

Energy Management in a Smart Grid Including Demand Response Programs Considering Internet of Things

A. Bolurian¹, H.R. Akbari^{1*}, T. Daemi¹, S.A.A. mirjalily² and S. Mousavi³

1. Department of Electrical Engineering, Yazd Branch, Islamic Azad University, Yazd, Iran.

2. Department of Mechanical Engineering, Yazd Branch, Islamic Azad University, Yazd, Iran.

3. Department of Industrial Engineering, Meybod University, Meybod, Iran.

Receive Date 17 November 2021; Revised 29 November 2021; Accepted Date 7 December 2021

*Corresponding author: h.akbari@iauyazd.ac.ir (H. Akbari)

Abstract

In this paper, we propose an integrated energy management system for grid-connected micro-grids taking into account the demand response programs, fossil fuel-based generators, renewable energy sources, and energy storage systems. In the proposed approach, the constraints of the problem are considered jointly in the model of the energy management systems, and are used for the micro-grid energy management planning and economic dispatch. One of the innovations of this paper is to use the Internet of Things (IoT) platform in order to adjust the maximum ramp rate of production units in the micro-grids due to the limitations of production capacity. Since the system considered models the general state of the internet communication of objects without the requirement to access the communication channel so that the energy of consumers should be minimized as the second objective function in this platform, whenever one of the objects has a message to send, it sends it without the need to reserve a resource and schedule. IoT can establish a good relationship between the power producers in a way that reduces the operating costs by exchanging the data. The optimization of energy consumption in the hybrid power grid studied in this work shows that the use of IoT platform can reduce the transmission line losses in addition to the operating costs. The output results of using data in the IoT context and comparing it with the traditional mode represent the superiority of the proposed approach.

Keywords: *Internet of Things, Energy Management, Optimization, Smart grid.*

1. Introduction

The existing power grids are very large and complex networks consisting of centralized power plants, transmission lines, and distribution networks. These networks have the ability to supply and transmit a large amount of electrical power to the loads. On the other hand, there is a lot of environmental pollution that enters the environment through the electricity industry. The share of electricity generation in the greenhouse gas emissions is 24%, and it is predicted that by 2030, the world electricity consumption will increase by 70%, and consequently, we will have the same amount of greenhouse gas emissions [1, 2]. On the other hand, the current performance of the power grids is hierarchically interconnected, meaning that the energy transmission route is only from the power company to the consumers, and that the power companies have no real-time information from the endpoints in that they have no authority. These networks must be able to

provide a maximum system load with an appropriate level of high reliability. The peak of electricity demand occurs only in a fraction of a year, which is a reason for the non-efficiency of the system [3].

The environmental and economic benefits of the micro-grids and their consequent expansion are closely related to how they are managed, intelligently controlled, and optimized. The primary goal of a micro-grid energy management system in operation is to deliver the electrical power to the consumer with a high reliability, and to optimize power generation towards the pre-determined goals [4]. An energy management program is performed by a central micro-grid controller, locally distributed controllers or a combination of the two. Currently, the approach of using local controllers has attracted more attention, which has led to the emergence of different hierarchical control strategies. In this

strategy, the local controllers have a high degree of intelligence, and do not need to communicate with the central controller for some of their decisions. An energy management program must determine the optimum point of active and reactive power with respect to all the constraints of the problem so that the load consumption power is properly distributed among all the generating sources, and the micro-grid remains stable during disturbances; therefore, the proper operation of the micro-grid according to the set goals is the main task of the energy management program [5, 6].

On the other hand, the new form of using the Internet today is known as the Internet of Things (IoT) among the users. In the IoT technology, all objects have a unique Internet address that can connect to the Internet. According to various statistics, the number of devices connected to the Internet is increasing every year, and a more suitable platform for using IoT is provided [7]. The IoT technology and machine-to-machine communication vary in the type of device communication, amount of data transferred, and data stored. IoT has many applications in various fields, one of the most important of which is the smart city. In a smart city, all parts of the city such as the transportation systems, lighting systems, highways, schools, libraries, hospitals, power plants, water supply networks, garbage collection systems, and many other urban facilities can be integrated, and by integrating their information, the quality of service delivery improve the sections one by one. The IoT technology is one of the key parts of the smart cities. The estimates show that by 2020, the technology will cover more than 30 billion objects [8].

The Intelligent energy management in the context of IoT means maximizing the energy efficiency through energy data collection, DR energy management, and energy sharing/exchange through the development of IoT-based intelligent energy technology. IoT provides intelligent energy management services, energy efficiency improvement, energy sharing, and exchange services through the connection and integration of energy supply or transmission systems or the use of the IoT. To this end, the framework in [9] has implemented the IoT energy management platform in the big energy data system.

The authors in [10] have examined the problem of micro-grid performance planning including renewable energy, which is performed in order to determine the placement of the units with the lowest cost, UC and related adjustment taking into

account the load, environmental, and system requirements. Uncertainty over renewable energy sources as well as the micro-grid capacity to operate in parallel with the main and independent power grid has created a challenge for optimization. The concept of PSS self-sufficiency probability is used to indicate whether the micro-grid is capable of responding to the load independent from the main network (self-sufficiency).

The authors in [11] have presented a random model in order to investigate the effect of uncertainty on the optimal management of micro-grid performance. The proposed random model considers the uncertainties including the load forecasting error and output (wind turbine and solar cell) as well as the market price. The proposed randomized method consists of two main phases. In the first step, using the distribution function PDF probability, each uncertain variable and roulette wheel mechanism creates several scenarios. The wing and the normal probability distribution function of the PDF are used in order to model the possible random variables. In the second stage, a new optimization strategy of the modified self-adapting firefly algorithm is used to solve each one of the specific problems of the first stage. Random optimization with equal and unequal constraints has been investigated. In order to demonstrate the satisfactory performance and performance of the proposed method, a network-connected micro-grid including the wind, solar, micro-turbine, fuel cell, and storage systems in the system have been selected for testing.

In [12], the optimal planning of energy resources and load management in the micro-grids has been evaluated. The electric vehicles offer a promising solution to reduce greenhouse gas emissions. On the other hand, their high influence can also affect the operation of the power system. This is especially important in island micro-grids. Similarly, load responsiveness has the potential to provide considerable flexibility in the operation of a micro-grid with a limited production capacity by changing the demand and introducing an effect of elasticity. This paper introduces a new mathematical model for optimal energy resource planning and intelligent load management, which includes intelligent charging of electric vehicles, load response, and performance of battery storage systems for micro-grids. Various studies have been conducted in order to evaluate the utilization of micro-grids when demand increases, and how the energy management model adapts to such increases [13-17]. The proposed model proposes

several energy management strategies by considering network constraints and different target functions from the perspective of network operation as well as from the perspective of the owners of electric vehicles and battery storage systems.

In this paper, a novel energy management framework is presented, which is the main contribution of this paper: 1) using the mixed integer programming (MIP) including the Benders decomposition approach to choose the most appropriate capacities of DGs regarding to reduce the operating costs through the demand response; 2) the IoT technology is used for data exchanging in order to realize whenever the suitable power generation supplies the demands or it may be in the peak hours and avoid malfunctions. For this purpose, first, the distributed generation sources are formulated mathematically in Section 2, and the objective function is presented with equal and unequal constraints. Then in Section 3, the optimization method in the GAMS software with the CPLEX solution method is described and the feasible area for the optimal answers is specified. The simulations and analysis of the results obtained are presented in Section 4, and finally, in Section 5, the conclusions will be presented.

2. Problem formulation

In this section, the issue of energy management in the presence of IoT is stated, and then its formulation is presented. Figure 1 shows a smart home/city that communicates between its components using Wi-Fi Internet. In a smart grid, the components of the entire network can be connected and exchanged over the Internet. In general, the smart grid discussed in this paper is an AC-DC hybrid grid powered by various energy sources, which are represented in figure 2.

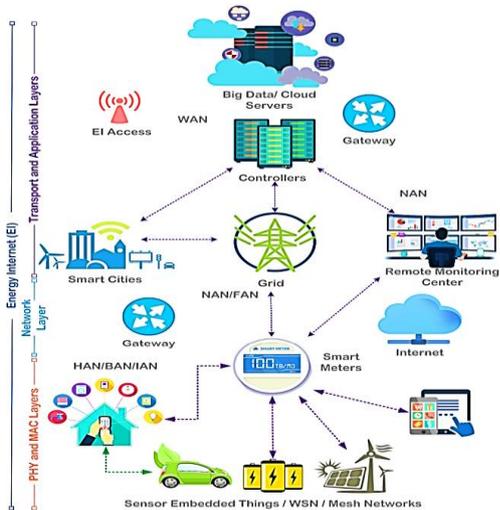


Figure 2. A typical smart area equipped with IoT.

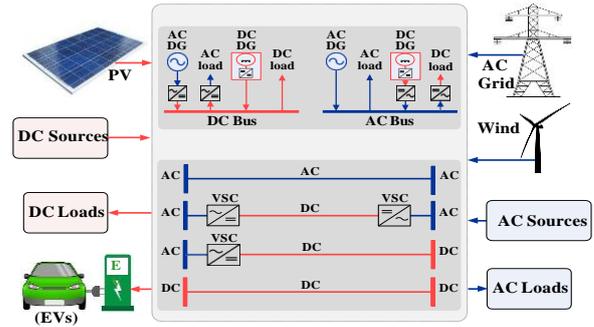


Figure 2. A simple hybrid micro-grid.

2.1. Energy storage

The operation cost of the battery for both the charging and discharging modes is mathematically calculated with (1) [18-20].

$$Cost_t^{Bat,Ch} = \frac{\left(\frac{C_{in}^B}{L_t^{B,Ch}} + C_M^B \right) U_t^{Ch}}{\eta^{B,Ch}} \quad (1)$$

$$Cost_t^{Bat,Dis} = \left(\frac{C_{in}^B}{L_t^{B,Dis}} + C_M^B \right) \frac{U_t^{Ch}}{\eta^{B,Dis}}$$

where C_{in}^B and C_M^B are the investment and maintenance costs, respectively. $L_t^{B,Ch}$ and $L_t^{B,Dis}$ are represented, the useful battery lifetime which are calculated with the following equations.

$$L_t^{B,Ch} = \frac{N_B N_C U_B Q_B}{P_t^{Ch}} \eta^{B,Ch} \quad (2)$$

$$L_t^{B,Dis} = \frac{N_B N_C U_B Q_B}{P_t^{Dis}} \eta^{B,Dis}$$

Similar to the cost of battery charging in charge states, the cost of a hydrogen storage system is related to the cost of hydrogen peroxide produced by electrolyzer to consume the fuel cell, as explained below.

$$C_t^{H_2,Ch} = \frac{U_t^{EL}}{\eta^{EL} \eta^{FC}} \left(\frac{C_{in}^{EL}}{L_t^{EL}} + C_M^{EL} \right) + \left(\frac{C_{in}^{FC}}{L_t^{FC}} + C_M^{FC} \right) \quad (3)$$

Furthermore, if the demand is to be provided by the hydrogen storage system, a fuel cell must be utilized as a generation power unit. Therefore, the cost of using the fuel cell is calculated in accordance with (4).

$$C_t^{FC} = \left(\frac{C_{in}^{FC}}{L_t^{FC}} + C_M^{FC} \right) U_t^{FC} \quad (4)$$

The equations (5) to (14) correspond to the technical constraints of the battery storage system. Equation (6) shows the initial energy of the

battery, and (7) and (8) represent the limitations of the minimum and maximum energy stored in the battery. In these constraints, the maximum and minimum battery charging and discharging power are shown in (9) to (12), and it should be noted that the battery cannot be charged or discharged simultaneously, which is compulsory in (13). Eventually, equation (14) shows the energy at any time interval for the battery utilization.

$$U_{t,Fc}^{ON} + U_{t,Fc}^{off} \leq 1 \quad (5)$$

$$SOC_{t0} = SOC_{initial} \quad (6)$$

$$SOC_t < SOC_{max} \quad (7)$$

$$SOC_t > SOC_{min} \quad (8)$$

$$P_t^{Ch} < P_{max}^{Ch} \cdot U_t^{Ch} \quad (9)$$

$$P_t^{Ch} > P_{min}^{Ch} \cdot U_t^{Ch} \quad (10)$$

$$P_t^{Dis} < P_{max}^{Dis} \cdot U_t^{Dis} \quad (11)$$

$$P_t^{Dis} > P_{min}^{Dis} \cdot U_t^{Dis} \quad (12)$$

$$U_t^{Dis} + U_t^{Ch} \leq 1 \quad (13)$$

$$SOC_t = \eta^{B,Ch} \cdot P_t^{Ch} - \frac{P_t^{Dis}}{\eta^{B,Dis}} + SOC_{t-1} \quad (14)$$

2.2. Photovoltaic array model

The solar cells convert the solar energy into the electrical power. Since the output power of solar arrays depends on the intensity of radiation and the temperature, their control point in order to absorb the maximum power is greatly important. In most of the methods, the optimal operating point is estimated using a linear approximation, which refers to the maximum power point tracking (MPPT) strategy. Equation (15) at the temperatures derived from P_t^{PV} of the PV cell with various radiation estimates the most potentially solar power. It is found that the output power depends strongly on the solar radiation and atmospheric temperature.

$$P_t^{PV} = G_t \cdot A_{PV} \cdot N_{PV} \cdot \eta^{PV} \quad (15)$$

η^{PV} is a function of the intensity of the solar radiation and the ambient temperature that is defined by the following equation:

$$\eta^{PV} = -\eta_{ref}^{PV} a \left(+G_t \cdot \frac{T_t - T_{ref}}{800} \right) + \eta_{ref}^{PV} \quad (16)$$

where η_{ref}^{PV} determines the cell efficiency at standard conditions, and T_{ref} and a are the standard temperature and the temperature coefficient, respectively. Furthermore, $NOCT$ is

the cell temperature at the operation conditions with the ambient temperature, T_t .

2.3. Wind turbine model

The wind turbine converts the wind energy into the electric power, which for the aerodynamic studies, the blades have aerodynamic coefficient curves. The conversion power of a wind turbine is obtained from (17), where $A = \pi r^2$ is the effective cross-section covered by the blades, ρ is the air density, and $C_p(\gamma, \beta)$ shows the aerodynamic characteristics. In this paper, the power output of a turbine wind is expressed using the curvature interpolation method, and for wind speed uncertainty modeling, the Weibull distribution function is used in order to generate the wind speed scenario. Therefore, the wind turbine output power at any time and in each scenario is expressed as (19).

$$P_{conversion} = \frac{1}{2} \rho \cdot A \cdot C_p(\gamma, \beta) \cdot V_t^w \quad (17)$$

$$P_t^{wind} = \begin{cases} 0 & ; V_t^w < V_{ci} \\ P_r \cdot \frac{V_t^w - V_{ci}}{V_r - V_{ci}} & ; V_{ci} < V_t^w < V_{cr} \\ P_r & ; V_r < V_t^w < V_{c0} \\ 0 & ; V_t^w > V_{c0} \end{cases} \quad (18)$$

where P_r , V_{ci} , V_{c0} , V_r , V_{cr} , and V_t^w are the nominal power, connecting speed, cut-off speed, speed in rated power, critical speed, and wind speed at time t , respectively.

2.4. Fuel cell and hydrogen storage

In the recent years, the usage of a hydrogen storage system has been developed in independent energy systems. In these storage classifications, when the production capacity of new sources of energy exceeds the demand load, the excess electricity production by electrolysis can lead to the production of hydrogen and reservoirs under pressure. This stored hydrogen can be used by the fuel cell in order to generate electrical power and provide part of the grid load when the grid load is more than existing DERs. Equations (19) to (21) rely on the technical limitations of the hydrogen storage system with excess power consumption by the electrolyzer. The hydrogen molecules from the electrolyzer are charged as a function of the power consumed by the electrolysis process, and will be stored in hydrogen under pressure tanks. The minimum and maximum power consumption limits by the electrolyzer are indicated in (19) to (20). Then the maximum limitation of the number of hydrogen molecules is expressed in (21), which

is a function of the power consumption of the electrolyzer.

$$P_t^{EL} < P_{max}^{EL} \cdot U_t^{EL} \quad (19)$$

$$P_t^{EL} > P_{min}^{EL} \cdot U_t^{EL} \quad (20)$$

$$N_{H_2}^{EL} = \frac{\eta^{EL} P_t^{EL}}{LHV_{H_2}} < N_{H_2,max}^{EL} \cdot U_t^{EL} \quad (21)$$

The initial pressure and the maximum and minimum limits of hydrogen tanks are formulated in (22) to (23), respectively.

$$P_{t0}^{H_2} = P_{initial}^{H_2} \quad (22)$$

$$P_t^{H_2} < P_{max}^{H_2} \quad (23)$$

$$P_t^{H_2} > P_{min}^{H_2} \quad (25)$$

When the grid demand exceeds the capacity of the DERs capacity and the storage systems, the fuel cell consumes hydrogen molecules stored in the hydrogen tanks and generates electrical energy. The maximum number of moles consumed by the fuel cell is introduced by (25), and the amount of power produced by the fuel cell, which is a function of the number of moles consumed, is shown in (25). Furthermore, the maximum and minimum limitations of the production capacity by the fuel cell are stated in equations (26) and (27).

$$N_t^{H_2,FC} = \frac{\eta^{FC} P_t^{FC}}{LHV_{H_2}} < N_{max}^{H_2,FC} \cdot U_t^{FC} \quad (25)$$

$$P_t^{FC} < P_{max}^{H_2} \cdot U_t^{FC} \quad (26)$$

$$P_t^{FC} > P_{min}^{H_2} \cdot U_t^{FC} \quad (27)$$

2.5. Demand response model

In this paper, the demand response program used is a type of the time of use (TOU) schedule process. The purpose of using the load response program is to smooth the load power curve using the load shift from peak intervals to the mid-range intervals, and thus reduce the operation costs. The demand response schedule can be modeled as whatever is represented in [25]. The grid operator can only transfer some parts of the load to other time intervals, while the mathematical formulations are in (35) and (36). The technical constraints of the demand response plan are expressed in (37) to (40). Equation (37) indicates the load amount never changes but it transfers from peak intervals to a low time loading. Correspondingly, the incremental load value should be less than the percentage of the base in which the percentage of reduction or increasing in the load must be smaller than a certain value. It

should be noted that this percentage is 20% in this work.

$$load(t) = (1 - DR(t))Load_0(t) + ldr(t) \quad (28)$$

$$Load_0(t) - load(t) = DR(t) \cdot Load_0(t) - ldr(t) \quad (29)$$

$$\sum_{t=1}^T ldr(t) = \sum_{t=1}^T DR(t) \cdot Load_0(t) \quad (30)$$

$$load(t)_{inc} < inc(t) \cdot Load_0(t) \quad (31)$$

$$DR(t) < DR_{max} \quad (32)$$

$$inc(t) < inc(t)_{max} \quad (33)$$

2.6. Optimization Problem

Finally, a new management strategy based on IoT is proposed in order to reduce the operating costs. The proposed objective function is the summation of the total cost of operating batteries in the two modes of charging and discharging, PVs, WTs, and FCs. The proposed objective function is modeled in (34), which should be minimized.

$$\min \sum_{t=1}^T \left(Cost_t^{Bat,Ch} + Cost_t^{Bat,Dis} + C_t^{PV} + C_t^{FC} + C_t^{wind} \right) \quad (34)$$

The total production capacity in the electrical grid should be equal to the total power consumption and the power loss. This constraint is indicated in (35), and it should be noted that the load factor has been replaced with a new load response program.

$$P^{wind} + P^{PV} + P^{Dis} + P^{FC} = P^{Ch} + P^{load} \quad (35)$$

$$\forall t \in \{1, 2, \dots, T\}$$

Since the system considered in this work models the general state of the Internet communication of objects without the need to access the channel, in order to optimize the energy of consumers, we consider the following measures. Consider a set of IoTs (set ϕ) in a geographic range. The data transfer from the objects to the server is done through the access points located in this range (Figure 1). Whenever one of the objects has a message to send, it sends it without the need to reserve a resource and schedule. Each access point of these different devices in the IoT has different patterns in the use of radio sources; more precisely, such as the time between two data transmissions, the signal bandwidth used, the transmission power, the data transmission rate, and the packet transfer time vary from device to device. In this section, we show the frequency bandwidth shared for communication with W and the spectral power density of the noise with N . Suppose that from the Φ set, the Φ_S subset we are

looking to gather information, and the traffic of other objects is considered as interference. The problem investigated in this section is the control of the telecommunication parameters for a set of IoT devices, Φ_s , based on the observation and interaction with the environment. Assume that at time 1, the t^{th} device from the Φ_s set requires to send data, in which case the problem is formulated as follows:

$$\max\{F(\text{Consumption}_{\text{IoT}(\text{devices})})\} \quad (36)$$

where $F(.)$ expresses the objective function and creates a balance between the energy consumption and the reliability of communication. Due to the difference in the quality of service (QoS) in different IoT applications, the definition of the $F(.)$, this function in each application could be different from other applications. In this work, the sum of the weighted and standardized values is considered to be in the (0,1) interval.

3. Optimization method

The main goal in this optimization is to find a set of solutions to the objective function including a set of linear constraints. In other words, the optimization problem is as follows:

$$\begin{aligned} &\text{Maximize } c_1x_1 + c_2x_2 + \dots + c_dx_d \\ &\text{subject to } \begin{cases} a_{11}x_1 + \dots + a_{1d}x_d \leq b_1 \\ \vdots \\ a_{11}x_1 + \dots + a_{1d}x_d \leq b_1 \end{cases} \end{aligned} \quad (37)$$

The objective function can be considered as a directional vector. As shown in figure (3), a $f_{\vec{c}}$ shows the objective function defined by the vector \vec{c} . In order to maximize the objective function, the farthest point must be found on the vector \vec{c} in the feasible region so that [21]:

$$\begin{aligned} \vec{C} &= (C_x, C_y) \\ f_{\vec{c}}(p) &= c_x p_x + c_y p_y \end{aligned} \quad (38)$$

In order to solve this problem, the CPLEX method is applied, which is widely used practically. The procedure is as follows:

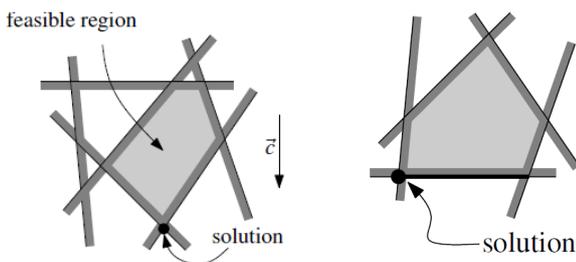


Figure 3. MILP flowchart: (a) feasible region, (b) optimal solution.

- The set of n linear constraints in a two-variable linear problem is denoted by $H = \{h_1, h_2, \dots, h_n\}$.
- The vector \vec{c} defines the objective function, and the purpose is to find a point in $p \in R^2$ where $f_{\vec{c}}$ is maximum and $p \in \cap H$.
- The linear problem is then represented by (H, \vec{c}) , and the feasible region that is marked as C .

Then in each step, a constraint is added and an optimal solution is obtained for the new sub-problem. Therefore, the answer to each one of the intermediate problems needs to be acceptable and unique. In other words, it is assumed that each intermediate feasible area has a unique optimal vertex but this condition may not always be met. Thus in order to ensure that the issue is finite, we add two new constraints, as follows:

$$\begin{aligned} m_1 &= \begin{cases} p_x \leq M & ; \text{ if } c_x > 0 \\ -p_x \leq M & ; \text{ elsewhere} \end{cases} \\ m_2 &= \begin{cases} p_y \leq M & ; \text{ if } c_y > 0 \\ -p_y \leq M & ; \text{ elsewhere} \end{cases} \end{aligned} \quad (39)$$

- M must be large enough that the added constraints do not affect the optimal solutions, where m_1 and m_2 are selected independently to the half pages of H . The subscription area of the m_1 and m_2 regions is also a corner area. Therefore, if the infinite problem has an answer, in this case, the smallest point in the lexical order will be the optimal point.
- With these two conventions, every linear problem that becomes feasible has a unique answer, which is the vertex of the feasible region, and this vertex is called the optimal vertex.
- Therefore, the problem will be solved by repeating this loop.

4. Simulation results and discussion

The simulations are performed on the standard IEEE 33-bus system, as shown in figure 4. The impedance specifications of the lines and loads of the system are given in [22]. The specifications of the distributed generation sources are also adapted from [23-24], given in table 1. The efficiency of this hybrid system is 96%, and its loss rate is converted into heat in the converters. The simulations in this section are done in two ways:

- 1- Regardless of Iot
- 2- Considering Iot

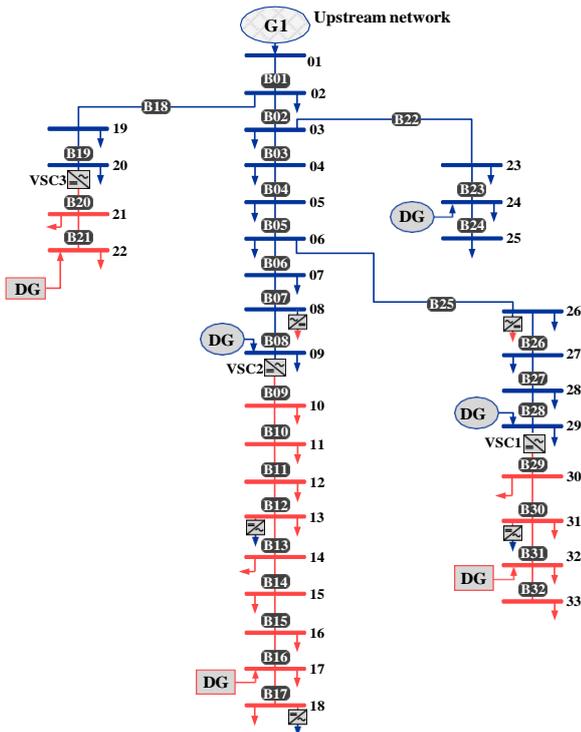


Figure 4. Standard IEEE 33-bus system.

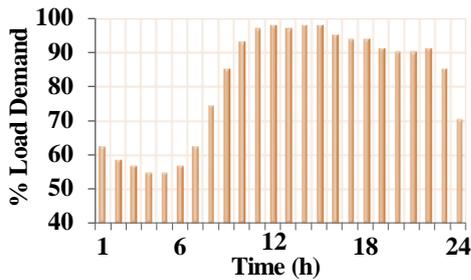


Figure 5. System load diagram.

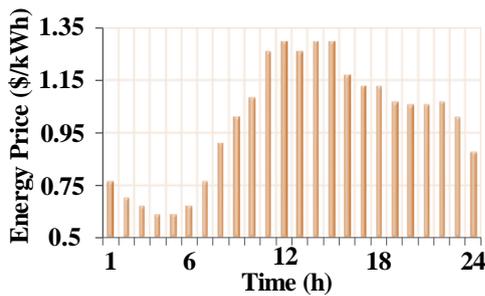


Figure 6. Cost of electricity tariffs.

In the first step, we first check the system inputs over a 24-hour period. Figure 5 is the system load diagram that must be provided. Figure 6 shows the cost of electricity tariffs, and figure 7 shows the best output power of photovoltaic sources. Finally, figure 8 shows the power output of the wind turbine, and figure 9 shows the power obtained from the fuel cell source at different hours.

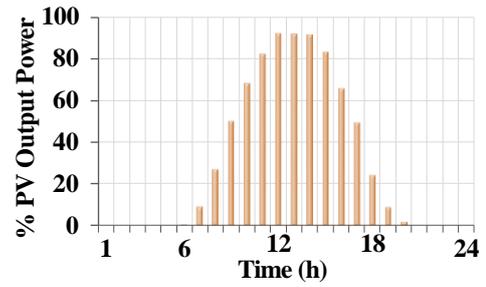


Figure 7. Best output power of photovoltaic source.

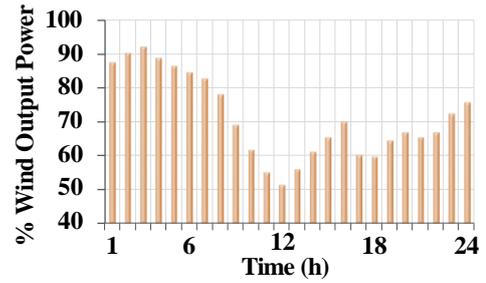


Figure 8. Power output of wind turbine.

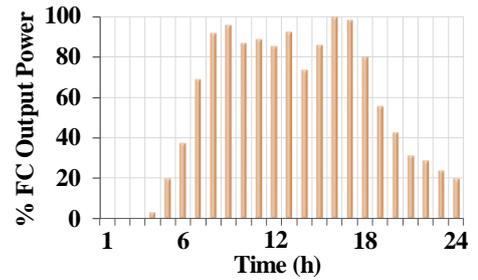


Figure 9. Power obtained from fuel cell source.

Table 1: DG types, costs, and power limitations.

DG No.	Type	P_{min} (kW)	P_{max} (kW)	Cost (\$/h)
1	PV	50	250	0.12
2	WT	50	300	0.21
3	ESS	50	250	0.42
4	FC	50	200	0.35
5	Tnak _{H2}	450 kg	1000 kg	0.19

Since the problem of optimal micro-grid energy management planning is a linear optimization problem with large-scale binary variables, the pure mixed-integer (MIP) optimization requires a high-power processor as well as a long time to solve the problem; Therefore, with the help of alternative computational methods, we should try to reduce the implementation time of optimization in such problems that have a large number of variables. For this purpose, in the proposed model,

the Benders decomposition method is used in order to overcome the complexity of the problem. The Benders decomposition method divides large and complex problems into smaller and simpler problems. The first part, called the main problem (MP), is actually the original problem in which some variables are taken out of the problem space and considered as a specific parameter. The second part of the Benders decomposition model includes the sub-problem (SP) or auxiliary problem; the auxiliary problem consists of a part of the initial problem in which some variables are valued based on the answer to the main problem. When the auxiliary problem is solved based on the answers obtained from the main problem, some constraints and conditions may not be met because the two main and auxiliary problems have been solved separately. In fact, the Benders decomposition method solves the two main and auxiliary problems repeatedly, and at each stage, the Benders decomposition section is produced and used in the next iteration. This repetitive method continues until no more port cuts are produced. This means that the optimal solutions obtained from the main problem do not violate the constraints of the auxiliary problem, and the same optimal solutions are the main problem. These conditions are reconsidered, and the information about each section is considered as a sensor node and the effect of each in expressing the network energy is expressed. Finally, the results of both methods (once with the help of the Benders decomposition method and once with the fuzzy genetic algorithm) are compared.

In order to implement the IoT platform, the various parts of the proposed system are first identified as the nodes or sensors in an IoT-based network (IoT-based networks are usually a small town with nodes that are modeled differently), which are implemented in the same size as the target network. For example, the one-time consumption in the proposed micro-grid is modeled as a point in the IoT network whose location is considered according to the location of the same load in the micro-grid. (In other words, the information about the components of a micro-grid as primary information in a sensor network are modeled using the fuzzy logic). Now after modeling the IoT network, we consider each desired part of the micro-grid, which is equivalent to a node in the IoT network, as a sensor or a piece that has the ability to transmit data wirelessly. In order to control the micro-grid, considering the effect of each part on the micro-grid, we apply these effects as a mathematical

model, and as a result, we optimize the micro-grid output, which is energy management.

In order to analyze the IoT network, in addition to considering the total micro-network energy, the IoT system energy itself must be optimized, and the MATLAB software is used for implementation. Its purpose is to optimize the performance of the micro-grid system in transmitting information to change the behavior of the micro-grid. After performing the simulation, the output results are listed in tables 2 and 3. It can be seen that if the IoT system is used, the operating cost will be reduced from \$1674.39 in the traditional case to \$1588.74. Meanwhile, the network losses have decreased from 951.84 kWh to 867.79 kWh.

Table 2. Operation costs comparison between IoT state and conventional mode.

Hour	Operation costs considering IoT (\$)	Operation costs without IoT (\$)
1	51.21	54.65
2	47.54	51.22
3	44.26	46.87
4	49.89	52.65
5	54.65	57.54
6	57.21	61.20
7	59.44	63.79
8	61.52	66.12
9	63.95	69.11
10	70.89	72.45
11	74.52	76.26
12	75.32	79.33
13	78.66	81.44
14	81.48	85.27
15	83.29	88.05
16	80.58	86.65
17	74.26	81.97
18	73.85	77.82
19	80.05	82.25
20	76.57	79.19
21	72.65	75.30
22	65.95	69.56
23	59.26	63.05
24	51.74	52.65
Total	1588.74	1674.39

Table 3. Network loss comparison between IoT state and conventional mode.

Hours	Network loss considering IoT (kW)	Network loss without IoT (kW)
1	25.84	29.52
2	21.30	23.45
3	23.48	25.23
4	24.36	27.15
5	26.11	29.95
6	27.29	29.75
7	30.54	33.46
8	32.68	34.22
9	33.32	36.34
10	36.26	38.05
11	37.96	41.26
12	39.79	42.39
13	40.26	46.48
14	44.23	48.25
15	47.94	52.36
16	51.75	55.12
17	52.15	59.58
18	48.02	52.05
19	46.35	49.16
20	43.05	45.30
21	39.65	43.15
22	34.16	39.25
23	31.78	36.14
24	29.52	34.23
Total	867.79	951.84

Figures 10 and 11 show how the production units come into orbit and their output power to supply the load profile, respectively. It is true that in both cases the total production capacity per hour is equal but because in the case of the IoT more renewable energy sources are used, the operating cost is calculated at the same lower amount.

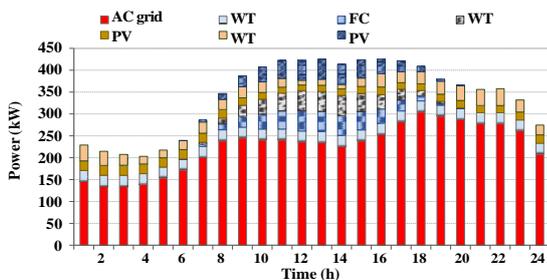


Figure 10. Power sharing for different kinds of DGs and AC grid without using IoT.

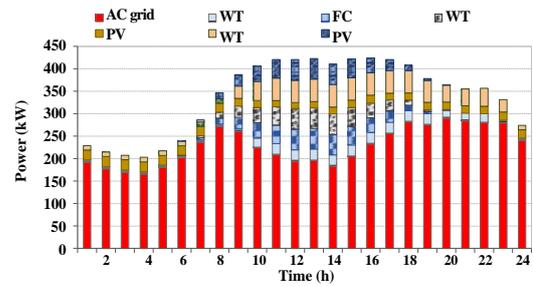


Figure 11. Power sharing for different kinds of DGs and AC grid considering IoT.

7. Conclusion

In this paper, an IoT-based mathematical framework was proposed in order to optimize energy consumption in the grid. Since the use of IoT can facilitate the exchange of data between the equipment of a micro-grid, in this work, this technology was used to enable a better decision-making and optimization. The output results show that optimizing energy consumption in the IoT platform can reduce the operating costs by about 5.3% and the network line losses by about 19%. This is important only by selecting the optimal sources of distributed generation in the micro-grid and determining their optimal output power to supply the load. The Benders decomposition method in the GAMS software simplifies the calculations, and reduces the time to achieve the optimal answer. Therefore, the simultaneous use of IoT with the Benders decomposition method is able to perform the optimal power management at the micro-grid as a desirable optimization framework. The challenges for simulating and implementing IoT in a network energy management system include the following:

- Delays in the telecommunication band width and Internet platforms that cause malfunctions in the optimal control of the equipment.
- High investment cost for implementing smart sensors in the IoT platform.
- Most network users are unfamiliar with the IoT applications, and require training classes.
- Need a powerful controller system in order to synchronize communication between the equipment.

Finally, several suggestions that can improve the efficiency of energy management in the IoT context are as follow:

- Using meta-heuristics algorithms for optimal coordination between the equipment.
- More accurate modeling of the components used in the IoT platform and their power consumption mathematical formulation.

- Integration of telecommunication and internet communications in order to increase the speed in sending and receiving the data.
- Use of neural network in order to estimate the incomplete received information.

8. Reference

- [1] R. Alayi and J. Javad Velayti, "Modeling/optimization and effect of environmental variables on energy production based on PV/wind TURBINE hybrid system," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, Vol. 7, No. 1, p. 101, 2021.
- [2] H. Khalili, A. Arash, and R. Alayi, "Simulation and economical optimization hybrid system PV and grid in Ardabil city" *Journal of Current Research in Science*, Vol. 3, No. 5, pp. 74-83, 2015.
- [3] R. Alayi, M. R. Basir Khan, and M. S. Mohmammadi, "Feasibility study Of GRID-CONNECTED PV system for peak demand reduction of a residential building in Tehran, Iran," *Mathematical Modelling of Engineering Problems*, Vol. 7, No. 4, pp. 563-567, 2020.
- [4] R. Alayi and H. Rouhi, "Techno-Economic analysis of electrical energy generation from Urban waste IN HAMADAN, IRAN," *International Journal of Design and Nature and Eco-dynamics*, Vol. 15, No. 3, pp. 337-341, 2020.
- [5] A. Kasaeian, A. Shamel, and R. Alayi, "Simulation and economic optimization of wind turbines and photovoltaic hybrid system with storage battery and hydrogen tank (case study the city of Yazd)" *Journal of current research in science*, Vol. 3, No. 5, pp. 96-105, 2021.
- [6] R. Alayi and F. Jahanbin, "Generation management analysis of a stand-alone photovoltaic system with battery" *Renewable Energy Research and Application*, Vol. 1, No. 2, pp. 205-209, 2020.
- [7] A. Khodaei, "Micro-grid Optimal Scheduling with Multi-period Islanding Constraints," in *IEEE Transactions on Power Systems*, Vol. 29, No. 3, pp. 1383-1392, 2014.
- [8] A. Khodaei, "Resiliency-Oriented Micro-grid Optimal Scheduling," in *IEEE Transactions on Smart Grid*, Vol. 5, No. 4, pp. 1584-1591, 2014.
- [9] T. Ku, W. Park, and H. Choi, "IoT energy management platform for micro-grid," *2017 IEEE 7th International Conference on Power and Energy Systems (ICPES)*, pp. 106-110, 2017.
- [10] B. Zhao, Y. Shi, X. Dong, W. Luan and J. Bornemann, "Short-Term Operation Scheduling in Renewable-Powered Micro-grids: A Duality-Based Approach," in *IEEE Transactions on Sustainable Energy*, Vol. 5, No. 1, pp. 209-217, 2014.
- [11] A. Fathy, K. Kaaniche, and T. M. Alanazi, "Recent Approach Based Social Spider Optimizer for Optimal Sizing of Hybrid PV/Wind/Battery/Diesel Integrated Micro-grid in Aljouf Region," in *IEEE Access*, Vol. 8, pp. 57630-57645, 2020.
- [12] F. Delfino, G. Ferro, M. Robba, and M. Rossi, "An Energy Management Platform for the Optimal Control of Active and Reactive Powers in Sustainable Micro-grids," in *IEEE Transactions on Industry Applications*, Vol. 55, No. 6, pp. 7146-7156, 2019.
- [13] S. Marzal, R. González-Medina, R. Salas-Puente, G. Garcerá, and E. Figueres, "An Embedded Internet of Energy Communication Platform for the Future Smart Micro-grids Management," in *IEEE Internet of Things Journal*, Vol. 6, No. 4, pp. 7241-7252, Aug. 2019.
- [14] R. M. González, F. D. Wattjes, M. Gibescu, W. Vermeiden, J. G. Sloopweg, and W. L. Kling, "Applied Internet of Things Architecture to Unlock the Value of Smart Micro-grids," in *IEEE Internet of Things Journal*, Vol. 5, No. 6, pp. 5326-5336, 2018.
- [15] J. Li et al., "Decentralized On-Demand Energy Supply for Blockchain in Internet of Things: A Micro-grids Approach," in *IEEE Transactions on Computational Social Systems*, Vol. 6, No. 6, pp. 1395-1406, 2019.
- [16] M. H. Cintuglu and D. Ishchenko, "Secure Distributed State Estimation for Networked Micro-grids," in *IEEE Internet of Things Journal*, Vol. 6, No. 5, pp. 8046-8055, 2019.
- [17] E. Harmon, U. Ozgur, M. H. Cintuglu, R. de Azevedo, K. Akkaya, and O. A. Mohammed, "The Internet of Micro-grids: A Cloud-Based Framework for Wide Area Networked Micro-grids," in *IEEE Transactions on Industrial Informatics*, Vol. 14, No. 3, pp. 1262-1274, 2018.
- [18] N. Rezaei, A. Ahmadi, A. H. Khazali, and J. M. Guerrero, "Energy and Frequency Hierarchical Management System Using Information Gap Decision Theory for Islanded Micro-grids," in *IEEE Transactions on Industrial Electronics*, Vol. 65, No. 10, pp. 7921-7932, Oct. 2018
- [19] B. Zhou et al., "Optimal Scheduling of Biogas-Solar-Wind Renewable Portfolio for Multicarrier Energy Supplies," in *IEEE Transactions on Power Systems*, Vol. 33, No. 6, pp. 6229-6239, 2018
- [20] J. Martinez-Rico, E. Zulueta, I. R. de Argandoña, U. Fernandez-Gamiz, and M. Armendia, "Multi-objective Optimization of Production Scheduling using Particle Swarm Optimization Algorithm for Hybrid Renewable Power Plants with Battery Energy Storage System," in *Journal of Modern Power Systems and Clean Energy*, Vol. 9, No. 2, pp. 285-294, 2021
- [21] M. Barros and M. Casquilho, "Linear Programming with CPLEX: An Illustrative Application Over the Internet CPLEX in Fortran 90," *2019 14th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1-6, 2019.

[22] S. H. Dolatabadi, M. Ghorbanian, P. Siano, and N. D. Hatziargyriou, "An Enhanced IEEE 33 Bus Benchmark Test System for Distribution System Studies," in *IEEE Transactions on Power Systems*, Vol. 36, No. 3, pp. 2565-2572, 2021.

[23] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-Side Management via Distributed Energy Generation and

Storage Optimization," in *IEEE Transactions on Smart Grid*, Vol. 4, No. 2, pp. 866-876, June 2013.

[24] M. Ross, C. Abbey, F. Bouffard, and G. Jos, "Multi-objective Optimization Dispatch for Microgrids with a High Penetration of Renewable Generation," in *IEEE Transactions on Sustainable Energy*, Vol. 6, No. 4, pp. 1306-1314, 2015.