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Dynamic economic and emission dispatch model considering wind power under Energy Market Reform: a case study

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Abstract

With the increasing issues in the environmental and the high requirement for energy, the Energy Market Reform (EMR) was introduced by the UK government. This paper develops a novel Dynamic Economic and Emission Dispatch (DEED) model for a combined conventional and wind power system incorporating the carbon price floor (CPF) and the Emission Performance Standard (EPS) that is supported by the EMR. The proposed model aims to determine the optimal operation strategy for the given system on power dispatch taking into account wind power waste and reserve and also the environmental aspect, especially the CPF of greenhouse gases and the emission limit of the EPS for different decarbonisation scenarios. Case studies for the demand profile in the Sheffield region in the UK with different time intervals is presented. The results indicate that renewable power is superior in both the economics and emissions to a mid to long-term energy strategy in the UK.

Keywords: Dynamic economic and emission dispatch; Electricity Market Reform; carbon price.

Nomenclature

Acronyms

AEP	American electric power
BEIS	Department for Business, Energy and Industrial Strategy
CCS	Carbon capture and storage
CEED	Combined economic and emission dispatch

CHP	Combined heat and power
CPF	Carbon price floor
DED	Dynamic economic dispatch
DEED	Dynamic economic and emission dispatch
ED	Emission dispatch
EMR	Electricity market reform
EPS	Emission performance standard
EU ETS	European Union emissions trading system
GA	Genetic algorithm
GHG	Greenhouse gases
PF	Pareto front
SQP	Sequential quadratic programming
STOR	Short term operating reserves
UC	Unit commitment

1 Roman alphabet

a_i, b_i, c_i	Coefficients in the cost function of the ith conventional generator (£/MW^{3}h, £/MW^{2}h, £/MWh)
c	Scale factor of Weibull distribution (m/s)
C	Total fuel cost in the electrical system (£/h)
$C_{OW,j}$, $C_{UW,j}$	Overestimation and underestimation in the cost of jth wind powered generator respectively (£/h)
$C_{P,i}$	Cost of the ith conventional generator (£/h)
$C_{W,j}$	Direct cost of the jth wind powered generator (£/h)

D	Total demand on the electrical system at time step t (MW)
d_i, e_i, f_i	Coefficients in the emission function of the i^{th} conventional generator (t/MW^3h, t/MW^2h, t/MWh)
E	Total emission in the electrical system (tCO_2e/h)
$E_{P,i}$	Emission of the i^{th} conventional generator (tCO_2e/h)
EE_{limit}	The emission limits of each conventional generator (tCO_2e/h)
F	Fitness function (£/h)
g_j	Coefficient of the cost function of the j^{th} wind powered generator (£/h)
k	Dimensionless shape factor of Weibull distribution
$k_{O,j}$, $k_{U,j}$	Coefficient of the overestimation/underestimation cost function of the j^{th} wind powered generator (£/h)
M	Number of wind powered generators
N	Number of conventional powered generators
P_i	Power output of the i^{th} conventional generator (MW)
$P_{i,min}$, $P_{i,max}$	Minimum and maximum power output of the i^{th} conventional generator (MW)
RRD_i, RRU_i	Ramp rate down/up of the i^{th} conventional generator (MW/h)
r	Carbon price (£/tCO_2e)
SR	Spinning reserve (MW)
T_t	Time of time step t (h)
V	Wind speed random variable (m/s)
W	Wind power random variable (MW)
W_j	Scheduled power output of the j^{th} wind powered generator (MW)
$W_{r,j}$	Rated wind power of the j^{th} wind powered generator (MW)
$W_{A,j}$	Available power output of the j^{th} wind powered generator (MW)

w	Wind power (the wind power random variable) (MW)
w_r	Rated wind power (MW)

Greek alphabet

v	Wind speed (the wind speed random variable) (m/s)
v_i	Cut-in wind speed (m/s)
v_r	Rated wind speed (m/s)
v_o	Cut-out wind speed (m/s)

1. Introduction

With the increasing environmental issues, the UK government is committed to the Climate Change Act by reducing emissions by 80% from their 1990 levels by 2050 [1-3]. In order to achieve this carbon target, the Electricity Market Reform (EMR) is stated in the Energy Act 2013 and it is supported by the Carbon Price Floor (CPF) and an Emission Performance Standard (EPS) [4, 5].

EMR was introduced by the UK government for three objectives, which are to keep the lights on (security), to keep energy bills affordable (affordability), and to decarbonise energy generation (sustainability) [5, 6]. Moreover, in order to improve the environmental conditions and reduce the greenhouse gases (GHG), the European Union Emissions Trading System (EU ETS) provides a market for the trading of the carbon allowances and sets the carbon price [7]. The CPF is a tax rate on the emission of one tonne of CO_2 or the equivalent GHG [8].

EPS is a regulatory component of the National Planning policy. It provides a limit on the emissions of new fossil fuel power stations [5, 9]. The UK Department for Business, Energy and Industrial Strategy (BEIS) states that one of the options to place the closure of unabated coal into effect is to modify the existing EPS on the emission limit per unit of generated electricity at any point in time, rather than have an annual limit [10].

In order to satisfy all the strategies in electrical system operation when taking into account the EMR, an improved Dynamic Economic and Emission Dispatch (DEED) model is proposed in this paper. The security of the system is approached by balancing the power flow, the affordability is satisfied by the economic dispatch (ED) of the system and the sustainability is considered by the renewable power and the emission dispatch in the system.

The ED of the thermal power generating units have been proposed since 1920, or even earlier [11, 12]. Further, in order to minimize the instantaneous operating cost of an electrical power system over a certain period, the dynamic economic dispatch (DED) was proposed in the 1980s [13-16]. With the growing environmental problems, combined economic and emission dispatch (CEED) models have been developed for an electrical system consisting of fossil-fired power plants in the 1990s [17-20]. Then the DEED model was developed in the 2000s [21]. It deals with the schedule of the generator outputs with the predicted load demands over a certain period of time in order to minimize the costs and the emissions simultaneously [22].

With the ever-increasing use of renewable power, the power system network now is not only allocating system power from conventional generators but also from renewable power plants, such as wind farms [23, 24], solar PV plants [25, 26] and hydro power stations [27, 28]. Nowadays, wind power is in the top two of the renewable energies in the UK and its capacity is still increasing [29].

Some of the researches on renewable power have focussed on the stochastic, robustness and security in the power system. For instance, Hreinsson et al. [30], proposed a stochastic $N-1$ security constrained unit commitment (UC) with wind power. Then, Morales-España et al. [31] demonstrated the dispatchable wind with an equivalent single-level mixed-integer program robust UC problem. Wang et al. [32] established a day-ahead UC model for forecast error and reserve decision by considering a time sequence segment-fitting method, three classes reserve strategies and time-varying confidence levels.

Moreover, some research has been performed on modelling the stochastic uncertainty in the nature of the wind speed and the waste penalty and reserve costs of wind power, where the waste penalty appears when the system is not using all the available wind power and the reserve costs related to the requirement of the reserve power when the available wind power is not enough [24, 33-36]. First of all, Hetzer et al. [33] created a new ED model for the conventional power generators and wind-powered generators. They introduced direct waste penalties and reserves costs of the wind power into the ED problem. In this model, the wind power scheduled from a particular generator is strongly dependent on the value of the reserves and the penalty cost factors associated with that generator. Then, Mondal et al. [36] introduced the emission dispatch into the ED model proposed by Hetzer et al. [33] using a gravitational search algorithm. They used price penalty factors to blend the emissions with the normal fuel cost. Moreover, Jin et al. [24] added an environmental objective function for the emission as well as the penalty and reserves wind power costs. In addition, Zhang et al.[37] improved Jin's research by implementing the hybrid Sequential Quadratic Programming – Particle Swarm Optimization (SQP-PSO) algorithm. Then, Dubey et al. [35] applied a hybrid flower pollination algorithm (HFPA) to the CEED model by Jin et al. [24] that includes the time dimension. Further, Durga Hari Kiran et al. [38] took into account demand response and pumped hydro storage. Furthermore, Hu et al. [39] first introduced CPF into the CEED model by using a Genetic Algorithm (GA) - SQP algorithm.

This paper aims to investigate a novel DEED model under UK energy policies, especially the emission aspect, and an analysis of the practical results based on the influence of the energy policies. Thus, this model considers CPF and EPS in the classical DEED problem incorporating wind power. Further, it deals with the dispatch in a power system with conventional power plants and wind farms. The aim of the dispatch is to operate the system under the minimum fuel cost and pollution conditions within the emission allowances. Thus, two objective functions for the minimal economic cost and emissions should be considered. As the dispatch problem aims at finding the optimal power outputs for each generator, this function investigates the relationship between the power outputs and the pollution. The emission function can be costed by CPF, which is the charge in the emissions by the UK and EU [2, 7].

This novel model aims to simulate different scenarios in the UK from 2010 to 2050 and an off-grid system with the demand profile in the Sheffield region of the UK is investigated as a case study. According to the distributed generation data by Northern Powergrid [40], the power stations supplying the Sheffield region currently consists mainly of coal-fired power plants, with some contribution from other very small generators, such as biomass and combined heat and power (CHP). However, wind power is already the largest capacity of renewable power in Yorkshire. As a part of Yorkshire, and from the Fifth Carbon Budget [3], Sheffield may start to use wind power in the near future. Therefore, this model considers conventional and wind powered generators.

The main contributions and the novel characteristics of this paper are the novel and reality method to simulate the emission dispatch optimization for the DEED model by taking CPF into account. Moreover, this research takes into account the EPS as an emission constraint; furthermore, a practical case in the Sheffield region is studied.

The proposed DEED model has the ability to effectively generate solutions for different time intervals in real-time dynamic dispatch. Moreover, this research uses current practical data to obtain the DEED solutions for the Sheffield region. Furthermore, the case study in the Sheffield region indicates that the renewable power is superior in both the economics and emissions in a mid to long-term energy strategy for the UK.

2. Methodologies

The aim of a DEED is to operate the system under the minimum fuel cost and pollution conditions within the emission allowances in a given time period. In the DEED model, the time dimension and the constraints that are effected by time are included in the model.

2.1. Objective functions

2.1.1. Cost functions

The cost function C(t) aims to minimize the running cost of the generators in the electrical power system that includes conventional and wind power over a certain period of time t. Thus, the governing equation is given as follows [33]:

$$\min C(t) = \sum_{t=1}^{T}[\sum_{i=1}^{N} C_{\mathrm{P,i}}^{\mathrm{t}}(P_{\mathrm{i}}^{\mathrm{t}}) + \sum_{j=1}^{M} C_{\mathrm{W,j}}^{\mathrm{t}}(W_{\mathrm{j}}^{\mathrm{t}}) + \sum_{j=1}^{M} C_{\mathrm{OW,j}}^{\mathrm{t}}(W_{\mathrm{j}}^{\mathrm{t}} - W_{\mathrm{A,j}}^{\mathrm{t}}) + \sum_{j=1}^{M} C_{\mathrm{UW,j}}^{\mathrm{t}}(W_{\mathrm{A,j}}^{\mathrm{t}} - W_{\mathrm{j}}^{\mathrm{t}})] \tag{1}$$

where C(t) is the total cost at the time step t, $C_{\mathrm{P,i}}^{\mathrm{t}}$ is the conventional power cost of the i^{th} generator at time step t, $C_{\mathrm{W,j}}^{\mathrm{t}}$ is the wind power cost of the j^{th} wind turbine at time step t, $C_{\mathrm{OW,j}}^{\mathrm{t}}$ is the overestimation cost of the j^{th} wind turbine at time step t, $C_{\mathrm{UW,j}}^{\mathrm{t}}$ is the underestimation cost of the j^{th} wind turbine at time step t, P_i^t is the power output of the i^{th} generator at time step t, W_j^t is the required power output of the j^{th} wind turbine at time step t and $W_{\mathrm{A,j}}^{\mathrm{t}}$ is the available power output of the j^{th} wind turbine.

In industry, the standard practice is that the fuel cost is a function of the power output of a conventional generator, such as a coal or gas turbine, and in the ED it is handled by the use of a polynomial function [41]. Usually, the cost objective function of the power output is expressed by a smooth quadratic function [14, 33, 42, 43], a cubic function [41, 44, 45], or a quadratic function with the non-smooth valve-point effects [22, 24, 35, 46, 47]. Figure 1 indicates the fuel cost as a function of the power output of a typical conventional generator unit [48]. In this research, the cost function with the inclusion of the time dimension is a quadratic function of the power output [33, 49], namely

$$C_{\mathrm{P,i}}^{\mathrm{t}}(P_{\mathrm{i}}^{\mathrm{t}}) = a_{\mathrm{i}} P_{\mathrm{i}}^{\mathrm{t}\,2} + b_{\mathrm{i}} P_{\mathrm{i}}^{\mathrm{t}} + c_{\mathrm{i}} \tag{2}$$

where a_i, b_i, c_i are the coefficients in the cost function of the i^{th} conventional generator.

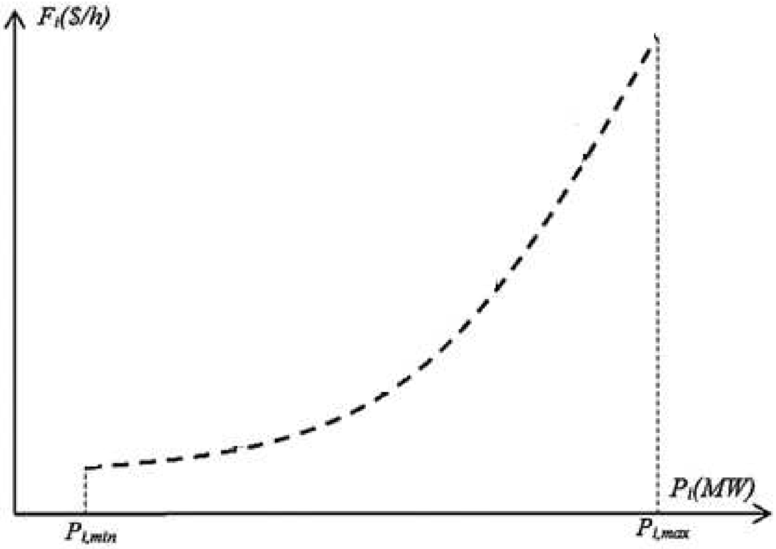

Figure 1 Fuel cost as a function of the power output of a typical conventional generator unit [48].

The direct cost function of the wind powered generator is calculated from the scheduled wind power used in the electrical network. It is assumed to be a linear function of the scheduled wind power and reflects the payment to the wind farm operator for the wind power [33]. It is defined as follows:

$$C_{\mathrm{W,j}}^{\mathrm{t}}\left(W_{\mathrm{j}}^{\mathrm{t}}\right) = g_{\mathrm{j}} W_{\mathrm{j}}^{\mathrm{t}} \tag{3}$$

where g_j is the coefficient of the cost function of the j^{th} wind turbine, which is also the price of the wind power. If the wind farm belongs the system operator, there is no wind power cost and g_j is 0 [33]. However, if the wind farm is outside the system, the owner needs to buy wind power and g_j is the price of the wind power.

The overestimation cost function of the wind powered generator is due to the available wind power being less than the scheduled wind power. The available wind power is the wind power available from the wind farm without any manipulations. This cost is for the reserve requirement related to the difference between the available wind power and the scheduled wind power [33], namely

$$C_{\mathrm{OW,j}}^{\mathrm{t}}\left(W_{\mathrm{j}}^{\mathrm{t}} - W_{\mathrm{A,j}}^{\mathrm{t}}\right) = \ k_{\mathrm{O,j}} \times (W_{\mathrm{j}}^{\mathrm{t}} - W_{\mathrm{A,j}}^{\mathrm{t}}) \tag{4}$$

$$= k_{\mathrm{O,j}} \times \left(\int_{0}^{W_{\mathrm{j}}} \left(W_{\mathrm{j}} - w\right) f_{\mathrm{W}}(w) dw + W_{\mathrm{j}} \times Pr\{w = 0\}\right)$$

where $k_{O,j}$ is the coefficient of the overestimation cost function of the j^{th} wind turbine.

This term is the reserve power cost of the wind power.

Similar to the overestimation cost function, the underestimation cost function of the wind powered generator is due to the penalty cost for not using all the available wind power [33], namely

$$C_{\mathrm{UW,j}}^{\mathrm{t}}\left(W_{\mathrm{A,j}}^{\mathrm{t}} - W_{\mathrm{j}}^{\mathrm{t}}\right) = k_{\mathrm{U,j}} \times \ \left(W_{\mathrm{A,j}}^{\mathrm{t}} - W_{\mathrm{j}}^{\mathrm{t}}\right) \tag{5}$$

$$= k_{\mathrm{U,j}} \times \left(\int_{W_{\mathrm{j}}}^{W_{\mathrm{r,j}}} (w - W_{\mathrm{j}}) f_{\mathrm{W}}(w) dw + \ (W_{\mathrm{r,j}} - W_{\mathrm{j}}) \times Pr\left\{w = W_{\mathrm{r,j}}\right\}\right)$$

where $k_{U,j}$ is the coefficient of the underestimation cost function of the j^{th} wind turbine.

This term is the waste power penalty of the wind power.

2.1.2. Emission functions

The purpose of the emission function is to minimize the pollution from conventional powered generation including the oxides of carbon, sulphur and nitrogen. Assuming that the wind turbines do not produce these pollutants, and the reserve power is from the energy storage that also does not produce pollutants, the emission function contains the conventional powered generators term only [43], namely

$$\min E(t) = \sum_{t=1}^{T} \sum_{i=1}^{N} E_{\mathrm{P,i}}^{\mathrm{t}}(P_{\mathrm{i}}^{\mathrm{t}}) \tag{6}$$

where E(t) is the total cost at time step t and $E_{\mathrm{P,i}}^{\mathrm{t}}$ is the emission of the i^th generator at time step t.

The conventional powered generators emission function is similar to the cost function, which is also formulated for practical cases as follows:

$$E_{\mathrm{P,i}}^{\mathrm{t}}(P_{\mathrm{i}}^{\mathrm{t}}) = d_{\mathrm{i}} {P_{\mathrm{i}}^{\mathrm{t}}}^2 + e_{\mathrm{i}} P_{\mathrm{i}}^{\mathrm{t}} + f_{\mathrm{i}} \tag{7}$$

where d_i, e_i, f_i are the coefficients in the emission function of the i^{th} generator.

2.1.3. Emission constrained costs

According to the EU ETS, the emissions from the power generation need to be paid for according to the carbon price, which is the amount that must be paid per tonne of emitted CO_2 [8]. Thus, the cost equation is constrained by the emission equation as follows:

$$\min F(t) = C(t) + r \times E(t) \tag{8}$$

where r is the CPF.

According to the Equation (8), the emission is simulated as an emission constrained cost by taking the CPF into account. Therefore the emission becomes an emission cost. Thus the multi-objective problem in the model becomes a single objective problem.

2.2. Constraints

Constraints in this model are considered to be in several aspects due to the operational security of the power network and the system components.

2.2.1. Real power balance

The first constraint is the real power balance, which is relevant to the system security and the minimization of the cost. In an ideal power network, the load and supply should be equal and this system power balance equation may be expressed as follows [33]:

$$\sum_{i=1}^{N} P_{\mathrm{i}}^{\mathrm{t}} + \sum_{j=1}^{M} W_{\mathrm{j}}^{\mathrm{t}} = D_{\mathrm{t}} \tag{9}$$

where D_t is the total demand on the electrical system at time stamp t.

2.2.2. Power output limit

The second constraint is the generator limit. The output limit for the conventional generator and the limit of the wind turbine may be expressed as follows [33]:

$$P_{\mathrm{i,min}} \le P_{\mathrm{i}}^{\mathrm{t}} \le P_{\mathrm{i,max}} \tag{10}$$

$$0 \le W_{\mathrm{j}}^{\mathrm{t}} \le W_{\mathrm{r,j}} \tag{11}$$

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum power output of the i^{th} conventional generator and $W_{r,j}$ is the rated wind power of the j^{th} wind powered generator.

2.2.3. Ramp rate

In addition, the ramp rate is a dynamic constraint of the conventional generators. In a dynamic system, a conventional powered generator has a maximum ramp rate which limits how fast it can change its output between time stamps. Therefore, situations can arise in which the generator cannot reach the desired higher power output due to the ramping limit even if the output is within its overall limit and it is given by [50]:

$$-(T_{\mathrm{t}} - T_{\mathrm{t-1}}) \times RRD_{\mathrm{i}} \le P_{\mathrm{i}}^{\mathrm{t}} - P_{\mathrm{i}}^{\mathrm{t-1}} \le (T_{\mathrm{t}} - T_{\mathrm{t-1}}) \times RRU_{\mathrm{i}} \tag{12}$$

where T_t and T_{t-1} are the time of the current time stamp t and the previous time stamp t-1, respectively, and RRD_i and RRU_i are the ramp rate down and ramp rate up of the i^{th} conventional generator, respectively.

2.2.4. Emission limit

Further, the emission allowance gives the emission levels of each generator, or the total emission limits at each time stamp. The emission allowance is an important constraint to satisfy the EPS [9] in the UK electricity system. The emission allowances of the conventional generators are given by

$$0 \leq E_{\mathrm{P,i}}^{\mathrm{t}}(P_{\mathrm{i}}^{\mathrm{t}}) \leq EE_{\mathrm{limit}} \tag{13}$$

where EE_{limit} is the emission limit of each conventional generator at each time stamp.

2.2.5. Spinning reserve

The last constraint is the spinning reserve, also known as the synchronized reserve, which is an online but unloaded reserve capacity. It can respond rapidly to maintain the grid security and reliability [51-53] and it is given by [35]:

$$\sum_{i} (P_{\mathrm{i,max}} - P_{\mathrm{i}}^{\mathrm{t}}) \geq SR^{\mathrm{t}} \tag{14}$$

where SR^t is the spinning reserve at time step t.

2.3. Wind power uncertainty modelling

To deal with obtaining an accurate solution of the CEED problem in an electrical system with conventional and wind resources, the stochastic nature of the wind speed and wind power can be modelled by the Weibull distribution [24, 33]. The probability density function (pdf) for a Weibull distribution of wind speed can be mathematically expressed as follows [24, 33]:

$$f_v(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{15}$$

where v is a random variable of the wind speed, k is the dimensionless shape factor of the Weibull distribution and c is the scale factor with the unit m/s.

The Weibull cumulative distribution function (cdf) of the wind speed can be expressed as follows [24]:

$$F_v(v) = \int_0^v f_v(v)dv = 1 - exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{16}$$

Because of the uncertainty in the wind speed, the power output of a wind turbine is unpredictable. For simplicity, the power output for a given wind speed is categorized as follows [24]:

$$w = \begin{cases} 0, & for\ v < v_{\mathrm{i}}\ or\ v > \ v_{\mathrm{o}} \\ w_{\mathrm{r}} \times \dfrac{v - v_{\mathrm{i}}}{v_{\mathrm{r}} - v_{\mathrm{i}}}, & for\ v_{\mathrm{i}} \ \le v \le v_{\mathrm{r}} \\ w_{\mathrm{r}}, & for\ v_{\mathrm{r}} \le v \le v_{\mathrm{o}} \end{cases} \tag{17}$$

where v_i is the cut-in wind speed of the wind turbine, v_o is the cut-out speed and v_r is the rated speed.

It can be seen that when the wind speed is less than the cut-in wind speed or higher than the cut-out wind speed, there is no power output. Then, if the wind speed is between the cut-in and rated wind speed, the power output is a linear function of the rated power. Otherwise, if the wind speed is between the rated and cut-out wind speed, the power output is equal to the rated power.

2.3.1. Discrete portions of the wind power Weibull cdf

For the discrete portions of the wind power output in equations (17), the probability of $w = 0$ can be calculated from equations (16) and (17), as follows [34]:

$$\begin{aligned} Pr\{w = 0\} &= Pr\{v \le v_{\mathrm{i}}\} + Pr\{v \ge v_{\mathrm{o}}\} \\ &= F_v(v_i) + \left(1 - F_v(v_o)\right) = 1 - exp\left(-\left(\frac{v_{\mathrm{i}}}{c}\right)^k\right) + exp\left(-\left(\frac{v_{\mathrm{o}}}{c}\right)^k\right) \end{aligned} \tag{18}$$

Similarly, the probability of $w = w_{rated}$ can be expressed by [34]:

$$\begin{aligned} Pr\{w = w_{\mathrm{r}}\} &= Pr\{v_r \le v \le v_o\} \\ &= F_v(v_o) - F_v(v_r) = exp\left(-\left(\frac{v_{\mathrm{o}}}{c}\right)^k\right) - exp\left(-\left(\frac{v_{\mathrm{r}}}{c}\right)^{\mathrm{k}}\right) \end{aligned} \tag{19}$$

2.3.2. Continuous portion of the wind power Weibull pdf

For the continuous portion, the wind speed distribution should be converted to the wind power distribution. This transform can be expressed as a linear relationship when the wind speed is between the cut-in and rated wind speed in equation (17), namely [24]:

$$\mathrm{W} = \mathrm{T(V)} = \mathrm{aV} + \mathrm{b}, \qquad v_i \le v \le v_r \tag{20}$$

$$a = \frac{w_r}{v_r - v_i}, \qquad b = w_r \times \frac{v_i}{v_r - v_i}$$

where T(V) is a transform of the V.

The wind power Weibull probability density function (pdf) can be expressed as follows [34]:

$$f_{\mathrm{w}}(w) = f_v\left(\mathrm{T}^{-1}(\mathrm{w})\right)\left[\frac{d\mathrm{T}^{-1}(\mathrm{w})}{dw}\right] = f_v\left(\frac{w-b}{a}\right)\left|\frac{1}{a}\right| = \frac{klv_{\mathrm{i}}}{cw_{\mathrm{r}}}\left(\frac{(1+\rho l)v_{\mathrm{i}}}{c}\right)^{k-1} exp\left(-\left(\frac{(1+\rho l)v_{\mathrm{i}}}{c}\right)^{k}\right) \tag{21}$$

$$l = \frac{v_r - v_i}{v_i}, \qquad \rho = \frac{w}{w_r}$$

2.4. Optimization Algorithm

The optimization problem in this research is bounded and constrained. Therefore the constraint handling technique is required.

2.4.1. Genetic algorithm

The genetic algorithm (GA) is a stochastic method to solve global optimization problems. GA is a good technique to avoid local optimization due to its crossover operator [54].

The implementation of the GA contains of five main stages: initialization, evaluation, selection, crossover and mutation.

i. Initialization: an initial generation population t is generated randomly. In this model, the generation population consists of the outputs of all the power generators.

ii. Evaluation: evaluate the fitness of the population t, which determined by the objective functions. The fitness of this model is the emission constrained costs, which is shown in equation (8).

iii. Selection: select the parent generation from the population t. The better individuals with better fitness are selected to be the parents of the next generation.

iv. Crossover: employ a crossover operator on the population t to create the next generation population t+1. The crossover choses two parents from the population t using the selection operator and the values of the two bit strings are exchanged at randomly chosen points.

v. Mutation: employ a mutation operator on the population t+1 for low probability. The mutation operator flips some bits in the population t+1 to generate the next generation.

Stages ii to v are repeated until the individuals are sufficiently accurate. The results become more and more optimal with time because only better individuals survive. Thus, the balance between optimization and simulation time is considered.

2.4.2. Sequential quadratic programming

The sequential quadratic programming (SQP) method is one of the iterative algorithms for solving smooth nonlinear optimization problems. The SQP method is similar to Newton's method for constrained optimization problems. An approximation is made of the Hessian matrix of the Lagrangian function by using the quasi-Newton method at each iteration. Therefore, subproblems of the quadratic programming (QP) are generated to form the original search direction to a line search procedure [55-57]. Theoretically, the resolution of the constrained smooth nonlinear optimization problem is very accurate through SQP, especially when the Karush-Kuhn-Tucker (KKT) conditions are applied [54, 58-62].

2.4.3. Hybrid GA-SQP algorithm

The GA algorithm is good for the global search. However, it needs a long simulation time and may not be very accurate in the local search [57]. On the other hand, SQP has been found to be a very accurate technique but it is very sensitive to its initial points [54, 58-63]. Therefore, a hybrid GA-SQP algorithm can reduce the computational time and ensure the accuracy [39, 54, 57, 63].

Firstly, using GA as a first stage global optimizer, in order to obtain some reasonable starting points, by exploiting the GA's global search ability. Secondly, use the obtained solution as found by GA is a starting point to the second stage local searching method SQP in order to refine the first stage result. Figure 2 indicates the flow chart of the hybrid GA-SQP optimisation algorithm.

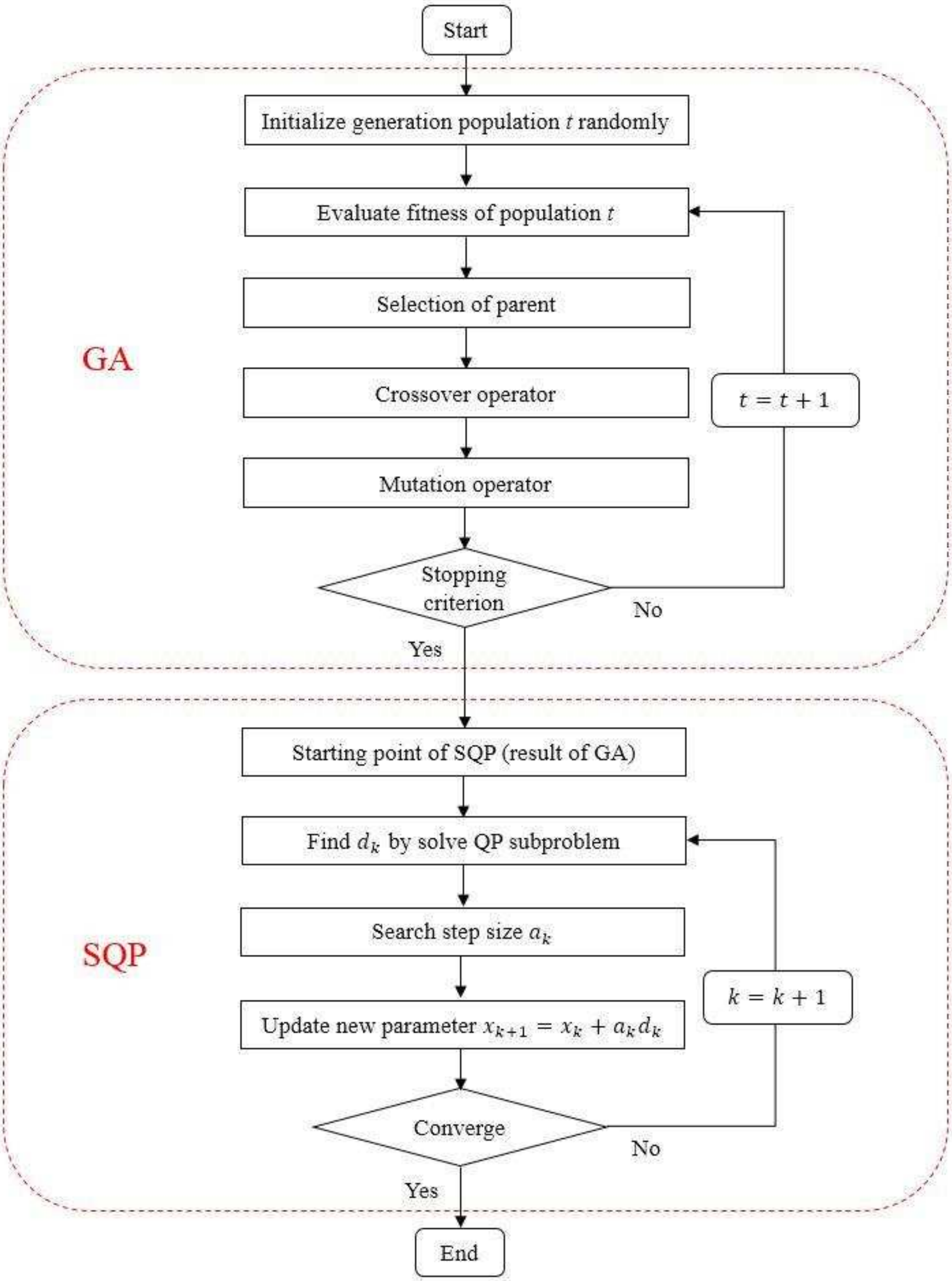

Figure 2 Flow chart of hybrid GA-SQP optimisation algorithm.

A MATLAB program that is based on the CEED model is developed for various scenarios investigated using the GA with an additive form penalty function for constraint handling. If no violation occurs, the penalty term will be zero. Otherwise, the penalty term will be a very large positive number in Matlab [64]. Then a constrained nonlinear optimization algorithm, SQP solver, is applied by using the result found by the GA as a starting point. The average run-time of each scenario is about 400 s and the computational cost [65] for this model is approximately 0.1 s.

3. Case study

This research aims to simulate and analyse a dispatch model under the UK policies. The employed optimization algorithm is GA-SQP [39] and it should be noted that the starting time step of the model is that obtained from the optimal steady state prediction for the first time step, namely the power output of the generators are able to achieve their optimized outputs at the first time step.

In Case 1, an IEEE 30 bus system with six conventional-powered generators and a large scale wind farm, which is shown in Figure 3, is used to illustrate the proposed model for the Sheffield region. Figure 4 shows the electricity demand in the Sheffield region on a typical weekday in March 2015. The red line in Figure 4 is a real half-hourly demand profile in the Sheffield region as provided by Northern Powergrid [66].

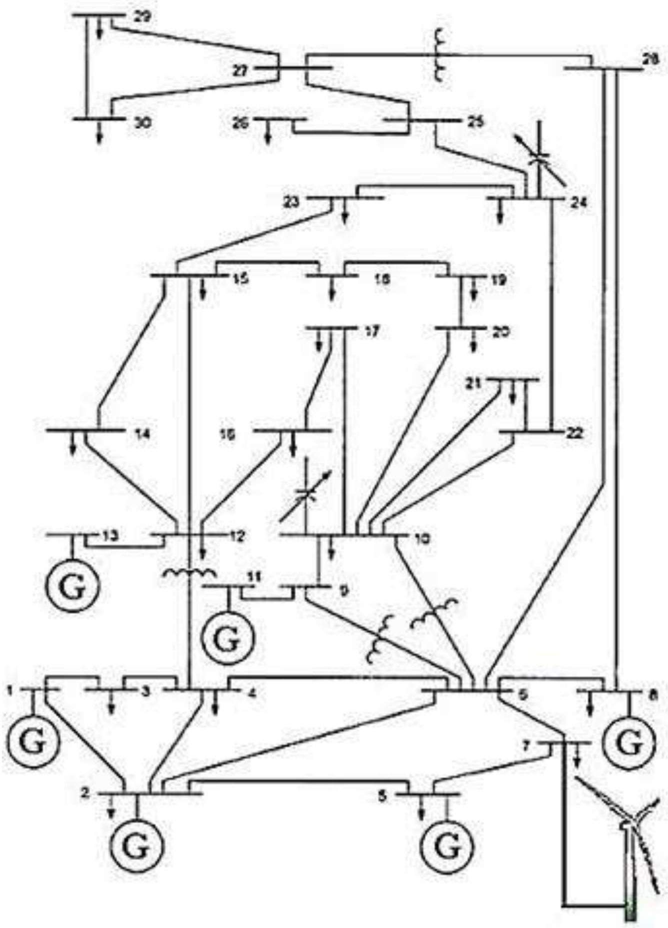

Figure 3 An IEEE 30 bus system with 6 conventional generators and a wind farm [67].

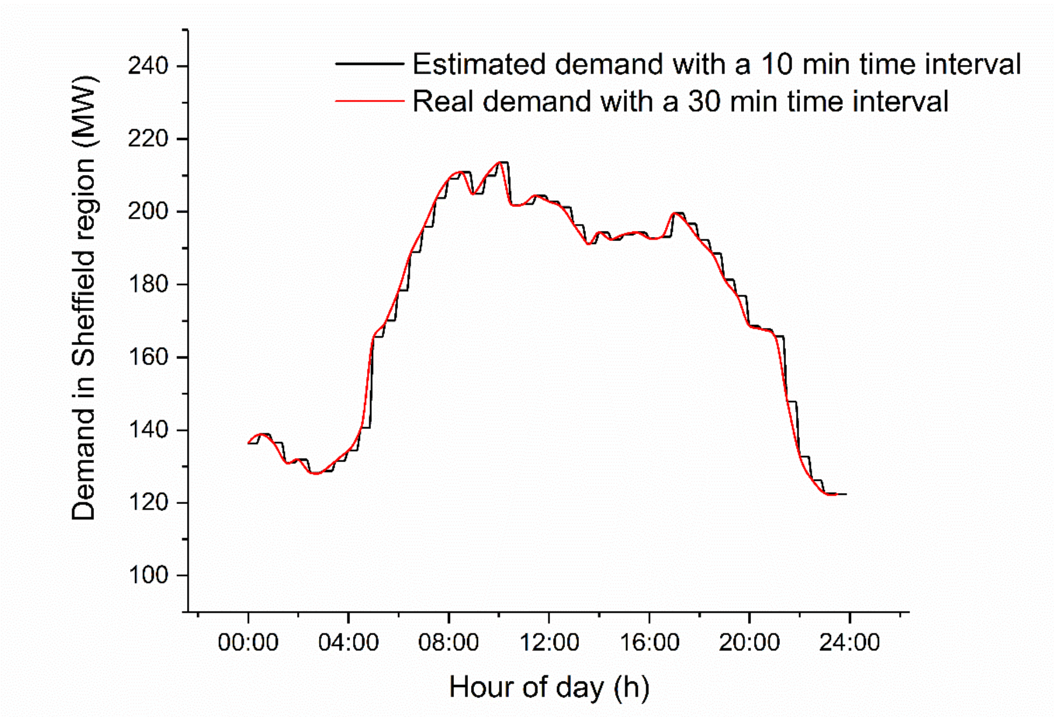

Figure 4 Electricity demand in the Sheffield region on a typical weekday in March 2015.

As a dynamic model, the main difference between the DEED and CEED models is the impact of the ramp rate. In Case 1, with half-hourly time interval demand, the changes in each time step are less than the ramp rate of a single generator. Therefore, it is unable to illustrate the impact of the ramp rate. In the National Grid, the day-ahead forecast is normally half-hourly embedded for wind generation and demand forecast. However, in the real-time dispatch, the control room team could react on a shorter timescale. Case 1 in this research with a half-hourly embedded power demand. The half hourly load demand data in Case 1 is a practical demand provided by the Northern Powergrid [40]. As the demand changes between 2 half-hourly time steps are black-boxed, assuming in the Case 1, the demand in a half hour changes linearly with time. Therefore, Case 2 is a DEED model with a 10 minute time interval (1/3rd of the given half-hourly demand) to find the impact of the time interval. Also, the demand in Case 2 is shown as the black line in Figure 4. This demand is modified from the half hourly time interval demand. It is estimated to remain constant in the following 20 minutes from the time step in Case 1 and starts to change linearly with time after the 20th minute. Figure 5 illustrates theoretical electricity demands by focussing on the first three steps in Figure 4 in order to clarify the demand in Case 2.

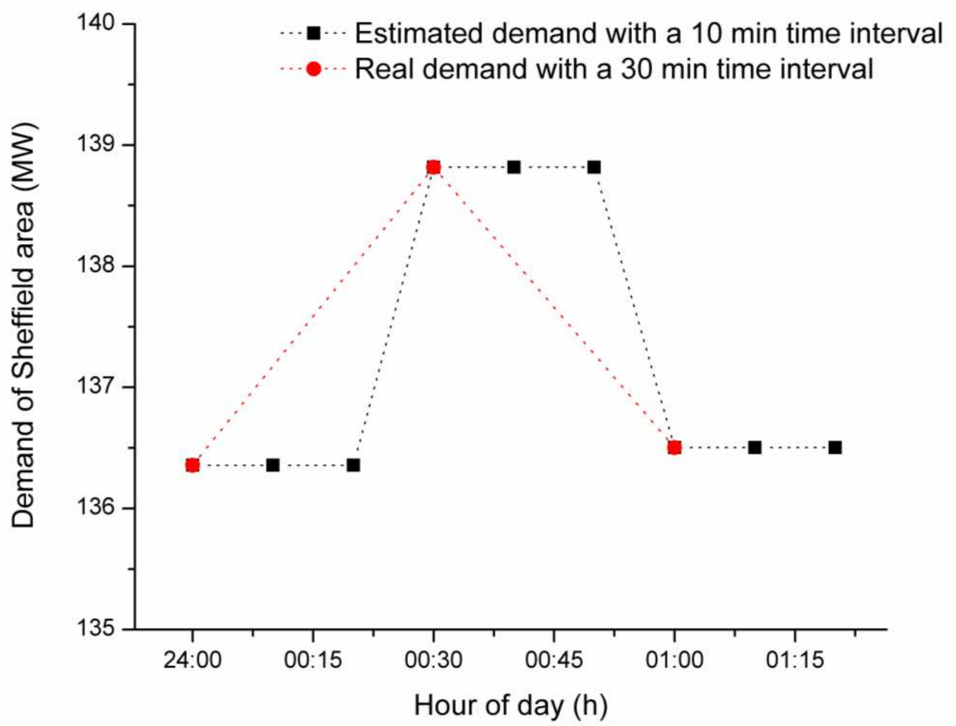

Figure 5 Illumination of the first three steps for the electricity demand in the Figure 4.

In order to model a system that has a practical significance and considers the current and future carbon price and emission standard performance, the fuel cost and the demand should also have been converted to the current value. The coefficients and constraints of the conventional power are collected from the IEEE 30 bus test system [68, 69] which is an American Electric Power (AEP) system in the Midwestern US with coal-fired generators. Table 1 presents the modified coefficients of the cost functions of the 6 coal-fired generators that takes into account the coal price in the UK at the 2016 level of 54.29 £/t [70]. The modified factor is about 16.5. Table 2 lists the coefficients of the emission functions [69].

Table 1 Coefficients in the cost functions and constraints in the power outputs of the IEEE 30 buses system with 6 thermal generators [69].

Cost function	a_i (£/MW^{2}h)	b_i (£/MWh)	c_i (£/h)	$P_{i,min}$ (MW)	$P_{i,max}$ (MW)
P1	0.0612	33.0461	0	50	200
P2	0.2892	28.9153	0	20	80
P3	1.0327	16.5230	0	15	50
P4	0.1378	53.6999	0	10	35
P5	0.4131	49.5691	0	10	30
P6	0.4131	49.5691	0	12	40

Table 2 Coefficients in the emission functions and constraints in the power outputs of the IEEE 30 buses system with 6 thermal generators [69].

Emission functions	d_i (t/MW^{2}h)	e_i (t/MWh)	f_i (t/h)
P1	0.0126	-1.2000	22.983
P2	0.0200	-0.1000	25.313
P3	0.0270	-0.0100	25.505
P4	0.0291	-0.0050	24.900
P5	0.0290	-0.0040	24.700
P6	0.0271	-0.0055	25.300

Table 3 shows the ramp rates of the 6 thermal generators of the IEEE 30 buses system [69].

Table 3 Ramp rates of the IEEE 30 buses system with 6 thermal generators [69].

Ramp rate	RRU (MW/h)	RRD (MW/h)
P1	65	85
P2	12	22
P3	12	15
P4	8	16
P5	6	9
P6	8	16

Furthermore, the spinning reserve in the UK is operated as Short Term Operating Reserves (STOR) [71]. It was 4 GW in 2010 and will be double this value by 2020 due to the rapidly increasing wind power capacity [53, 72]. In order to increase the robustness and reduce the unpredictability of the wind power, the spinning reserve is required to be a fast response to unpredictable generators. Therefore, the increase in wind power leads to more STOR to standby. This represents about 9.4% of the total capacity in 2020 and thus the spinning reserve is approximated to be 9.4% in this system.

The wind power cost is the strike price in the delivery year at 105 £/MWh for 2021/22 [73, 74]. The under and over estimation wind power cost are according to the wind turbine in [75], where the overestimation coefficient is 14 £/MWh and the underestimation coefficient is 7.7 £/MWh.

In this research, the carbon price in the UK from 2010 to 2050 are used in the model according to the Fourth Carbon Budget by the Committee on Climate Change [2], which are shown in Table 4. The carbon price in 2010 is zero because the carbon price floor policy only started in 2013.

Table 4 The carbon price floor (CPF) in the UK [2].

Year	2010	2020	2030	2040	2050
Carbon price (£/tCO_2e)	0	27	70	135	200

3.1. Case 1

Two types of analysis will be applied to this case, one is the inter-day and the other is the intra-day. The inter-day analysis gives the optimization results in different scenarios for the whole day and the intra-day analysis indicates the hourly optimization results in different scenarios on a typical day.

3.1.1. Inter-day results

For an inter-day analysis, 60 scenarios using 3 different factors, namely wind power penetration, CPF and EPS, are considered. The scenarios are under 3 different wind power penetrations, 10%, 20% and 30%, respectively, and 5 CPF, which is due to the scenarios in different years in Table 4.

From the calculation of the unlimited emission scenarios, the minimum emission level is about 200 tCO_2e/h at 10% wind power penetration, 180 tCO_2e/h at 20% penetration and 160 tCO_2e/h at 30% penetration. Therefore 5 different emission limits of EPS are undertaken, namely unlimited, 230 tCO_2e/h and 210 tCO_2e/h for all wind penetrations, 190 tCO_2e/h for 20% and 30% penetration and 170 tCO_2e/h for 30% penetration only. The corresponding demand is the demand in Case 1.

Moreover, as the electricity demand in Figure 4 is given every half an hour, in order to analyse the inter-day results, bases in the energy-power convert equation, where the time step in Case 1, is 0.5 h. On assuming that the power output is constant between every 2 time steps, the estimated energy in a day could be found. Further, the optimized results at each time step will be approximately multiplied by 0.5 h in order to obtain the total cost and emission of the typical day.

Figure 6 shows the Pareto Front (PF) of the emission and total cost on a typical day for the given system for a day with 10% to 30% wind power penetration, different CPF and unlimited to highly restricted emission limits of EPS.

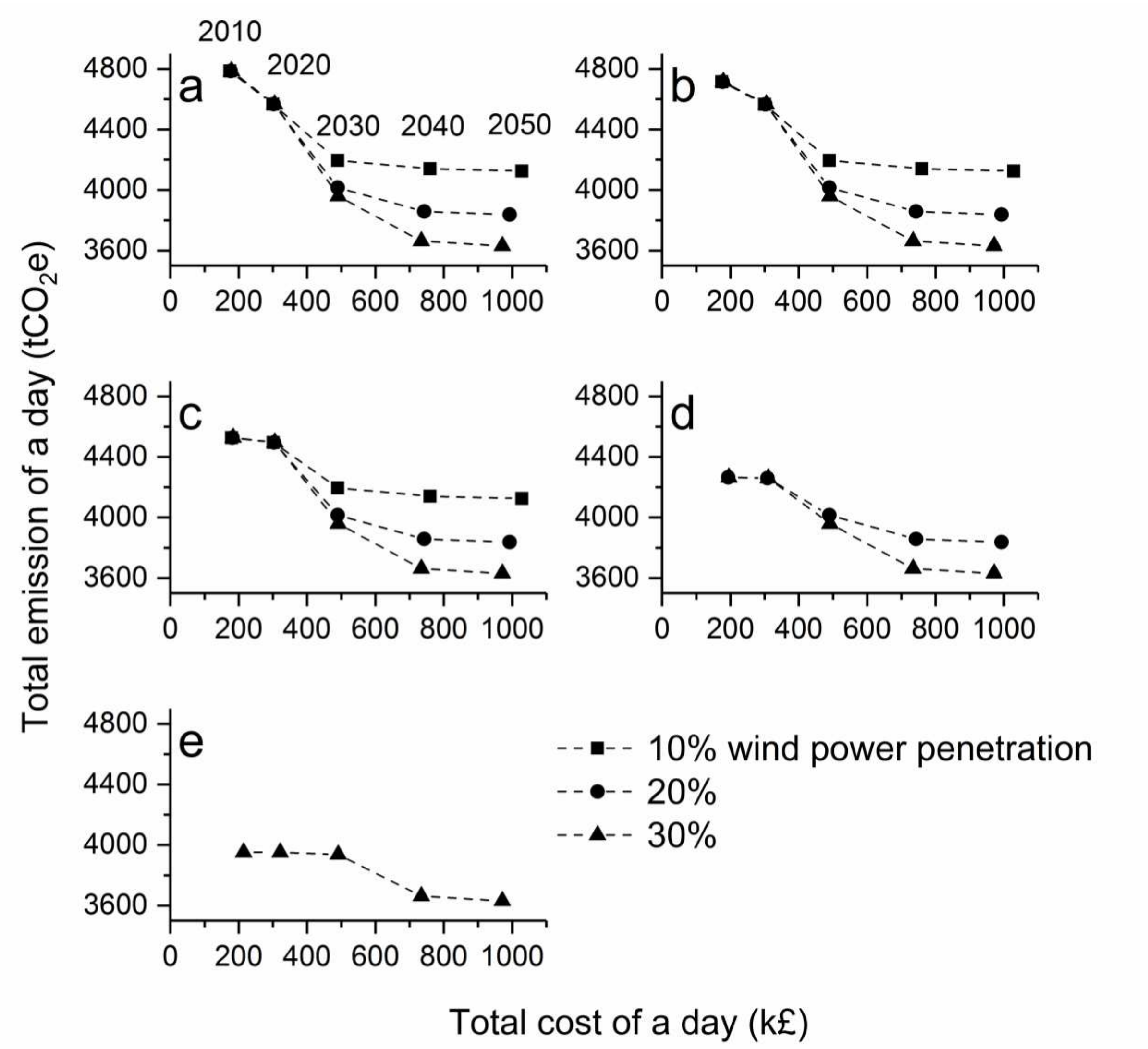

Figure 6 Case 1: PF for the given system of a day with (a) no emission limit, (b) 230 tCO_2e/h, (c) 210 tCO_2e/h, (d) 190 tCO_2e/h, and (e) 170 tCO_2e/h emission limit of EPS.

As shown in Figure 6, for the given electrical system with the constant fuel and wind power cost (without considering inflation), the total cost in the Sheffield region on the typical day increases by about a factor of 6 from 2010 to 2050, from £170k when the carbon price is 0 in 2010 to £1030k when the carbon price is increased to 200 £/t CO_2e in 2050 due to the CPF applied.

From Figure 6, it can be seen that the EPS dominates the cost and the emissions before 2020 and the wind power penetration does not significantly affect the cost and emission. This is because the wind power cost is higher than the fuel and emissions costs. In 2020, the emissions under the 190 tCO_2e/h emission limit in (d) reduces by 6.7% compared to the no EPS model (a) in the system with 20% wind power penetration. However, the cost only increases 2.0%. Further, the emission under the 170 tCO_2e/h emission limit (e) reduces to 8.7% with 30% wind power penetration and the cost increases by 5.4%.

Moreover, according to (a) to (d) in Figure 6, the wind power penetration becomes a high impact factor on the cost and emissions due to the high CPF after 2020. In 2050, high wind power penetration shows its superiority in both the cost and emissions. The cost of the scenarios with 30% wind penetration are 5.6% and 3.5% less than the cost for the 10% and 20% wind penetration, respectively, at the same EPS conditions. Meanwhile, the emissions in the scenarios with 30% wind penetration are 12.0% and 7.0% less than the cost of the 10% and 20% wind penetration, respectively.

3.1.2. Intra-day results

In the intra-day analysis, 2 scenarios are considered, namely the Gone Green scenario and the No Progression scenario [76]. Gone Green is a scenario where the energy policies and innovations are effective in reducing the emissions to achieve the 2050 carbon reduction target, which is 80% of the 1990 level. In addition, No Progression is a scenario where the power activities are as at present where fossil fuels dominate the power generation and there are only a few renewable resources installed, and the energy policies are as at present. The two scenarios are modelled in Table 5 according to the data provided by [2, 72, 76, 77]. The data has been modified because the renewable resources in the Sheffield region are less than that over all the UK. Therefore, the Gone Green scenario in this case in Table 5 has a lower renewable penetration and higher emission limit compare to that in the overall UK scenario, which is 34% in 2020 and zero emission in 2045 [78].

Table 5 Case 1: Future energy scenarios for the Gone Green and No Progression.

Year	Gone Green		No Progression	
	Wind power penetration (%)	Emission limit of EPS (tCO_2e/h)	Wind power penetration (%)	Emission limit of EPS (tCO_2e/h)
2010	10	n/a	10	n/a
2020	10	230	10	230
2030	20	210	10	230
2040	30	190	10	210
2050	30	170	20	210

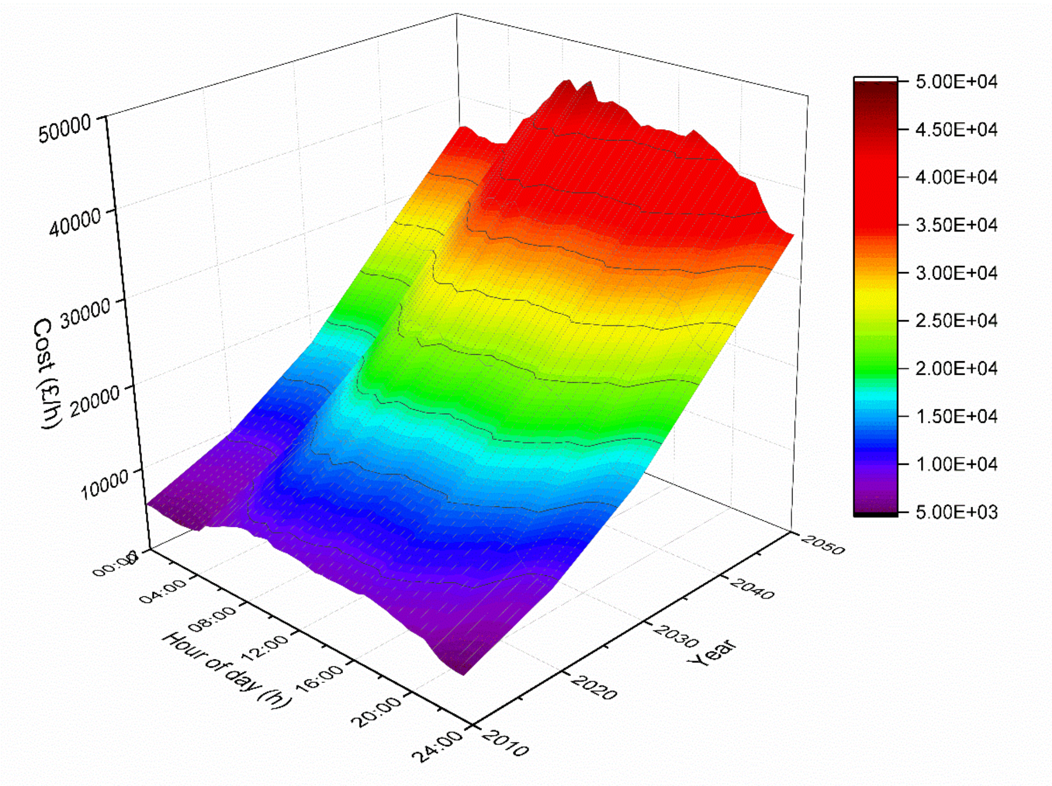

Figure 7 Case 1: Cost of the Gone Green scenario from 2010 to 2050.

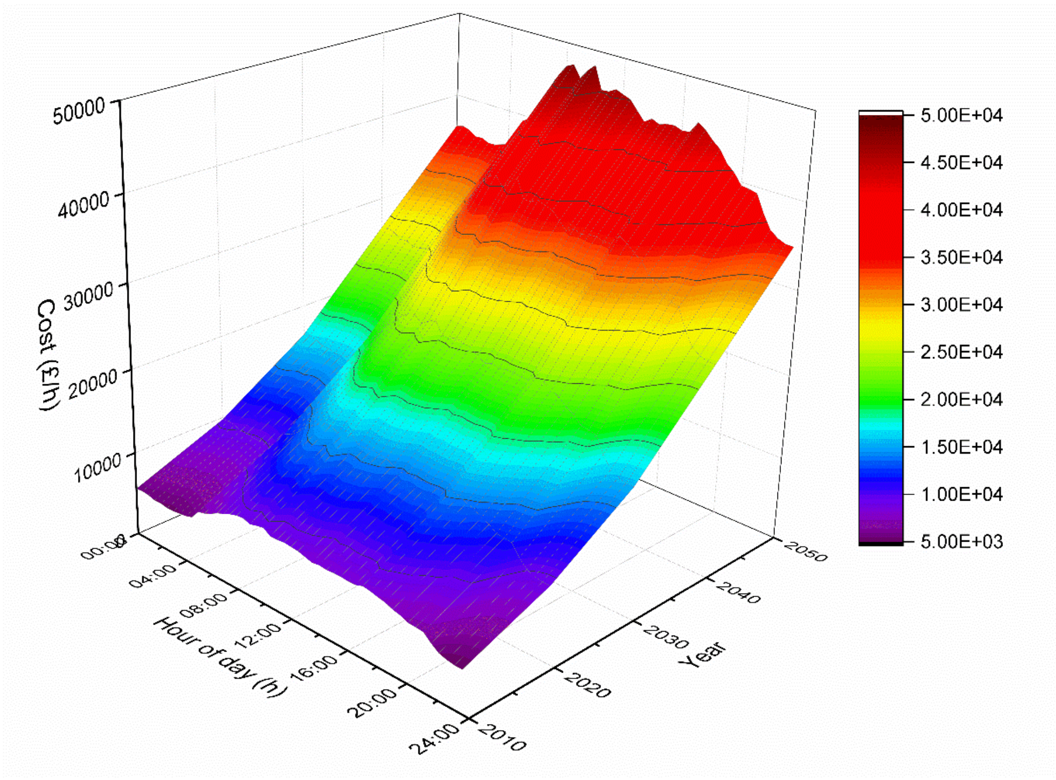

Figure 8 Case 1: Cost of the No Progression scenario from 2010 to 2050.

Figures 7 and 8 are the cost of the Gone Green and No Progression scenarios, respectively, and it can be seen that the cost increases exponentially from 2010 to 2050. Further, the cost increases in the Gone Green scenario is 5% less than that in the No Progression scenario in this model and this is because of the high CPF and wind power penetration.

Meanwhile, the cost difference within a day becomes not that significant. In 2010, the cost at the peak time is about 1.8 times that at the off peak time. However, this value becomes 1.3 in the Go Green scenario and 1.4 in the No Progression scenario in 2050. This is because of the emission differences in these two scenarios as shown in Figures 9 and 10. With increasing carbon price, the emissions lead to a higher influence in cost compared to the fuel cost.

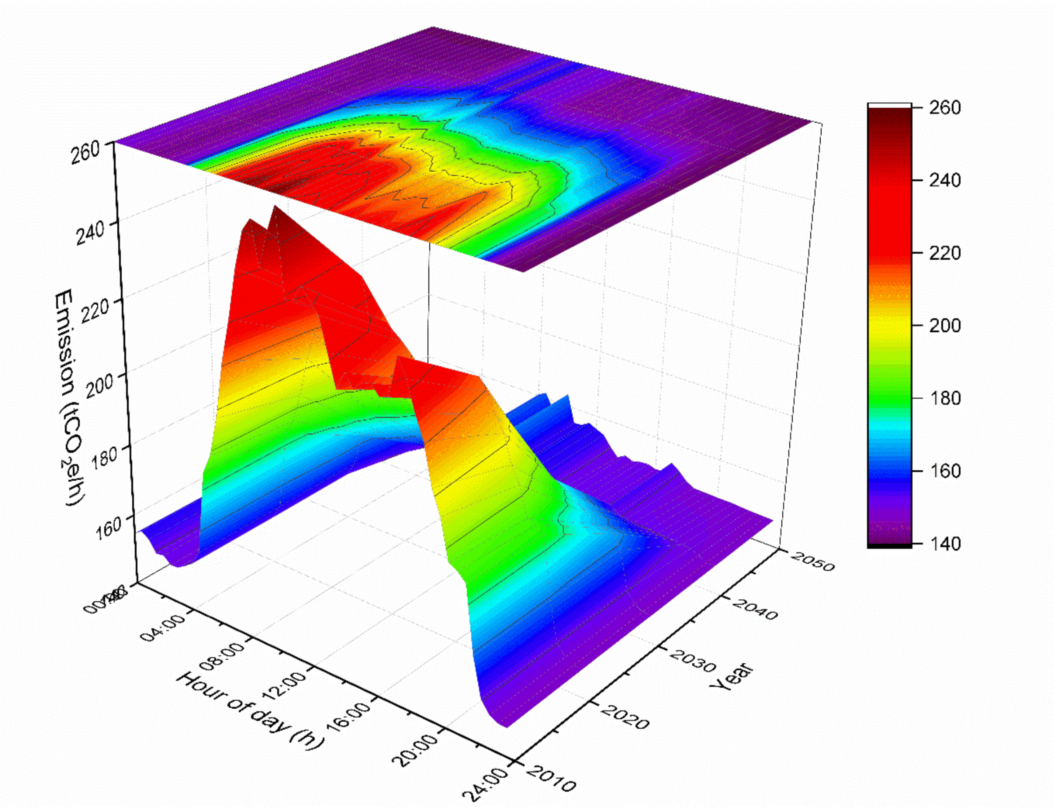

Figure 9 Case 1: Emissions in the Gone Green scenario from 2010 to 2050.

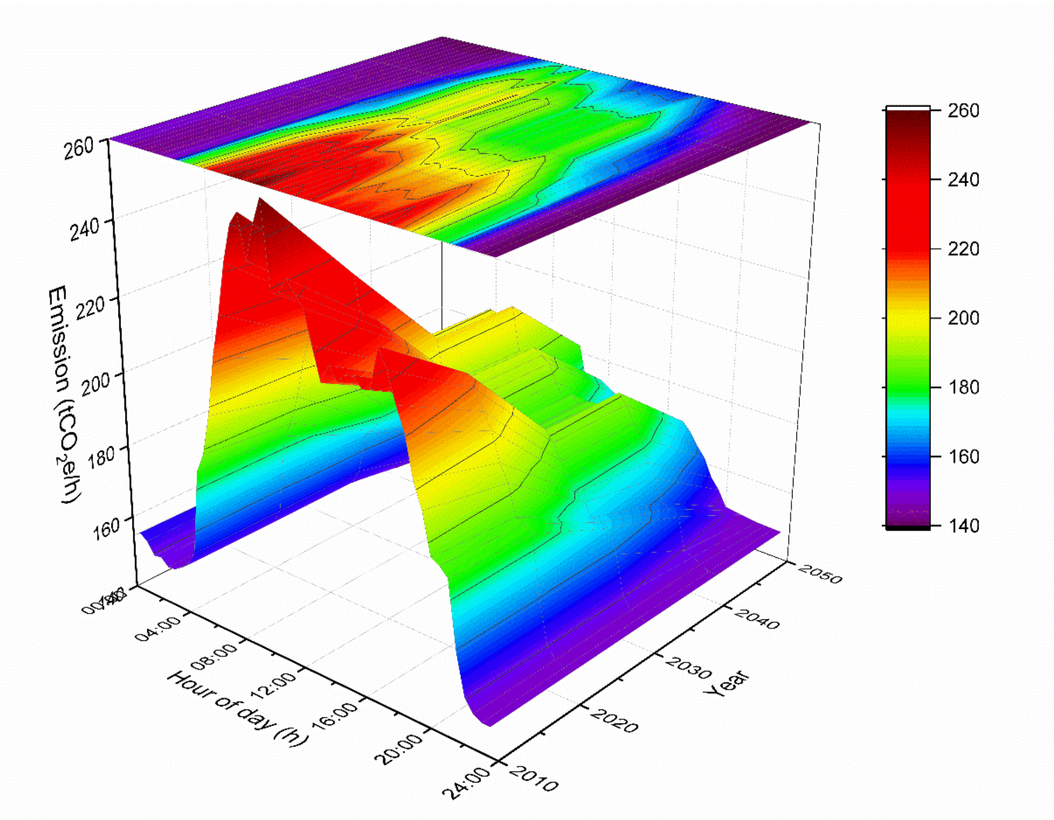

Figure 10 Case 1: Emissions in the No Progression scenario from 2010 to 2050.

Figures 9 and 10 show the emission of the Gone Green and No Progression scenarios, respectively, from 2010 to 2050. Clearly, it can be seen that the emissions in the Gone Green scenario are much lower than in the No Progression from 6:00 to 17:00 after 2030. In the Gone Green scenario, the emissions are reduced by 36% at the peak time and by 24% on average from 2010 to 2050. However, in the No Progression scenario, the emissions are reduced by 29% at the peak time and by 20% on average.

3.2. Case 2

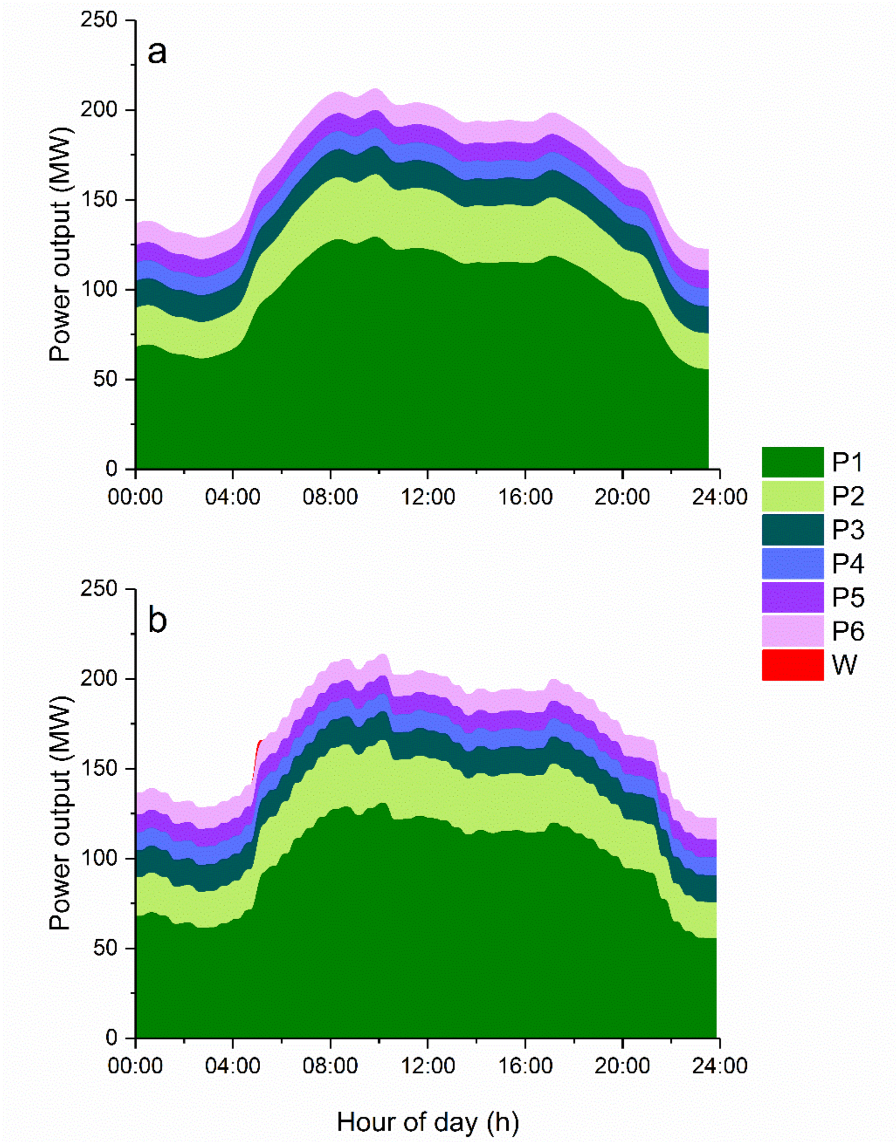

Figure 11 Power output at (a) Case 1: 30 min time interval, and (b) Case 2: 10 min time interval, where P1 to P6 are conventional generators 1 to 6 and W is the scheduled wind power.

In this case, the model is in the scenario with 20% wind power penetration and no EPS and zero £/tCO_2e CPF. This is because the maximum demand difference between two continuous time steps is higher than the 10% wind penetration but less than 20%. In addition, in the scenario with no EPS and zero £/tCO_2e CPF, the impact of the change in the ramp rate can be seen more clearly.

It can be seen clearly from Figure 11 that the power output changes between each time step, but in (b) it is sharper. In addition, it is noticeable that before 6:00 am there is a sudden increase in the electricity demand requirement. In (a), as the conventional power generators have enough time to increase, the scheduled wind power is not used due to the high price in the no EPS and CPF scenario. Moreover, in (b), the conventional power generators are unable to supply enough power in that short time interval due to the limited ramp rate of the conventional generators. Therefore, the wind power is used at this time step, which is shown under the red colour area. The different time intervals in the demand may lead to the different power outputs.

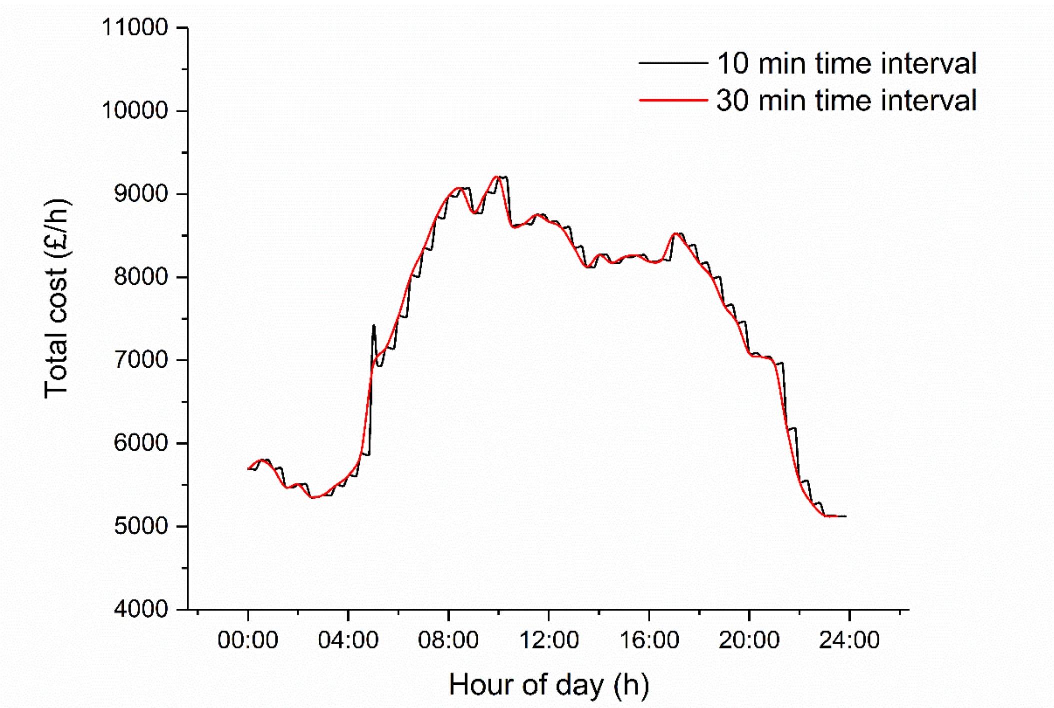

Figure 12 Case 1 and 2: Total cost at each time step of a typical day in the Sheffield region with the 10 min and 30 min time intervals, respectively.

Figure 12 is the total cost at each time step on a typical day in the Sheffield region with the 10 min and 30 min time intervals, respectively, which is derived from Equation (8)(6). It is observed that the costs are slightly different at the same instant of time. This is because the different previous stage leads to different generator usage in the current stage, and this is especially clear at about 6:00 am, where the wind power is used in Figure 11 (b), which is under the red colour area, the cost increases dramatically.

Moreover, for the 10 min model, although the cost of the first time step of the three time steps with the same demand is higher than that of the 30 min model, the costs in the following time steps still tend to the same optimal result as for the 30 min model.

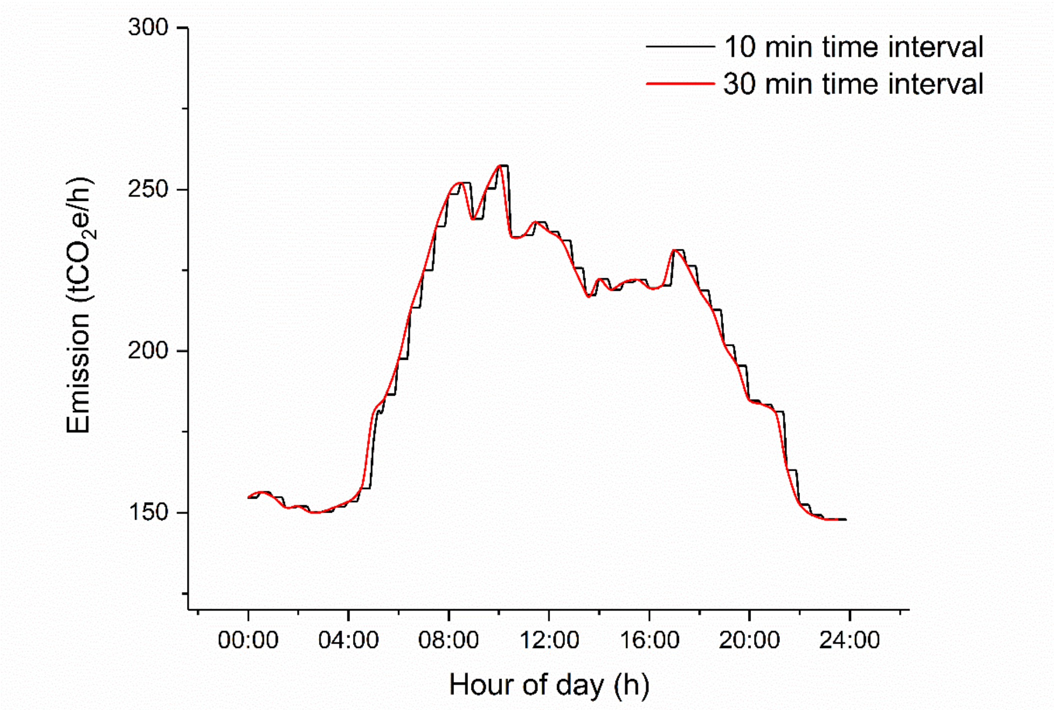

Figure 13 Case 1 and 2: Emissions at each time step on the typical day in the Sheffield region with the 10 min and 30 min time intervals, respectively.

Figure 13 shows the emissions at each time step on the typical day in the Sheffield region with the 10 min and 30 min time intervals, respectively, which is derived from Equation (6). In Figure 13, the emissions at 06:00 with the 10 min time interval is less than that of the 30 min time interval and this is because the use of the wind power leads to less emissions.

4. Discussion

From the inter-day results for the Case 1, it can be seen that the total cost increases dramatically due to the carbon price applied for the given electrical system with the constant fuel and wind power cost (without considering inflation). This produces the increase in the electricity price or the reduction in the profit for the system owner.

In addition, the EPS dominates the cost and emissions from 2010 to 2020 as the wind power costs are higher than the fuel and emissions costs. After 2020, the wind power penetration has a high impact factor on the cost and emissions due to the high carbon price. Therefore, by 2050, the high wind power penetration, namely the renewable power, shows its superiority and advantages in both the cost and emissions in power generation.

Moreover, the intra-day results of Case 1 describe the cost and emissions of the Go Green and No Progression scenarios. The emissions reduction in the Go Green scenario compared to the No Progression scenario is higher than the cost reduction for the given electrical system. However, this model does not consider the reduction in the wind power strike price and the application of Carbon Capture and Storage (CCS) technologies for the future scenarios. According to [74, 79-81], the strike price of wind power will keep on reducing. However, as yet, the far future strike price is not given. In addition, CCS can reduce by 90% the emissions from the generator [82]. However, the coal CCS strike price will increase to above 140 £/MWh by 2020 [83, 84], which is even higher than the strike price of the wind power. Further, it is important to note that there will be no CCS applied to industry in the UK until the 2020s and there are no planned projects in the Sheffield region before 2030 [83-86].

In the Case 2, when the demand changes greatly, the model can supply the demand by using only the cheapest generators. However, if the model has a shorter time interval, or changes dramatically, then more generators and the rapid response resources will be used to supply the demand. Of course, this increases the total cost. Furthermore, this model can work effectively and satisfy different time intervals in real-time dynamic dispatch.

To conclude, the benefit to the system owner of using renewable power may not be that significant as in recent years. However, under the current UK policy, installation of every 10% renewable power penetration will result in an approximate 3% cost reduction for the given system. Therefore, in a mid to long-term strategy, renewable power will have its superiority in both the economic and emissions aspects.

In future research, start-up (hot, warm, cold) and shut-down decision and costs are interesting operation phase and cost terms interesting operation phase and cost terms that worth be taken into account, especially in a power system with increasing penetration of wind power. The flexibility of a power systems is a challenging issue that needs to be considered.[87, 88]. In addition, the uncertainty in the load is also an interesting and important part in the smart grid. Some recent researches investigate the uncertainty in the load by taking into account the confidence level [89], demand response [38] or demand side management [90, 91].

5. Conclusion

In this paper, a DEED model has been developed under current UK energy policies, which considers coal-powered generators and wind-powered generators with emission allowances. This DEED model considers both the economic and environmental aspects in the dynamic electrical system. It minimizes the total fuel cost and the emission cost of the system while satisfying the demand and power system constraints over a dispatch period. Further, it introduces EPS and CPF constraints and considers the UK energy policies in the model. Two case studies in the Sheffield region are supplied by an IEEE 30 bus system with six coal-powered generators and a wind-powered generator at different scenarios are performed.

It observed from the results obtained that the proposed DEED model has the ability to effectively generate solutions for different time intervals in the real-time dynamic dispatch. This research uses current practical data in the UK to obtain operational strategy. Further, the total cost increases dramatically due to the carbon price applied. In addition, the EPS dominates the cost and emissions before 2020, then the wind power penetration has a high impact factor on the cost and emissions due to the high CPF. Moreover, the emissions reduction in the Go Green scenario compared to the No Progression scenario is higher than the cost reduction.

Furthermore, the energy strategy faces to the challenge of high CPF and low EPS in the future, and the emission cost will become to dominate the total cost. Therefore, a more general conclusion that can be highlighted is that the renewable power has the superiority in both the economics and emissions to a mid to long-term strategy to the UK and the restrictions should be imposed on the conventional power with high emissions.

Acknowledgement

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References

[1] CCC, Meeting Carbon Budgets – the need for a step change 2009.
[2] CCC, The Fourth Carbon Budget Reducing emissions through the 2020s 2010.
[3] CCC, The Fifth Carbon Budget: The next step towards a low-carbon economy. 2015.
[4] Legislation.gov.uk. Energy Act 2013. 2013 [cited 2017 28 December]; Available from: https://www.legislation.gov.uk/ukpga/2013/32/introduction.
[5] DECC, Electrisity Market Reform: Policy Overview. 2012.
[6] CCC, Next steps on Electricity Market Reform – securing the benefits of low-carbon investment. Committee on Climate Change, 2013.
[7] Commission, E., The EU Emissions Trading System (EU ETS). 2013.
[8] Commission, E. Emissions cap and allowances. [cited 2017 28 December]; Available from: https://ec.europa.eu/clima/policies/ets/cap_en.
[9] Legislation.gov.uk. The Emissions Performance Standard Regulations 2015. 2015 [cited 2017 28 December]; Available from: https://www.legislation.gov.uk/ukdsi/2015/9780111127186.
[10] BEIS, Coal Generation in Great Britain The Pathway to a Low-Carbon Future: Consultation Document 2016.
[11] Happ, H.H., Optimal power dispatchߞA comprehensive survey. IEEE Transactions on Power Apparatus and Systems, 1977. **96**(3): p. 841-854.
[12] Chowdhury, B.H. and S. Rahman, A review of recent advances in economic dispatch. Power Systems, IEEE Transactions on, 1990. **5**(4): p. 1248-1259.
[13] Wood, W.G., Spinning Reserve Constrained Static and Dynamic Economic Dispatch. Power Apparatus and Systems, IEEE Transactions on, 1982. **PAS-101**(2): p. 381-388.
[14] Somuah, C.B. and N. Khunaizi, Application of linear programming redispatch technique to dynamic generation allocation. Power Systems, IEEE Transactions on, 1990. **5**(1): p. 20-26.

[15] Han, X.S., H. Gooi, and D.S. Kirschen, Dynamic economic dispatch: feasible and optimal solutions. Power Systems, IEEE Transactions on, 2001. **16**(1): p. 22-28.

[16] Bechert, T.E. and H.G. Kwatny, On the optimal dynamic dispatch of real power. IEEE Transactions on Power Apparatus and Systems, 1972. **PAS-91**(3): p. 889-898.

[17] Holstein, M.P. and W.J. Brands, Impacts on least cost planning and system operations of monetizing environmental externalities. Proceedings of the American Power Conference, 1992. **54**(2): p. 1048-1054.

[18] Bernow, S., B. Biewald, and D. Marron, Full-cost dispatch: Incorporating environmental externalities in electric system operation. The Electricity Journal, 1991. **4**(2): p. 20-33.

[19] Muthuswamy, R., et al., Environmental and economic power dispatch of thermal generators using modified NSGA-II algorithm. International Transactions on Electrical Energy Systems, 2015. **25**(8): p. 1552-1569.

[20] Mahdi, F.P., et al., A holistic review on optimization strategies for combined economic emission dispatch problem. Renewable and Sustainable Energy Reviews, 2018. **81**: p. 3006-3020.

[21] Basu, M., Particle swarm optimization based goal-attainment method for dynamic economic emission dispatch. Electric Power Components and Systems, 2006. **34**(9): p. 1015-1025.

[22] Basu, M., Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. International Journal of Electrical Power and Energy Systems, 2008. **30**(2): p. 140-149.

[23] Yao, D.L., S.S. Choi, and K.J. Tseng. Design of short-term dispatch strategy to maximize income of a wind power-energy storage generating station. in Innovative Smart Grid Technologies Asia (ISGT), 2011 IEEE PES. 2011.

[24] Jin, J., et al., Environmental/economic power dispatch with wind power. Renewable Energy, 2014. **71**: p. 234-242.

[25] Nottrott, A., J. Kleissl, and B. Washom, Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems. Renewable Energy, 2013. **55**: p. 230-240.

[26] Wu, H., X. Liu, and M. Ding, Dynamic economic dispatch of a microgrid: Mathematical models and solution algorithm. International Journal of Electrical Power & Energy Systems, 2014. **63**(0): p. 336-346.

[27] Huang, S.-J., Enhancement of hydroelectric generation scheduling using ant colony system based optimization approaches. IEEE Transactions on Energy Conversion, 2001. **16**(3): p. 296-301.

[28] Soares, S., et al. Dynamic dispatch of hydro generating units. in Power Tech Conference Proceedings, 2003 IEEE Bologna. 2003. IEEE.

[29] Søren Krohn, P.-E.M., Shimon Awerbuch The Economics of Wind Energy: A report by the European Wind Energy Association. 2009.

[30] Hreinsson, K., M. Vrakopoulou, and G. Andersson, Stochastic security constrained unit commitment and non-spinning reserve allocation with performance guarantees. International Journal of Electrical Power & Energy Systems, 2015. **72**: p. 109-115.

[31] Morales-España, G., Á. Lorca, and M.M. de Weerdt, Robust unit commitment with dispatchable wind power. Electric Power Systems Research, 2018. **155**: p. 58-66.

[32] Wang, C., et al., Day-ahead unit commitment method considering time sequence feature of wind power forecast error. International Journal of Electrical Power & Energy Systems, 2018. **98**: p. 156-166.

[33] Hetzer, J., D.C. Yu, and K. Bhattarai, An Economic Dispatch Model Incorporating Wind Power. Energy Conversion, IEEE Transactions on, 2008. **23**(2): p. 603-611.

[34] Roy, P.K. and S. Hazra, Economic emission dispatch for wind–fossil-fuel-based power system using chemical reaction optimisation. International Transactions on Electrical Energy Systems, 2015. **25**(12): p. 3248-3274.

[35] Dubey, H.M., M. Pandit, and B. Panigrahi, Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch. Renewable Energy, 2015. **83**: p. 188-202.

[36] Mondal, S., A. Bhattacharya, and S.H. nee Dey, Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration. International Journal of Electrical Power & Energy Systems, 2013. **44**(1): p. 282-292.

[37] Zhang, Y., et al., Wind–thermal systems operation optimization considering emission problem. International Journal of Electrical Power & Energy Systems, 2015. **65**: p. 238-245.
[38] Durga Hari Kiran, B. and M. Sailaja Kumari, Demand response and pumped hydro storage scheduling for balancing wind power uncertainties: A probabilistic unit commitment approach. International Journal of Electrical Power & Energy Systems, 2016. **81**: p. 114-122.
[39] Hu, F., et al., Combined economic and emission dispatch considering conventional and wind power generating units. International Transactions on Electrical Energy Systems, 2017.
[40] Powergrid, N., Appendix 7 Yorkshire.
[41] Krishnamurthy, S. and R. Tzoneva. Impact of price penalty factors on the solution of the combined economic emission dispatch problem using cubic criterion functions. in 2012 IEEE Power and Energy Society General Meeting. 2012.
[42] Li, F. and R.K. Aggarwal, Fast and accurate power dispatch using a relaxed genetic algorithm and a local gradient technique. Expert Systems with Applications, 2000. **19**(3): p. 159-165.
[43] Dhillon, J.S. and D.P. Kothari, The surrogate worth trade-off approach for multiobjective thermal power dispatch problem. Electric Power Systems Research, 2000. **56**(2): p. 103-110.
[44] Truong, K.H., et al., Swarm Based Mean-Variance Mapping Optimization for Solving Economic Dispatch with Cubic Fuel Cost Function, in Intelligent Information and Database Systems: 7th Asian Conference, ACIIDS 2015, Bali, Indonesia, March 23-25, 2015, Proceedings, Part II, N.T. Nguyen, B. Trawiński, and R. Kosala, Editors. 2015, Springer International Publishing: Cham. p. 3-12.
[45] Lamont, J.W. and E.V. Obessis, Emission dispatch models and algorithms for the 1990s. IEEE Transactions on Power Systems, 1995. **10**(2): p. 941-947.
[46] Peng, C., et al., Dynamic economic dispatch for wind-thermal power system using a novel bi-population chaotic differential evolution algorithm. International Journal of Electrical Power & Energy Systems, 2012. **42**(1): p. 119-126.
[47] Decker, G.L. and A.D. Brooks, Valve Point Loading of Turbines. Transactions of the American Institute of Electrical Engineers. Part III: Power Apparatus and Systems, 1958. **77**(3): p. 481-484.
[48] Khoa, T.H., et al., Solving economic dispatch problem with valve-point effects using swarm-based mean–variance mapping optimization (MVMOS). Cogent Engineering, 2015. **2**(1): p. 1076983.
[49] Boqiang, R. and J. Chuanwen, A review on the economic dispatch and risk management considering wind power in the power market. Renewable and Sustainable Energy Reviews, 2009. **13**(8): p. 2169-2174.
[50] Cheung, K.W., A. Sadjadpour, and L. Jones, Smart Dispatch and Demand Forecasting for Large Grid Operations with Integrated Renewable Resources. UWIG Workshop on Variable Generation Forecasting Applications to Utility Planning and Operations Technologies, 2011.
[51] Yann Rebours, D.K., What is spinning reserve? . The University of Manchester, 2005.
[52] Caiso, Spinning Reserve and Non-Spinning Reserve 2006.
[53] Keith Bell, P.D., Modassar Chaudry, Nick Eyre, Matthew Aylott, Response from the UK Energy Research Centre (UKERC) to the House of Lords Science and Technology Committee Inquiry into the resilience of electricity infrastructure. The UK Energy Research Centre, 2014.
[54] Alsumait, J.S. and J.K. Sykulski. Solving economic dispatch problem using hybrid GA-PS-SQP method. in IEEE EUROCON 2009. 2009.
[55] MATLAB. Constrained nonlinear optimization algorithms. [cited 2017 29 June]; Available from: https://uk.mathworks.com/help/optim/ug/constrained-nonlinear-optimization-algorithms.html#f26622.
[56] Houston, U.o., Optimization I; chapter 4: sequential quadratic programming. Department of Mathematics.
[57] Yengui, F., et al., A hybrid GA-SQP algorithm for analog circuits sizing. Circuits and Systems, 2012. **3**(02): p. 146.
[58] Victoire, T.A.A. and A.E. Jeyakumar, Hybrid PSO–SQP for economic dispatch with valve-point effect. Electric Power Systems Research, 2004. **71**(1): p. 51-59.
[59] Elaiw, A.M., X. Xia, and A. Shehata, Dynamic economic dispatch using hybrid DE-SQP for generating units with valve-point effects. Mathematical Problems in Engineering, 2012.

[60] Sivasubramani, S. and K.S. Swarup, Hybrid SOA–SQP algorithm for dynamic economic dispatch with valve-point effects. Energy, 2010. **35**(12): p. 5031-5036.
[61] Attaviriyanupap, P., et al., A hybrid EP and SQP for dynamic economic dispatch with nonsmooth fuel cost function. IEEE Transactions on Power Systems, 2002. **17**(2): p. 411-416.
[62] Cai, J., et al., A hybrid FCASO-SQP method for solving the economic dispatch problems with valve-point effects. Energy, 2012. **38**(1): p. 346-353.
[63] Mansoornejad, B., N. Mostoufi, and F. Jalali-Farahani, A hybrid GA–SQP optimization technique for determination of kinetic parameters of hydrogenation reactions. Computers & Chemical Engineering, 2008. **32**(7): p. 1447-1455.
[64] MATLAB. eps. [cited 2018 22 January]; Available from: https://uk.mathworks.com/help/matlab/ref/eps.html.
[65] Matlab. Estimate Computation Costs. [cited 2018 31 July]; Available from: https://www.mathworks.com/help/physmod/simscape/ug/estimate-computation-costs.html.
[66] Powergrid, N., Sheffield Area Maximum Demands.
[67] Phonrattanasak, P. Optimal placement of wind farm on the power system using multiobjective bees algorithm. in Proceedings of the World Congress on Engineering. 2011.
[68] Washington, U.o. Power Systems Test Case Archive. 1993 [cited 2017 26 July]; Available from: https://www2.ee.washington.edu/research/pstca/pf30/pg_tca30bus.htm.
[69] Appendix A: DATA FOR IEEE-30 BUS TEST SYSTEM. [cited 2016 27 June]; Available from: https://www.researchgate.net/file.PostFileLoader.html?id=5825f310ed99e1b0707b8be2&assetKey=AS%3A427276501295104%401478882064060.
[70] BEIS, Average prices of fuels purchased by the major UK power producers (QEP 3.2.1). 2017.
[71] Grid, N. What are Reserve Services? [cited 2017 26 July]; Available from: http://www2.nationalgrid.com/uk/services/balancing-services/reserve-services/.
[72] Breidenbaugh, A., Load Participation in Ancillary Services, in DOE Framing Workshop. 2011.
[73] KPMG, Second CfD Allocation Round. 2016.
[74] BEIS, Contracts for Difference: An explanation of the methodology used to set administrative CFD strike prices for the next CFD allocation round 2016.
[75] Guvenc, U., Combined economic emission dispatch solution using genetic algorithm based on similarity crossover. Scientific Research and Essays, 2010. **5**(17): p. 2451-2456.
[76] Grid, N., Future Energy Scenarios. 2016.
[77] DECC, Electricity Market Reform Delivery Plan. 2013.
[78] Pommerening, P., et al. Future grid 2050 in context of UK gone green scenario. in 2016 IEEE NW Russia Young Researchers in Electrical and Electronic Engineering Conference (EIConRusNW). 2016.
[79] DECC, Investing in renewable technologies – CfD contract terms and strike prices. 2013.
[80] DECC, CFD Auction Allocation Round One - a breakdown of the outcome by technology, year and clearing price. 2015.
[81] OXERA, CfDs: the (strike) price is right? 2015.
[82] Cormos, C.-C., Integrated assessment of IGCC power generation technology with carbon capture and storage (CCS). Energy, 2012. **42**(1): p. 434-445.
[83] ETI, Building the UK CCS sector by 2030 Scenarios and Actions. 2015.
[84] CCSA, Delivering CCS:Essential infrastructure for a competitive, low-carbon economy.
[85] Institute, G.C. Large-scale CCS facilities. [cited 2017 31 July]; Available from: http://www.globalccsinstitute.com/projects/large-scale-ccs-projects#overview.
[86] Institute, G.C., The global status oF CCS 2016 summary report. 2016.
[87] Koltsaklis, N.E., et al., A mid-term, market-based power systems planning model. Applied Energy, 2016. **179**: p. 17-35.
[88] Koltsaklis, N.E., I. Gioulekas, and M.C. Georgiadis, Optimal scheduling of interconnected power systems. Computers & Chemical Engineering, 2018. **111**: p. 164-182.
[89] Cheung, K.W. and R. Rios-Zalapa. Smart dispatch for large grid operations with integrated renewable resources. in Innovative Smart Grid Technologies (ISGT), IEEE PES. 2011. IEEE.

[90] Alham, M.H., et al., A dynamic economic emission dispatch considering wind power uncertainty incorporating energy storage system and demand side management. Renewable Energy, 2016. **96, Part A**: p. 800-811.
[91] Narimani, M.R., J.Y. Joo, and M.L. Crow. Dynamic economic dispatch with demand side management of individual residential loads. in 2015 North American Power Symposium (NAPS). 2015.