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Proposing an Efficient Wind Forecasting Agent Using Adaptive MFDFA

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Abstract

High penetration by distributed energy sources (DERs) such as wind turbines (WT) and various types of consumer have triggered a need for new approach to coordination and control strategy to meet the stochastic wind speed of the environment. Here, a Multi Agent System is used to deliver strengthened, distributed, self-governing energy management of a multiple micro-grid to adapt to changes in the environment. Prediction of wind speed is crucial for various aspects, such as control and planning of wind turbine operation and guaranteeing stable performance of multiple micro-grids. The main purpose of the proposed system is to account for wind variability in the energy management of a multiple micro-grid based on a hierarchical multi-factor system. In this study, the prediction is based on adaptive multifractal detrended fluctuation analysis (Adaptive MFDFA). A genetic algorithm is used to solve the optimization problem. Eventually, the proposed strategy is applied to a typical MG which consists of micro turbine (MT), wind turbine (WT) and energy storage system (ESS). Evaluation of the results show that the proposed strategy works well and can adapt the level of confidence interval in various situations.

Keywords: Energy management system, multiple micro-grid, multi-agent systems, wind forecasting, Adaptive MFDFA

1. Introduction

Environmental concerns and the rising demand for electrical energy have triggered a move in recent years to renewable energies such as wind and solar power, but there are issues over reliability, quality, flexibility and cost. Units of storage and distributed energy resources (DER) [1] are placed close to the loads and could be divided into two groups: distributed generation (DG) and distributed storage (DS). DER systems that could be employed in both isolated and on grid setups are called micro-grids (MG). A micro-grid is a collection of Non-Responsive Loads (NRL), Responsive Load Demand (RLD), normal loads as well as DERs that are employed by a distribution feeder [2]. A micro-grid is an independent, controllable and single energy system which consists of load types, energy storage [1] and control devices, and in which DG and ES are connected directly parallel to the user's side. For large grids, the micro-grid can be considered as a controlled cell; and for the user's side, the micro-grid can meet unique demands such as lower power supply loss and higher local reliability.

1. Multiple micro-grids consist of different types of DER, giving a complex structure.

2. Current DERs are a combination of effective patterns including continuous and discrete time. These patterns may affect each other [3].

3. Availability of renewable energy production is usually periodic and variable [4].

4. DERs work in different modes and may need to change their state in response to environmental changes.

The energy management system in MG tries to maximize the use of renewable energies – instead of fossil fuels – since they do not consume fuel and their environmental pollution is minimal. Moreover, it must guarantee system reliability with respect to energy planning. MG energy management systems and multi agent systems have been addressed in the literature in order to solve decision making for energy management.

Smart control strategy is also required to give the energy supply system reliability and flexibility [5]. Therefore, in light of the goals regarding optimal energy management, the management and architecture of control based on the hierarchical multi-agent system (HMAS) are presented in this paper. Considering the structure of the energy management system for multiple micro-grids, the hierarchical multi-agent system technique is a good fit for implementing a smarter and more efficient energy management system [6]. Many of the studies relating to energy management have referred to multi-agent methods. To date, most research has focused on issues relating to micro-grid energy management with a multi-agent approach. In [7] an energy optimization man-

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agement problem was studied based on multi-agent systems through four operational states and relations among them; although this research only dealt with the problem of transmission of optimal power between DERs in different states. In [8] a multi-agent control strategy for island mode was presented. This research took the approach of coordination of a multi-agent platform, including level agent coordination, different regions agents and various agents of the components used in a coordinated control strategy. This system was implemented to test the feasibility of control strategy using Java language. In[9] a decentralized control structure, based on a multi-agent system for automatic utilization of a micro-grid, using power electronic interface is presented. The system presented consists of four DERs shown in a Matlab/Simulink environment. In [9] a hierarchical control model is presented using a multi-agent system in order to utilize a micro-grid through a power electronic interface. To do this, five types of agents including grid agent, central agent, generation agent, load agent and cut off agent were designed to be utilized using MATLAB and SIMULINK software. In [10] a conceptual approach of a multi-agent system for controlling DERs in a micro-grid is shown. In this paper, three types of agents are defined: regional agent [1], local agent (LA) and service agent [11]. In addition, a two-layer control strategy for achieving local autonomy and global optimization, in both grid mode and island mode, is proposed. In [12] a multi-agent system based on control structure for a micro-grid is presented. The structure architecture includes cooperative methods so the user can achieve defined goals.

In [13] a new oriented hierarchical multi-agent distributed control system for a micro-grid was designed and built conceptually. This multi-agent system consists of the agent of management of several micro-grids, the agent of control of a micro-grid and the local agent. The entire system is interrelated through CORBA technology. In [14] a general framework is presented for controlling a micro-grid based on multi-agent systems and a multi-agent confirmatory learning algorithm for automatic utilization in island mode of micro-grid. In [15] a completely distributed multi-agent system based on a reconstruction algorithm is presented. The paper also presents the distributed algorithm for determining coefficients. In [16] the design of micro-grid energy resources that can supply the required energy load for one year without outage was examined. This will cause oversizing of the micro-grid, meaning that EMS must be designed to avoid overcharging in energy storage devices.

In [17] the process of moving power systems toward smart grids (SG) is examined and advanced control methods, advanced measurement technologies and telecommunication grids for the current power grid are integrated. Micro-grid is a management structure and an innovative control at distribution level that causes implementation of the SG concept at the distribution system level. In [18] problems of energy management of a micro-grid, irrespective of energy resources, are very variable and the speed of updating orders must be high enough to track unexpected load changes and distributed generations with time constants close to the time constants of the control system. In [18] the DEMS-MG approach assigned the responsibilities and tasks of controlling DERs in order to coordinate and negotiate with each other in order to deliver management and optimization of a micro-grid. This approach leads to reduced vloumes of shared information and in turn reduces the need for an expensive communication grid. In addition, DEMS-MG provides plug and play capability for additional installation of DER units and loads in the micro-grid.

In [19] a DEMS-MG based on MAS for a micro-grid is implemented using MATLAB simulation software environment; however, given the limitations of the simulation platform, a simple negotiation mechanism between the limited agents and functions of EMS-MG was used. In order to deliver multi-objective management of a micro-grid in different time proportions, there is need to integrate – in the related architecture and coordination design – EMS-MG information in the cross sections between different controls. In [20] a multistep hierarchical optimization algorithm is proposed based on a multi-agent system (MAS) factoring in adjustable power and demand response for reducing operational cost of MMG systems through MAS.

In recent decades, much effort has gone into predicting wind parameters in the short to medium term, falling into two main categories. The first group is based on statistical techniques and includes Numerical Weather Prediction (NWP) methods. This method, also called the time series model, is the simplest method that is used. The main assumption is that the wind velocity of the next step is estimated from previous wind speed data using statistical methods such as Mean Square Error (MSE) Minimization [21]. The second group is based on artificial intelligence. Several predictive methods have harnessed artificial neural networks and fuzzy logic for the purpose of wind speed modeling as a completely non-linear physical phenomenon to predict the amount of wind speed in the next step. Most methods of this type have achieved more promising results than methods used previously [22].

The main purpose of the proposed method is to include wind uncertainty in the energy management of a multiple micro-grid based on a hierarchical multi-factor system. In this study, the prediction is based on adaptive multifractal detrended fluctuation analysis (Adaptive MFDFA). A genetic algorithm is used to solve the optimization problem.

The proposed strategy is applied to a typical MG consisting of a micro-turbine (MT), wind turbine (WT) and energy storage system (ESS).

In this study, the proposed strategy is based on hierarchical multi-agent systems for multiple micro-grids. As an applied study, the proposed method based on Adaptive MFDFA was implemented for JADE energy management of the micro-grid through hierarchical multi-agent systems. The main contributions of this paper are to:

1. Propose an energy management system for MGs, using the strategy for wind power forecasting.

2. Propose an Adaptive MFDFA to deal with uncertainty in wind power forecasting.

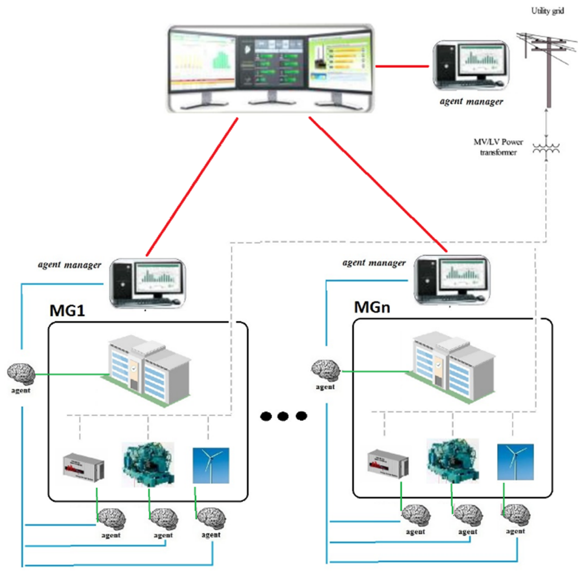

Figure 1: Configuration of the proposed typical system

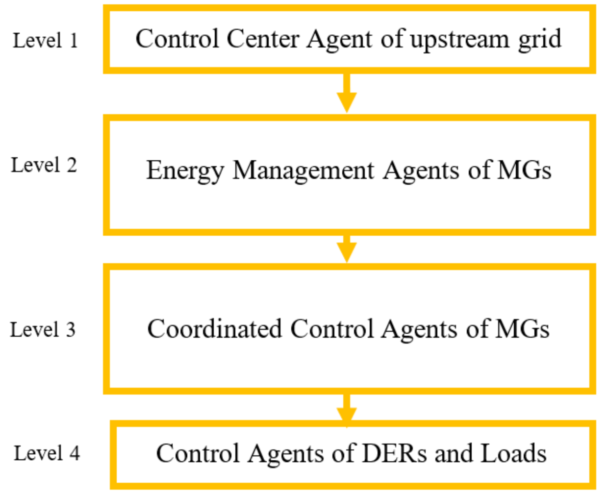

Figure 2: The recommended hierarchical multi-agent system structure

3. Propose a GA to increase performance in an optimization problem consisting of discrete and continuous variables.

4. Apply the TOPSIS method as a decision maker in MGs scheduling.

2. Energy management based on hierarchical multi-agent system

In this section (i) the recommended micro-grid structure is presented, (ii) the agents and their tasks and relationships to each other are determined and (iii) the algorithm and strategy of multiple micro-grid energy management is presented by a hierarchical multi-agent system based on the JADE platform. A schematic representation of the studied MG is shown in Fig. 1. Moreover, this MG is connected to the main electricity grid. Each of the system components are individually modeled based on related features and constraints. Some MGs namely MG1, MG2 and MGn were considered in the distribution network for this study. Each MG contains a battery energy storage system (BESS), wind turbine (WT), residential consumer (RC), commercial consumer (CC) and industrial consumer (IC), residential, commercial and industrial loads.

Fig. 2 shows the recommended MAS hierarchical system structure. The high level agent (levels 1 and 2) is a measurement agent whose design goal is optimization of the whole system. Energy management strategies are determined in a decision making module and will be implemented through an executive module. The medium level agent (level 3) is a measurement agent whose design goal is changing the performance modes between the agents in order to increase reliability and flexibility of distributed energy resources. Controlling coordinated switching is determined in the decision making module and will be implemented through the executive module. The low level agent (level 4) is a combinatory agent including reactive and measuring layers. The reactive layer is defined as the layer of recognition, understanding and action, and is the priority for rapid response to environmental emergency conditions. The measuring layer is defined as the layer of supposition, tendency and concept which is high level intelligence for planning how to use the agents to achieve goals. Generally, the purpose of designing the low level agent is to monitor the amount of reference power regulated by the high level agent and the mode of performance regulated by the medium level agent. Local control strategies are designed in the measurement layer.

3. Adaptive MFDFA Method

3.1. Background

In practice, each time series has two characteristics of broadband tail and clustering of volatility. In fact, the main motivation for using multi-fractal models is due to these two features. The fractal property is referred to as the non-changing of some of the features during transformation [23]. The fractal property states that some distributions have a scale stability feature. This means that their behavior is preserved under different transformations at different scales. More generally, a process should follow the following law to be recognized as a fixed process:

$$x(ct) = H^c x(t) \tag{1}$$

In this formula t is a suitable measure of scaling. $x(t)$ is the series of observations in which 0 <H <1. H is the Hurst exponent which shows the degree of stability.

Several definitions of fractal dimension can be found across a number of studies [24]. Some of the most important dimensions of the fractal are dimensions of consistency, dimensions of correlation, box count dimensions and dimensions of information.

Multifractal criteria or processes, or abnormal scaling, are created precisely by implicit emphasis on the hybrid nature

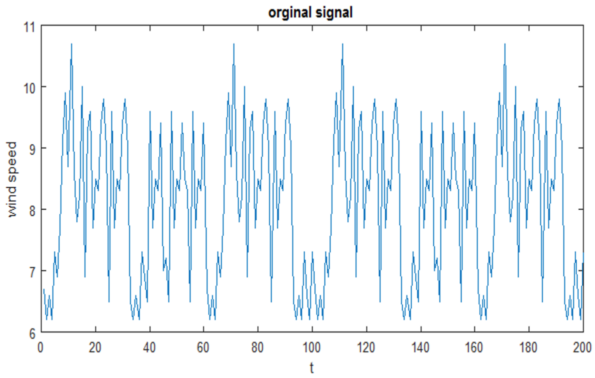

Figure 3: Time series of wind speed signal

of these processes. In fact, multifractals are a generalization of the famous finding of long-term dependence of volatility: this finding states that different criteria of volatility are characterized by varying degrees of long-term dependence, which reflects the typical behavior of the typical multifractal processes.

3.2. Wind power forecasting method

Factoring uncertainty into the planning of multiple micro-grids that harness renewable energy lends added complexity. Unpredicted distribution generation is one of the challenges when balancing production and consumption. The purpose of this section is to examine the production behavior of wind turbines, using adaptive multifractal detrended fluctuation analysis (Adaptive MFDFA).

In this analysis, we used the wind speed signal at 0-11 by interval [25] and applied the Adaptive MFDFA algorithm. Fig. 3 shows the variations in wind speed in the time interval. After recording the wind velocity, the complexity and multiplicity variations are evaluated. Since the MFDFA method can only examine the types of trends, we combine the adaptive method in this paper.

The steps in this algorithm are summarized as follows [24, 26]: Initially, assuming the input data, the wind will be z_j so that j = 1, ..., N. This time series is split into closed windows of length 2n + 1 so that each neighboring segment is n + 1 point. For each window of length 2n + 1, a polynomial Y is constructed. In order to produce a continuous process function and avoid sudden jumps, we use the weighted function for the overlapping parts of the v:

$$\Upsilon_{\upsilon}^{overlap}(j) = \left(1 - \frac{j-1}{n}\right)\Upsilon_{\upsilon}(j+n) + \frac{j-1}{n}\Upsilon_{\upsilon+1}(j) \qquad (2)$$

So that $j = 1, .., n+1$. Eventually, the time series for overlapping and disintegrating sections are as follows:

$$x_j = z_j - \Upsilon_v(j)\,;\, x_j = z_j - \Upsilon_v^{overlap}(j) \qquad (3)$$

Then, the output of the adaptive method which is gained with acceptable accuracy of its trends is considered as input to the MFDFA method, so that we first get the $Y(i)$ profile from the wind signal:

$$Y(i) = \sum_{k=1}^{i} [x_k - \langle x \rangle] \qquad i = 1, \ldots, N \qquad (4)$$

We divide the profile of $Y(i)$ into equal lengthwise windows without overlapping:

$$N_s = int(N/s) \qquad (5)$$

In the next step, we calculate the local process of each window, and then we will calculate the amount of time variance around it:

$$F^2(s,\nu) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(\nu-1)s+i] - y_\nu(i)\}^2 \qquad (6)$$

S is the scale, Y is the investigated profile, ν the window number, $y_\nu(i)$ the function fitted on that window $F^2(s,\nu)$ is the localized variance calculated for the ν the window with the scale s. The minimum squared fit is used to calculate the local trend of each window. We now obtain the mean of all windows for calculating the q-fold fluctuation function:

$$F_q(s) = \frac{1}{2N_s}\sum_{\nu=1}^{2N_s}\{F^2(s,\nu)^{\frac{q}{2}}\}^{\frac{1}{q}} \qquad (7)$$

Finally, we draw the log-log curve of the function F in s for each q:

$$F_q(s) \sim S^{h(q)} \qquad (8)$$

So that h (q) is called the Hurst exponent, which is a measure of self-confidence and time series correlation properties. This view corresponds to the following formula with the scaling view. So we have:

$$\tau(q) = qh(q) - 1 \qquad (9)$$

In multi-fractal signals, τ (q) is nonlinear to q. The singularity spectrum is also related to h (q) as follows:

$$f(\alpha) = q[\alpha - h(q)] + 1, \quad \alpha = h(q) + qh'(q) \qquad (10)$$

For f (α), the width and shape of the multi-fractal spectrum reflect the time variations of the Hurst representation locally. In other words, it reflects time variations in local-scale invariant-scale structures. The wind velocity fluctuation function and the wind velocity singularity spectrum using the Adaptive MFDFA algorithm are shown in Figures 4 and 5, respectively.

Then the wind speed fluctuation function of the wind speed and singularity spectrum at a given time interval can be computed by the Adaptive MFDFA algorithm for predicting wind speed for the next steps. This prediction is grounded in two bases:

1. Spatial and automated correlation properties of the LST time series;

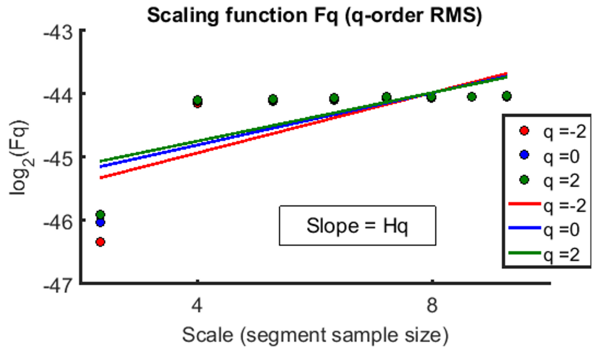

Figure 4: Fluctuation function of wind speed

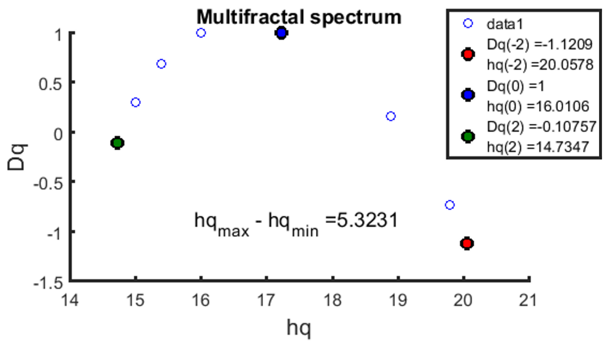

Figure 5: Singularity spectrum of wind speed

2. Adaptation of the collection with the past order.

Therefore, in order to predict wind speed at the next time, the last time point of the wind speed is set to the fluctuation function f_i, i from 1 to | f |, And add $D_{newi}(q)$ for each time according to equation (11).

$$D_{newi}(q) = qh_{newi}(q) - 1 \tag{11}$$

Then, the amount of deviation from the value of D is calculated according to equation (12).

$$deviation_j = \sqrt{\frac{1}{q_b - q_a + 1} \sum_{q=q_a}^{q_b} [D(q) - D_{newi}(q)]^2} \tag{12}$$

Finally, $D_{newi}(q)$, which has the minimum deviation function, is calculated as $D_{newi}(q)$ for construction of the new time series. It is worth noting that this approach is used to predict at the next time.

4. Strategy

Regardless of the Adaptive MFDFA method for forecasting wind speed, we are faced with uncertainty in this study. Therefore, the integration of WTs in MG utilization should be considered. Hence, reliability of predicted wind power is important for optimized scheduling of DGs and ESS [1, 27]. In the proposed strategy, uncertainty in wind power forecasting is considered as a stochastic process and the value of wind power capacity is considered lower than the forecast value [11].

In order to optimize the operation of multiple micro-grids, including DGs and ESS with consideration of uncertainty and responsive load demand, the proposed strategy contains the following steps:

- Step 1 - Receive input data including multi-year wind speed data, estimated load, micro-turbine production cost, upstream grid rate, and information on consumer in the responsible load schedule.
- Step 2 - Implement a program to predict the amount of distributed energy resources based on the proposed method.
- Step 3 - Analysis of the objective function to achieve the minimum cost of each micro-grid.
- Step 4 - Observance of active power balance and other constraints problem.
- Step 5 - Extracting the results of the optimization program, including the production of microturbines and wind turbines, the rate of exchange with the upstream grid, amount of charge and discharge of the battery storage, reduction of load power and the rate of use of responsive loads. Flowchart of the algorithm is presented in Fig. (6).

4.1. Interaction between Agents

The micro-grid manager (MGO) receives information from and interacts with the upstream grid manager and is responsible for coordination of the units with each other. The agent micro-turbine, after calculation of the cost of its generated power, announces the cost and range of generated power to the MGO during the next 24 hours. The wind turbine also informs the MGO about its generated power amount along with its cost in the next 24 hours. The storage unit is considered with a view to reducing the cost of utilization and supply of load power of micro-grid and is placed subordinate to the MGO agent. The loads agent, according to an incentive-based response plan, determines its range of power reduction and announces it to the MGO. The agent of the upstream grid also announces to the MGO the prices of the upstream grid within the next 24 hours.

The MGO, after processing and optimization of the plan, determines the amount of charge and discharge of the storage in the next 24 hours, and also determines the amount of reductions of loads use in the next 24 hours, per hour. It informs the microturbine agent about the amount of generated power of microturbines. It determines the amount of power required for exchange with the upstream grid and announces it to the related agent.

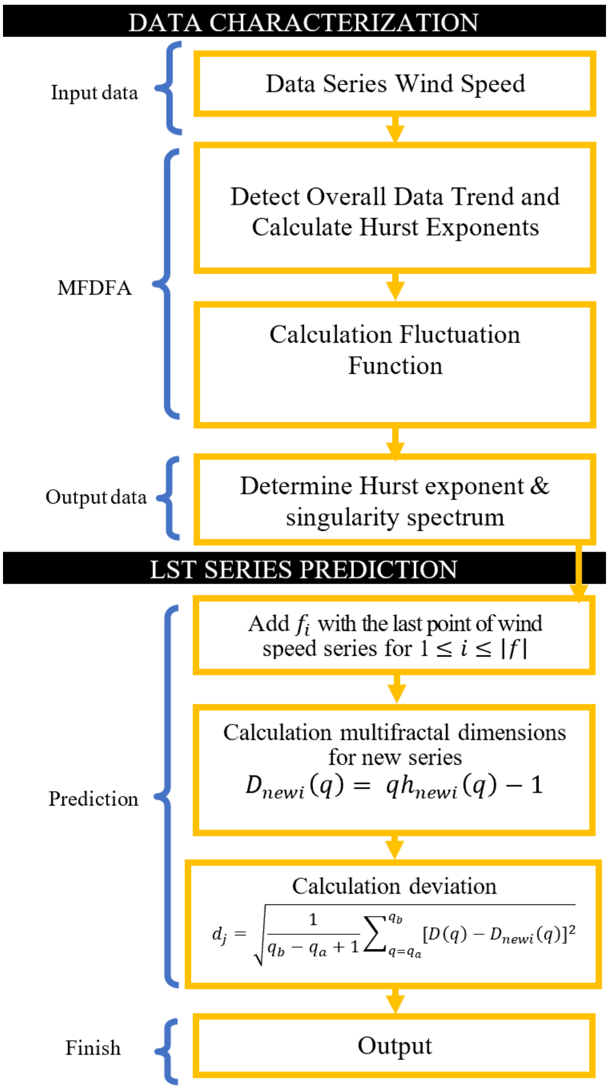

Figure 6: Diagram of the proposed prediction system

5. Formulation

This section focuses on designing and implementation of the energy management strategy through interaction between high-level agents and other agents. The recommended multi-agent system consists of several agents, each one acting in coordination with the MGO in order to utilize the micro-grid and gain a presence in the upstream grid market.

5.1. Microturbine (MT) agent

This agent announces the production cost including the coefficients of fuel cost function, investment, and maintenance along with the range of its delivered power, to the MGO, in order to have a share in the optimized utilization plan which is held by the MGO. The micro-turbine's cost includes the cost of consumed fuel, maintenance and investment. This agent announces to the MGO the cost of its consumed fuel along with its coefficients according to the equation (1), [28].

$$F_{MTi}(P_{MT_i}) = a_i + b_i P_{MTi} + C_i (P_{MTi})^2 \tag{13}$$

In this regard, F_{MTi} represents the cost of consumed fuel of unit i in \$/h; P_{MTi} represents the unit's generated power production in kilowatts. a_i, b_i, and c_i are the cost coefficients of production unit i in \$/h, \$/kwh, and \$/(kw)^{2}h respectively. The costs of investment can be calculated respectively according to equations (14) and (15) in \$/kwh. The relationships related to AEP_{net} and FCR can be seen in equations (16) and (17), respectively [29, 30].

$$C_{Capital,MTi} = \frac{FCR \times ICC}{AEP_{net}} \tag{14}$$

$$C_{O\&M\ ,\ MTi} = \frac{O\&M + LRC}{AEP_{net}} \tag{15}$$

$$AEP_{net} = P_{rated} \times CF \times 8760 \tag{16}$$

$$FCR = \frac{a(1+a)^n}{(1+a)^n - 1} \tag{17}$$

5.2. Wind turbine (WT) agent

This agent includes unmanageable wind turbines that announce the amount and cost of units' generation during the next 24 hours to the MGO. The output power of wind turbine WTGP as a function of wind speed is expressed in equation (16), [31].

$$P_{WTG} = \left\{ \begin{array}{ll} 0 & v \le V_{ci} \ and \ \ v \ge V_{co} \\ \frac{v - V_{ci}}{V_r - V_{ci}} P_r & V_{ci} < v < V_r \\ P_r & V_r \ < \ v < V_{co} \end{array} \right\} \tag{18}$$

The cost of production of one kilowatt-hour, which includes the costs of investment and maintenance, can be calculated using equation (18). Other relationships related to costs can be seen in equations (19) to (23) respectively [30, 31]].

$$C_{WTG} = C_{Capital\ ,\ WTG} + C_{O\&M\ ,WTG} \tag{19}$$

$$C_{Capital,WTG} = \frac{FCR \times ICC}{AEP_{net}} \tag{20}$$

$$C_{O\&M\ ,WTG} = \frac{O\&M + LCR}{AEP_{net}} \tag{21}$$

$$AEP_{net} = P_{rated} \times CF \times 8760 \tag{22}$$

$$FCR = \frac{a(1+a)^n}{(1+a)^n - 1} \tag{23}$$

5.3. Load agent

The load agent program is encouragement-centered. The load agent announces its program, which is the range of power, to the MGO. Different types of power consumers with different behaviors and consumption patterns will be considered in this paper. The types of consumers in the load program are presented below.

5.3.1. Residential consumer

There are a number of different electrical appliances in a house. Residential load agent programs usually try to either reduce consumption or cause load displacement. Load reduction is done through disconnecting appliances such as heating system, air-conditionings, cooling systems, lamps and refrigerator and freezer. MGO receives the data through communication ways and observes the reduction limitations in its programming. Equations (24) and (25) are the ones required for modeling the behavior of residential consumer k. The total energy reduction per hour in each house must be lower than the maximum recommended amount [32].

$$C_{Capital,WTG} = \frac{FCR \times ICC}{AEP_{net}} \tag{24}$$

$$C_{Capital,WTG} = \frac{FCR \times ICC}{AEP_{net}} \tag{25}$$

RC (k, t) and $RC^{Max}(k,t)$ are the maximum proposed reduction load in the grid and the amount of load reduction planned for residential consumer k at time t, respectively. Also, $RP(k,t)$ and $q^R(k,t)$ represent the reward for each kilowatt of energy reduction and the reduction of electricity consumption of household k at time t, respectively.

5.3.2. Commercial consumer

Commercial consumers usually announce to the MGO the amount of maximum load that they can reduce in a desirable reward. Equations (26) and (27) are the ones required for modeling the behavior of commercial consumer b [32].

$$CC(b,t) \leq CC^{Max}(b,t) \tag{26}$$

$$CP(b,t) = CC(b,t) \times q^c(b,t) \tag{27}$$

$CC(b,t)$ and $CC^{Max}(b,t)$ are the maximum proposed reduction in the proposed grid and the planned amount of load for consumer b at time t, respectively. Also$q^c(b,t)$ and $CP(b,t)$ represent the reward for each kilowatt of energy reduction and the reward for reducing electricity consumption b at time t, respectively.

5.3.3. Industrial consumer

Industrial consumers are usually known as heavy loads. Since each plant includes several production lines, disconnection and reduction of electrical energy in each production line has a special offer according to the product produced in the production line. Therefore, industrial customers usually present their load reduction offer as a multi-step package. For each hour, the industrial consumer sends its price amount offer as a package. In each hour, L_{max} is the maximum load reduction and $L_{min}$is the minimum load reduction that the industrial consumer can make. Equations (28) to (31) are used to model the behavior of industrial consumer j [32].

$$L^i_{Min}?L^i \leq L^i_{Max} \tag{28}$$

$$0 \leq L^i_k \leq L^i_k - 1 \tag{29}$$

$$IC(j,t) = \sum_k L^i_k \tag{30}$$

$$IP(j,t) = \sum_k O^i_k L^i_k \tag{31}$$

Where $IC(j,t)$ and $IP(j,t)$ are the sum of the scheduled load reduction and the j-th industrial consumer's reward at t, respectively. Also O^i_k is the price amount for step k and level i.

5.4. Upstream grid agent

This agent is introduced as an upstream grid in order to act as a mediator between the MGO and the upstream grid and conduct information exchanges and coordination for financial and electrical exchanges.

5.5. MGO agent

MGO agent uses all generation sources existing in its power grid such as wind turbines and micro-turbines in order to be able to provide electrical demand of loads with high security and lowest cost, and also announce the amount of required power in order for exchange with the upstream grid as a regular program during the next 24 hours to the upstream grid agent. In this regard, the MGO uses a storage unit to reduce the micro-grid's costs. Its charge and discharge program, after optimization, is determined for the next 24 hours.
The MGO, considering equation (32) and after optimization, determines the amount of charge and discharge of the storage for the next 24 hours [31, 32].

$$SOC^t = SOC^{t-1} + \left(\eta_{charge} \times P^t_{dcharge}\right) - \left(\frac{1}{\eta_{dcharge}} P^t_{dcharge}\right) \tag{32}$$

In this equation, SOC^t shows the amount of battery charge in kilowatt hours; η_{charge} and $\eta_{dcharge}$ represent the charge and discharge efficiency of the battery respectively; P_{charge} is the power in which the battery is charged and $P_{dcharge}$ is the power in which the battery is discharged. These powers are the program for storage in the next 24 hours, determined by the MGO after optimization. The cost of storage is considered as the sum of costs of maintenance and depreciation according to equations (33) and (34).

$$C_S = \left(C_{WC,bat} \times \left|P^t_s\right|\right) \tag{33}$$

$$C_{WC,bat} = \frac{C_{rep,bat}}{N_{bat.Qlifetime}\sqrt{\eta}} \tag{34}$$

In these equations, CS and $C_{WC,bat}$ represent battery cost in \$ and depreciation cost in \$/kWh, respectively. The cost of battery depreciation is directly related to the cost of changing batteries $C_{rep,bat}$in \$/kwh and on the other hand, is inversely related to the square root of the efficiency η, the lifetime $Q_{lifetime}$ and the number of battery cells N_{bat}.

5.6. Target function

In the recommended method, MGO tries to minimize the total costs of multiple micro-grids, taking into account the technical constraints of the micro-grid. In fact, micro-grid utilization management can be defined as an optimization issue, which results in the efficient generation points and the units in or outside of the circuit being determined with a view to observing the total reduced cost and the equal and unequal constraints.

$$
\begin{gathered}
F(x) = \sum_{t=1}^{24} [a+b+c] \\
Where: \\
a = \sum_{i=1}^{N_{MT}} \left\{ \begin{array}{c} F_{MT_i}(P_{MT_i}) + (C_{capital,MT_i} + \\ C_{O\&M,MT_i}) \times P_{MT_i} \end{array} \right\} \\
b = P_s^t C_s^t + P_{grid}^t B_{grid}^t \\
c = \sum_b CP(b,t) + \sum_k RP(k,t) + \sum_j IP(j,t)
\end{gathered} \tag{35}
$$

In this equation, P_{grid}^t and P_s^t are the power of charge and discharge of the storage and the power exchanged with the upstream grid in t time, respectively. N_{MT} is the number of micro-turbines existing in the micro-grid and B_{grid} is the price of power exchange with the upstream grid. IP (j, t), CP (b, t) and RP (k, t) are the rewards paid to the loads. Given that the storage power in charge and discharge situations becomes negative or positive, the absolute value sign in | P^t_s | shows that in both charge and discharge times, a cost is imposed on the battery.

5.7. Problem solving flowchart

Equation (35) is the objective function of the problem, which includes the cost of operation for the use of microturbines, the cost of charging and discharging the storage device, the cost of exchanging power with the upstream network and the cost of responsive responsive loads. The purpose of the article is to minimize costs from viewpoint of operation of for each micro-grid. The minimum and maximum power generation rates in microturbines, wind turbines and storage capacities in the battery are shown by equations (13) and (18) and (32), respectively. Relationships (24) to (31) are the load model after applying the load response program. Fig. 7 shows the problem-solving flowchart.

6. Simulation studies

6.1. Test system and main assumptions

In this section, the proposed approach is implemented on a multiple micro-grid system (MMG) as shown in figure 1. MMGs are assumed to have one storage unit, different types of DG units and different types of loads, as reported in Tables 1, 2, 3, and figure 8. (WTG and MT respectively denote wind and microturbine units).

The micro-grid structure consists of a wind unit with a nominal power of 15 kW and a speed variation rate between Vci = 0 m/s and Vco = 25 m/s, the storage device contains 30 batteries with a maximum charging and discharge power of 30 kW, a microturbine of three units with the maximum nameplate profile for home, commercial, and industrial loads of 30 kW, 30 kW, and 25 kW, respectively. Note that these data are not based on a real-world system and they are arbitrarily assumed for the purpose of demonstrating the performance of the proposed framework [21].

Table 1: Renewable DG unit characteristics

Unit	Type	Number	Max capacity
1	WTG	1	15 kW
2	MT	3	30 kW

Table 2: Load characteristics

Unit	Type	Daily Peak	Max Capacity in hour
1	industrial	610 kW	33 kW
2	commercial	607 kW	36 kW
3	residential	457 kW	27 kW

6.2. JADE

In order to validate the method of energy management of multiple micro-grids based on the multi-agent systems recommended in this section, a multiple micro-grid has been modeled in JADE software environment. The reason for using JADE is that it conforms to FIPA standards and creates a space where the programmer can directly focus on the design of the operating system.

The platform created by JADE allows users to easily focus on controlling and monitoring the power balance in a micro-grid. JADE is a platform to facilitate the implementation of multi-agent systems, including: i) a runtime environment where JADE agents are enabled, ii) a library of programming classes used to develop agents, and iii) a collection of graphic tools that can display the activity of the agents at runtime.

6.3. Result and discussions

The micro-grid is connected to the upstream grid and exchanges energy with it. The micro-grid manager has the task of energy management and appropriate utilization of the micro-grid. An agent is considered for each of the units and is responsible for local control of the unit under its supervision. The recommended multi-agent system includes the wind turbine agent, battery storage agent, microturbine agent, responsive load agent, micro-grid management agent, ordinary load agent and upstream grid agent.

Table 3: Energy storage unit characteristics

Unit	Min-Max SOC (kWh)	Max Charge/Discharge Power (kW)	Charge/Discharge Efficiency
1	5-100	-30 / +30	0.9

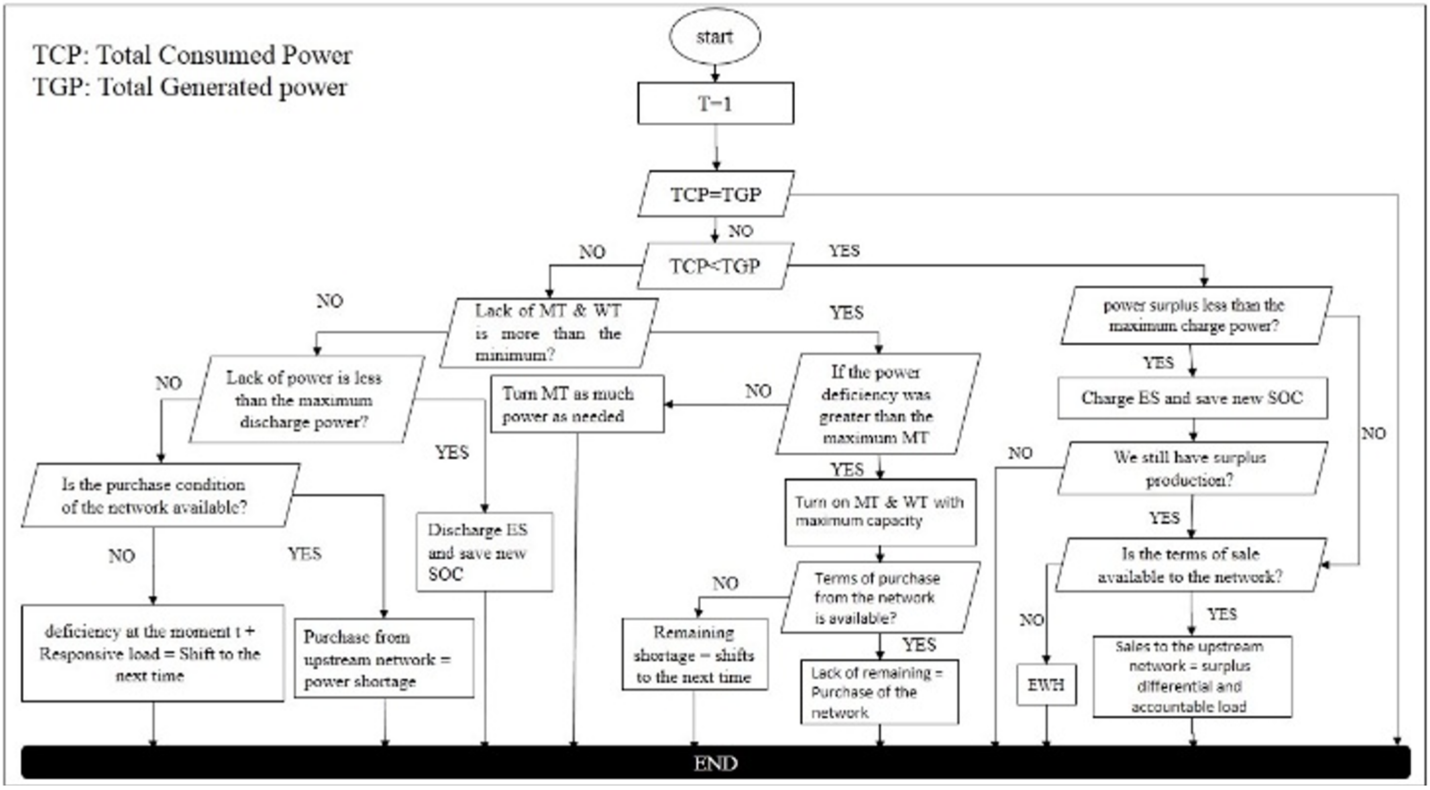

Figure 7: Flowchart of the strategy of energy management systems

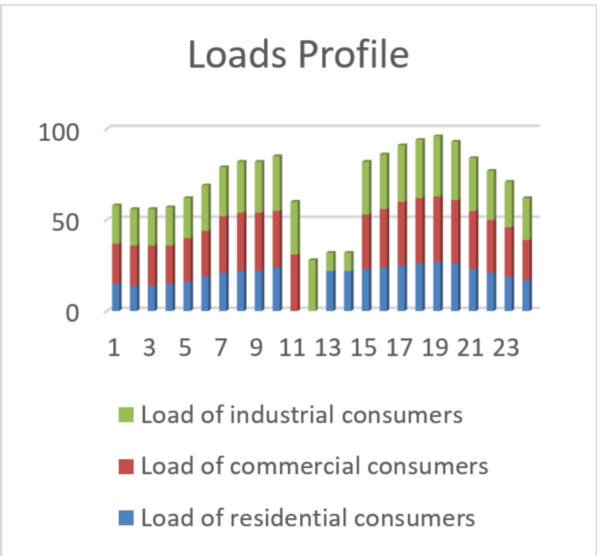

Figure 8: Different types of load profile per each hour

The performance scenario for the energy management system of the multiple micro-grid during the next 24 hours for different generations and consumptions has been simulated and the results of the simulations are provided below.

The purpose of the hierarchical multi-agent system in all scenarios is to deliver the optimal energy exchange between micro-grid and upstream grid and to determine (i) the most appropriate generated power for distributed energy sources, storage resources and (ii) the amount of power reduction for different types of loads with the lowest possible cost during a 24-hour period.

In this situation, the multiple micro-grid is connected to the upstream grid. The energy storage unit and distributed energy sources, including three micro-turbines and wind units are also available in the micro-grid. The surplus of generated energy can be stored in the storage unit if required and used to cover a shortfall.

The used loads include residential, commercial and industrial loads. After implementation of the strategy EMS using HMAS power generation and storage in scenario 1 and 2 are shown in figures 9 and 10.

For the first and second scenarios, figures 9 and 10 show that when the multiple micro-grid has a power shortage, energy storage systems are used to compensate the power shortage and try to reduce the energy supplied by the upstream grid. When the multiple micro-grid is over-powered, it provides energy for energy storage systems and exchanges power through the upstream grid. The power reduction of types of consumers is shown in figures 11 to 12.

It can be seen from figures 11 and 12 that the proposed system has been able to use multiple micro-grids for the first and second scenarios during multiple power grid shortages to compensate for decreasing the load power of the customers, and try to decrease the energy received by the upstream grid.

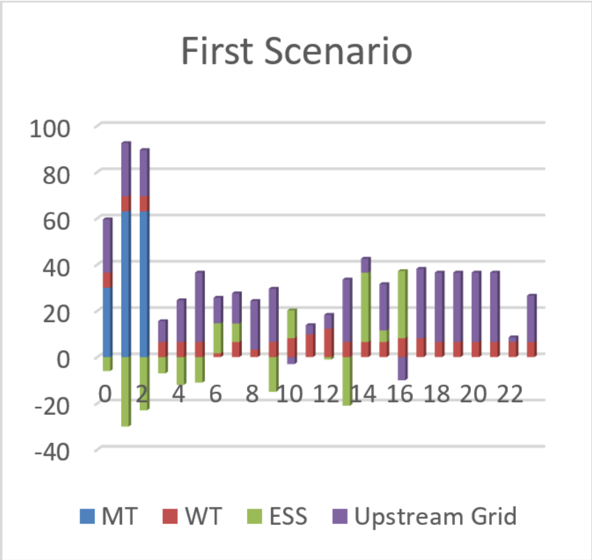

Figure 9: Power generation and storage in scenario 1 per each hour

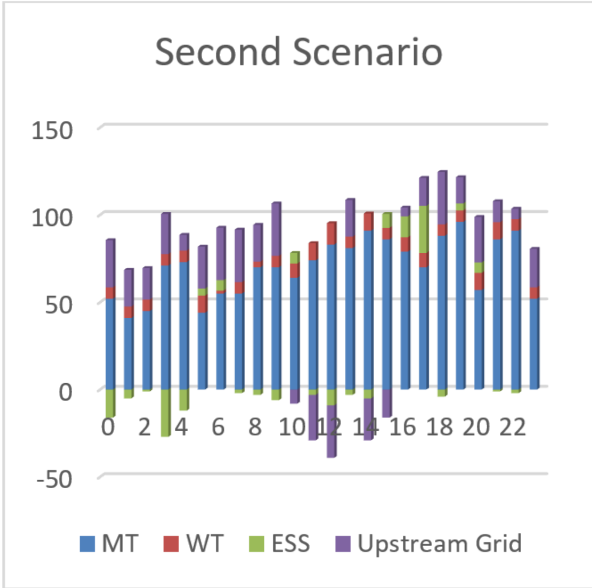

Figure 10: Power generation and storage in scenario 2 per each hour

Easy to implement, adjustable DERs, the ability to encourage all loads (including domestic, commercial and industrial) and computationally inexpensive mixed integer linear programming (MILP) models allow the EMS to efficiently manage the energy of distribution energy resources, storages and loads in multiple micro-grids. The incorporation of adjustable power of DER and incentive-based responsive loads will underpin the supply reliability of the multiple micro-grid (MMG) in addition to reducing operating costs. The results of scenarios 1 and 2 show that in all scenarios the planner intends to buy electricity from the utility grid in the lower price hours whereas and in other hours it supplies electricity from the WTs and the battery. The results also strongly suggest that the battery will save energy in the low price hours of the utility grid and release it in the high price hours.

7. Conclusion

This study discusses a hierarchical multi-agent system (HMAS) for modeling and energy management of multiple micro-grids consisting of distributed energy sources such as a wind turbine (WT), micro-turbine (MT), storage devices (DS) and various types of loads. An energy management system (EMS) strategy for multiple micro-grids was implemented on some levels, based on multi-agent systems (MAS) in JADE software environment with an optimization capability. The main goals considered are: 1) balancing supply and demand energy in the micro-grid; 2) increasing the use of energy sources of distributed generation in the micro-grid; 3) determining the optimal amount of energy generated by various types of distributed energy sources of the micro-grid; 4) determining the optimal amount of reduction of energy consumed of various loads of the micro-grid; 5) determining the optimal amount of charge and discharge of the storage system of the micro-grid.

The paper presents the results of simulation of processing of different possible states of the recommended model. The recommended method determined the energy management policy for distributed and storage energy resources in the multiple micro-grid with the lowest possible cost.

References

[1] K. Methaprayoon, C. Yingvivatanapong, W.-J. Lee, J. R. Liao, An integration of ann wind power estimation into unit commitment considering the forecasting uncertainty, IEEE Transactions on Industry Applications 43 (6) (2007) 1441–1448.

[2] A. Hajizadeh, M. A. Golkar, Intelligent power management strategy of hybrid distributed generation system, International Journal of Electrical Power & Energy Systems 29 (10) (2007) 783–795.

[3] Z. Jiang, L. Gao, R. A. Dougal, Flexible multiobjective control of power converter in active hybrid fuel cell/battery power sources, IEEE Transactions on Power Electronics 20 (1) (2005) 244–253.

[4] Z. Jiang, L. Gao, R. A. Dougal, Adaptive control strategy for active power sharing in hybrid fuel cell/battery power sources, IEEE Transactions on Energy Conversion 22 (2) (2007) 507–515.

[5] C.-x. Dou, B. Liu, Hierarchical hybrid control for improving comprehensive performance in smart power system, International Journal of Electrical Power & Energy Systems 43 (1) (2012) 595–606.

[6] T. Logenthiran, D. Srinivasan, A. M. Khambadkone, Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system, Electric Power Systems Research 81 (1) (2011) 138–148.

[7] Z. Jun, L. Junfeng, W. Jie, H. Ngan, A multi-agent solution to energy management in hybrid renewable energy generation system, Renewable Energy 36 (5) (2011) 1352–1363.

[8] D. Shao, Q. Wei, T. Nie, A multi-agent control strategy in microgrid island mode, in: Proceedings of 2011 6th International Forum on Strategic Technology, Vol. 1, IEEE, 2011, pp. 429–432.

[9] N. Cai, X. Xu, J. Mitra, A hierarchical multi-agent control scheme for a black start-capable microgrid, in: 2011 IEEE Power and Energy Society General Meeting, IEEE, 2011, pp. 1–7.

[10] W.-D. Zheng, J.-D. Cai, A multi-agent system for distributed energy resources control in microgrid, in: 2010 5th International Conference on Critical Infrastructure (CRIS), IEEE, 2010, pp. 1–5.

[11] J. Sarshar, S. S. Moosapour, M. Joorabian, Multi-objective energy management of a micro-grid considering uncertainty in wind power forecasting, Energy 139 (2017) 680–693.

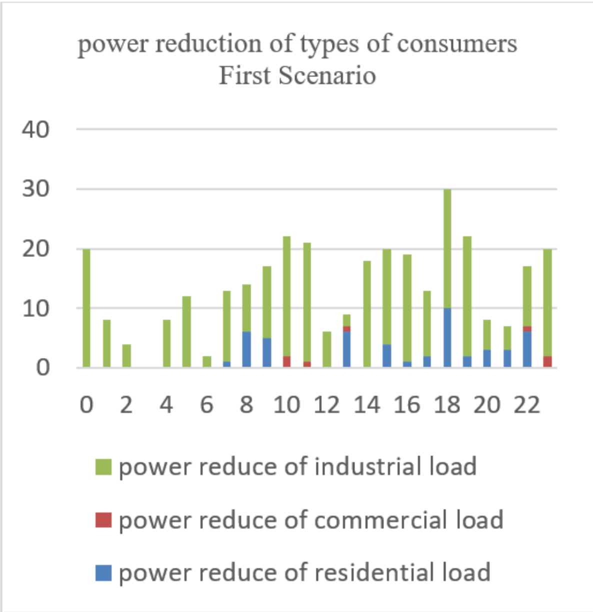

Figure 11: Power reduction of types of consumers in scenario 1 per each hour

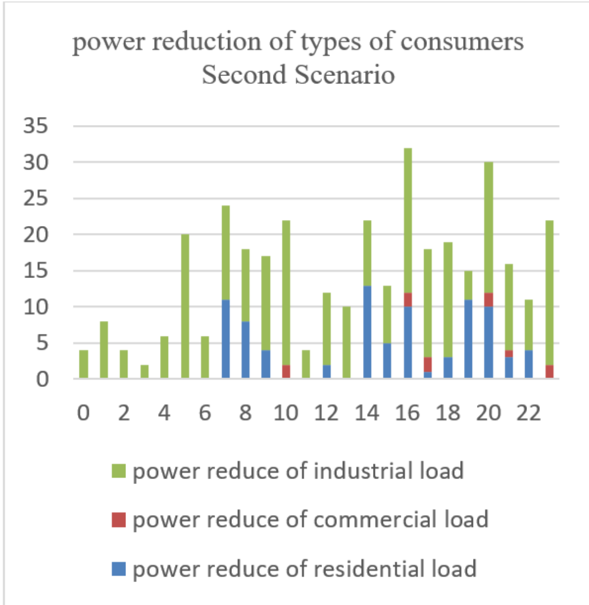

Figure 12: Power reduction of types of consumers in scenario 2 per each hour

[12] C. M. Colson, M. H. Nehrir, Algorithms for distributed decision-making for multi-agent microgrid power management, in: 2011 IEEE Power and Energy Society General Meeting, IEEE, 2011, pp. 1–8.

[13] G. Zheng, N. Li, Multi-agent based control system for multi-microgrids, in: 2010 International Conference on Computational Intelligence and Software Engineering, IEEE, 2010, pp. 1–4.

[14] A. Dimeas, N. Hatziargyriou, Multi-agent reinforcement learning for microgrids, in: IEEE PES General Meeting, IEEE, 2010, pp. 1–8.

[15] Y. Xu, W. Liu, Novel multiagent based load restoration algorithm for microgrids, IEEE Transactions on Smart Grid 2 (1) (2011) 152–161.

[16] M. Castañeda, L. Fernández, H. Sánchez, A. Cano, F. Jurado, Sizing methods for stand-alone hybrid systems based on renewable energies and hydrogen, in: 2012 16th IEEE Mediterranean Electrotechnical Conference, IEEE, 2012, pp. 832–835.

[17] J. Hu, J. Zhu, G. Platt, Smart grid-the next generation electricity grid with power flow optimization and high power quality, in: Journal of international Conference on Electrical Machines and Systems, Vol. 1, Journal of International Conference on Electrical Machines and Systems, 2012, pp. 425–433.

[18] D. E. Olivares, C. A. Cañizares, M. Kazerani, A centralized optimal energy management system for microgrids, in: 2011 IEEE Power and Energy Society General Meeting, IEEE, 2011, pp. 1–6.

[19] T. Logenthiran, D. Srinivasan, A. M. Khambadkone, H. N. Aung, Multi-agent system for real-time operation of a microgrid in real-time digital simulator, IEEE Transactions on smart grid 3 (2) (2012) 925–933.

[20] V.-H. Bui, A. Hussain, H.-M. Kim, A multiagent-based hierarchical energy management strategy for multi-microgrids considering adjustable power and demand response, IEEE Transactions on Smart Grid 9 (2) (2016) 1323–1333.

[21] L. Soder, Simulation of wind speed forecast errors for operation planning of multiarea power systems, in: 2004 International Conference on Probabilistic Methods Applied to Power Systems, IEEE, 2004, pp. 723–728.

[22] G. G. Wu, Z. Dou, Wind pattern recognition in neural fuzzy wind turbine control system, in: NAFIPS/IFIS/NASA'94. Proceedings of the First International Joint Conference of The North American Fuzzy Information Processing Society Biannual Conference. The Industrial Fuzzy Control and Intellige, IEEE, 1994, pp. 381–385.

[23] M. Mozaffarilegha, H. Namazi, M. Ahadi, S. Jafari, Complexity-based analysis of the difference in speech-evoked auditory brainstem responses (s-abrs) between binaural and monaural listening conditions, Fractals 26 (04) (2018) 1850052.

[24] D. Chakrabarti, C. Faloutsos, F4: large-scale automated forecasting using fractals, in: Proceedings of the eleventh international conference on Information and knowledge management, ACM, 2002, pp. 2–9.

[25] M. Das, S. K. Ghosh, Short-term prediction of land surface temperature using multifractal detrended fluctuation analysis, in: 2014 Annual IEEE India Conference (INDICON), IEEE, 2014, pp. 1–6.

[26] A. K. Maity, R. Pratihar, A. Mitra, S. Dey, V. Agrawal, S. Sanyal, A. Banerjee, R. Sengupta, D. Ghosh, Multifractal detrended fluctuation analysis of alpha and theta eeg rhythms with musical stimuli, Chaos, Solitons & Fractals 81 (2015) 52–67.

[27] M. Motevasel, A. R. Seifi, Expert energy management of a micro-grid considering wind energy uncertainty, Energy Conversion and Management 83 (2014) 58–72.

[28] F. Y. Eddy, H. Gooi, Multi-agent system for optimization of microgrids, in: 8th International Conference on Power Electronics-ECCE Asia, IEEE, 2011, pp. 2374–2381.

[29] S. Tegen, E. Lantz, M. Hand, B. Maples, A. Smith, P. Schwabe, Cost of wind energy review national renewable energy laboratory, Tech. rep., Technical Report (2011).

[30] L. Fingersh, M. Hand, A. Laxson, Wind turbine design cost and scaling model, Tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States) (2006).

[31] A. Zakariazadeh, S. Jadid, P. Siano, Smart microgrid energy and reserve scheduling with demand response using stochastic optimization, International Journal of Electrical Power & Energy Systems 63 (2014) 523–533.

[32] X. Wu, X. Wang, C. Qu, A hierarchical framework for generation scheduling of microgrids, IEEE Transactions on Power Delivery 29 (6) (2014) 2448–2457.