

Wind turbines and photovoltaic panels are typical DER devices in the microgrids, which have been feasibly installed. The wind and solar energy are weather driven resources, where their variability ranges from minutely/ hourly to yearly. The instability of renewable sources causes voltage fluctuation and intermittent power generation, posing the obstacle for maintaining power system operations and planning power system operations. Similarly, the electricity consumption shows its seasonality in a calendar year. Thus, developing appropriate forecasting technologies to predict power generation and load demand is highly significant in order to overcome the supply-demand mismatch issue. The forecasting time horizon is classified into the very short-term (from second to half an hour), short-term (half an hour to 6 h), medium-term (6 h–1 d), long-term (1 d–1 week), based on the energy management requirement. For instance, very short-term forecasting aims at achieving dynamic control for renewable power generators and load tracking. Short-term forecasting is used for scheduling energy flow among power sources, loads and storage devices. Medium-term and long-term forecasting are responsible for price settlement, load dispatch and maintenance scheduling, respectively.

A number of methodologies have been developed and combined to predict wind speed or/and wind power on varied forecast scale. In present case studies, the widely used forecasting tools developed are can be classified into three typical approaches:

physical model, statistics model and computational intelligent model. The numerical weather prediction (NWP) model is the basis of physical approach, where the variability of meteorological processes is described by atmospheric mesoscale model or global databases of meteor measurements. In terms of statistical methods, the forecasting value has a linear correlation with historical data in a specified time duration. The frequently used statistic methods consist of autoregression (AR), moving average (MA), autoregression moving average (ARMA), autoregression integrated moving average (ARIMA). Meanwhile, Box-Jenkins approach is an effective tool to identify the components and parameters in time series, while Kalman filter technique, also cited as a parametric model, is implemented based on historical data. Hence, the artificial intelligent approach neglects physical process from input variables and output performance and replaces it with a 'black box', which is composed of a single model or hybrid model. The widely used single models include fuzzy logic, artificial neural network (ANN), support vector regression (SVR), wavelet transform (WT), genetic algorithm (GA), expert systems. The hybrid system is to integrate one or more algorithms to pursue a higher forecasting accuracy. The most widely accepted hybrid model is the adaptive neural fuzzy inference system (ANFIS). The forecasting algorithms are summarized in Figure 2.

Figure 2. Overview of the forecasting techniques.



3.1. Statistic approaches

With regard to the statistical approaches, Kavasseri and Seetharaman (2009) utilized the fractional-ARIMA to improve forecasting accuracy on the one-day and two-day horizon. The proposed statistic approach improves 3.08% and 6.52% regarding the square of Forecast Mean Square Error (FMSE), respectively. Ishikawa and Namerikawa (2013) applied an innovative Kalman Filter technology to estimate the parameters for wind speed, where the wind speed forecasting model was improved by Just in Time (JIT) model on the basis of NWP performance. Similarly, the predictive wind power was optimized with JIT model based on the wind turbine operation characteristics. The simulation results showed the maximum error rate for the proposed model was lower than with single JIT model and other complex models. In reference (Wang, Hu, Srinivasan, & Wang, 2018), authors proposed heteroscedastic and robust spline regression model to provide an accurate power forecasting curve even in the presence of inconsistent data.

3.2. Intelligent algorithms

In recent 20 years, most researchers put their focus on computational algorithms in developing a non-linear map without studying the inner physical model. Many case studies indicate ANN is an effective tool to simplify the forecasting problem (Alexiadis, Dokopoulos, Sahsamanoglou, & Manousaridis, 1998; Carolin Mabel & Fernandez, 2008; Flores, Tapia, & Tapia, 2005; Kaur, Kumar, & Segal, 2016; Mohandes, Rehman, & Halawani, 1998; ~~Shuhui~~Li et al., 2001[Q5]). The biggest challenge for ANN application in wind power prediction is to select appropriate input variables. For example, (Li, Wunsch, O'Hair, & Giesselmann, 2001) found the wind speed, wind direction and individual characteristic of the wind turbine exercised significant influence on the power output, based on the analysis of onsite weather and power generation data. Mabel et al (Carolin Mabel & Fernandez, 2008) further considered turbine real operational hours as an influencing factor besides normal weather factors (humidity and wind speed), so that the dataset can be more relevant by removing the data generated at abnormal operating hours. Additionally, the forecasting accuracy of the ANN is also affected by the attributes of the ANN, involving the number of hidden layer, neurons and iteration, and training approaches (Kaur et al., 2016). More recently, the probabilistic wind power forecasting has become a new research topic, aiming at estimating confidence interval of the forecasting value with intelligent approaches. For example, (Wan, Xu, Pinson, Dong, & Wong, 2014) developed an extreme learning machine (ELM) model to account for the uncertainty in forecasting in different seasons, based on the historical wind power time-series data. In reference (Yan, Liu, Han, Gu, & Li, 2014), a robust probabilistic wind power forecasting model was presented to adjust model parameters, such as kernel function and kernel width in various scenarios, in order to optimize the dimension of the forecasting model.

3.3. Hybrid models

Generally, the hybrid model developed for forecasting solution can be divided into two types. One of the solutions is to combine statistical method and intelligent approach while another method is to combine several intelligent methods. Cadenas and Rivera (2010) introduced an ARIMA-ANN hybrid model, where ARIMA model aimed to obtain a roughly prediction value. Then, ANN was implemented to deal with the nonlinear tendency of forecasting error. The evaluation index-mean absolute error (MAE) showed the hybrid model outperforms individual ANN and ARIMA model. In reference (Catalão, Pousinho, & Mendes, 2011), the model was developed by integrating the wavelet transform into ANFIS technology. The wavelet transform was employed in the data pre-processing stage, where the trend and high-frequency information in the original data series were filtered into a group of series. Afterwards, ANFIS was implemented in parameters identification for each series. Similarly, in (Catalao, Osorio, & Pousinho, 2011), the authors developed an evolutionary particle swarm optimization (EPSO) technology to adjust the parameters of membership function in the ANFIS model. It was demonstrated that the mean absolute percentage error (MAPE) of the proposed approach was highly improved compared to the traditional statistic approaches and simple intelligent methods.

3.4. Applications to solar power

Two mainstream approaches have been employed to estimate solar power generation. It is straightforward to establish a nonlinear map between the solar irradiance and solar power. Another method is to calculate the corresponding power generation based on the characteristic of solar photovoltaic and predicted solar irradiance. Correspondingly, the intelligent algorithms and statistical methods have also been available for solar irradiance prediction (Chen, Gooi, & Wang, 2013; Dorvlo, Jervase, & Al-Lawati, 2002; Grimaccia, Leva, Mussetta, & Ogliari, 2014; Mellit & Pavan, 2010; Wang, Mi, Su, & Zhao, 2012). Wang et al. (2012) were dedicated to integrating ANN into statistical feature parameters (ANN-SFP) to predict the forecasting accuracy in uncertain weather conditions. The ANN-SFP model was performed well in solar forecasting on a cloudy day compared with other conventional ANN models. Mellit, Massi Pavan, and Lughi (2014) focused on solving the short-term solar power forecasting problem in a large-scale PV plant located in Southern Italy, where three distinct ANN models were developed for three weather types (sunny, partly cloudy and overcast). In reference (Liu, Fang, Zhang, & Yang, 2015), an improved solar power forecasting model was developed to enhance forecasting accuracy under the extremely weather condition, where the aerosol index was regarded as a key component to indicate solar radiation attenuation. The estimated results demonstrated its superiority over the conventional model with the consideration of temperature, humidity and wind speed data for the forecasting results. Chen et al. (2013) proposed a hybrid model combining fuzzy logic and neural network, where temperature, sky information and solar irradiance level were grouped under the fuzzilization process. The accuracy rate of the hybrid model was considerably improved, compared with the single intelligent algorithms.

4. Short-term load forecast

Short-term load forecasting aims at planning an optimal electricity distribution schedule to satisfy the periodical and seasonal load consumption. Meanwhile, the load consumption is influenced by many factors, such as calendar type, weather, climate and special activity. Similarly, most of the forecasting approaches applied for power forecasting are available for load forecasting solutions. The major techniques can be categorized as statistic parametric methods, non-parametric intelligent methods and hybrid models.

4.1. Statistic approaches

Hong, Min, Baran, and Lee Willis (2010) investigated hourly demand and causality of the electricity consumption. A trial-and-error approach was applied to determine the structure of multiple linear regression models to solve this time-varying nonlinear problem. In reference (Taylor, 2012), a new method using singular value decomposition based on exponential smoothing formulation was presented and it superiority was identified in this empirical study. Many other researchers have also picked up a variety of input parameters, involving weather factors (temperature, wind indexes), calendar type and historical load data, in order to refine the forecasting model. For example, Fan and Hyndman (2012) investigated the relationship between the electricity demand and driver variables with a semi-parametric additive model in order to solve the short-term forecasting issue for Australian National Electricity Market. However, more recent forecasting techniques have concentrated on the probabilistic forecasting. For example, Guan, Luh, Michel, and Chi (2013) applied the hybrid Kalman filter to train a neural network to exactly capture the linear and nonlinear relationship between the input load factors and output measurement, thus solving the confidence interval estimation problem.

4.2. Intelligent algorithms

The accuracy of the load forecasting mostly depends on the size and confidence of the dataset. In (Raza & Khosravi, 2015), authors concluded that the best combination of the input set involves the previously related load data, weather variables (e.g. dry bulb, dew point) and calendar types to predict load demand in a particular hour in a specific day. Hernandez et al. (2013) integrated an ANN-based model into microgrids to forecast the hourly load in a day. Various types of historical load data are employed to predict the load demand of the forecasted day. Additionally, the Principal Component Analysis (PCA) was implemented for outlier detection. Buitrago and Asfour (2017) integrated the neural network with a classic control theory. On the first stage, the training process was implemented in an open-loop to determine the node weighting. Then, the loop was closed to generate the one-hour ahead forecasted load by referring its current output load forecast and weather variables. Mamlook, Badran, and Abdulhadi (2009) proposed a fuzzy inference model to achieve its outperformance, by taking into account the weather information. The fuzzy rules were designed by the local historical load data. Khosravi, Nahavandi, and Creighton (2011) constructed a short-term load forecasting model with the aims of decreasing load uncertainty and optimizing the power dispatch scheme.

The fuzzy logic applied in load forecasting has been proven to have its great advantages because it can appropriately describe ambiguous input variables, such as weather parameters and calendar type. However, the method requires collecting a large amount of historical load data, weather data in order to obtain accurate fuzzy rules. Furthermore, the fuzzy rules are normally obtained from the specific area, which might be infeasible in a large scale area.

4.3. Hybrid models

Tuaimah and Abbas (2014) presented a fuzzy-logic-related hybrid model consisting of two stages. Interval Type 2 Fuzzy Logic System (IT2 FLS), as an improved fuzzy logic approach, was applied to handle the uncertainty in forecasting accuracy or unexpected exogenous outputs, where the genetic algorithm was used for optimizing parameters used in IT2 FLS model. The forecasted models for summer and winter were developed respectively. Cevic and Cunkas (2015) grouped datasets with various week time and off-week time. The forecasted mode was developed by employing ANFIS in order to predict hourly load consumption, considering the impact of historical load, weather and season factors on the prediction results. Consequently, the MAPE of the hybrid model was up to 1.7%, which demonstrated its outperformance over a single fuzzy logic.

5. Microgrid control and optimization

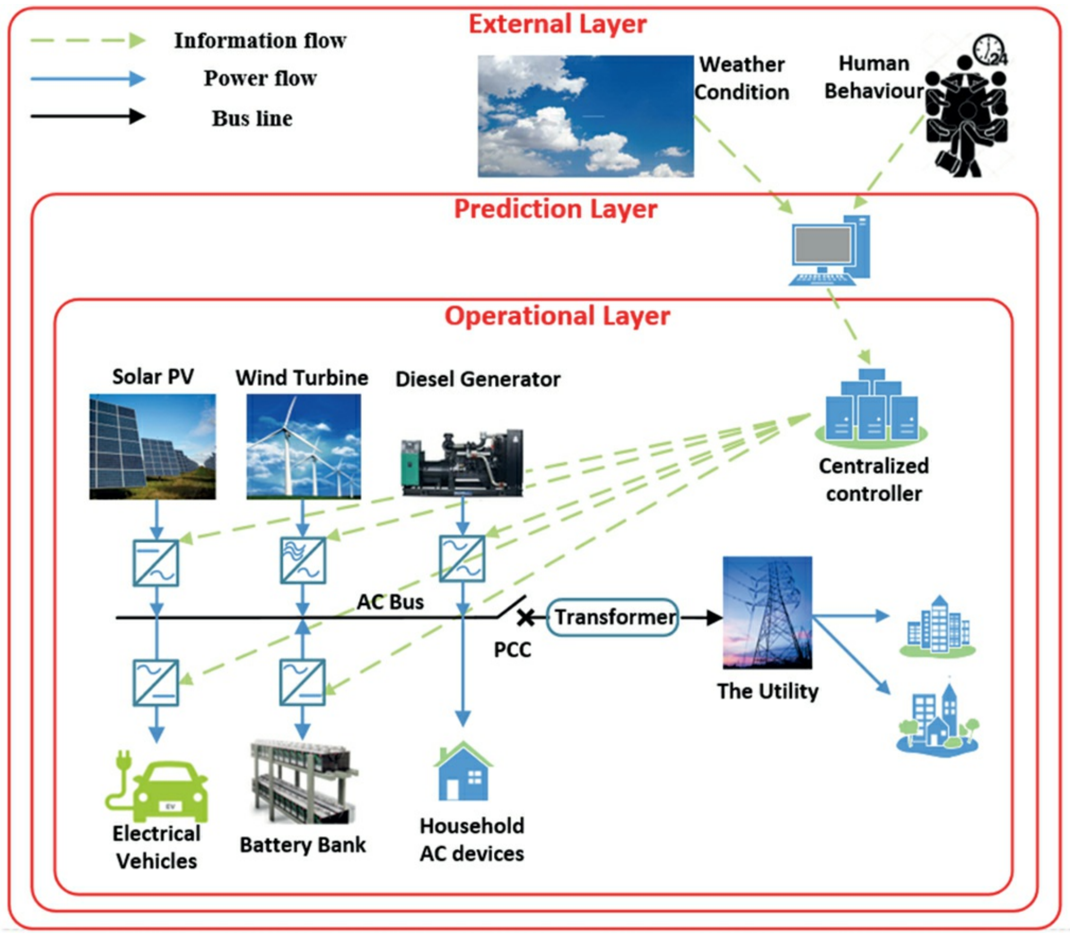
The problem of optimal energy management in a microgrid system has been widely investigated. The optimal unit commitment (UC), the stability of bus voltage and power dispatch among the distributed generators, storage devices and demand response are involved in order to achieve the multi-objectives (Olivares, Cañizares, & Kazerani, 2011). The consumer's economic benefit can be maximized by making the most of the on-site distributed generators and reducing the dependence on the main grid. Additionally, greenhouse mission is regarded as another significant index to be achieved in some studies, in order to minimize the carbon emission. EMS in the existing studies are mainly classified into three categories, namely centralized controllers, decentralized schemes and distributed control strategies. Many studies have proposed the application of centralized control strategies and distributed control scheme by using the MAS and optimization algorithms, which are reviewed in this paper.

5.1. Centralized control scheme and optimization

At present, based on the forecasting model for distributed generators and electricity consumption, many comprehensive centralized control schemes have been proposed. The centralized EMS consists of a central controller with direct commands to each DER device, data acquisition of the characteristic and parameters about the microgrid's operation and information acquisition from the forecasting system, in order to optimize an appropriate UC and dispatch of the resources with regard to the pre-set objectives.

Taking the AC microgrid as an example, a typical hierarchical structure can be shown in Figure 3, which combines the forecasting system with the physical hardware system. The noble structure is made of an external layer, a prediction layer and an operational layer, where the external layer is dedicated to data collection, including live weather data from the national weather forecasting station and electricity consumption data from the energy monitoring system. As for the prediction layer, many advanced forecasting algorithms introduced in the proceeding section of this paper can be implemented to predict the weather condition and local demand. In the operational layer, representative energy management strategies can be integrated into the power converter to dynamically manage energy flow among the devices, based on the prediction information. The objectives of this centralized control algorithm are to achieve energy and load forecasting, dynamic energy management control and provide commands to physical devices to respond accordingly.

Figure 3. A hierarchical microgrid structure.[Q11]



A few researchers have concentrated on use of the comprehensive centralized control strategies based on forecasting results, without considering physical models of the distributed generators (DGs) and various loads. In (Palma-behnke et al., 2013), authors employed an online approach called rolling horizon strategy to schedule energy storage devices and solve UC issues by using mixed integer programming optimization, based on two-day-ahead power forecasting results. Additionally, demand management mechanism was integrated to shift consumer's behaviour and maximize renewable energy utilization. The performance showed that the operation cost was minimized with the proposed UC-rolling horizon method compared with the conventional offline UC approach. Olivares et al. (2011) constructed a centralized EMS for microgrid operating in stand-alone mode, which was composed of three main blocks, i.e. multi-stage economic load dispatch (ELD) block, generation/load forecasting block and UC block. The forecasting module was the premise for ELD and UC block. UC was responsible for providing the on-off decision for dispatchable DGs and state monitoring of the microgrid units. Once state information was received from UC, the multi-stage ELD calculated the optimal dispatch for DER and provided the reference signal to the lower device controller. Chaouachi, Kamel, Andoulsi, and Nagasaka (2013) formulated the microgrid energy control problem as a multi-objective problem. A multi-objective intelligent energy management (MIEM) control strategy was presented based on the online short-term power and load forecasting results, where a generalized neural network ensemble was utilized for making a prediction. The MIEM is composed of multi-objective (MO) linear programming and battery scheduling, where a fuzzy logic-based expert system is utilized for battery scheduling. The MO optimization is responsible for providing power reference signal for microgrid components. Similarly, many studies employed the multi-objective optimization method to address the energy management problem, where majority objectives were set to be the financial cost, the environmental impact and network operation conditions. Another multi-objective optimization model used in (Fan, Liu, & Zhang, 2015) aimed at minimizing financial cost and maintaining acceptable temperature with lower cost, on the basis of a heuristic technique, real-time pricing and the classification of household appliance. In (Wafaa & Dessaint, 2017), the authors investigated a vector objective function involving operating cost, voltage stability and emission effect. It aimed at reducing the risk of voltage instability and forecasting the voltage collapse point, which was challenged by the weather uncertainty.

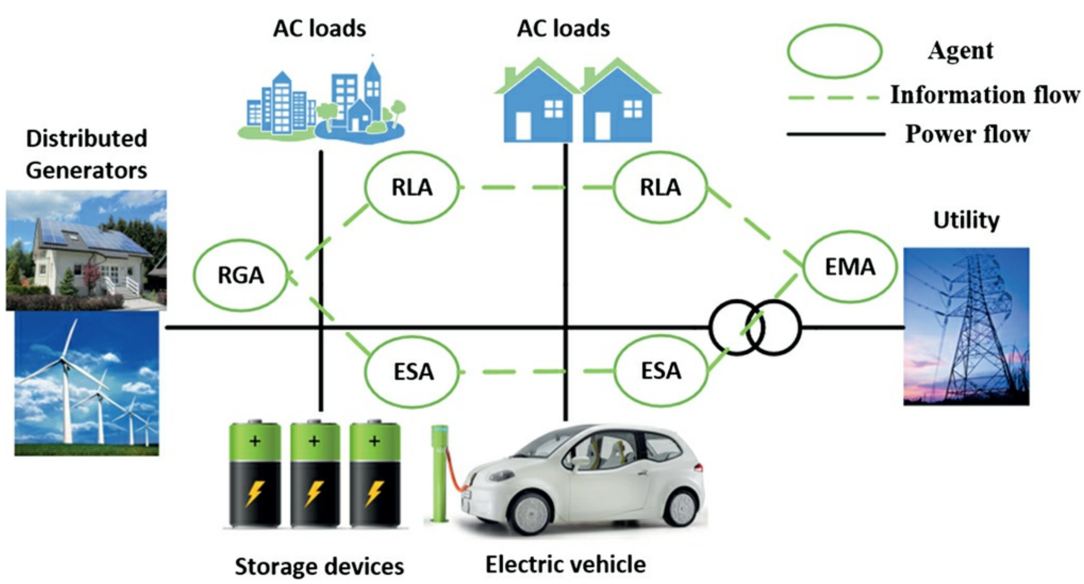
However, the biggest problem for centralized control scheme is that the entire of microgrid units are over-dependent on the central control system, which may cause huge risks once the central controller breaks down. On the other hand, the bidirectional communication between the central controller and each microgrid participant would be essential under such architecture. The uncertainty due to time delays in the communication process might be inevitable, indicating the measurement and control signal may be not accurate enough or get lost in the communication channel (Han, Zhang, Li, Coelho, & Guerrero, 2017). Moreover, the sampling rates of measurement or control signal should be as fast as possible, while the data volume of the central controller is limited. Under this situation, the cost of the central controller is significantly increased and system stability will be unavoidably defective.

To address such problems inherent in the centralized controller, the decentralized scheme is proposed as it enables to tolerate the potential failure of the communication system and thus has a better plug-and-play ability, which can be easy to accommodate more microgrid participants (Han et al., 2017). The local controller of each microgrid participant has to obtain the voltage and frequency information at PCC to adjust its control performance. However, a high bandwidth bidirectional communication connection is necessary for a large scale of microgrid system. If local controllers regulate the grid frequency simultaneously, the system robustness would be destroyed. Therefore, the cooperation and coordination of the local controllers are very challenging. The complexity of control system is also increasingly emerging with the high penetration of distributed generators.

5.2. Control strategy for distributed MAS-based microgrid

MAS, as a union of agents, has been applied for solving the problem which cannot be solved by a single agent, owing to its strong robustness and reliability by using proper communication, coordination and allocation within the agent group to solve the complex problems. In a distributed energy network, the power flow information of the microgrid participants, such as loads, DGs and energy storage systems can be considered as the agent, respectively. For example, Figure 4 shows a typical MAS-based energy management system for a microgrid system, where there are various agents including Renewable Generation Agents (RGA), Responsive Load Agents (RLA), Energy Market Agent (EMA) and Energy Storage Agent (ESA). Among these agents, RGA and RLA collect the data from DER and customers while EMA is responsible for electricity price regulation. ESA indicates distributed energy storage system in the microgrid system (Kaur et al., 2016). Alternatively, the local bus can also be described as the agent, where each agent obtains the local generation and load information. The agent enables to update the local information and communicate with neighbourhood agents. Furthermore, the entire system shows its strong flexibility and scalability, once more DGs and loads are added to the original MAS. A MAS approach involves design of a suitable model consisting of topology graph and mathematical models to build the system architecture and control strategy.

Figure 4. Multi-agent based distributed energy management system for microgrid.[Q11]



The cooperative and coordinative problem is a great challenge for MAS. Consensus control is thus considered as the most commonly used approach to solving the cooperative problem, which have been found wide applications in the unmanned aerial vehicle, formation control, distributed sensor networks and distributed energy system. The objective of consensus control is to design appropriate protocols so that all of the agents in the MAS can emerge to achieve a certain desired behaviour. The rule of communication among the multiple agents in the microgrid can be designed by consensus protocol, which expresses the process of information exchange for each agent with its neighbourhoods. The implementation of a consensus protocol is supposed to be an ideal protocol to achieve the cooperative control in a microgrid system.

As for an autonomous AC microgrid or DC microgrid, the purposes of coordination and cooperation of energy storage system is reflected in supporting frequency stability and dynamic supply-demand balance. An optimal schedule scheme of the battery energy storage system (BESS) allows renewable generators to operate in maximum peak power tracking mode constantly based on the forecasting information of power generation and load demand, in order to maximize the efficiency of the local resource and minimize the residence electricity billing. However, the charging/discharging rate of the energy storage system is one of the main factors of charging/discharging efficiency. Recently, researchers have discovered various strategies that can be utilized to minimize the power loss caused by charging/discharging operation and keep active power balance. Generally, a distributed control scheme under the MAS framework has been employed for storage devices management. In a BESS-based MAS framework, each local storage device is considered as an agent having communication with its neighbourhood agent to satisfy supply-demand mismatch in a cooperative way. Normally, the control scheme proposed for each agent is composed of two control levels. The top control level is dedicated to implement control algorithms and provide charging/discharging rate and power reference information for the lower controller. The lower control level concentrates on power system modelling and aims to control BESS to track the power reference. An optimal distributed control scheme should be flexible, robust and address the problem with a cost-effective way (Kumar Nunna & Srinivasan, 2016; Morstyn, Hredzak, & Agelidis, 2014; Morstyn, Hredzak, Member, & Vassilios, 2016; Xu, Zhang, Hug, Kar, & Li, 2015; Zhang, Rahbari-asr, Duan, & Chow, 2016; Zhao & Ding, 2018).

In (Xu et al., 2015), the authors considered charging efficiency as the objective function, while charging rate and state-of-charge of the BESS were main impacting factors. The approach utilized system frequency as the indicator of supply-demand imbalance index. The scalability of the strategy was investigated through the 100-bus system. However, under the general multi-agent framework, the local information of the agent is updated by the interaction with its neighbourhood agent, which indicates the participants are forced to share their vital and invisible information such as cost function or gradient information. In order to protect the privacy of each participant, Zhao ~~et al.,~~ & Ding (2018[Q6]) presented another cooperative optimal solution for multiple battery energy storage system in a microgrid to maintain the supply-demand mismatch under the wind power generation uncertainties. Similarly, Zhang et al. (2016) presented an offline cooperative distributed energy scheduling algorithm, which allowed limited information for agent communication and facilitated reconfiguration of the distributed system. Likewise, in (Kumar Nunna & Srinivasan, 2016), a dynamically updated energy management schedule was presented by altering the operation of storage devices and controllable demand response load to overcome the day-ahead forecasting error and system uncertainty. As for BESS management scheme in the DC microgrid, Morstyn et al. (2014) proposed a cooperative control system based on equal power sharing between storage devices, which is more effectively to avoid voltage failures compared to the traditional droop control. Furthermore, in (Morstyn et al., 2016), the authors further offered a MAS-based cooperative control strategy to configure power-sharing with a hybrid energy storage system in a DC microgrid system, where ultracapacitors and batteries were scheduled to power the load with varied frequency under respective scenarios.

6. Future trend

Although great efforts have been made in developing forecasting algorithms for intelligent energy management, the microgrid system still needs to meet a number of challenges such as the forecasting accuracy against weather uncertainty, the robustness of power management, and voltage and frequency regulation. At present, the research activities have been found to be concentrated mainly in the following areas:

- Certain probabilistic algorithms to forecast both power and load demand have attracted more attractions. The probabilistic prediction can be superior in terms of accounting for the variability of the power and load demand (Sáez, Ávila, Olivares, Cañizares, & Marín, 2015), due to the intermittency and uncertainty of renewable resources and user behaviours. On the other hand, development of new forecasting techniques concentrating on improving model efficiency and accuracy under online and real-time scenarios will be one of the future research topics in this field.
- The research on the time-varying topology of the microgrid system is still rare while the insertion and excision of (DGs) are very common in a practical microgrid. An effective control protocol to address the problem under the switching topology will be the interesting topics in order to optimize the architecture and control scheme for the microgrid system.

7. Conclusions

This paper reviews various forecasting algorithms and microgrid energy management approaches. Microgrid technologies are also reviewed, including key components, operation modes and distribution buses. Short-term forecasting methodologies for power generation and load demand have been considerably investigated to build an intelligent microgrid system for solving the power-load dispatch issue. These methodologies are generally classified into statistics approaches, computational intelligent algorithms and hybrid models. The most influencing factors on power generation forecasting are associated with weather information, involving wind speed and solar irradiance depending on the types of DERs available. The load consumption can be affected by weather condition, calendar type and human behaviours. The paper furthermore discusses and classifies the mainstream energy management control schemes. A generalized centralized control scheme is introduced, fully taking into account the forecasting capabilities and the control strategies for the power converters. As for the distributed control schemes, consensus control can be considered as an ideal solution to address the cooperation and coordination problem in a MAS-based microgrid system.

Funding

[Q1]This work is funded by ~~Centre for Global Eco-Innovation at~~ [Q2]~~Lancaster University, partly funded by~~ [Q3]European Regional Development Fund through the Centre for Global Eco-Innovation at Lancaster University, with the partnership of Microgrid Entrust LLP[Q4].

Disclosure statement

No potential conflict of interest was reported by the authors[Q7].

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2. **Fig3.jpg**
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