Optimal Design of an On-Grid MicroGrid Considering Long-Term Load Demand Forecasting: A Case Study

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Abstract

In this article, an optimal on-grid MicroGrid (MG) is designed considering long-term load demand prediction. Multilayer Perceptron (MLP) Artificial Neural Network (ANN) is used for time-series load prediction. Yearly demand growth has also been considered in the optimization process based on the forecasted load profile. Two different case studies are performed with the forecasted and historical load profiles, respectively. According to the results, by considering the predicted load profile, realistic results of net present cost (NPC), cost of energy (COE), and MG configuration would be achieved. The NPC and COE are obtained as 566,008$ and 0.0240 $/kWh, respectively. It is also demonstrated that utilizing battery storage systems (BSSs) is not

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economic in the proposed approach. The introduced MG also produces lower emissions compared to the system with the historical load profile. In this regard, 563,909 kg of CO_2 is produced over the optimization year, which is 35,623 kg lower than the case with no load growth rate. According to the sensitivity analysis results, when the inflation rate increases from 18.16 % to 32.36 %, the COE's value rises to 0.021 USD/kWh accordingly. In contrast, the NPC of the system decreases significantly from above 400×103 USD to about 200×103 USD as the inflation rate increases from 18.16 to 32.36.

Keywords: Artificial neural networks (ANNs), load forecasting, microgrids (MGs), renewable energy sources (RESs), multilayer perceptron (MLP).

1 Introduction

Renewable energy sources (RESs) are becoming alternatives for fossil fuels all over the world. However, fossil fuels are the primary source of energy in Iran. These resources produce a large number of greenhouse emissions, such as carbon dioxide (CO_2). One of the adverse outcomes of uncontrolled fossil fuel usage is placing Iran among the world's top greenhouse emission producers [4]. In 2018, two primary energy sources for electricity generation, i.e., natural gas and oil, emitted 123.5 MtCO2 and 45.0 MtCO2, respectively [1]. In fact, one-third of emitted greenhouse associated with Iran's energy sector is linked to the power sector [5]. Reviewing previous energy policies, authorities in Iran have conceived that distributed generation is the key solution to global warming and low-cost energy production [5–7]. RESs, as prominent distributed energy resources, give ample opportunities to the power system operators, like simple utilization and observation [1, 2]. The integration of distributed energy resources (DERs) has formed new local electric grids, namely MicroGrids (MGs). Several RESs such as, wind turbine (WT) and photovoltaic (PV), are used in MGs, which can result in the economic operation of MGs [3].

On the other hand, the MGs' load demand plays a significant role in the long-term planning and optimal MGs design. Because of the lower inertia of MGs, smooth load time-series in such systems are degraded. Therefore, fluctuations in MGs' daily load curve compared to traditional power are incredibly remarkable. Furthermore, forecasting MGs' upcoming load values is difficult since they have lower-scaled load values [4]. Load-related terms should be considered in MGs' design to avoid the additional system cost. Therefore, considering future trends of MGs' demand and load fluctuations is critical for design goals, ensuring economic and technical benefits. Residential MGs play an essential role in the proliferation of RESs in each country. Integrating RESs into the existing residential systems can ensure reliable power provision at much lower CO_2 emission and decrease the electricity cost [12]. As RESs are significantly dependent on environmental conditions, the necessity of hybridization is apparent for guaranteeing continuous power provision [13, 14]. Furthermore, utilizing surplus energy (SE) from the RESs and environmental emission recovering waste heat from a conventional generator, and fuel cell could lower system operation costs [15]. Therefore, the optimal sizing of components and operation of hybrid energy systems should be addressed appropriately.

Electrical sizing of RESs and BSS are highly dependent on the load profile. Larger load consumption means that we need to increase the capacity of the components. Naturally, as we consider load growth rates based on the consumer's historical load profiles, more realistic values are expected. This principle has been neglected in previous studies [18–20]. Some other studies emphasized electrical and thermal load consumption of hybrid energy systems [15, 21]. In real-world applications, residential households consume both electrical and thermal power. Hence, a hybrid energy system that serves thermal and electrical loads is essential for the residential sector. In [4], the authors proposed an off-grid hybrid system for supplying electricity and thermal loads in Australia's five climate zones. They found that the combination of PV/WT/battery/micro gas turbine has the least cost of energy (COE) for all the zones. However, this study lacks methodology for considering electrical/thermal load growth rates for multi-year optimization of hybrid energy systems. Another study [5] assessed both electrical and thermal load profiles to optimize a rural area in Iran. They found that PV/WT/biogas is the most economical configuration. On the other hand, utilizing BSS and fuel cells was not financially beneficial despite their ability to increase the system flexibility. This study also neglected to consider thermal and electrical load growth rates.

The literature is rich with studies focusing on grid-connected MGs configuration with HOMER software [5–8]. The software can find a system design having the minimum economic cost of MG. The key criterion used for the energy systems' economic evaluation is the total net present cost (NPC) [9]. In a recent paper [5], authors proposed an optimal design of MG, including RESs such as PV, WT, energy storage system (ESS), and none-RES such as combined heating and power (CHP). They also considered time-of-use (TOU) rates for their electricity prices. They have concluded that electricity pricing rates significantly impact the optimal configuration and NPC of the system. In another study, authors of [6] proposed an optimal MG which is equipped with PV, WT, ESS, fuel cell (FC), microturbine (MT), hydrogen tank and, utility grid. According to the paper results, ESS, like a backup battery storage system (BSS), has few interactions with the system over the planning horizon.

Furthermore, RESs generations account for the largest share of energy generation in the MG. In another study, authors of [7] performed techno-economic research on off-grid and grid-connected MGs in China. According to the results, it would be more economical if MG is based on PV and WT units. Besides, the feasibility of BSS in the suggested MG was checked in this study. Results show that utilization of the BSS in the MG could reduce system emissions and costs. Authors of [8] investigated the best sizing of a campus MG including diesel generator (DG), WT PV, and ESS units For off-grid and grid-connected modes. Optimization results indicated that the combination of PV and grid is the best configuration in the on-grid operating mode. In addition, the combination of PV and BSS is the optimal configuration for the off-grid operating mode.

Multiple studies are available in the literature investigating the optimal design of MGs in grid-connected and off-grid operating modes. Nevertheless, the majority of studies utilized historical load data for the optimal design of MGs. However, in order to obtain real-world results, load prediction should be considered in long-term MG planning. Because the fluctuation of daily loads is significant in MG operation. There is a scientific lack of literature for planning an optimal grid-connected MG with HOMER software considering annual load growth based on long-term load forecasting. Therefore, as a new approach, long-term load forecasting has been used to optimize the MG designing procedure. According to the observed load data, Multilayer Perceptron (MLP) Artificial Neural Network (ANN) was used for time-series forecasting of demand profile. Simulation results have shown that realistic COE and NPC values could be achieved using forecasted load data for the optimal design of an on-grid MG.

2 Long-term Load Prediction Using MLP-ANN Time-series

MLP-ANN has wide applications in various fields of theoretical studies and engineering, e.g., pattern recognition and function approximation. MLP-ANN consists of three distinct layers of nonlinearity activating nodes: an input layer, hidden layer, and output layer. Generally, MLP has one or

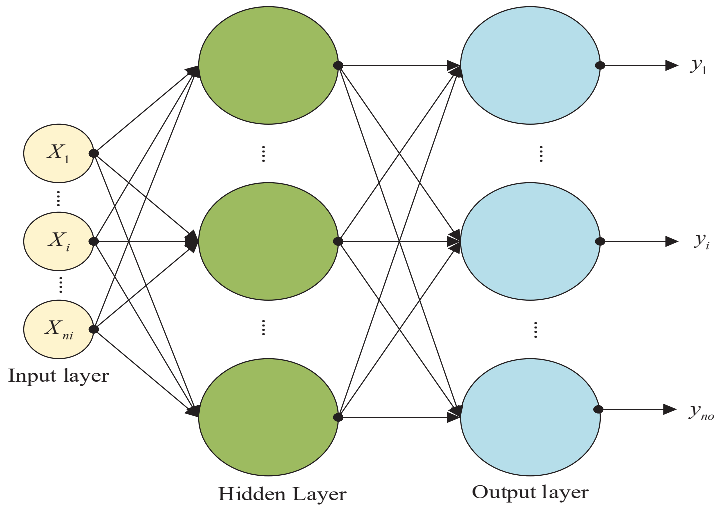

Figure 1 The architecture of an MLP-ANN.

more hidden layers between the input and output layers. For the training algorithm, the back-propagation (BP) algorithm is applied. The BP algorithm is a supervised learning technique frequently used as a training algorithm in the MLP structure. The architecture of the MLP-ANN network is illustrated in Figure 1. X_{nh} is input node and y_{no} is the output node. More details on MLP-ANN is available in [10].

Times-series forecasting is utilized by predicting future values based on previously observed values. It is a very efficient method for hourly load series forecasting. Time-series prediction is achieved by different methods of implementation, e.g., regression, moving average, Exponential Smoothing and, ANNs. In this paper, MLP-ANN is utilized for time series long-term load forecasting. For this reason, five years of load data have been used for next year's load values. Various statistical criteria have measured the accuracy of forecasting, for instance, standard deviation (STD), mean square error (MSE), root mean square error (RMSE), and linear regression (R) [11].

3 Structure of On-grid MG

In order to investigate the effects of forecasted load values in a real case study, a grid-connected MG is proposed in this paper. Figure 2 shows the proposed MG structure, which consists of PV, WT, BSS, converter, and utility grid.

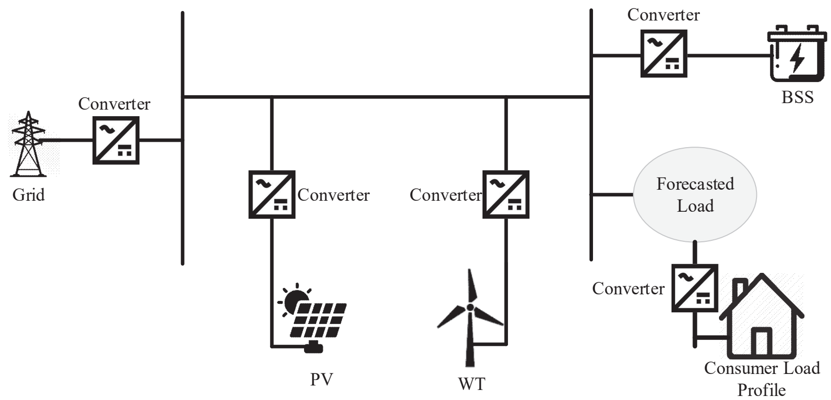

Figure 2 The architecture of the proposed MG system.

3.1 PV Unit Model

In order to calculate the generated power of the PV unit on *i*-th day at hour t, the following equation is used [12].

$$P_{PV}^{i,t} = \eta_m \times \eta_{conv} \times A_m \times G_r^{i,t} \times (1 - \beta_r(T_c^{i,t} - T_r)) \tag{1}$$

Where, η_m and η_{conv} are the PV module and the converter efficiencies. A_m is the surface of the PV module (m^2), $G_r^{i,t}$ describes total solar radiation (W/m^2), $T_c^{i,t}$ is the temperature of PV cell, T_r represents reference temperature, β_r is also the thermal factor. The output energy of the PV unit is described in (2).

$$E_{PV}^{i,t} = P_{PV}^{i,t} \times \Delta t \tag{2}$$

Where Δt is the time interval.

3.2 WT Unit Model

WT is used for converting wind power to electrical power. In this paper, the following equation is used to model the WT unit [6]:

$$P_{WT}^{t} = \begin{cases} a \times (V^t)^3 - b \times P_R & V_{ci} \le V \le V_r \\ P_R & V_r \le V \le V_{co} \\ 0 & V_{ci} \le V \le V_r \end{cases} \tag{3}$$

In (3), V^t is the wind speed; a and b are parameters of the WT; P_R is rated power of WT; V_{ci}, V_{co} and, V_r are respectively cut-in, cut-out and rated wind speed of WT.

3.3 BSS Unit Model

BSS is used as a backup energy source in the MG architecture. In other words, BSS is charged during the abundant generation of RESs and is discharged when BSS is cheaper than the grid purchased price. BSS output energy is calculated according to (4) [12].

$$E_{BSS}^{i,t} = V_{BSS} \times C_{BSS} \times (SOC^{i,t-1} - SOC^{i,t}) \tag{4}$$

Where, V_{BSS} is nominal BSS voltage; C_{BSS} is nominal BSS capacity (Ah); $SOC^{i,t}$ is the state of charge (SOC) of BSS on *i*-th day at hour *t*.

In addition, the converter unit is used to convert ac/dc and dc/ac currents. More information about MG converters is available in [13].

4 Case Studies and Results

In this section, two case studies have been implemented to investigate the effects of load forecasting on MG's optimal sizing and design. Input data for RESs and grid converter are illustrated in Table 1. Due to financial and space issues, decision-makers of the understudy building have imposed limitations on the RESs and other system components' maximum capacity. The implemented limitation is 100 kW for each component (BSS, PV, WT, and converter). Hence, the algorithm must find the optimum capacity of the components between 0 and 100 kW. The average rates for interest and inflation over five years are assumed as 18% and 16.18%, respectively [14].

The utilized time-of-use (TOU) and feed-in tariff (FiT) electricity prices in Tehran are shown in Table 2. Yearly weather data such as solar GHI, temperature, and wind speed have been collected from NASA surface meteorology.

To better understand the proposed MG operation, environmental indicators such as emissions produced by the MG have been considered. Due to the fact that RESs are popular for non-emission electricity production, the emission produced by the utility grid has merely been considered for further investigations. Table 3 shows the values of pollutants used in simulations.

4.1 Case Study 1: Optimal Design of MG Using Long-term Load Forecasting Data

Three years of historical load data (from 2015/01/01 to 2017/12/31) of a large building has been used for forecasting next year's load profile i.e.,

Table 1 Input data of components [12]

PV	
Lifetime	25 yrs
Efficiency	16.25 %
Operation Temperature	45°C
Temperature Coefficient	−0.380
Capital Cost	350 $/kW
Replacement Cost	350 $/kW
Operation & Maintenance	10 $/yr
Degradation	1 %/year
WT	
Rated power	1 kW
Rated wind speed	12.5 m/s
Start-up wind speed	2.5 m/s
Rated voltage	24/48 V
Capital Cost	725 $/kW
Replacement Cost	725 $/kW
Operation & Maintenance	10 $/yr
BSS	
quantity	20
Lifetime	10 yrs
Nominal capacity	1 kW
Nominal voltage	12 V
Initial state of charge	100 %
Minimum state of charge	20 %
Capital Cost	124 $/qty
Replacement Cost	124 $/qty
Operation & Maintenance	10 $/yr
Converter	
Efficiency	95 %
Lifetime	15 yrs
Capital Cost	137.50 $/kW
Replacement Cost	137.50 $/kW
Operation & Maintenance	10 $/kW

Table 2 Tehran electricity tariff [12]

Time of Day	Time Interval	Electricity Purchased Price ($/kWh)	Electricity FiT ($/kWh)
Off-peak	23:00 to 7:00	0.0048	0.12
mid-peak	7:00 to 19:00	0.0190	0.12
Peak	19:00 to 23:00	0.0480	0.12

Table 3 Considered values for the pollutants [12]

Pollutant	Value	Unit
Carbon dioxide	632	g/kWh
Sulfur dioxide	2.74	g/kWh
Nitrogen oxides	1.34	g/kWh

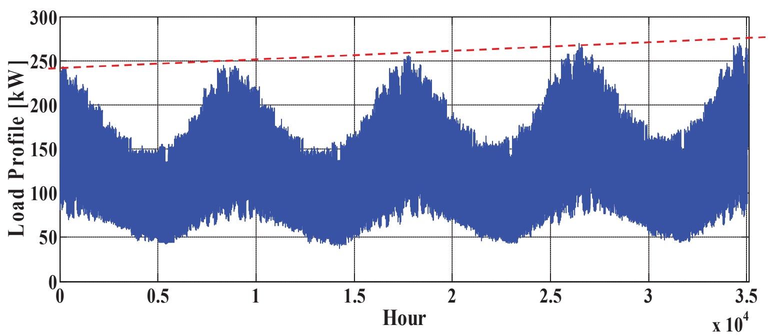

Figure 3 Four years of load profile.

Table 4 Statical results for long term load forecasting

MSE	RMSE	STD	R
12.95	3.59	3.59	0.9967

2018/01/01 to 2018/12/31. The building is located in Tehran, Iran. The load data is achieved using the mounted smart meter in the building. As can be seen in Figure 3, there is upward growth in yearly load consumption. The results of load forecasting are shown in Table 4 and Figure 4. Both RMSE and STD values are obtained as 3.59. Moreover, regression graphs for train and test data in Figure 4 indicate the implemented algorithm's accuracy for load prediction. The forecasted load profile is also demonstrated in Figure 5.

Comparing actual and forecasted load profiles (Figure 6), an overall 4.08%/yr increase in forecasted load values has been achieved. Hence, it

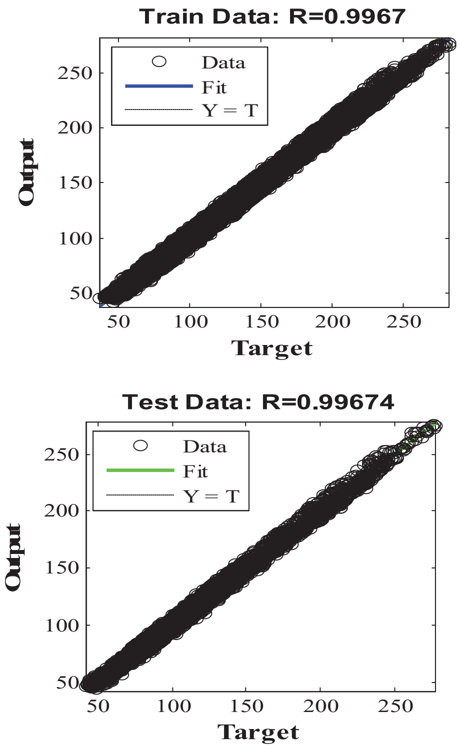

Figure 4 Regression results of the load forecasting.

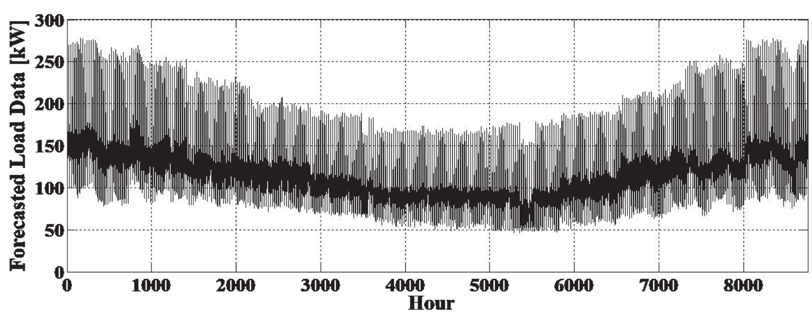

Figure 5 Forecasted load data based on the historical values.

is necessary to consider this annual load increase in the procedure simulation. As an input of multi-year optimization, we have considered the 4.08%/yr increase in load values for the next 25 years, which is the project lifetime.

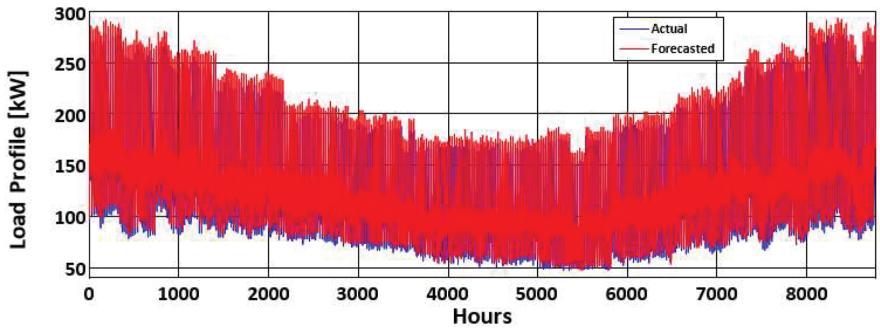

Figure 6 Comparison of actual and forecasted load profiles in the year 2018.

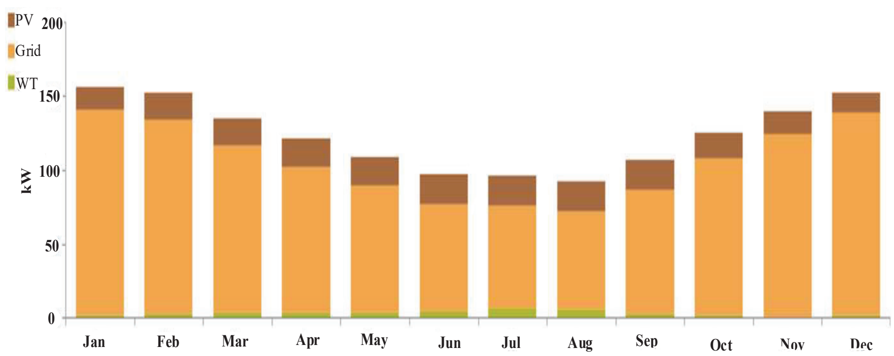

Figure 7 Monthly average electric production.

By implementing the forecasted load profile to the HOMER software's input, optimization of the system has been run. Simulation results are shown in Table 5. Based on the results, the optimum MG configuration is obtained as PV+WT+grid. The NPC and COE are also achieved as 566,008$ and 0.0240 $/kW, respectively. Since the load consumption exceeds the RES production, most of the generated electricity by the PV unit has been used for internal usage. Therefore, as shown in Figures 7 and 8(a), the grid provides most of the consumed electricity of the system. However, according to Figure 8(b), the PV unit has sold a portion of the generated electricity to the utility grid during days 224 to 229 (August) with an overall 128 kWh. Renewable penetration (RP) is achieved by 9.52%, which is lower than the delivered electricity by the grid to the load. Moreover, optimum MG architecture indicates that BSS utilization is not economically beneficial because BSS plays the role of a backup energy source and does not involve in daily energy cycles.

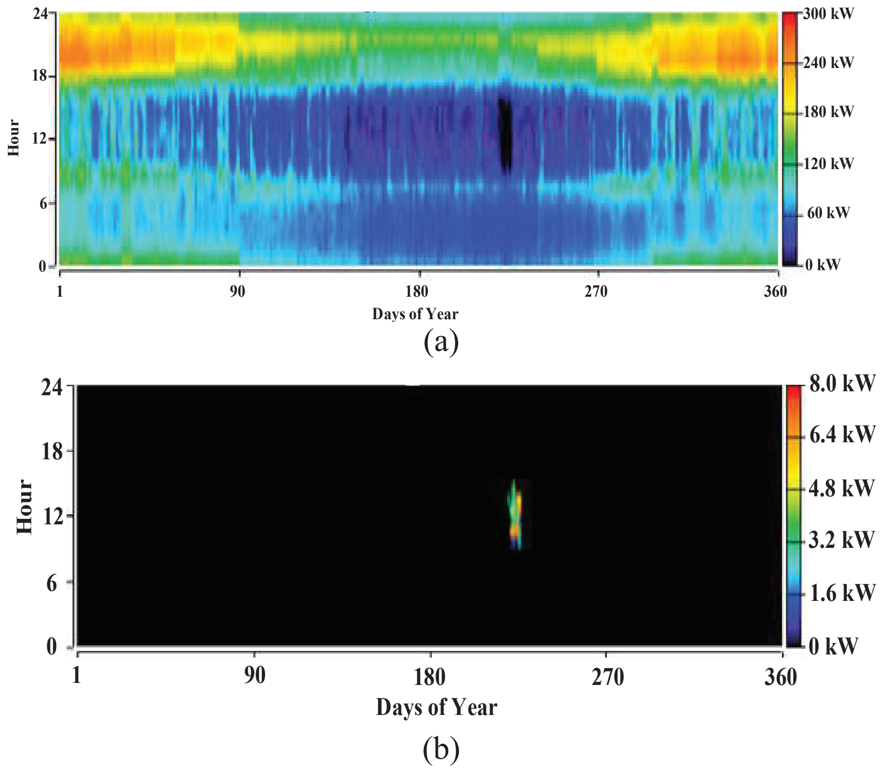

Figure 8 Electricity (a) Purchased from utility grid; (b) sold to the utility grid.

Table 5 Optimization results for the case study 1

WT [kW]	PV [kW]	Converter [kW]	BES [qty]	NPC [$]	Grid	COE [$/kW]
25	100	60	–	896,744	Yes	0.0253
25	100	60	1	897,228	Yes	0.0253

4.2 Case Study 2: Optimal Design of MG Using Actual Historical Load Data

This case study is proposed to compare the optimization results of the system with forecasted load data with the system in which no load is predicted. For this purpose, actual load data of the understudy building has been used for optimization (from 2018/01/01 to 2018/12/31). Most of the previous literature studies have utilized actual historical load data, and they have not considered annual load increasing.

Table 6 Optimization results for case study 2

WT [kW]	PV [kW]	Converter [kW]	BES [qty]	NPC [$]	Grid	COE [$/kW]
–	50	30	–	492,192	Yes	0.0235
–	50	30	1	942,677	Yes	0.0235

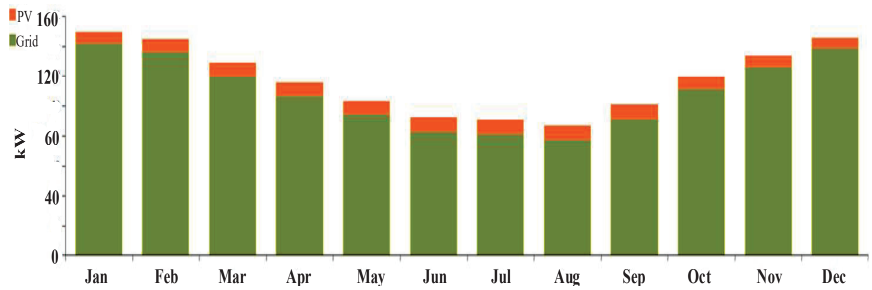

Figure 9 Monthly average electric production.

Simulation results are shown in Table 6. Unlike the previous case study, the optimum system configuration is achieved by PV+grid. The capacity of the PV unit is also reduced to 30 kW since the upward growth of the load profile has not been considered in simulations. Furthermore, similar to previous studies [5–8], a fixed load profile is used for optimization. The optimum converter capacity has also been decreased due to the lower capacity of the PV unit. Moreover, NPC and COE values have been reduced compared to the case with forecasted load data. RP of the system is reduced to 6.37 %, which implies the lower contribution of RESs in the system load supply. Monthly energy production by the optimum system is illustrated in Figure 9. As can be observed, the production of the PV unit is reduced in comparison with the previous case study. In other words, more electricity is imported from the utility grid. It is also worthy of mentioning that no electricity has been sold to the utility grid in the current case.

5 Discussion and Sensitivity Analysis

Table 7 shows the produced emission in both cases. It is clear that the first case study, which is optimized with the forecasted load profile, has less emission compared to the second case study. Moreover, in the second case study, we observed that the utility grid supplies most of the load demand. In the first case study, due to higher RESs capacity and RP, less electricity is imported

Table 7 Comparing the produced emission by both suggested case studies

Case Study	Carbon Dioxide [kg/yr]	Nitrogen Oxides [kg/yr]	Sulfur Dioxide [kg/yr]
1	563,909	2,445	1,196
2	599,532	2,599	1,271

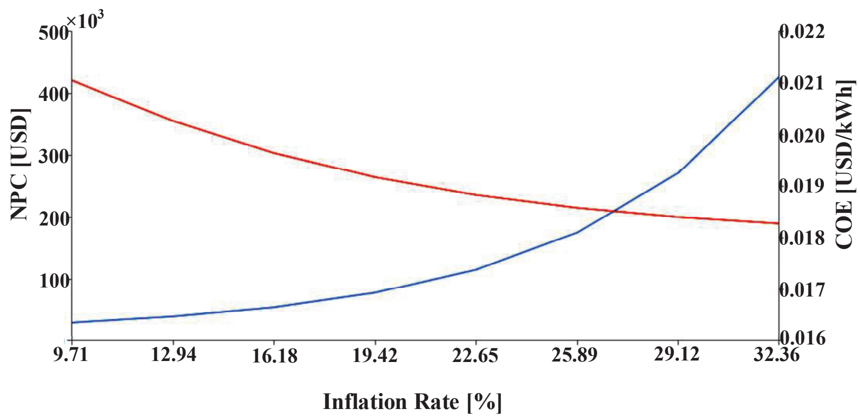

Figure 10 Sensitivity analysis on the inflation rate.

from the utility grid than the second case study. Therefore, the first case study with a forecasted load profile is more environmentally friendly than the second case with the actual historical load profile.

Figure 10 shows sensitivity analysis on the inflation rate, as an essential system parameter, and corresponding effects on NPC and COE of the microgrid. According to this figure, the inflation rate has a drastic impact on the financial results of the system. When the inflation rate increases from 18.16 to 32.36, the COE's value rises to 0.021 USD/kWh accordingly. In contrast, the NPC of the system decreases significantly from above 400×10^3 USD to about 200×10^3 USD as the inflation rate increases from 18.16 to 32.36.

Comparing the overall results of both case studies, it can be understood that the optimal design of MG is strongly dependent on the values of the utilized load profile. Considering load forecasting technology in the optimal design of MGs would result in realistic and accurate optimization results. Although the financial results of the second case study are more satisfying, influential design parameters such as future load growth have not been considered in the simulation algorithm. Hence, more real and accurate results are obtained by considering the load growth based on the forecasted load data in the simulation process.

The optimum configuration of both cases also shows that using BSS as a backup energy source is not economical. All simulations under a reliable grid connection have been done. Therefore, if grid outages occur, it is technically beneficial to use BSSs in the MG system.

6 Conclusion

In this study, an optimal grid-connected MG is proposed based on the forecasted load profile. To compare the results of the proposed MG, two case studies were performed. In the first case study, the predicted load profile with annual growth of 4.080% has been utilized, while in the second case, actual load data with no-load forecasting has been applied. Simulation results indicated that the optimum configuration for the system with the forecasted load profile is PV+WT+grid. For the second system with the actual load profile, the optimum design would be PV+grid. However, utilizing BSS was not economic in both case studies. Moreover, realistic NPC and COE costs have been achieved using the forecasted load profile. Also, the MG in case study 1 produced less emission compared to the second system. In the proposed case study 1, the NPC and COE are obtained as 566,008 $ and 0.0240 $/kWh, respectively. However, in the second case study, NPC and COE are achieved as 492,192 $ and 0.0235 $/kWh. In the case with no forecasting, RP of the system is reduced to 6.37 %, which implies the lower contribution of RESs in the system load supply. In this regard, 563,909 kg of CO_2 is produced over the optimization year, which is 35,623 kg lower than the case with no load growth rate. According to the sensitivity analysis results, when the inflation rate increases from 18.16 % to 32.36 %, the COE's value rises to 0.021 USD/kWh accordingly. In contrast, the NPC of the system decreases significantly from above 400×103 USD to about 200×103 USD as the inflation rate increases from 18.16 to 32.36.

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