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Optimization of distributed energy resources in an industrial microgrid

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Abstract

This paper introduces a model of an industrial microgrid with distributed energy resources (DERs). The model is applied to an existing manufacturing facility in Ireland. The test facility is connected to the main electricity grid but also has onsite generating units; a wind turbine and a combined heat and power (CHP) unit. The model generates a facility load forecast using historical data. A scenario analysis is then performed to investigate the effect of operating DERs, including demand response (DR), on carbon emissions and energy costs in an industrial microgrid. An energy storage component is then introduced and the viability of installing this technology is investigated.

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Keywords: Distributed energy resources; Indutrial microgrid; Load forecast; Green manufacturing; Energy management

1. Introduction

In 2015, industrial facilities accounted for 39.3% of electricity demand in Ireland, the largest share by sector, and one fifth of total energy demand [1]. In the past, the electricity demand of industrial facilities has been met by large-scale central power plants, and distributed via transmission and distribution systems, which often lead to losses [2]. This, along with the growing pressure to increase production of electricity from renewable sources, has led to a push to integrate distributed energy resources (DERs) into electricity supply [3]. As industrial facilities invest in DERs, these sites become industrial microgrids, whose operational objectives are expanded to energy efficiency, emission control and the use of alternative energy resources, and an investigation into the resulting benefits is the motivation for this study [4].

The Consortium for Electric Reliability Technology Solutions (CERTS) defines a microgrid as the aggregation of loads and sources operating as a single systems, that provides both power and heat [5]. Microgrids are utilized in a range of settings. Campus microgrids are often deployed on college campuses, prisons or military bases, allowing for central control and ensuring a level of service when disconnected from the main grid. Microgrids are also installed on islands or in remote areas where a connection to the grid is not viable. Industrial microgrids are being developed with an increase in DERs installed onsite.

DERs are energy resources that are typically located at the user's sites where the energy is used [5]. They consist of small, modular power sources, storage technologies and controllable loads [6]. The power sources can be dispatchable, such as onsite combined heat and power (CHP) unit, or they can be non-dispatchable, such as solar cells and wind turbines. Non-dispatchable power sources are of an intermittent nature and fluctuate in their output, due to their dependence on weather conditions [6]. The peak load of a facility can occur when the energy yield from an intermittent source is low. Energy storage technologies can aid in reducing the energy imbalance between supply and demand by storing energy and delivering it at a later time. Controllable loads are loads (electrical and thermal) that can be adjusted or reduced at critical times and for which the demand can be scheduled among a set of pre-defined operating points [7]. Controllable loads respond to a control signal and achieve a step change in power consumption, which can be based on a pricing signal, or a disturbance in power supply [8].

This paper introduces a model of a grid connected industrial microgrid with distributed energy resources installed onsite. The test facility is a large manufacturing plant in the south of

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Ireland. An overview of the facility is given in Fig. 1. The microgrid system is comprised of (a) the electricity load for the industrial facility, which is controllable via demand response (DR), (b) a 3MW wind turbine, providing intermittent power, (c) a controllable 405kW CHP unit, and (d) a 150kW lithium ion battery for energy storage (this is not currently installed at the facility but is included here as analysis on it's possible contribution is performed).

External to the facility is the incoming power from the electricity grid. Energy flow at the point of common coupling (PCC), the point where the on-site network meets the grid, is bi-directional. When an excess of electricity is produced by the DERs on-site, it is exported to the grid and revenue is earned by the facility. The remainder of the paper is laid out as follows: Section 2 of this paper describes the related literature in this field. Section 3 outlines the model framework and methodology for this investigation. Section 4 details the results of the model and concluding remarks are included in Section 5.

2. Review of related literature

Modeling of the DERs in a microgrid provides insight into the operation of the grid and opportunities to optimize the control of the individual units and the grid itself. Quiggin et al. [9] used a linear programming approach to model a microgrid with a mix of renewable power sources, energy storage technologies and DR systems. The mixed-renewable microgrid operation resulted in a reduction of demand fluctuations and improved energy balance between supply and demand. Tazvinga et al. [10] used model predictive control techniques to control the power flow of a hybrid power supply system with DERs, providing a degree of robustness against uncertainties. Wang et al. [11] proposed a power supply and demand management scheme for a microgrid with DERs to minimize the electrical generation cost and to optimize the operating schedule considering uncertainties due to intermittent renewable sources. Zhang et al. [12] developed a distributed energy management system for microgrids with a high penetration of renewable energy, based on power scheduling. The optimization problem was solved to minimize the microgrid cost. In [13], Ding et al. proposed a mixed integer linear programming based energy management model for an industrial facility with DERs. Using day-ahead electricity prices, the model optimized the operation of the DERs in order to shift peak demand and resulted in lower energy costs for the facility. Moura and de Almeida [14] proposed a multi-objective optimization method incorporating DR to define the mix of DERs, maximize their contribution to peak load, while minimizing cost and intermittence. In [15], Mohammadi et al. used a genetic algorithm optimization method to determine the optimum mix of DERs on a grid connected microgrid participating in a hybrid electricity market. Hawkes and Leach [16] developed a linear programming cost minimization model for the design and unit commitment of a microgrid with DERs, and found that grid connected microgrids were more economical than networks without a strong grid connection.

Operation of DERs in a microgrid can be further enhanced through accurate load forecasting. Lee et al. [17] applied artificial neural networks to short-term load forecasting of day ahead hourly electric loads of a power system, with the inputs restricted to past loads and resulted in a forecasting error of 2%. In [18], Park et al. use weather data in addition to past loads as predictors, and utilize artificial neural networks to forecast load.

In order to efficiently schedule dispatchable power sources in a microgrid, it is critical to utilize accurate predictions of power output from non-dispatchable generators such as solar and wind. Lydia et al. [19] detailed a review of the different methodologies for modeling of wind turbine power curves, both parametric and non-parametric. The research found that models where the characteristic equations are based on the actual power curve of the turbine are most accurate. In [20], parametric and non-parametric models are developed and are solved using advanced algorithms. The differential evolution algorithm applied to a five-parameter logistic function represents the best parametric model and the neural networks

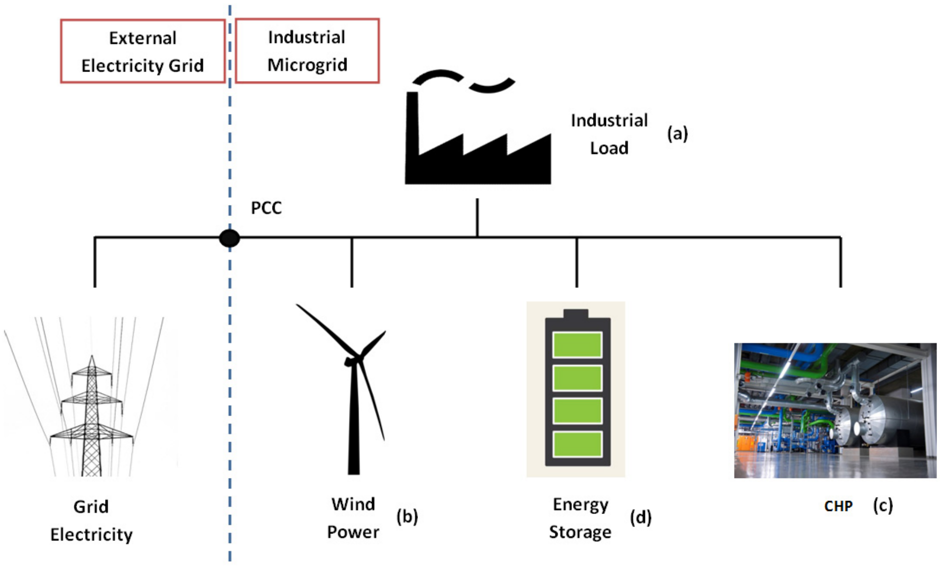

Fig. 1. Overview of test facility.

algorithm represents the best non-parametric model. Kusiak et al. [21] developed a nonlinear parametric model using evolutionary algorithms to analyze performance of wind farms, which also improved accuracy by filtering outliers. Hanrahan et al. [2] developed a power flow visualization technique for industrial sites and found that the maximum economic benefits for on-site wind generation are achieved when combined with a controllable CHP unit. Additionally, the use of energy storage technologies may provide further benefits to the operation of a microgrid with intermittent renewable power sources. Chen et al. [22] developed a methodology based on mixed integer linear programming to determine the optimal size of energy storage for both grid connect and islanded microgrids.

Conventionally, an imbalance in the load and supply of electricity in a power system was rectified through a rapid increase in supply, often costly with high emissions. However, with a microgrid system, it is to desirable to make operational modifications on the demand side, through demand side management (DSM) and DR techniques. Logenthiran et al. [23] presented a load shifting DSM strategy as a minimization problem, which was solved using a heuristic based evolutionary algorithm. The study showed that peak demand was reduced, and large savings were achieved by residential, commercial and industrial facilities. Finn and Fitzpatrick [24] investigated the ability of implementing a price based DR scheme to increase the share of wind energy used at two industrial facilities, and found that shifting demand to low price times showed favorable results.

3. Modeling approach

3.1. Model framework

The objective of this model is to calculate the cost and emissions associated with utilizing a range of resources in satisfying the electricity load of an industrial site. The model was constructed using the Matlab simulation environment (Mathworks, USA). The model has different components that use inputs such as historical data to produce predicted forecasts of load, DER supply and DR. Initially, the model forecasts the electricity load of the industrial. A series of scenarios are modeled in which varying combinations of energy resources are utilized to satisfy the forecasted load. The cost and emissions associated with each scenario are presented.

3.1.1. Load forecast

The load forecast component predicts the short-term future load based on historical data. This dataset, which is used to generate predictors, includes historical weather data, historical load data for the entire industrial site, and seasonality.

The model is then calibrated using artificial neural networks. The input and target data are defined, as well as the hidden layer size and training function. The data is divided up into a training set, validation set and testing set, 70%, 15% and 15% respectively. The Levenberg-Marquardt training algorithm is used to train the model. The model is then run using forecast inputs for the 24-hour period. The resulting output is the forecasted electricity load for the industrial site.

The performance of the trained network is evaluated using the test set. The mean absolute percentage error (MAPE) represents the mean of the absolute error in percent between actual and estimated loads. The coefficient of determination, R^2, is also used to determine the accuracy of the model. The MAPE for the test set is 4.1%, and the R^2 value is 0.94. This indicates a high level of accuracy in forecasting the load of the facility.

3.1.2. Price and emissions components

The price component generates an electricity cost for the various energy sources being investigated. To predict the cost of electricity imported from the grid, the facility provided billing records with actual rates. The rates vary based on time of day and season. During the months of November through February, the facility pays a winter rate which includes a peak hour rate between 17:00 and 19:00 hours. For every other month of the year, a summer rate is paid with no peak hour rate. The rate structure also includes weekday, weekend and nighttime rates. The cost of electricity generated by the wind turbine is presented as a per kWh maintenance cost [25]. This is also applicable to the cost of electricity generated by the CHP, which was obtained via a third-party contract. There is also a fuel cost associated with the CHP, which is also available via the billing records. The emissions component uses standard emissions factors associated with each fuel type to predict the CO_2 emissions associated with each energy resource [1].

3.1.3. Wind power component

Onsite wind power generation is modeled in the wind power component. Historical data is used to determine the relationship between wind speed and power output. The data is split into an 80% training set and a 20% test set. The power curve is fitted using the smoothing spline technique, which is suitable for noisy data. The smoothing spline, *s*, minimizes

$$p\sum w_i\left(y_i - s\left(x_i\right)\right)^2 + \left(1-p\right)\int\left(\frac{d^2s}{dx^2}\right)^2 dx \qquad (1)$$

where p is the smoothing parameter and w_i represented the weights. A smoothing parameter of 0.5 and weights of 1 are specified for this fitting. The power curve fitting is shown in Fig. 2. The model is run for the 24-hour period and generates a forecasted wind power output.

As with the load forecast component, the performance of the model is analyzed using the test dataset. However, MAPE cannot be used in this case, as the actual power data includes values of zero, which results in infinite MAPE. Therefore, the mean arctangent absolute percentage error (MAAPE) is used, which is a slope as an angle, instead of a slope as a ratio used in MAPE [26]. The MAAPE for the test set 16%, and the R^2 0.99. This indicates that there is a strong correlation between the predicted and actual power output of the turbine.

3.1.4. Combined heat and power component

The CHP unit is an alternative means of producing electricity and is run when the cost of CHP electricity is less than grid electricity. The cost of CHP electricity is dependent on the amount of CHP heat that is utilized on site. For this study, it is assumed that 100% of the heat generated by the CHP unit is utilized onsite. Given this assumption, it is more economical to generate electricity on site from 08:00 to 00:00. Control of the CHP output is based on the load of the site and the output of the wind turbine. When the output of the wind turbine is less than the site load, the CHP operates between maximum and minimum output, to meet the demand deficit.

The relationship between electrical output and gas input is determined as linear and is then used to determine the gas input (in kWh) associated with CHP electrical output. The fuel conversion efficiency, equation (2) is used to determine the cost of the electricity generated by the CHP [27]

$$Cost = \frac{GasConsumption - \frac{Therm_{out}}{\alpha}}{Elec_{out}} \times GasPrice \qquad (2)$$

where α is the efficiency of the conventional technology that would otherwise be used to generate useful thermal energy (boiler efficiency).

3.1.5. Demand response component

The DR scheme implemented in this study focuses on load reduction based on pricing. The pricing structure discussed in section 3.1.2 indicates that during the winter months, a peak hour rate is paid between 17:00 and 19:00. This equates to a 70% increase in the electricity rate during the peak period over the regular daytime rate. A reduction in load during the peak period of the order of 8.3% is implemented in the DR component of the model [14] .

3.1.6. Energy storage component

The energy storage system (ESS) is modeled to investigate the potential benefit of its operation with the wind turbine. Electricity is stored when the price of grid electricity is low, and discharged when the price is high. The amount of electricity charged/discharged can be controlled between zero and the maximum charging/discharging rate. When electricity prices are low overnight, the wind turbine begins to charge the ESS. If the wind turbine output exceeds the maximum charging rate of the ESS, then the ESS is charged at its maximum charging rate and the excess power is supplied to the facility. When the ESS is fully charged, the wind turbine output is used to satisfy the facility demand. When the peak hour rate period begins at 17:00, the electricity stored in the ESS is used to power the industrial facility.

4. Results

The model was run on February 14th, 2017. Fig 3 shows the load profile for that 24-hour period. The industrial load, represented by the solid black line, varies between 1 MW and 1.5 MW throughout the day. The output from the wind turbine is represented by the yellow area. In the first half of the day, the wind turbine output exceeds the facility load. However, as the day progresses, wind power drops. The CHP, represented by the green area, starts up at 11:00, to compensate for the decrease in wind power. It remains running at full output until 23:00, when it begins to taper. The effect of DR on the load of the facility is shown by the dashed black line. As illustrated, during the peak rate hours of 17:00 to 19:00, demand is reduced. The blue area represents the amount of electricity discharged by the ESS. The wind turbine begins to charge the ESS until the capacity is reached. This offset in wind power is represented by the dashed blue line at the beginning of the day. The energy stored is discharged and at 17:00 and used to satisfy the industrial load.

4.1. Cost analysis

Operating DERs in an industrial microgrid leads to favorable economic results. Fig. 4 shows the electricity cost associated with the facility throughout the day. Dependence on the grid to satisfy entirely the demand of the site clearly results in the highest costs. However, operating the wind turbine and CHP unit can significantly reduce the cost, as the grid electricity is offset by the cheaper electricity generated on site. For the first 5 hours of the day, when the output from the wind turbine exceeds the industrial load, electricity is exported to the national grid. This results in revenue being generated for the facility. This can be seen as the negative cost value in Fig. 4. Although the facility continues to export electricity for 5 more hours (until 10:00), the maintenance cost associated with the wind turbine and the increase in demand results in some cost being paid during this time. However, it is much less than the cost of using grid electricity only. During the peak rate period, from 17:00 to 19:00, an increase in cost occurs in both scenarios 1 and 2. However, when the CHP unit is utilized along with the wind turbine, the power sources onsite generate enough power to satisfy the demand, and no electricity is purchased from the grid at the high prices. The effect of implementing DR during this period further reduces the load, thereby increasing the amount of electricity generated on site that is exported to the grid. The effect of operating the ESS is represented by the green line and differs from the previous scenario only when the ESS is charging and discharging. The

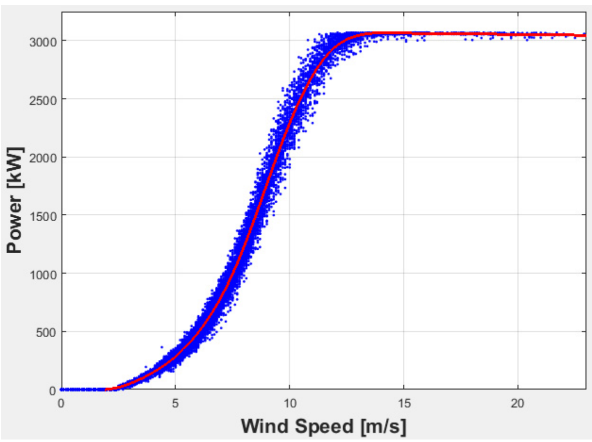

Fig. 2. Smoothing spline wind turbine power curve fitting.

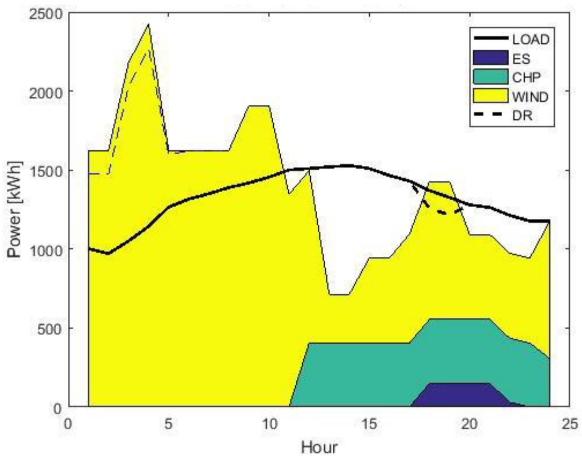

Fig 3. Load profile for 14th February 2017.

cost is slightly higher when charging as a portion of the wind turbine output is being used to charge the ESS, resulting in less electricity being exported to the grid, and less revenue being generated. However, the benefit occurs later in the day when the price of electricity is high. When the electricity price peaks, the ESS begins discharging to satisfy the industrial load. This, again, results in more electricity being exported to the grid.
The total cost for the day for each scenario is displayed in Fig. 5. The greatest reductions in cost occur by utilizing the onsite generators. Operating the wind turbine alone results in a 58% reduction in cost for this 24-hour period. Operating the CHP unit in conjunction with the wind turbine offers a reduction in cost of 69%. Implementing DR further reduces costs by 3%. Although the ESS does offer a further reduction of 1%, this may be overwhelmed by the large installation costs of energy storage technologies.

4.2. Emissions analysis

Analysis of the effect of operating DERs in an industrial microgrid on emissions produces similar results. Fig. 6 outlines the level of emissions throughout the day. As with cost, the highest levels of CO_2 are produced when grid electricity is used to meet the entire demand. This is due to the high emission factor associated with electricity in Ireland, as the grid is highly dependent on fossil fuels. An extensive amount of CO_2 emissions are displaced through the operation of the onsite DERs, and for the first half of the day, the emissions produced by the industrial microgrid are negative. This is a result of significant amounts of wind power being generated on site, which emits no CO_2. The entire industrial load is met by the wind turbine, and excess power is exported to the grid, essentially lowering the emissions of the grid itself, through the displacement of fossil fuel generated grid electricity. When running, the CHP unit also lowers the level of emissions produced. As the implementation of DR reduces the industrial load for a period of time, the amount of grid electricity used during this period is reduced, resulting in fewer carbon emissions. The operation of DERs in the industrial microgrid results in a tremendous reduction in total emissions in this 24-hour period, as shown in Fig. 7 . Once again, the largest reduction occurs when the onsite generators are operated to reduce, and in some instances, eliminate, dependence on the national grid. During this particular period, the wind turbine output results in an 88% reduction in carbon emissions, with a 97% reduction associated with operating the CHP unit with the wind turbine. Emissions are further reduced by 30% through the implementation of DR.

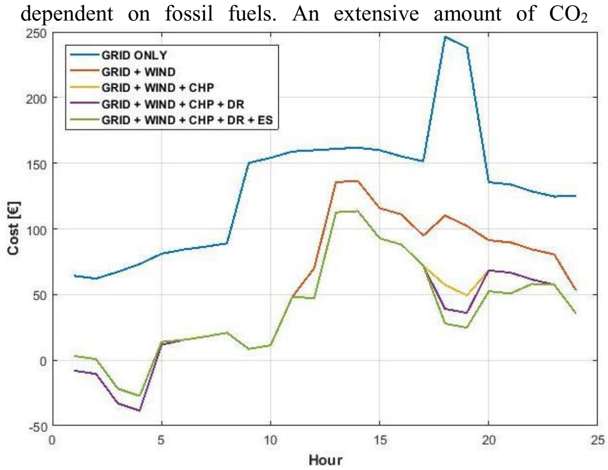

Fig. 4. Cost profile for 14th February 2017.

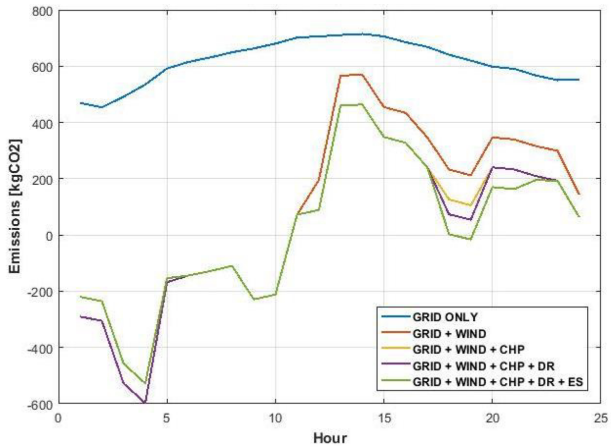

Fig. 6. Emissions profile for 14th February 2017.

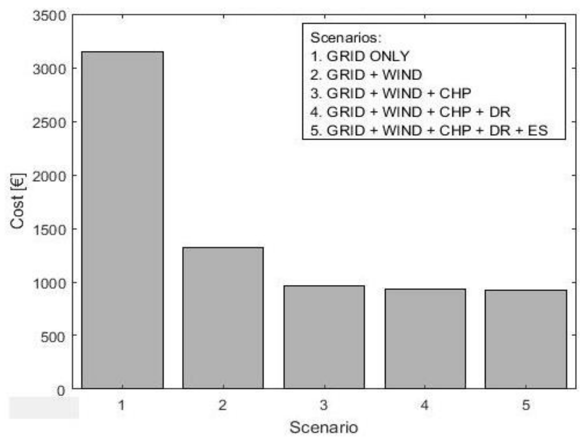

Fig. 5. Total cost for 14th February 2017.

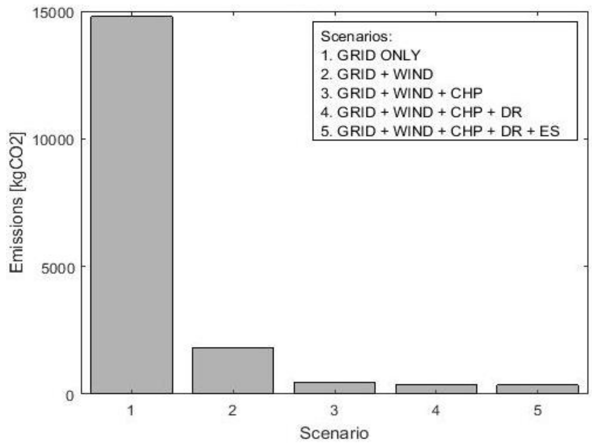

Fig. 7. Total emissions for 14th February 2017.

5. Conclusions

The effect of operating DERs in an industrial microgrid was investigated in this study. A model was developed of an industrial microgrid with a grid connection, dispatchable and non-dispatchable power sources, a controllable industrial load and energy storage system. The model generates a load forecast and analysis is performed investigating the effects of operating DERs in the industrial microgrid on energy cost and carbon emissions. The study has shown that there are benefits associated with operating DERs in an industrial microgrid. When compared with an industrial facility that is supplied with grid electricity only, it is clear that ample savings can be achieved through the utilization of DERs. The results clearly highlight that the largest savings are achieved when onsite generators are used to displace electricity imported from the grid. This is ideal for industrial facilities with large heat loads, as the heat generated by the CHP unit is utilized entirely. However, further study is required to investigate the operation of a CHP unit in a site with varying heat load, and to determine the optimal control scheme to maximize the economic benefit. Enacting DR leads to further savings, as the load is reduced in times of high electricity prices. A vast reduction in CO_2 emissions can also be attained through DER utilization in an industrial microgrid. This is due to large energy yields from renewable sources, in this case wind, which produce little or no carbon emissions. In such cases, the renewable electricity generated onsite may be exported to the grid, thus lowering the carbon footprint of the external electricity grid. The effects of ESS in industrial microgrid proved to be minimal in this study. Thus, further research is required into areas such as optimal sizing of an ESS, and control of charging and discharging.

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