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Optimal Energy Management for Microgrids Considering Uncertainties in Renewable Energy Generation and Load Demand

Haotian Wu [1,*], Hang Li [2] and Xueping Gu [1]

1 School of Electric and Electrical Engineering, North China Electric Power University, Baoding 071003, China; xpgu@ncepu.edu.cn
2 CEPREI (Beijing) Industrial Technology Research Institute Co., Ltd., Beijing 100041, China; lihang@jimat-tech.com
* Correspondence: dgy@zua.edu.cn; Tel.: +86-1780-100-8662

Received: 22 July 2020; Accepted: 28 August 2020; Published: 2 September 2020

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Abstract: This paper proposes an efficient power management approach for the 24 h-ahead optimal maneuver of Mega–scale grid–connected microgrids containing a huge penetration of wind power, dispatchable distributed generation (diesel generator), energy storage system and local loads. The proposed energy management optimization objective aims to minimize the microgrid expenditure for fuel, operation and maintenance and main grid power import. It also aims to maximize the microgrid revenue by exporting energy to the upstream utility grid. The optimization model considers the uncertainties of the wind energy and power consumptions in the microgrids, and appropriate forecasting techniques are implemented to handle the uncertainties. The optimization model is formulated for a day-ahead optimization timeline with one-hour time steps, and it is solved using the ant colony optimization (ACO)-based metaheuristic approach. Actual data and parameters obtained from a practical microgrid platform in Atlanta, GA, USA are employed to formulate and validate the proposed energy management approach. Several simulations considering various operational scenarios are achieved to reveal the efficacy of the devised methodology. The obtained findings show the efficacy of the devised approach in various operational cases of the microgrids. To further confirm the efficacy of the devised approach, the achieved findings are compared to a pattern search (PS) optimization-based energy management approach and demonstrate outperformed performances with respect to solution optimality and computing time.

Keywords: ant colony optimization; energy management; microgrids; optimization; pattern search optimization; renewable energy; wind power; uncertainty

1. Introduction

The increasing deployment of distributed generations (DGs), the advantage of renewable energy in reducing carbon emissions, the intermittency of renewable generations, the advent of advanced controllers and the need to have a more reliable and resilient power grid are some of major causes for the ongoing energy transition reforms globally [1–3].

A microgrid (MG) is the assemblage of integrated electricity consumers, distributed generations (DGs) and distributed energy storages (DESs) at a distribution grid voltage level with clear electrical margins. The DGs can be the conventional or fuel-fired dispatchable power resources, such as a diesel generator, microturbine, fuel cell and other related energy sources [4]. The DGs can also contain renewable energy resources (RESs)—for example, wind power generation, photovoltaic (PV) solar generation, biomass and other technologies. While the distributed sources (DSs) can include batteries, flywheels and super-capacitors. Microgrids have a black starting ability and can function either in island mode or in grid-coupled mode [5]. They are not coupled with the upstream utility network when operating in the island mode. However, in the grid-coupled mode, MGs function in connection with the utility grid and exchange (buy or sell) power with the main grid.

Grid-coupled microgrids can export or import electrical energy to/from the larger electricity network. The power exchange with the upstream electricity network has generally been traded with a static, presettled price. Nevertheless, with the recent advent of smart sensor products and technology, it has become possible to precisely measure power generation and demands instantaneously or in real-time. This has created the opportunity for the change to time-of-use dynamic pricing schemes for electricity trading nowadays [6]. Well-established control techniques that can integrate a number of generation resources and storage devices in a microgrid framework are developing to provide electricity users access to obtain sustainable and secure electric power nearby [7,8]. It also paves the way for selling energy during excess power production or at expensive-price hours and buying energy during production shortage or cheap-price hours.

An energy management system (EMS) is a fundamental component of MG control and operational supervision. It takes input information from the generation sources, energy storage devices, load demands and main grid to properly allocate the microgrid energy resources (or decide the amount and duration of energy utilization). If this EMS decision is performed by solving some desired objective function (it can be the minimization of cost or maximization of profit), it is called an optimal EMS. The power-trading advancement inspires microgrid aggregators to adjust their power-exchange engagements with the upstream grid based on time-of-use dynamic pricing schemes in order to reduce power generation costs (fuel expenses), guarantee the enhanced utilization of RESs and DSs and improve the energy-trading profit. To accomplish these objectives, robust and optimal EMS should be implemented and integrated in the microgrid control architecture [6,9–11].

There have been several research works, by various individuals and institutions, on microgrid EMS in the previous couple of years. These works on microgrid EMS have had different objectives, configurations, scenarios and contexts. Some of these works are presented below.

A sensitivity study that augmented EMS, considering the rating of the energy storage system (ESS) and the growing trend of electric loads, was proposed for a microgrid system in Taiwan [12]. It aimed to search the optimal operation points of the microgrid energy resources for maximum profit. The EMS for optimal energy trading between two interconnected microgrid systems was presented in [13]. The objective was to minimize the power generation and transportation costs. In this work, centralized versus decentralized control schemes were investigated, employing iterative approaches and convex optimization techniques.

The work proposed in [14] developed an EMS to find the operating power set points of power sources in an MG. The work was based on an artificial neural network (ANN) and emphases to lower the total power generation expense of a MG that was involved in energy trading with the main electricity grid. Livengood [15] proposed a power management device known as an energy box to manage the electricity consumption of residential communities in a real–time dynamic electricity pricing scenarios. In this work, a stochastic dynamic program was used to solve the EMS objective problem using predictions of the electricity demand, meteorological variables and electricity price. The EMS decisions were the charging/discharging power of the ESS and amount of main grid import/export power.

An EMS with a hierarchical optimization framework was implemented in [16]. It focused on reducing the power generation spending and maximizing the power trading profit of a MG participating in a wholesale electricity-trading platform.

An optimal EMS model implemented employing a mixed-integer-linear-program (MILP) was formulated in [17] for minimizing operation expenditures in community microgrids in a dynamic price electricity market. The microgrid consisted of heating/cooling demands, ESS and dispatchable demands. Malysz [18] described an online power management technique to economically operate ESS devices of grid-coupled microgrids. The technique used a MILP described over a rolling scheduling period, employing forecasted electric loads and renewable power productions.

A genetic algorithm (GA)-based EMS [4] and modified particle swarm optimization (MPSO)-based EMS [5] were proposed for isolated microgrids containing multiple DGs and DSs. These EMS were targeted to reduce the operation costs of the MGs and effectively utilize the renewable and energy storage devices based on predictions of the electricity demand and renewables. References [5,7] proposed optimal EMS configurations depending on the prediction information of the electricity demands and renewable power productions for grid-connected microgrids in a variable electricity price environment. The proposed optimization problems were aimed to maximize profit and solved using the regrouping particle swarm optimization (RegPSO) technique.

Most of the aforementioned research works on microgrid energy management considered an ESS with one storage unit. The possible potential benefit of a microgrid ESS with more than one storage devices has not been investigated. Besides, the microgrids considered did not include multiple and integrated energy resources. Furthermore, the optimization techniques used to solve the EMS optimization problems did not ensure a global optimum solution, which, in turn, obstructed the exploitation of the maximum benefit of the microgrid in the power trading with the upper utility network.

In this paper, we propose an efficient power management technique for the 24 h-ahead optimal operation of mega-scale grid-coupled microgrids that consists of wind energy, a diesel generator, an energy storage system with several units and local (critical and noncritical) loads. The major target of the devised energy management methodology is to reduce the microgrid expenditure for fuel, operation and maintenance and main grid power import. It also targets maximizing the MG profit by exporting electricity to the upstream utility network. The optimization framework considers the stochastic ties of the wind power and electricity consumption in the MG, and pertinent predictions are employed to manage the stochastic ties. The optimization model is formulated for the 24 h-ahead scheduling period with a one-hour resolution, and it is solved using the ant colony optimization (ACO)-based meta-heuristic technique. Actual data and parameters obtained from an operating MG platform in Atlanta, GA, USA are employed to formulate and validate the proposed energy management approach. To assess and compare the efficacy of the devised method, another heuristic technique called a pattern search (PS) was also developed to obtain the EMS solution. The ACO was able to obtain the global best solution of the microgrid EMS problem. In addition, we chose ACO, as it has few parameters to update during the optimization process compared to other AI methods. The main contribution of the paper is the optimization formulation of microgrids considering the uncertainties of the renewable and load demands using integrated forecasting tools. From the optimization point to point, the contribution of the paper lays in implementing the ACO to solve such microgrid energy management optimization problems.

The arrangement of the other sections of the paper is described below. Section 2 outlines the case study microgrid and the proposed EMS optimization model. Section 3 describes the devised EMS framework and the working mechanism of the ACO. The simulation findings and comparative analysis are presented and discussed in Section 4. The study is summarized in Section 5.

2. Case Study Microgrid Framework and Proposed EMS Optimization Model

2.1. Microgrid Framework—Case Study Microgrid

The case study microgrid delivers power to various loads in an industrial park. The schematic illustration of the MG configuration is depicted in Figure 1. It contains wind power, diesel generator and ESS with two storage units. The ESS devices are a vanadium redox battery (VRB) and lithium-ion battery (Li–Ion). The MG is coupled with the upstream electricity network via a 10-kV busbar at the Point of Common Coupling (PCC). The real parametric values of the MG elements depicted in Figure 1 are employed in this work.

The EMS optimization problem, based on the case study microgrid framework, will be formulated in the following subsections. The MG operates in the grid-coupled mode. It can either export electricity to the upstream utility grid or import electricity from the utility power network. The MG EMS targets minimizing the total operating cost, consisting of the fuel expense, operation and maintenance (O&M) expense and grid power purchasing expense. Conversely, the EMS targets to maximize the profit that equals the income due to the power export to the utility grid minus the fuel and O&M costs.

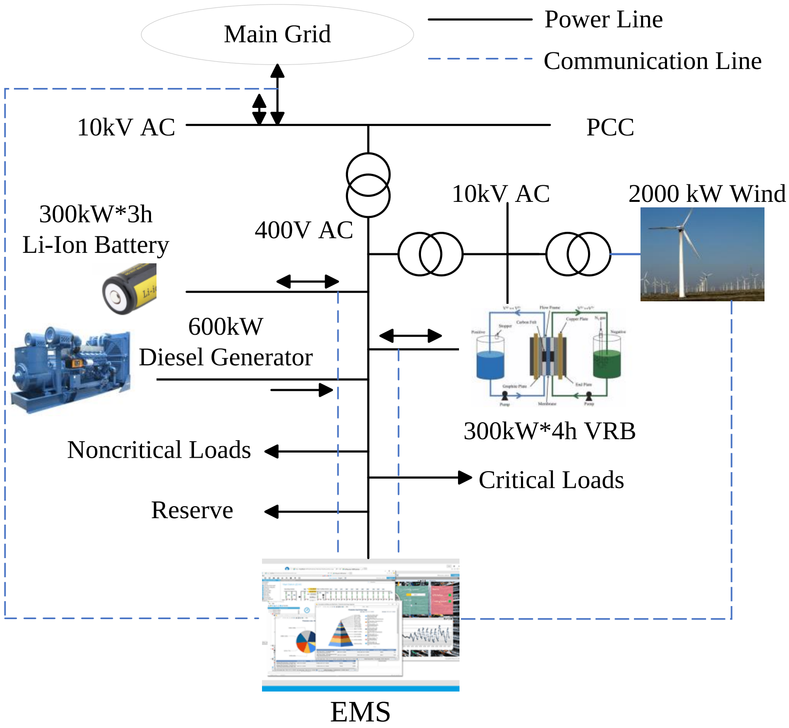

Figure 1. Framework of the case study microgrid. EMS: energy management system.

The decision variables are the charging/discharging powers and state of charges (SOCs) of the ESS devices, the generation from the diesel generator and the amount of energy trading with the upstream utility gird (i.e., grid power).

2.2. Objective Function

The optimization problem is formulated based on the following, the input information [19,20]:

- Electricity demand prediction
- Wind power prediction
- Electricity price prediction
- MG system data and component parameters

This information should be known in advance for the EMS to execute the desired optimal decisions.

As described above, the EMS aims to reduce the expense of buying electricity from the upstream utility network (or exploit the profit of selling electricity to the utility network), the fuel cost and O&M costs in the MG. The objective function is formulated as follows:

$$Min \sum_{t=1}^{N} \Delta T \Big\{ c(t)P_g(t) + \sum_{k=1}^{G} \big(F_k(P_k(t)) \cdot \xi_k(t) + SU_k(t) + SD_k(t) + c_{OM,k}(t)P_k(t) \big) + c_{OM,w}(t)P_{wind}(t) + \sum_{u=1}^{S} c_{OM,u}(t)P_{ESS,u}(t) \Big\} \quad (1)$$

where N is the scheduling horizon that equals 24 for the day-ahead hourly optimization framework; ΔT is the duration of the time steps that equals one hour for the hourly optimization model; *c(t)* is the electricity price (forecasted or prespecified) at time t, and it equals the purchasing price when the microgrid imports electricity from the upstream utility network and the selling price when the microgrid exports electricity to the main grid; $P_g(t)$ is the electricity of the utility grid—the sign convention here is that $P_g(t)$ is positive when the MG purchases electricity, negative when the MG exports power and zero when no electricity is being transferred between the MG and upper utility network; G is the number of dispatchable DGs in the MG; $P_k(t)$ is yield power of dispatchable DG k and F_k is fuel cost function of dispatchable DG k, and it is defined as follows for the diesel generator [8]:

$$F_k\big(P_k(t)\big) = a_k P_k(t)^2 + b_k P_k(t) + c_k \tag{2}$$

where a_k, b_k, and c_k are the generator cost function parameters; $\xi_k(t)$ is the commitment status of DG k, and its value is 1 if the DG is operating and 0 if the DG is off and $SU_k(t)$ is the startup cost of DG k, and it is expressed below.A

$$SU_k(t) = \begin{cases} SU, & \text{if } \xi_k(t) - \xi_k(t-1) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where SU is a fixed startup cost, and $SD_k(t)$ is the shutdown cost of DG k, and it is described below.

$$SD_k(t) = \begin{cases} SD, & \text{if}\xi_k(t) - \xi_k(t-1) = -1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where SD is a fixed shutdown cost, $c_{OM,k}(t)$ is the O&M expense of DG k, $c_{OM,w}(t)$ is the O&M expense of the wind plant, $P_{wind}(t)$ is the predicted wind power, S is the quantity of the ESS devices, $c_{OM,u}(t)$ is the O&M expense of the ESS device u and $P_{ESS,u}(t)$ is the charge/discharge power of the ESS unit u at time t. The sign convention here is that $P_{ESS,u}(t)$ is positive while the storage devices discharge, negative while they charge and zero when the ESS is not in operation.

2.3. Constraints

The objective problem described above is subjected to constraints formulated in the next subsections.

2.3.1. Power Limits of Dispatchable DGs

$$P_k^{min}(t) \le P_k(t) \le P_k^{max}(t) \tag{5}$$

where $P_k^{min}(t)$ and $P_k^{max}(t)$ are the lower and upper yield power restrictions on dispatchable DG k, respectively. This constraint is the manufacturer power generation capacity of the DGs.

2.3.2. Power Exchange Limits

$$-P_g^{max}(t) \le P_g(t) \le P_g^{max}(t) \tag{6}$$

where $P_g^{max}(t)$ is the maximum permissible electricity exchange between the MG and the main electricity network. This constraint represents the physical limit (capacity) of the switch and transformer connecting the microgrid and the main grid.

2.3.3. Power Balance Constraint

$$\sum_{k=1}^{G} P_k(t) + \sum_{u=1}^{S} P_{ESS,u}(t) + P_{wind}(t) + P_g(t) = P_l(t) \tag{7}$$

where $P_l(t)$ is the predicted electric load of the MG. This constraint is based on the power system stability concept where the sum of all power generations should be equal to the sum of all power demands.

2.3.4. Power Limits of ESS Devices

$$P_{ESS,u}^{min}(t) \leq P_{ESS,u}(t) \leq P_{ESS,u}^{max}(t) \tag{8}$$

where $P_{ESS,u}^{min}(t)$ and $P_{ESS,u}^{max}(t)$ are the lower and upper charging/discharging power of the ESS unit u, respectively. This constraint designates the manufacturer charging and discharging power limits of the energy storage devices.

2.3.5. Dynamic Operation of ESS Units

$$SOC_{ESS,u}(t+1) = SOC_{ESS,u}(t) - \frac{\eta_{ESS,u}(t)P_{ESS,u}(t)}{C_{ESS,u}} \tag{9}$$

$$SOC_{ESS,u}^{min}(t) \leq SOC_{ESS,u}(t+1) \leq SOC_{ESS,u}^{max}(t) \tag{10}$$

where $SOC_{ESS,u}(t)$ is the state of charge of the ESS device u, $\eta_{ESS,u}(t)$ is the charging/discharging efficiency of the ESS device u, $C_{ESS,u}$ is the storage capacity of the ESS unit u and $SOC_{ESS,u}^{min}(t)$ and $SOC_{ESS,u}^{max}(t)$ are the lower and upper SOCs of the ESS unit u at time t. The constraint in Equation (9) expresses the state of charge dynamics of the energy storage device while charging and discharging. The state of charge increases while charging and decreases during discharging. The constraint in Equation (10) denotes the manufacturer-designed storage capacity of the energy storage devices.

Therefore, the decision variables that the EMS optimizer determines are $P_g(t)$, $P_k(t)$, $P_{ESS,u}(t)$ and $SOC_{ESS,u}(t)$ for all t, k and u.

3. Proposed Optimization Solution Approach

The focus of the proposed energy management is to execute safe 24 h-ahead hourly decisions for economic maneuvers of the microgrid. The EMS considers the volatility of renewables, electric loads and electricity prices and uses appropriate forecasts for these values. It also takes into account the fuel expense, O&M costs, various operational and design constraints and system parameters. Figure 2 depicts the schematic representation of the proposed EMS configuration showing the information exchange into and out of the EMS.

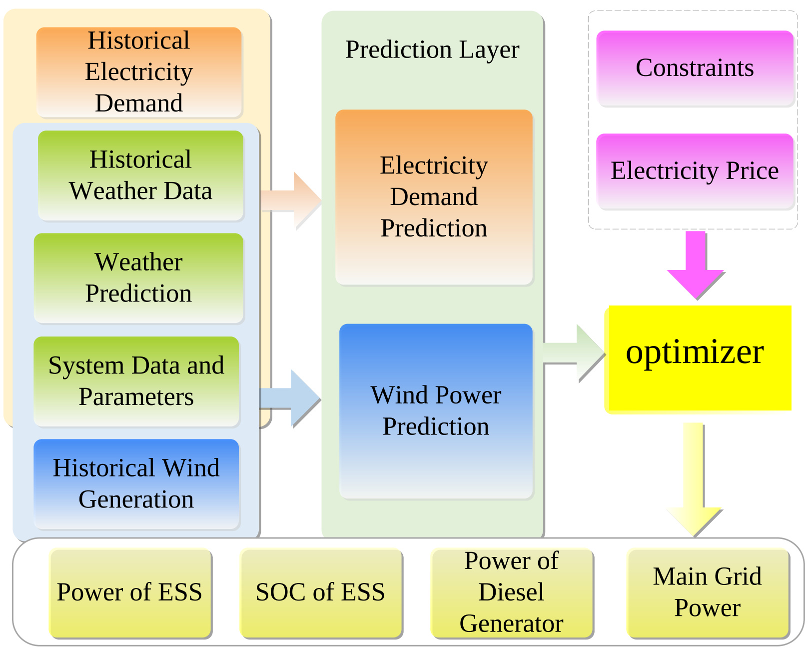

Figure 2. Proposed microgrid energy management system (MG EMS) configuration. SOC: state of charge and ESS: energy storage system.

Ant Colony Optimization (ACO)

The ACO is employed, in this study, for solving the EMS optimization problem formulated in Section 2. The ACO belongs to artificial intelligence (AI)–based modern optimization techniques. It is a likelihood optimization tool to solve functions that are described with graphical search routes. It was stimulated by the activities of ants to search the best routes of food destinations.

The ACO has been broadly used in computer technology and operation researches [21–23]. By mimicking the way real ants communicate each other, the ACO algorithm operates based on the pheromone exchanges among artificial ants [24]. Artificial ants designate population-based modern optimization methods inspired by the behavior of real ants. The combination of artificial ants and searching techniques have come to be one of the solution approaches for plenty of problems consisting of certain sorts of graphs—for example, vehicles and internet routings.

The brief working mechanism of the ACO algorithm is presented as follows. First, the ACO forms a graph through optimization or decision variables, and multiple ants are randomly placed in n nodes (places). The places visited by the ants are recorded by the list rec_a. The rec_a is established for every ant a. The initial pheromone intensity $\zeta_{ij}(0)$ is fixed at zero from all sides. The ants can prefer the next node based on the pheromone intensity in all sides of that node. The likelihood $\rho_{ij}^{a}(t)$ that the ants travel from parameter i to j at the iteration is formulated below.

$$\rho_{ij}^{a}(t) = \begin{cases} \dfrac{\zeta_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}(t)}{\sum_{q\notin rec_a}\zeta_{iq}^{\alpha}(t)\cdot\eta_{iq}^{\beta}(t)}, & j \notin rec_a \\ 0\,, & \text{otherwise} \end{cases} \tag{11}$$

where η_{ij} is a heuristic memo that is computed as $1/d_{ij}$, where d_{ij} is the Euclidean norm of the space from parameter i to j, $\zeta_{ij}(t)$ is the pheromone intensity of the path from parameter i to j at iteration t and α and β are the memo heuristic weight and expectation heuristic weight applied to assign the coefficients for heuristic information and pheromone intensity. While the ants complete the travels, the memo (information) intensity on each path is updated by the following expression.

$$\zeta_{ij} \leftarrow (1-p)\cdot\zeta_{ij} + p\cdot\sum_{a=1}^{m}\Delta\xi_{ij}^{a} \tag{12}$$

where $p \in (0,1]$ is the weight parameter known pheromone-evaporation ratio, and $\Delta\zeta_{ij}^{a}$ is the pheromone enhancement over the route from parameter i to j during the travels, and it is defined below.

$$\Delta\zeta_{ij}^{a} = \begin{cases} \dfrac{Q}{L_a}\,, & (i,\ j)\ \in\ \text{route of } a \\ 0\,, & \text{otherwise} \end{cases} \tag{13}$$

where Q is a fixed term called pheromone strength, and L_a is the path distance of ant a. The ACO iteration terminates when all the ants reach the same solution. Figure 3 illustrates the ACO algorithm flowchart. The parameters of the ACO algorithm used in the study are given in Table 1.

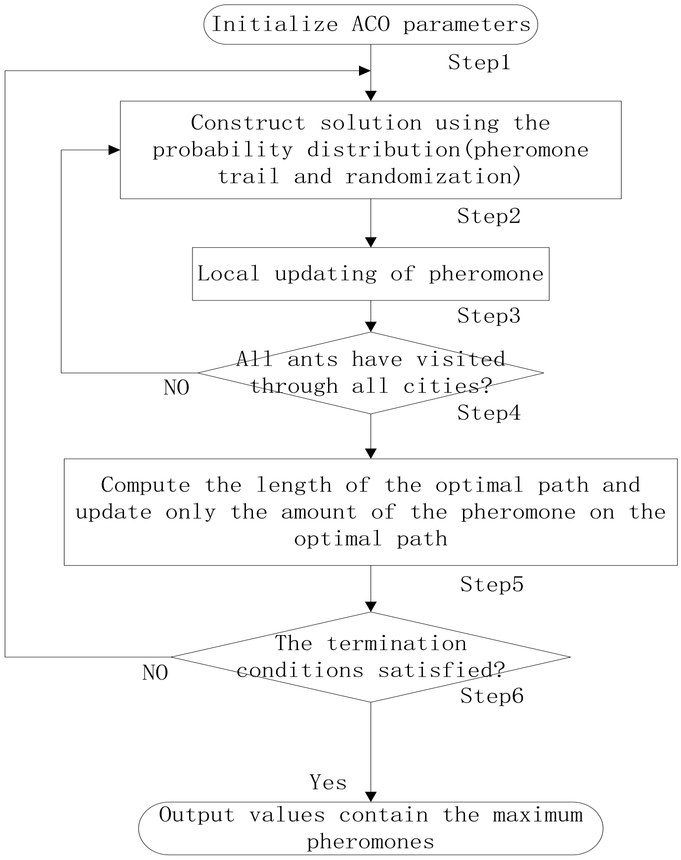

Figure 3. Flowchart of the ant colony optimization (ACO) algorithm.

Table 1. Ant colony optimization (ACO) parameters. EMS: energy management system.

Parameter	Value
# of iterations	100
# of variables	Number of EMS decision variables
Number of ants	20
Initial pheromone	0
Information heuristic coefficient	1.0
Expectation heuristic coefficient	1.0
Pheromone intensity	2
Pheromone evaporation	0.9

4. Simulation Results and Discussions

Case Study

A large-scale grid-connected microgrid containing a 2000-kW wind generator, 600-kW diesel generator and 2100-kW·h ESS (300-kW·4-h VRB and 300-kW·3-h Li–Ion battery) is considered as a case study microgrid platform in this paper. It is a practical microgrid framework in Atlanta, GA, USA, which is designed to supply electricity to industrial park loads with a peak aggregate capacity of 3000 kW.

The lowest and peak SOC limits of the ESS devices are set as 20% and 100%, respectively. The initial SOCs (at 00:00 or 12:00 a.m.) of the ESS devices are assumed to be 20%. The maximum charging/discharging power of the ESS units is taken as 300 kW. The ideal charging and discharging efficiency (100%) is assumed. The diesel generator maximum generation is set as 600 kW, and its parameters are given in Table 2. The maximum grid power exchange is set as 4000 kW, which equals the capacity of the grid-coupling transformer. SU is a fixed startup cost of the diesel generator. SD is a fixed shutdown cost of the diesel generator.

Table 2. Diesel generator parameters.

Parameter	Unit	Value
a	$(\$/kWh)^2$	0.00025
b	\$/kWh	0.0156
c	\$/h	0.3312
SU	\$/h	0
SD	\$/h	0

SU is a fixed startup cost of the diesel generator. SD is a fixed shutdown cost of the diesel generator.

Several scenarios of the generation and load demands have been investigated to validate the proposed EMS optimization approach based on the information of the case study microgrid. However, for the purpose of illustration and summarizing the findings, the performance of the proposed approach will be discussed next based on a single-day scenario. The 24-ahead predictions of the wind power and electricity demand are depicted in Figures 4 and 5, respectively.

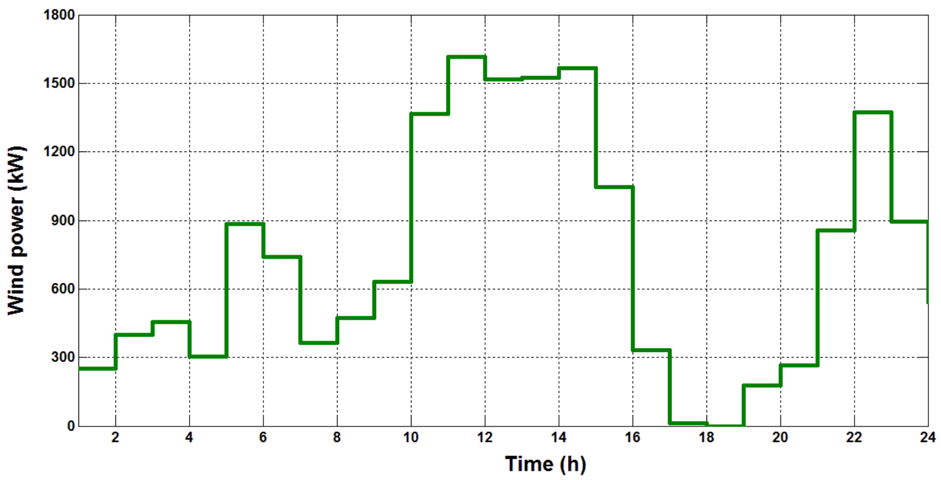

Figure 4. Wind generation prediction.

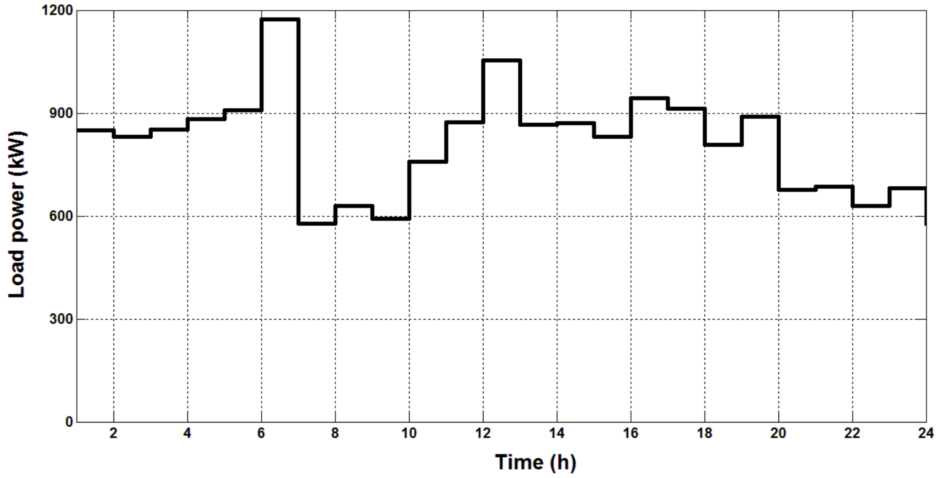

Figure 5. Electric load demand prediction.

The electricity price is shown in Figure 6. The price data is the actual energy cost of industries and big institutions in Atlanta, GA, USA. It is shown that the power-selling bill to the upstream utility network is constant through the operating day, while the electricity purchasing bill from the upstream utility network is dynamic (time-of-use pricing scheme) within the day and has three step-prices within a day (low price period, moderate price period and peak price period).

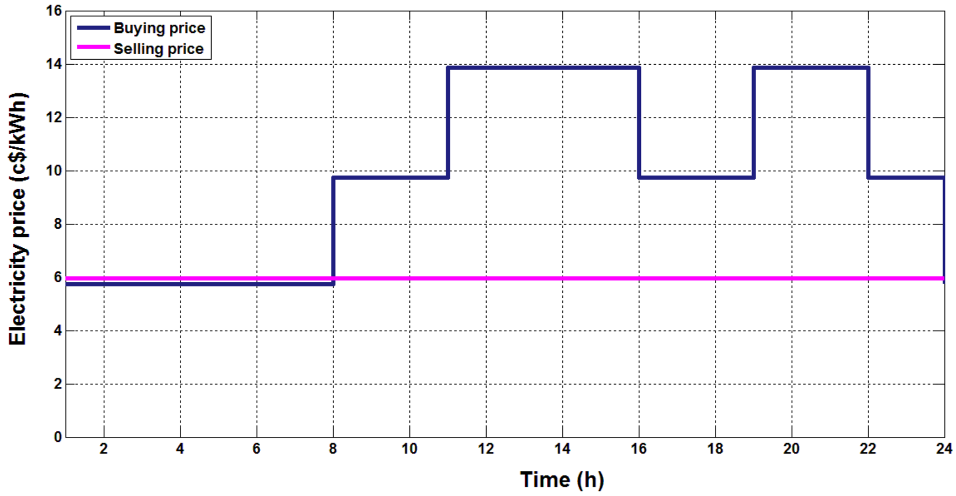

Figure 6. Electricity buying and selling prices.

Table 3 specifies the parameters associated with the O&M expenses for the various components of the microgrid.

Table 3. Operation and maintenance (O&M) cost parameters for various microgrid components. VRB: vanadium redox battery and MG: microgrid.

MG Component	O&M Cost (c$/kWh)
Wind generator	0.3767
Diesel generator	0.5767
VRB	0.003
Li-Ion battery	0.0015

Figure 7 depicts the ACO-based optimal solution for the formulated EMS objective function. The associated SOCs of the ESS devices are also illustrated in Figure 8.

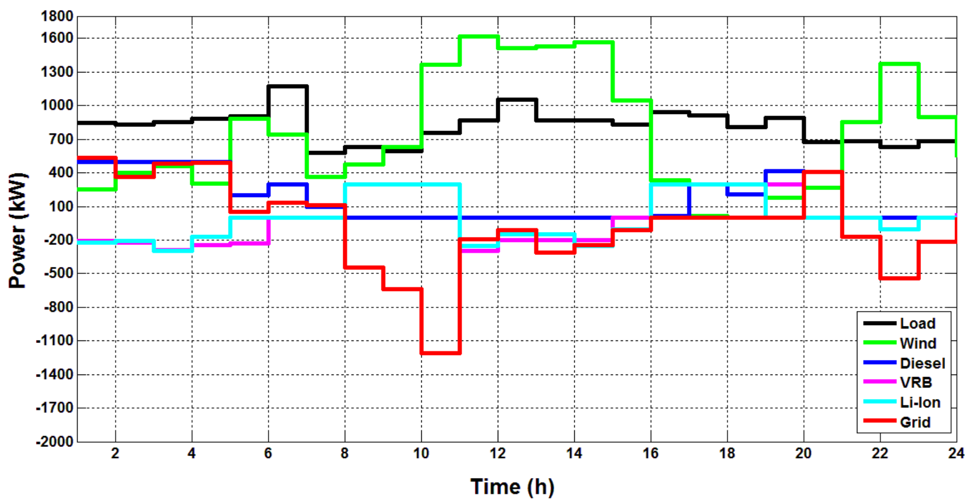

Figure 7. ACO-based optimal EMS solution. VRB: vanadium redox battery.

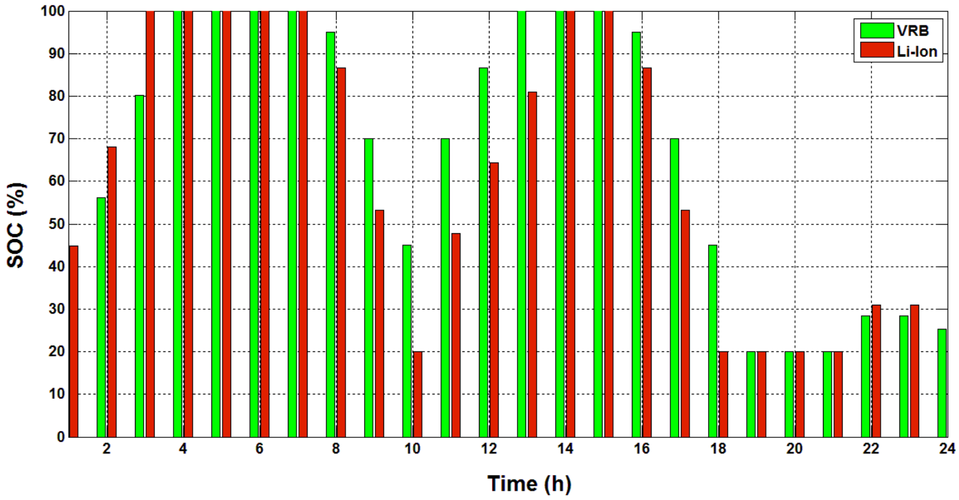

Figure 8. SOCs of the ESS units obtained using ACO.

As clearly observed in Figures 4–8, during the time interval (00:00, 7:00) or (12 a.m., 7 a.m.) the produced wind power cannot deliver the full electricity consumption. However, the utility electricity bill is cheapest in this time interval, and therefore, the MG purchases power from the upstream utility network to support the wind generation to supply the load demand and charge the ESS. The diesel generator also supplies power to support the wind generation in this period. The ESS devices continuously charge and become full in this period.

In the period (7:00, 10:00) or (7 a.m., 10 a.m.), the wind power generation increases and becomes more than the load demand. The ESS units are at their full charge state in this time. Hence, the MG exports the excess energy from the wind power and ESS units in this period and earns profit. The diesel generator stops producing to lower the fuel expense, in this period, as there is excess renewable power production.

During the period (10:00, 15:00) or (10 a.m., 3 p.m.), which is the peak electricity price time interval, the microgrid still has more surplus electricity due to more production by the wind plant. Thus, the MG still keeps selling electricity to the upper utility network and charges the energy storage devices. The diesel generator does not produce power in this period, since there is still excess renewable power production in the MG.

During the period (15:00, 19:00) or (3 p.m., 7 p.m.), the wind power generation decreases and becomes lower than the load demand. The ESS units are at full in this period, and the electricity bill is medium. The microgrid supplies the load demand in this period using the generations from the ESS units and the dispatchable DG, in addition to the wind generation. The MG neither buys nor sells power from/to the utility network in this period.

The wind power generation increases again in the period (20:00, 23:00) and becomes greater than the microgrid electricity consumption. The microgrid exports the surplus generation to the main grid and charges the ESS devices in this period. The diesel generator power is zero in this period to lower the fuel expense, since there is plenty of renewable power production in the MG

Figure 9 shows the PS-based solution of the microgrid EMS optimization problem for the case study microgrid.

The hourly power production fuel cost comparison between the two EMS optimization approaches is shown in Figure 10. It is shown that the ACO-based EMS optimization solution has resulted in lower fuel costs in most of the operating hours of the day.

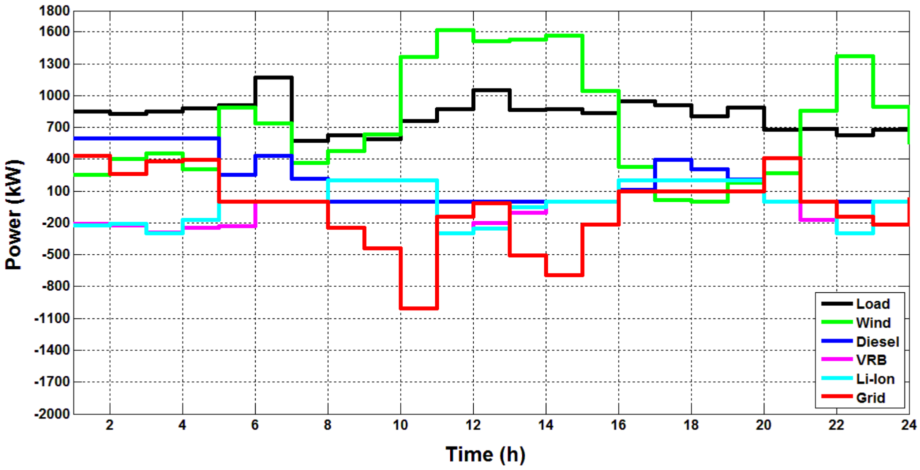

Figure 9. Pattern search PS-based EMS solution.

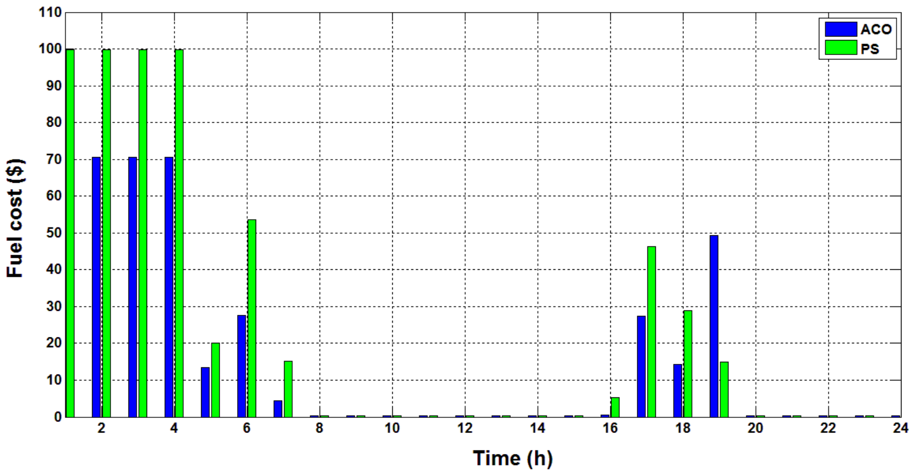

Figure 10. Power production fuel cost comparison.

The hourly main grid power purchasing cost comparison between the two EMS optimization methods is shown in Figure 11. It is observed that the ACO-based EMS optimization solution has given lower purchasing costs in most of the operating hours of the day.

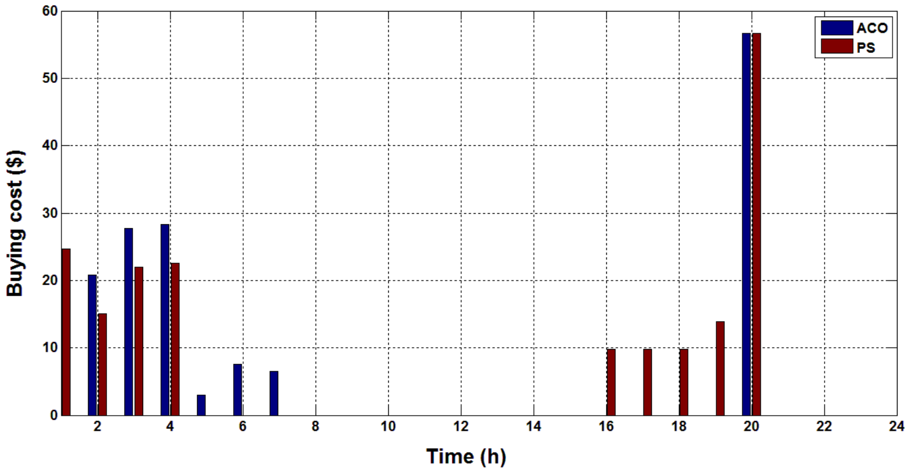

Figure 11. Grid power purchasing cost comparison.

As it is shown in Figures 10 and 11 above, the fuel cost and power purchasing cost are almost zero, as the microgrid has sufficient renewable energy production from the wind during this period.

The comparison of the hourly income of exporting electricity to the upstream utility network between the two EMS optimization techniques is shown in Figure 12. It is clearly shown that the ACO-based EMS optimization solution has achieved a higher income in several hours of the day.

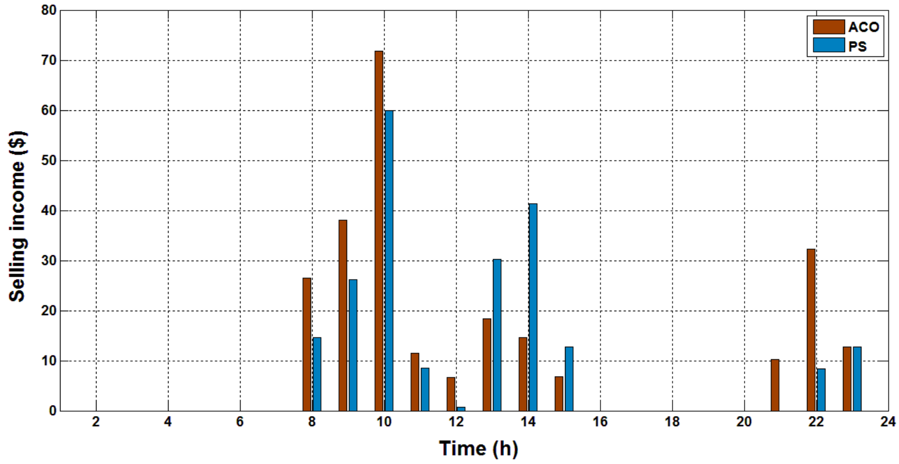

Figure 12. Power selling income comparison.

Table 4 presents the daily power generation fuel cost, grid power purchasing cost and power-selling income by both EMS optimization solutions. It is observed in the table that the proposed ACO-based EMS solution has achieved a lower total fuel cost and grid power purchasing expense and higher total power selling income.

Table 4. Daily cost and income summary. PS: pattern search.

Solution Approach	Total Daily Cost and Income ($)		
	Fuel Cost	Grid Power Purchasing Cost	Grid Power Selling Income
ACO	423.74	180.83	249.56
PS	587.12	186.03	215.58

Table 5 presents the computational time elapsed by both methods to obtain their solutions using the MATLAB/Simulink software (MATLAB2016a, MathWorks.lnc, Natick, MA, USA) platform on a PC with an Intel core i7 CPU, 4.0 GHz processor and 8GB RAM. The ACO-based method has given the optimal solution within a shorter computation time.

Table 5. Computation time comparison.

Solution Approach	Time (s)
ACO	9.52
PS	17.36

5. Conclusions

The optimal energy management approach for a wind-diesel generator ESS microgrid operating in the grid-connected mode was devised based on the ACO algorithm in this paper. The devised approach considers the volatility of wind generation and electricity consumption in the MG, and suitable 24 h-ahead predictions have been used to manage the volatilities. The experimental findings have verified the performance and benefits of the proposed microgrid EMS approach. The approach has achieved lower fuel expenditure and reduced costs of buying electricity from the upstream utility network. It has also resulted in a higher income from the electricity export to the upstream utility grid. The obtained solution has shown effective utilization of the renewable generation and ESS devices. The obtained simulation results have been compared with the PS-based EMS solution and gave outperforming performances with respect to cost, income and computation time. Thus, the obtained numerical results and illustrative demonstrations verify that the proposed EMS approach is effective and robust for the day-ahead power control of MGs with multiple energy resources and storage units. Stochastic energy management with a more robust representation of the uncertainties of the renewable and load demands will be the future research direction and extension of the findings of this paper.

Author Contributions: H.W. and H.L. collected all the microgrid information, developed the optimization model, implemented the optimization algorithm and drafted and revised the paper. X.G. revised the paper format, reviewed the paper and simulated consulting. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The State Key Lab of Alternative Electrical Power System of North China Electric Power University and the Power Supply Company of Henan Shangqiu supported the research.

Conflicts of Interest: The authors declare no conflict of interest.

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