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Integrating renewable energy into the manufacturing facility is the ultimate key to realising carbon-neutral operations. Although many firms have taken various initiatives to reduce the carbon footprint of their facilities, there are few quantitative studies focused on cost analysis and supply reliability of integrating intermittent wind and solar power. This paper aims to fill this gap by addressing the following question: shall we adopt power purchase agreement (PPA) or onsite renewable generation to realise the eco-economic benefits? We tackle this complex decision-making problem by considering two regulatory options: government carbon incentives and utility pricing policy. A stochastic programming model is formulated to search for the optimal mix of onsite and offsite renewable power supply. The model is tested extensively in different regions under various climatic conditions. Three findings are obtained. First, in a long term onsite generation and PPA can avoid the price volatility in the spot or wholesale electricity market. Second, at locations where the wind speed is below 6 m/s, PPA at $70/MWh is preferred over onsite wind generation. Third, compared to PPA and wind generation, solar generation is not economically competitive unless the capacity cost is down below $1.5 M/MW.

Keywords: zero-carbon operations; power purchase agreement; distributed energy resource; sustainable manufacturing; demand response

1. Introduction

The industrial sector accounts for almost one-third of primary energy use worldwide in 2007, and approximately 25 per cent of world carbon dioxide (CO2) emissions are resulted from the energy use of industrial processes (IEA 2008). A typical semiconductor fab facility requires 15–30 Megawatts (MW) power to maintain its routine production (Hu and Chuah 2003). This is equivalent to emitting 100–200 thousand tonnes of carbon per annum because the majority of today's electricity is generated from burning fossil fuels. To produce one MWh of electricity, on average 704 kilogrammes (kg) of CO_2 is released to the air when burning coal, gas or oil (EIA 2016). In addition to the environmental impact, the annual utility bills of the facility reach as high as $20 million. The carbon footprint becomes more severe in heavy industries, such as steel, oil refinery and cement production, where a single facility using conventional electricity is responsible for up to 4–5 million tonnes of carbon emissions per annum (Tang et al. 2014). Hence, reversing the climate change and lowering the energy cost are the main impetuses driving the manufacturing industries to seek a cost-effective and eco-friendly energy solution.

To battle the climate change, many industrial consumers view renewable energy as the key to mitigating the environmental impacts and attaining business sustainability. There are two green technologies currently adopted by industries to achieve low-carbon operations: power purchase agreement (PPA) and onsite renewable generation. In PPA, consumers directly sign a long-term contract with large wind and solar farms for buying renewable electric energy. In the first half of 2015 alone, nearly 1600 MW of renewables capacity was contracted through corporate PPAs in the USA (Baker and McKenzie 2015), as opposed to a total of 650 MW from 2008 to 2012 (Staple and Bromaghim 2015). In fact, the contractual price in 2015 is surprisingly low and down to the average of $50/MWh compared to over $100/MWh in 2008 (Bolinger, Weaver, and Zuboy 2015). Companies leading the PPA include Google, Walmart, Amazon, Facebook, Dow Chemical, Apple and Microsoft. For instance, Google's overall contracted renewable power capacity has reached 2000 MW in 2015. The company plans to triple its energy purchases with the goal of attaining 100 per cent of renewable operations for its facilities worldwide by 2025 (Huddleston 2015). While the price is often fixed with relatively low rate, these long-term energy contracts could last for 15–20 years. PPA is considered as a win–win energy agreement

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between renewable energy developers and large industrial consumers. On one hand, it secures the revenue stream of the renewable energy developer despite the generation intermittency. On the other hand, consumers are able to achieve the environmental commitment as well as ward off the price volatility in the spot or wholesale market.

Onsite generation, also known as distributed generation (DG), is another viable approach to realising low carbon operation. A DG system usually consists of one or several distributed energy resources (DER) that are installed near the industrial facility for power generation. Typical DER units include wind turbines (WT), solar photovoltaics (PV), fuel cells, micro-turbines and combined heat and power (CHP). The capacity of a DER unit is relatively small in a range between 50 KW and 10 MW. Onsite WT and PV systems are particularly appealing because they have several advantages, such as reducing carbon emissions, mitigating transmission losses and strengthening grid resilience. For instance, Honda installed two WT units at its transmission plant in Russells Point, OH in 2013 (Stinpetru 2014). Both turbines can produce 67–72 MWh per day at the high wind speed, satisfying 16 per cent of electricity need of the plant. Anheuser-Busch's Budweiser facility in Fairfield, California installed 3.1 MW wind capacity and 1.2 MW PV array (6500 panels), providing 40 per cent of the green electricity to the brewery factory (Hickey 2014). Worldwide, a total of 142,000 MW DG capacity including wind and solar was installed in 2012, representing 39 per cent share of new capacity addition (Oven 2014).

Though renewable DG technologies are promising, the main obstacles to the large-scale use of these technology are the power intermittency and installation cost. First, the output of WT and PV is difficult to predict due to the stochastic wind speed and weather condition. Energy storage systems can resolve the power intermittency issue, but low-cost, high-density storage systems are still not available. Second, the cost of installing and maintaining PV units is still expensive compared with the centralised generation. To facilitate the integration of onsite wind and solar generation, two fundamental questions shall be addressed. First, which energy solution is more cost-effective: PPA or wind- and solar-based DG system? Second, is it technically feasible to harness onsite wind and solar power to achieve zero-carbon industrial operations without energy storage? To answer both questions, this paper proposes a stochastic optimisation model to investigate the trade-off between PPA and a DG system in terms of energy reliability, system cost and environmental benefits. We propose a grid-connected DG system comprised of WT, PV and PPA to power a medium-size industrial facility, and optimise the generation capacity by achieving the following goals: (1) minimising levelised cost of energy; and (2) attaining zero-carbon emissions. To verify and validate the proposed solution, the proposed energy model is tested in 10 different locations of the world with diverse climatic conditions.

The contributions of the paper are twofold. First, we present a quantitative method to seek zero-carbon industrial operations through the synthesis of PPA and DG system. Although PPA and DG have been discussed extensively in literature, a joint energy supply model with both PPA and DG has rarely been investigated. Second, the results from this study can be used as a guideline for industrial consumers to determine the best energy strategy to attain carbon-neutral operations in the presence of uncertainties, including climatic conditions, utility price and government regulations. It also serves as a benchmark to compare with other environmental initiative programmes, such as energy efficiency, emission tax and carbon trade-and-cap.

The remainder of the paper is organised as follows. Section 2 reviews existing low-carbon operational methods in industries. Section 3 describes the working principle of the grid-connected DG system, and formulates our stochastic planning model that optimises the capacity mix of onsite and offsite renewable power. Section 4 performs cost-benefit

ASOS	Automated surface observing system
CO2	Carbon dioxide
DER	Distributed energy resource
DG	Distributed generation
DOE	Design of experiments
DR	Demand response
FIT	Feed-in tariff
I/C DR	Interruptible/curtailable demand response
KW	Kilowatt
KWh	Kilowatt-hour
LCOE	Levelised cost of energy
MW	Megawatt
MWh	Megawatt-hour
O&M	Operation and maintenance
PPA	Power purchase agreement
PV	Photovoltaics
WT	Wind turbine

analyses of the DG system using design of experiments (DOEs). In Section 5, actual climatic data from 10 locations of the world are used to test the feasibility of the proposed energy solution. Section 6 concludes the paper. Abbreviations of major terminology are provided below.

2. Literature review

Existing literature pertaining to the modelling and design of low-carbon manufacturing operations can be classified into four categories: (1) energy conservation; (2) carbon trade, cap and tax; (3) onsite renewable generation; and (4) renewable power purchase. Research related to each method is reviewed below.

The idea of energy conservation is to increase the machine usage or reduce its idle time so that less electricity is wasted during the production time. Mouzon, Yildirim, and Twomey (2007) propose an optimal scheme to shorten the equipment idle time by controlling the on-and-off of underutilised machines, hence minimising the total energy use. Mashaei and Lennartson (2013) develop a control strategy for a closed-loop flow shop plant based on a pallet system where energy savings are achieved by reducing the machine runtime and the pallet motions. Choi and Xirouchakis (2014) formulate a linear programming model in an aggregate production environment to minimise a weighted objective function that comprises energy, inventory and backorders. Similarly, Masmoudi et al. (2017) optimise the lot-sizing problem at each production period by minimising the cost comprised of electrical, inventory and set-up expenses. All these studies revolve around the search for the best production plan or machine schedule to lower the power consumption, hence reducing the carbon emissions.

Emissions cap-and-trade is a market-based mechanism designed to control and curb carbon and pollutant generation, and it has been implemented in many countries. Two prominent examples are the European Union Emissions Trading Scheme and the Sulphur Dioxide Emissions Trading Scheme in the United States. We present hereafter related studies that revolve around the design and operations of production and inventory systems under carbon cap-and-trade scheme. Letmathe and Balakrishnan (2005) develop a mixed integer linear mathematical model to optimise the product mix, operating procedures, and production quantities under environmental regulations and emissions penalties. Their goal is to decide how to sell products and carbon emission allowances such that the total profit is maximised. Hua, Cheng, and Wang (2011) and Bouchery et al. (2012) study how firms manage carbon footprints in transportation and warehousing facilities under the cap-and-trade regulation by comparing the optimal cost with that for the classical economic order quantity model. Gong and Zhou (2013) develop a dynamic production model to meet the random market demand by choosing between a costly yet green technology and a cheap but dirty technology. They characterise the optimal emissions trading and production policies to minimise the expected production cost. Hammami, Nouira, and Frein (2015) incorporate carbon tax and emission caps in a multi-echelon production-inventory system under lead-time constraints, and show that individual caps can significantly lower the overall emissions, but may paradoxically increase the emissions per unit product. This paper also pursues a low carbon production system, but our approach differs from carbon cap-and-trade in that we directly install and integrate green energy technologies in manufacturing facilities.

In a DG mode, renewable energy units are installed in proximity to the industrial facility for energy supply. Villarreal et al. (2013) design an onsite generation system comprised of WT and PV to power a semiconductor fab. The model is tested in five US fabs under different wind and weather conditions, and the optimal capacity mix is determined based on DOEs and response surface method. Moon and Park (2014) optimise a multi-machine, multi-process manufacturing scheduling problem by taking into account partial renewable supply from onsite generation and storage system. Li et al. (2017) investigates the technical feasibility of realising a net-zero-carbon manufacturing facility that solely relies on distributed wind and solar power. Pechmann, Schöler, and Ernst (2016) investigate a virtual power plant consisting of wind, solar, biomass and storage to satisfy the energy demand of a medium-size manufacturing firm. The results show that adopting a partial self-supply of renewable energy, especially roof-top PV is lucrative under current renewable incentive scheme in Germany. Similar to these works, our study also aims to attain low-carbon industrial operations. The main difference is that we synthesise distributed energy with offsite renewable power purchase program to achieve zero emissions, while existing onsite generation models usually exclude PPA.

The literature review indicates that there is a lack of quantitative studies in which corporate PPA and onsite DG are integrated to achieve high supply reliability and low energy cost. Motivated by this gap, we formulate a stochastic programming model to minimise the levelised energy cost by optimising the mix of onsite and offsite renewable power generation. We further derive managerial insights that would be impossible to obtain if PPA and DG are studied separately.

3. Model formulation

3.1 *Integration of onsite and offsite renewables*

We propose a grid-connected DG system to power a manufacturing facility in pursuit of zero-carbon emission target. As shown in Figure 1, the onsite DG system consists of WT, PV, substation and feed-in tariff (FIT) mechanism, in which onsite WT and PV arrays are owned by the manufacturing firm. FIT is a government policy in which the owner of the DG system can export surplus renewable energy to the main grid and receives monetary compensation as a reward. Since the DG system is connected with the main grid via the substation, the firm can also import offsite renewable energy under PPA. Large wind farms, solar parks and hydropower plants are the main supplier of offsite renewable energy.

Three scenarios should be considered in operating a grid-connected DG system. First, if the output power of the DG system is smaller than the demand, the gap can be filled by importing the offsite renewable power through the substation. Second, if the DG output is larger than the demand, the surplus renewable energy can be fed into the main grid via FIT. Third, under PPA, part of or the entire facility's electricity demand can be satisfied by offsite renewable energy suppliers. The facility realises zero-carbon emissions provided that the cumulative electricity use in a year is fully offset by the onsite and/or offsite renewable energy.

Demand response (DR) is a supply–consumption balance scheme in which the electricity consumers change the load profile to better match with the available power. Large industrial firms usually sign a specific DR contract with the utility company, and agreed to curtail the load upon request. In return, the firm participating in DR is able to pay a reduced electricity rate or receive other forms of financial benefits such as a lump-sum payment. The duration of a DR event usually does not exceed eight hours (Baldick, Kolos, and Tompaidis 2006). We focus on interruptible/curtailable (I/C) DR contract because it is the most widely used programme for large industrial consumers. Let D_t be the power demand of the facility at time t, and L_t be the demand to be curtailed at t. The load curtailment of a typical I/C DR event falls in $0 < L_t \leq 0.2E[D_t]$. For detailed analysis and modeling of I/C DR programs, readers are referred to the study by Aalami, Moghaddam, and Yousefi (2010).

3.2 *Stochastic planning model*

The following notations are used in the zero-carbon facility planning model in this paper.

The zero-carbon energy generation model is stated as follows: The facility aims to minimise the levelised cost of energy (LCOE) while attaining 100 per cent of renewable energy penetration. LCOE is defined as the annualised cost of the energy system divided by the cumulative energy generated in a year. In power industry, LCOE serves as a basic instrument for both utility companies and energy developers to compare the aggregate costs of capital equipment, operations and maintenance (O&M), reliability performance, carbon tax and government subsidies with different generating technologies and lifetimes (Cory and Schwabe 2009). Denoted as Model P1, the DG design model is stated as follows.
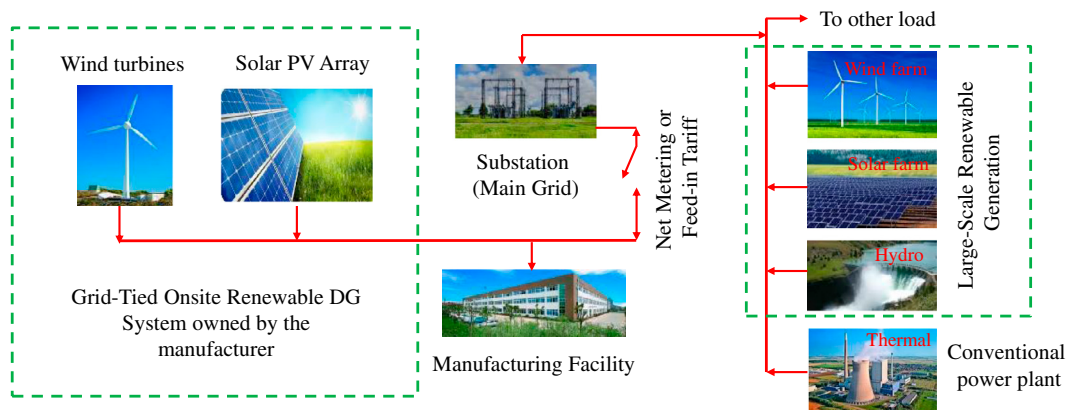

Figure 1.　A hybrid energy system consisting of DG and PPA schemes.

3.2.1 *Model P1*

Minimise:

$$
f(\mathbf{P}^c, G) = \frac{1}{\sum_{t=1}^{h}\left(D_t - \{L_t\}^+\right)}\left\{ \phi(n,r)\sum_{i=1}^{m} a_i P_i^c + \sum_{t=1}^{h}\sum_{i=1}^{m}(b_i - c_i)P_{it} + \varepsilon\sum_{t=1}^{h}\{L_t\}^+ \\
+ h\rho_2 G + \sum_{t=1}^{h}\left[(\rho_1 I(Z_t) + qI(-Z_t))\left(D_t - \sum_{i=1}^{g}P_{it} - G - \{L_t\}^+\right)\right]\right\}
$$

(1)

Subject to:

$$
Z_t = D_t - \sum_{i=1}^{g} P_{it} - \{L_t\}^+ - G, \quad \text{for } t = 1,2,\ldots,h
$$

(2)

$$
\sum_{t=1}^{h}\left(\sum_{i=1}^{g} p_{it} + \{L_t\}^+\right) + hG = \sum_{t=1}^{h} D_t,
$$

(3)

$$
0 \le G \le E[D_t]
$$

(4)

$$
P_1^c, P_2^c, \ldots, P_g^c \ge 0,
$$

(5)

Note that $\mathbf{P}^c = \{P_1^c, P_2^c, \ldots, P_g^c\}$ and G are the decision variables. In particular, $\mathbf{P}^c$ represents the power capacity of onsite generation type i for $i = 1, 2, \ldots, g$, and G is the purchased renewable power. The objective function (1) is formulated to minimise the LCOE in which the numerator is the annualised energy cost and the denominator is the yearly electricity consumption of the facility. The energy cost includes onsite WT and PV installation, O&M expenses, carbon credits, production loss due to curtailed load, renewable power purchase, utility bills and feed-in tariff. Note that carbon credits and feed-in-tariff are indeed the incomes of the industrial facility and, therefore, are subtracted from the total cost. The goal is to determine $\mathbf{P}^c$ and G such that the LCOE is minimised. $\phi(n, r) = [r(1 + r)^n]/[(1 + r)^n - 1]$ is the capital recovery factor where r is the interest rate, and n is the number of years to pay off the onsite DG equipment cost. Note that $\{L_t\}^+ = L_t$ if $L_t > 0$, and is 0 if $L_t \le 0$. Also $I(Z_t)$ is the indictor function, and Z_t is the net power defined in Equation (2). If $Z_t > 0$, then $I(Z_t) = 1$, or 0 if $Z_t \le 0$. If $Z_t > 0$, it means D_t is larger than the sum of the renewable power and the curtailed load, and vice versa. Constraint (3) states that the sum of onsite renewable energy (plus DR curtailment) and the offsite purchased energy in a year equals the total electricity consumption of the facility; hence realising the zero-carbon emission goal. Constraint (4) defines the cap of PPA which is the mean of the facility load. Constraint (5) states the non-negativity requirements of the decision variables. All other parameters are explained in Table 1.

Table 1. Notations of DG planning model.

Notation	Meaning
ϕ	Capital recovery factor
n	Number of years to pay off the DG investment cost
r	Annual interest rate or discount factor
m	Number of available DER type
a_i	Capacity cost of DER type i (unit: \$/MW)
b_i	Operating and maintenance cost of DER type i (unit: \$/MWh)
c_i	Carbon credits for generating type i (unit: \$/MWh)
h	Annual operating hours of the facility assuming 24/7 mode
ε	Production losses in demand response event (unit: \$/MWh)
ρ_1	Price of conventional electricity (unit: \$/MWh)
ρ_2	Price of offsite renewable energy, i.e. the PPA price (unit: \$/MWh)
q	Feed-in tariff (unit: \$/MWh)
G	Offsite renewable power purchased (unit: MW)
$\mathbf{P}^c$	$\{P_1^c, P_2^c, \ldots, P_m^c\}$, where P_i^c is the power capacity of DER type i
$\mathbf{P}$	$\{P_1, P_2, \ldots, P_m\}$, where P_i is the random output power of DER type i
D_t	Electricity demand of the facility at time t (unit: MW)
L_t	Load curtailment level at time t (unit: MW)
Z_t	Net power of the DG system at time t (unit: MW)

3.3 *Simulation-based optimisation algorithm*

Model P1 is a non-linear, non-smooth stochastic optimisation model. Scenario trees and simulation-based optimisation algorithm can be used to search for a good solution that is expected be close to the optimal solution. Readers are referred to (Birge and Louveaux 2011; Gosavi 2015) for a complete treatment of global optimisation problems using non-traditional computational methods.

This paper adopts the simulation-based optimisation to tackle the non-linear programming model in P1. The iterative process to find the optimal **P** and G based on simulation-based optimisation is described in Figure 2. This simulation algorithm involves three loops representing PPA, onsite WT and PV generation. Note that G^{max} is the upper limit of purchased renewable power, and P_i^{max} is the upper capacity limit of generation type i. Both G^{max} and P_i^{max} can be determined based on the load profile of the facility. Without loss of generality, only loops $i = 1$ and 2 are shown in Figure 2. If $m > 2$, then there are m loops of incremental operations on $P_i = P_i + \Delta P_i$ for $i = 1, 2, \ldots, m$. The mathematic models for simulating hourly wind and PV generation are available in (Li et al. 2017). For demand responses, we use the same probabilistic model proposed by Santana-Viera et al. (2015) to characterise the I/C DR contract that involves Poisson calls and uniformly distributed curtailment duration. The optimisation algorithm is implemented in MatLab running on a Dell PC featuring Intel(R) Core™2 Duo CPU @2.93 GHz and 8 GB memory.
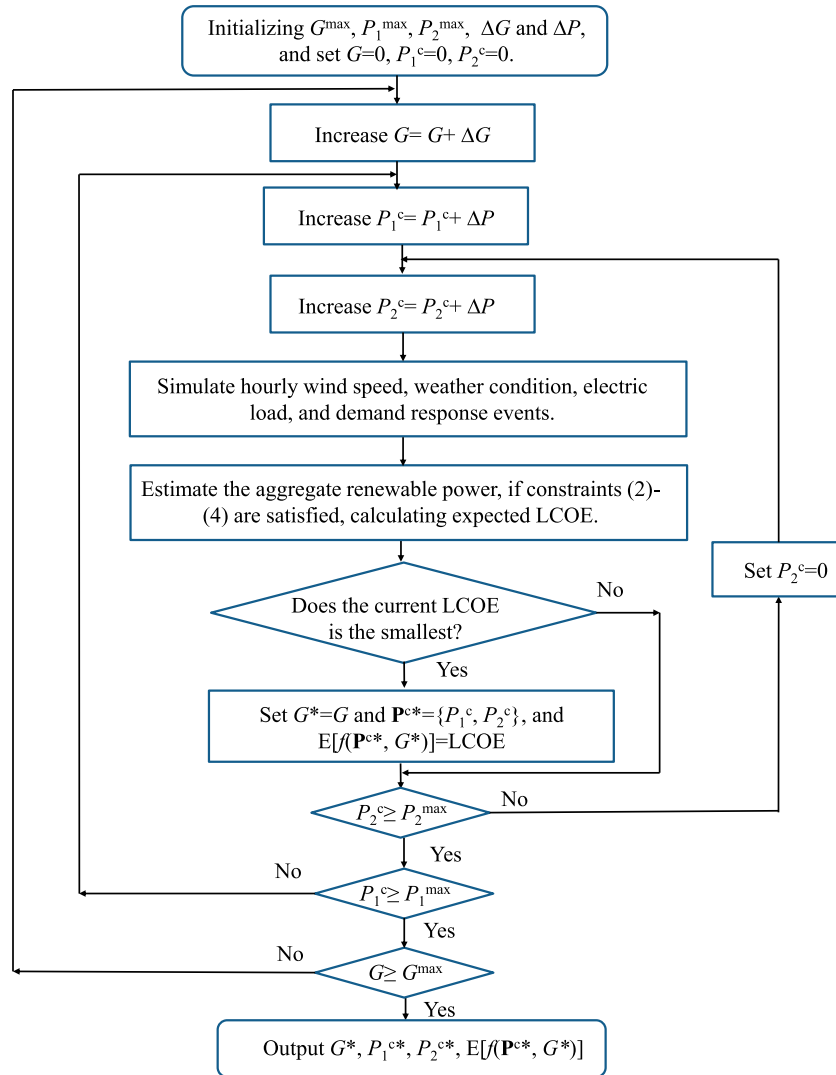

Figure 2.   Flow chart of optimisation algorithm for PPA, WT and PV.

4. Numerical study using DOEs

4.1 *Background information*

The electricity consumption data of a wafer fab in Austin, TX, USA is used to characterise the annual power demand profile. Since the fab facility operates 24 h a day and 7 days a week, the hourly demand, represented by the mean and standard deviation, is used to capture the fab's electricity consumption profile in each month. As shown in Table 2, the hourly mean demand and its standard deviation capture two piece of information: (1) the daily demand profile by simulating the demand hour-by-hour based on the normal distribution; and (2) the seasonality effect through different mean demand across 12 months. Moreover, according to Table 2, the electric demand between February and March is among the lowest with the average of 8.846 and 8.853 MW, respectively. It ramps up from April and reaches the peak at 10.334 MW in September before declining to 9.267 MW in January the next year. Since the facility is physically located in Austin, hot summer weather coupled with market spikes contribute to the variation of electricity demands.

WT and PV are the onsite generating units to be installed near the wafer fab. The cut-in, rated and cut-off speeds of WT are $v_c = 2$, $v_r = 10$, and $v_s = 25$ m/s, respectively. The efficiency of PV panel is $\eta = 0.15$, and its operating temperature is assumed be $T_o = 45\,°C$. These values, though vary in different location and time, are frequently used in literature as the standards in estimating the wind and solar generation (Freris and Infield 2008). The lifetimes of WT and PV equipment usually are assumed to be $n = 20$ years, and the loan interest rate $r = 0.05$. It is common to assume the contingency calls under the I/C DR programme follow the Poisson process with $\lambda = 5$ calls/year. The maximum curtailment duration is $T_{max} = 8$ h/event, and the level of each curtailment is $L_{max} = 1.91$ MW, namely $0.2E[D_t]$. The actual DR duration and the curtailment level could be smaller than T_{max} and L_{max}, respectively. We take the extreme values so as to cover the worst DR scenarios in a year. For PPA data, Bolinger et al. (2015) show that the price of renewable power purchase contract continues to decline such that newly contracted price can compete with conventional electricity. Hence, we set $\rho_2 = \$70/MWh$. Other cost items related to WT and PV are available in Table 3.

Table 2. Mean and standard deviation (Stdev) of load per hour (Li et al. 2017).

Month	January	February	March	April	May	June
Mean (MW)	9.267	8.846	8.853	8.930	9.397	9.588
Stdev (MW)	0.232	0.221	0.221	0.223	0.235	0.240
Month	July	August	September	October	November	December
Mean (MW)	10.068	9.983	10.334	10.237	10.093	9.448
Stdev (MW)	0.252	0.250	0.258	0.256	0.252	0.236

Table 3. Cost parameters of WT and PV equipment.

Notation	Description	DOE (Section 4)	Testing cities (Section 5)	Unit
a_1	Capacity cost of WT	1.5×10^6	1.5×10^6	$/MW
a_2	Capacity cost of PV	4×10^6	4×10^6	$/MW
b_1	O&M cost of WT	14	14	$/MWh
b_2	O&M cost of PV	8	8	$/MWh
ρ_1	Price of conventional electricity	70	70 or variable	$/MWh
ρ_2	Price of renewable power in PPA	70	70 or variable	$/MWh
q	Feed-in tariff	70	70	$/MWh
ε	Production losses in a DR event	10,000	10,000	$/MWh
λ	Demand response call rate	5	5	Calls/year
T_{max}	Maximum duration of a DR event	8	8	Hours
L_{max}	Maximum level of curtailed load	1.91	1.91	MW

4.2 *Experimental set-up*

The power output and the energy cost of WT and PV units are determined primarily by three factors: wind speed, weather condition and site latitude. While WT output is dominated solely by wind speed, the PV output is dependent on the weather condition and the latitude. We apply the DOE method to investigate how these factors jointly determine the output of the onsite DG system. To that end, a $7 \times 3 \times 2 = 42$ factorial experiment is performed, corresponding to seven wind speeds, three types of weather condition and two latitudes.

For the wind speed, we increase the mean value from 3 to 9 m/s with an increment of 1 m/s. The standard deviation is assumed to be 15 per cent of its mean value. We consider three weather conditions: strong sunshine $W_1 = \{70, 20, 10\}$, medium sunshine $W_2 = \{40, 30, 30\}$, and weak sunshine $W_3 = \{20, 30, 50\}$, where the numbers in the bracket represent the percentage of sunny, partially cloudy and overcasting days across a year, respectively. Given the fact that the majority of the human beings reside between South 45 and North 45° of the Earth, two levels of latitude are considered: 30° and 45°. Due to the symmetry of the Earth, only the latitudes of northern hemisphere are considered. To ease the comparison, 42 designs are classified into six cases shown in Table 4. Two additional designs, denoted as Cases 7 and 8, are presented to examine whether PV can compete with the wind generation if the equipment cost is reduced to $1.5 and $1 M/MW, respectively.

4.3 *Results analysis and discussion*

For each design in Table 4, Model P1 is solved to minimise the LCOE by finding the optimal generation mix of purchased power G, WT capacity P_1^c, and PV capacity P_2^c. Since $E[D_t] = 9.587$ MW, the capacity of G is assumed to be an integer taking a value from $\{0, 1, \ldots, 9\}$. Note that $G = 10$ MW is not considered because it exceeds $E[D_t]$. A total of 42 instances are optimised and the results of each instance are summarised in Table 5. The following observations are made from Cases 1 to 6.

- As anticipated, the LCOE decreases with the wind speed regardless of the weather condition and the latitude. If wind speed is 6 m/s or lower, then LCOE falls in a range between $76/MWh and $97/MWh. If wind speed reaches 9 m/s, then LCOE drops to a lower range between $40/MWh and $48/MWh.
- Regardless of the weather condition and the latitude, with $\rho_2 = \$70$/MWh, PPA is preferred if the local wind speed is less than 6 m/s. The optimal offsite power is 8–9 MW, covering the majority of the facility's demand. Onsite wind generation starts to displace PPA if the wind speed reaches or exceeds 7 m/s.
- Given that the installation cost of PV is $4 M/MW (i.e. 1.67 times higher than WT), there is no cost advantage to use PV even under the strong sunny weather W_1. In Cases 1 and 2 where the overcast days are only 10% in a year, PPA is still preferred over onsite PV as long as the local wind speed is 6 m/s or less. Obviously, the small amount of PV installation in Cases 1 and 2 simply offset the demand spike of the industrial facility.

Cases 7 and 8 aim to analyse how the PV installation cost influences its penetration rate in a hybrid energy portfolio comprised of PPA and WT. With the advancement of design and manufacturing technologies, it is foreseeable that the PV cost will continue to decline in the next 10–20 years. We solve Model P1 by lowering the PV cost from $4 M/MW to $1.5 M/MW and $1 M/MW so that the costs of PV and WT are comparable. Under the strong sunny weather W_1 with latitude 30°, we search for the optimal generation mix and the results are shown in the two rightmost columns of Table 5. Two observations can be made by comparing Case 7 with Case 1. First, Case 7 shows that at $1.5 M/MW, PV can compete with wind generation if the local wind speed is less than 6 m/s; however, PPA is still preferred over PV

Table 4. Levels of wind speed, weather condition and latitude.

Case	Wind speed	Weather condition	Latitude	PV ($M/MW)
1	{3, 4, 5, 6, 7, 8, 9}	{70, 20, 10}	{30}	4
2	{3, 4, 5, 6, 7, 8, 9}	{70, 20, 10}	{45}	4
3	{3, 4, 5, 6, 7, 8, 9}	{40, 30, 30}	{30}	4
4	{3, 4, 5, 6, 7, 8, 9}	{40, 30, 30}	{45}	4
5	{3, 4, 5, 6, 7, 8, 9}	{20, 30, 50}	{30}	4
6	{3, 4, 5, 6, 7, 8, 9}	{20, 30, 50}	{45}	4
7	{3, 4, 5, 6, 7, 8, 9}	{70, 20, 10}	{30}	1.5
8	{3, 4, 5, 6, 7, 8, 9}	{70, 20, 10}	{30}	1.0

Table 5. Optimal generation mix for Cases 1 to 8.

Wind	Case	1	2	3	4	5	6	7	8
3 (m/s)	PPA (MW)	9.0	9.0	9.0	9.0	9.0	9.0	9.0	0.0
	WT (MW)	0.0	0.2	0.0	0.8	0.5	0.8	0.0	0.2
	PV (MW)	3.0	3.2	3.5	3.5	4.2	4.5	3.0	43.8
	LCOE ($/MWh)	88.3	87.3	89.8	93.5	97.2	95.5	84.6	63.4
4 (m/s)	PPA (MW)	9.0	9.0	9.0	9.0	9.0	9.0	9.0	0.0
	WT (MW)	0.5	0.5	3.0	3.7	3.8	4.0	0.0	0.3
	PV (MW)	2.5	2.8	2.2	2.2	2.3	2.5	3.0	43.5
	LCOE ($/MWh)	87.4	86.8	87.8	87.1	89.8	90.7	83.5	56.5
5 (m/s)	PPA (MW)	9.0	9.0	9.0	9.0	9.0	9.0	9.0	0.0
	WT (MW)	4.5	4.0	4.0	4.0	4.0	4.0	0.0	0.0
	PV (MW)	0.0	0.5	0.5	0.5	0.5	0.5	3.0	44.0
	LCOE ($/MWh)	83.9	83.3	82.4	81.3	79.5	86.8	84.5	52.0
6 (m/s)	PPA (MW)	8.5	9.0	9.0	8.0	8.0	8.0	9.0	0.0
	WT (MW)	5.0	2.5	2.5	7.0	7.0	7.0	0.7	0.3
	PV (MW)	0.0	0.2	0.5	0.0	0.0	0.0	2.3	43.2
	LCOE ($/MWh)	79.5	77.6	80.4	76.1	79.7	83.3	88.2	58.2
7 (m/s)	PPA (MW)	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0
	WT (MW)	26.0	26.2	25.2	26.2	26.2	26.3	25.8	1.3
	PV (MW)	0.0	0.3	0.5	0.2	0.3	0.2	0.8	41.8
	LCOE ($/MWh)	67.4	63.4	73.4	57.1	68.8	62.8	66.3	57.7
8 (m/s)	PPA (MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	WT (MW)	17.5	17.5	17.5	17.8	17.8	17.7	17.5	17.3
	PV (MW)	1.0	0.7	0.8	0.2	0.2	0.3	0.3	1.2
	LCOE ($/MWh)	51.2	50.2	52.5	48.6	49.9	49.1	48.4	55.5
9 (m/s)	PPA (MW)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	WT (MW)	13.0	13.0	13.0	13.5	13.5	13.5	13.0	17.5
	PV (MW)	0.5	1.0	1.0	0.0	0.0	0.0	0.7	0.5
	LCOE ($/MWh)	46.6	39.5	48.7	42.7	39.0	42.9	47.9	52.0

because of low cost. Second, Case 8 shows that if the PV cost drops to $1 M/MW, PV can displace PPA and WT in areas where the wind speed is 7 m/s or less. Above that speed, WT takes over PV and PPA.

4.4 *Discussion of DG stability*

In a conventional power grid, electric energy can only flow from central power plants to end consumers through transmission and distribution lines. With the advent of onsite DG systems, bi-directional power flow becomes possible and necessary. Since utility-scale storage systems are still costly to implement, surplus power from local DG system has to be fed into the main grid under FIT scheme. However, reverse current may cause voltage stability issue, and also create dispatch challenges due to the intermittency of renewable generation. To maintain the grid stability, a common practice is that surplus power exported to the grid is consumed locally. This design criterion is reflected in Constraint (3) where the annual demand is exactly offset by the onsite and offsite renewable generation. Hence, it reduces the amount of surplus power exported to the main grid, and maintains the voltage at a stable level.

5. Application in real-world environment

5.1 *Background introduction*

The cities from Li et al. (2017) are used to test the proposed DG and PPA model, and the information about latitude, wind speed and weather condition are duplicated in Table 6. The climatic data of each city are retrieved from the National Climate Date Centre (NCDC 2014) and Weather Underground (WU 2014). The daily wind speed data are recorded by the Automated Surface Observing Systems (ASOS) that are typically situated in the local airport, and the ASOS wind sensors are placed 8–10 m above the ground. Note that Rio Gallegos and Wellington are located in the southern hemisphere. The rest of the cities are in the northern hemisphere. In particular, Shanghai, Sanya and Tokyo are in Asia. Munich is in Europe. Boston, New York and Phoenix are in North America, and Honolulu is on the Pacific

Table 6. Wind speed and weather condition of ten cities (Li et al. 2017).

No.	City	Country	Latitude (degree)	AWS (m/s)	SWS (m/s)	Sunny (days)	PC (days)	Overcasting (days)
1	Rio Gallegos	Argentina	51.63	7.16	1.07	144	84	137
2	Shanghai	China	31.20	5.02	2.15	181	41	140
3	Sanya	China	18.25	6.51	3.11	235	42	88
4	Munich	Germany	48.13	5.14	1.04	65	110	190
5	Tokyo	Japan	35.68	5.22	0.40	179	22	164
6	Wellington	New Zealand	41.29	8.05	1.21	79	100	186
7	Phoenix	USA	33.30	2.78	0.32	211	85	70
8	Boston	USA	42.36	5.68	0.56	168	64	133
9	Honolulu	USA	21.30	5.09	0.50	169	39	157
10	New York	USA	40.71	5.30	0.60	107	102	156

Note: AWS = average wind speed, SWS = standard deviation of wind speed, PC = partially cloudy.

Table 7. Carbon credits and utility price (utility means conventional electricity).

Case	c_1 ($/MWh)	c_2 ($/MWh)	ρ_1($/MWh)	ρ_2 ($/MWh)	Utility pricing	PV cost ($M/MW)
A	0	0	70	70	Flat	4.0
B	0	0	70	50	Flat	4.0
C	0	35	70	70	Flat	4.0
D	0	0	70	70	3% up	4.0

island. Since the latitude of these cities varies between 18.25° and 51.63° in both northern and southern hemispheres, these sites cover the majority of the regions where the people live.

To cover a variety of generation scenarios, we investigate five cases subject to different carbon credit, feed-in tariff, utility price and PV installation cost. The data are obtained from the literature and government reports with the best effort to reflect the reality (Freris and Infield 2008; NREL 2013). The US Government uses $37/ton as the 'social cost' of carbon to guide current energy regulation policies (Moore and Diaz 2015). Here the carbon credit of $35/MWh is used to generate 1 MWh, the carbon emission is close to one ton using coal. As shown in Table 7, Case A serves as the benchmark with a flat rate of $70/MWh for conventional electricity and no carbon credits to onsite wind and solar generation. Cases B is designed to estimate the LCOE assuming the PPA price is reduced from $70/MWh to $50/MWh. In Case C, we estimate the LCOE when $35/MWh carbon credit is granted to onsite PV. Carbon credit to WT is not considered as wind generation has been cost-effective. Finally, Case D aims to analyse whether LCOE will change significantly if the conventional utility price increases 3% annually.

5.2 *Result discussions and future studies*

For each city, we solve Model P1 and determine the optimal generation mix of PPA, WT and PV for the given parameters. As shown in Figure 3(a), in the benchmark of Case A, PPA is preferred over onsite wind and solar generation in locations where the average wind speed is less than 6.5 m/s. However, in Rio Gallegos, Sanya and Wellington, onsite WT is more economical than PPA and PV. Though Phoenix possesses the strongest sunshine, PPA turns out of be more cost-effective than onsite PV as the latter involves high installation cost.

In Case B, we reduce the PPA price from $70/MWh to $50/MWh. From Figure 3(b) it is interesting to see that onsite wind generation remains competitive in Rio Gallegos and Wellington, but Sanya now has a mixed capacity of 7 MW PPA and 8 MW WT. This example shows that onsite wind generation still can compete with PPA at a rate of $50/MWh, provided that the local average wind speed is above 7 m/s.

In Case C, Model P1 is solved for the optimal generation mix assuming that onsite PV receives $35/MWh carbon credit. By comparing to Case A, the results in Figure 3(c) show that carbon credit has limited effect to incentivise the adoption of onsite PV because the current energy cost of PPA and WT are far below the LCOE of PV.
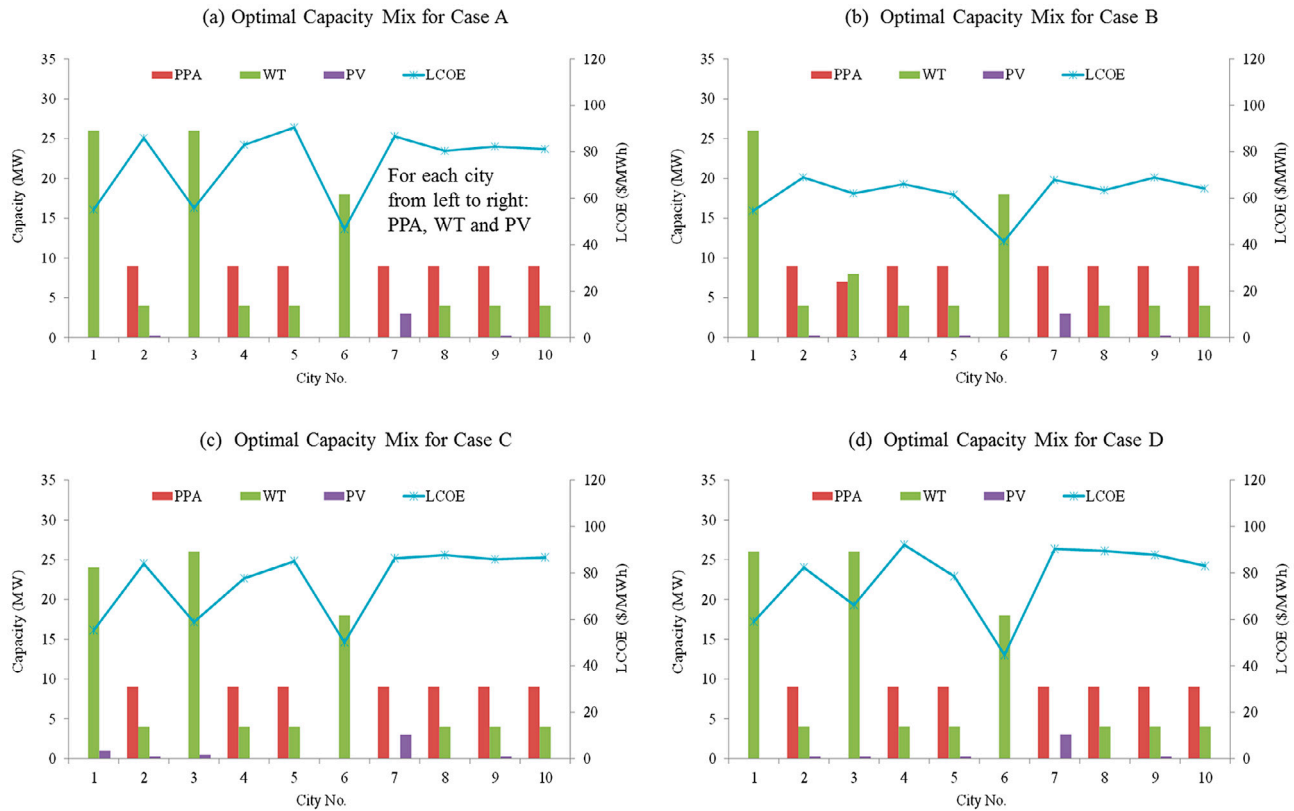
Figure 3. Optimal capacity mix and LCOE for Cases A to D.

In Case D, we assume that the conventional electricity price increases three per cent annually. This means $\rho_1 = \$70/$ MWh in year 1, and it goes up to $122.7/MWh in year 20. Since PPA is typically a long term contract with larger renewable energy developers, it is reasonable to assume that the price of PPA remains at $\rho_1 = \$70/$MWh over a 20-year horizon (Baker and McKenzie 2015; Bolinger, Weaver, and Zuboy 2015). We expect that LCOE may increase as a result of the increased rate of conventional electricity. By comparing the corresponding cities between Figures 3(a) and 3(d), there is no obvious change in both capacity mix and LCOE. This observation indicates that manufacturing companies who participate in PPA or adopt onsite renewable generation can avoid the price volatility in the spot or wholesale electricity market.

Seasonality is a common phenomenon often observed in wind and solar generation. For instance, the wind profile in winter or spring of a particular site could be stronger than in summer or fall, or vice versa. In this paper, since the LCOE is defined as the annualised system cost divided by the total renewable energy output over a year (see Objective function (1) and Constraint (3)), seasonality has limited effects on the annual renewable generation as we consider the aggregate power across the year. In addition, the DG system in this paper is connected with the main grid under feed-in tariff scheme. Such grid-tied configuration streamlines or mitigates the seasonality effort because of the power exchange between the DG and the main grid. However, incorporating the seasonality effect becomes necessary if the DG system operates in islanded mode (i.e. disconnected from the main grid). We believe that this topic deserves further investigations in future studies.

6. Conclusion

This paper proposes a hybrid energy supply model to achieve carbon-neutral industrial operations through the integration of onsite renewable generation and power purchase agreement. To minimise the levelsed cost of energy, simulation-based optimisation is used to search for the optimal capacity mix of offsite and onsite wind and solar power. The hybrid energy solution is tested under a three-factorial design that includes nine levels of wind speed, three types of weather conditions and two site latitudes. The results show that WT is preferred over PPA if the average wind speed is above

7 m/s. PPA is more cost-effective than onsite WT if the local wind speed is below 6 m/s. Onsite PV becomes competitive only if the installation cost drops to \$1.5 M/MW. The model is further tested in 10 cities of the world, and the results are consistent with the findings from the factorial DOEs. First, PPA is a cost-effective approach to achieving zero-carbon industrial operations offered at \$70/MWh. However, onsite wind generation shows a better economic performance if the local wind speed is above 6.5 m/s. Second, PPA and onsite generation can avoid or mitigate the variation or growth of utility price in the long run.

For future studies, the proposed zero-carbon manufacturing model can be extended to supply chain systems that involve production, transportation, warehousing and retail facilities. One can also relax the net-zero emission constraint by incorporating emerging technologies, such as virtual power plants, vehicle-to-grid operations and transactive energy systems.

Disclosure statement

Funding

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