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Integrated Renewable Electricity Generation Considering Uncertainties: The UK roadmap to 50% power generation from wind and solar energies

Sharifzadeh Mahdi[1], Helena Lubiano-Walochik, Nilay Shah
Centre for Process Systems Engineering (CPSE), Department of Chemical Engineering
Imperial College London, London SW7 2AZ, United Kingdom.

Abstract

Renewable energies can play an important role in mitigating the emissions associated with electricity power generation and diversification of the energy supply. The challenge is that renewable resources such as wind and solar have intermittent production patterns and their incorporation into conventional electricity grids will increase the degree of uncertainty. The present research proposes a comprehensive framework in which design and operation of the electricity grid are considered simultaneously and the uncertainties in the wind and solar generation as well as demand are systematically taken into account. The case of retrofitting the current UK electricity grid to include 50% renewable power generation by 2030 was posed as the demonstrating example. The research problem was formulated as a piece-wise linear mixed integer optimization under uncertainty and solved using CPLEX v12.0 in GAMS. The results suggested that it is possible to retrofit the electricity grid using renewable generators while optimizing the overall profitability and ensuring the secure supply of electricity. It was also observed that at the price of higher computational costs, stochastic optimization generates more realistic and robust solutions for the design and operation of the smart electricity grid.

Keywords

Integrated renewable energy systems, wind power, solar energy, stochastic mixed-integer optimization, uncertainty.

[1] **Corresponding Author:** Dr Mahdi Sharifzadeh; Room C603, Roderic Hill Building, South Kensington Campus, Imperial College London, UK. SW7 2AZ. E-mail: mahdi@imperial.ac.uk ; Tel: +44(0)7517853422

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Nomenclature

s	Scenario number
S	Set of all scenarios
n	Node number
N	Set of all nodes
t	Time in hours
T	Set of all times
g	Generator number
G	Set of all generators
i	Natural gas plant number in node n
IN	Set of all natural gas plants in node n
k	Nuclear plant number in node n
KN	Set of all nuclear plants in node n
l	Transmission line number
LN	Set of all transmission lines connected to node n
$prob_s$	Probability of scenario
obj_s	Objective function value of scenario
$D_{s,n}(t)$	Demand at node n at time t in scenario s
$PT_{s,n,i}(t)$	Power generated by i natural gas power plant in scenario s at node n at time t
$PN_{s,n,k}(t)$	Power generated by k nuclear power plant in scenario s at node n at time t
$PW_{s,n}(t)$	Wind power generated in scenario s at node n at time t
$PS_{s,n}(t)$	Solar power generated in scenario s at node n at time t
$PP_{s,n}(t)$	Power pumped from storage to node n in scenario s at time t
$PSt_{s,n}(t)$	Power pumped to storage from node n in scenario s at time t
$f_{s,l}(t)$	Electricity flow in line l at time t in scenario s
$q_{s,l}(t)$	Electricity loss in line l at time t in scenario s
$f_{l,max}(l)$	Maximum electricity flow in line l
η_p	Efficiency of storage
$x_{s,n,i}$	Binary variable to indicate state of natural gas power plant
$y_{n,k}$	Binary variable to indicate state of nuclear power plant
$RUT_{n,i}$	Ramp-up rate for natural gas plant i at node n
$RDT_{n,i}$	Ramp-down rate for natural gas plant i at node n
$a_{n,i}, b_{n,i}$	Fuel efficiency linearization equation constants
$WP_{s,n}(t)$	Wind power available in scenario s, at node n at time t
$SP_{s,n}(t)$	Solar power available in scenario s, at node n at time t
IWC_n	Installed wind capacity at node n
ISC_n	Installed solar capacity at node n
$ES_n(t)$	Energy stored at node n at time t
$ES_{n,max}$	Maximum energy that can be stored at node n
$\theta_{s,n}(t)$	Node angle at time t in scenario s
B_l	Line susceptance
G_l	Line admittance
${\delta_1}_s, {\delta_2}_s$	Piecewise linearization segment
v, v_r, v_{ci}, v_{co}	Wind speed, rated wind speed, cut in wind speed, cut out wind speed
η_s	Solar panel efficiency
R	Solar radiation
A_c	Solar panel area

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1. Introduction

Electricity has a crucial role in economic and societal wellbeing. In 2013, 18% of the global energy consumption was in the form of electricity [1]. Additionally, electricity power generation and transmission contributed to climate change through greenhouse gas emissions. A quarter of global emissions are associated with generation of electricity [2]. There are various national and international targets for reducing greenhouse gas (GHG) emissions from electricity generation. The Europe 2020 program aims to reduce the emissions by 30% in the year 2020. The UK government has set the target to reduce emissions by 80% across all sectors by 2050 with respect to 1990 levels [4]. The power sector has a crucial role, as it is responsible for 31.8% of the global GHG emissions [5]. According to a technical report by Committee on Climate Change (CCC), achieving such level of GHG reductions requires at least 50% renewable power generation from wind and solar energy resources [6]. The application of renewable energy resources such as wind and solar for electricity generation can mitigate pollution and enhance the energy security by diversification of its supply. However, currently, only 23.7% of the global electricity generation comes from renewable sources [7]. The equivalent values for Europe [8], UK [9], and US [10] are 28%, 17.8% and 13%, respectively.

Augmenting the installed renewable electricity capacity implies large capital investments. Therefore, identifying the best locations and capacities of the new renewable technologies that are to be installed, is of crucial importance. Additional operational complications arise from incorporation of renewable resources into conventional electricity grids. On one side, the electricity demand is subject to a high degree of uncertainty. Examples of such stochastic behaviour include hourly, daily and seasonal variation in electricity demand, or fluctuations due to extreme weather and local events. On the other side, the renewable electricity supply also suffers from uncertainties such as variation of solar radiation and wind speed. Therefore, the operation of renewable electricity generation is as important as system design and installation. Two options are available to balance the electricity supply deficit: using either standby fossil-driven power generation capacity or electricity storage. The challenge is that operating power plants on throughputs different from their nominal operating point can be inefficient. Similarly, having electricity storage imposes additional costs and electricity losses. The problem to tackle is finding the correct combination of renewable, fossil fuel and energy storage technologies which flexibly satisfies the requirement of electricity demand, while maximizing the profitability of the overall electricity network.

The economic and environmental benefits of integrating renewable resources into electricity generation have been studied extensively in academia and industry. Table 1 summarizes the research in the field. As can been seen, the diverse array of research can be broadly classified in to two categories. In the first category, researchers have considered the design of electricity grids. The key decisions include the location of power generators, the energy storage sites, their associated capacities, and their interconnecting transmission network. In the second category, the design of the electricity grid is assumed to be fixed and the operational decisions such as generated electricity, electricity transmission and the rate of energy storage at each location for each time period are optimized. These studies may or may not have considered the range of uncertainties in the electricity demand, solar radiation or wind speed. The applied solution algorithms are highly diverse and include artificial intelligent methods such as simulation studies, genetic algorithms (GA) and particle swarm optimization (PSO), and mixed integer linear and nonlinear optimization programming under uncertainty. The details of these methods are reviewed in the following, briefly.

In the first category, which involves decisions concerned only with the design of electricity grid, several approaches can be found. Kornelakis and Koutroulis [11] applied a two-step optimization where first the number of photovoltaic modules and their specifications were selected to meet the dimensional constraints. Then, a genetic algorithm was applied to find the optimal configuration that maximizes the net profit. Kornelakis [12] applied multi-objective Particle Swarm Optimization (PSO) for the optimal design of photovoltaic grid-connected systems. The considered objectives include economic as well as environmental measures. They reported the PSO algorithm to be very efficient in finding the Pareto optimal solutions, establishing the trade-off between the competing objectives. Mondol [13] et al. optimized the size of photovoltaic systems in different European cities and the results showed the economic savings strongly depend on the available solar radiation. The authors also considered different feed-in tariffs to calculate the annual savings. Hernández, et al. [14] studied optimal allocation and sizing of photovoltaic systems constrained by transmission network. They applied a multi-objective optimization in order to minimize the costs whilst maintaining voltage stability in the grid. Zebarjadi and Askarzadeh [15] sized an optimal grid-connected photovoltaic system taking into account the price of electricity. The results also indicated that the decision regarding whether to install storage or to take electricity from the grid, very much depends on the electricity price. Cetinay et al. [16] optimized the location of wind farms taking into consideration grid constraints. The feasibility of each site was evaluated through arithmetic mean of wind speed, the theoretical wind power density and the capacity factor of a prospective wind power plant in the site. Pereira et al. [17] studied the integration of wind farms and pumped hydroelectric plants, taking into account strict targets for CO_2 reductions. They used a deterministic approach and studied different combinations of generators. Carapelluci and Giordano [18] presented a new method to synthetically generate wind speed scenarios based on diurnal variations. These scenarios were used in different sites to calculate the size of the wind power system needed in both grid-connected and off-grid situations. Wang et al. [19] studied the optimal location for wind generation systems considering transmission constraints. The results suggested that the optimal location of wind energy systems is close to congested transmission lines in order to remedy the variabilities of the wind power.

Alsayed, et al. [20] applied weighted environmental and economic criteria for designing photovoltaic and wind turbine grid-connected systems. Several combinations of wind and solar energy systems were evaluated ranging from 100% solar to 100% wind and the criteria results were compared in order to find the optimal solution. González et al. [21] investigated the optimal sizing of a photovoltaic and wind power system by minimizing the net present value. A non-renewable energy case was compared to a case that includes renewable energy. It is found that the presence of renewable energy translates into savings. The optimization was followed by a sensitivity analysis of various types of the wind and solar technologies and required investment costs. Mitchell et al.[22] studied the optimal sizing of a wind, solar and storage systems both for the case of a stand-alone application as well as when connected to the electricity grid. A very simple Excel model combined with data for the average demand, wind speeds and solar radiation was used in order to calculate the optimal generation mix and the need for storage. Dufo-López et al.[23] studied hybrid photovoltaic and wind electricity generation systems. They considered both sending the electricity to the grid as well as producing hydrogen as an energy carrier. They concluded that in the scenarios when wind speed is low, solar electricity is more economic. Wang and Singh[24] studied a grid-connected power system including wind and solar. They applied a PSO-Based Multi-Criteria optimization algorithm in order to identify the Pareto front solutions that demonstrate the trade-off between cost and reliability. The solutions included number of new wind and solar modules as well as needed storage for a grid-connected system. Torrent-Fontbona and Lopez [25] optimized the location of renewable generation sites using Particle Swarm Optimization, Genetic Algorithms and Simulated Annealing. They suggested that PSO-based method outperforms the others. Türkay and Telli [26] studied standalone and grid connected hybrid energy systems. In the standalone scenario all the electricity was supplied by the renewables (wind and solar), while in the grid connected scenario 75% was supplied by the grid. They applied a tool called HOMER[27], for optimal sizing of the energy system considering an economic objective. They reported that storage can potentially reduce the overall costs. Yang et al. [28] used a two-stage stochastic optimization to optimally size a distributed energy system with uncertainties in the demand, energy price and renewable energy intensity. The study compared the deterministic and stochastic approaches and the effect of the uncertainties on the total annualised cost.

Mazhari et al. [29] studied the simulation and optimization of photovoltaic power generation when integrated with energy storage and a grid. The solution included the optimal combination of photovoltaic modules and storage to minimizing cost and ensuring reliability of the grid. They applied a simulation-optimization framework to find the optimal schedule for the designed system. Pineda et al. [30] studied the expansion planning of a grid in terms of new wind power systems and new transmission lines. They demonstrated the need to account for uncertainty in the renewable power generation by comparing the stochastic solution to the solution where wind speed forecast errors were ignored. Kayal and Chanda [31] use a weighted multi-objective optimization that minimizes annual average power loss, maximizes voltage stability and minimizes the network security index. The solution included the optimal size and allocation of solar and wind energy generators.

The second category involves decisions that concerning the production scheduling for the electricity grid. In this category, Hytowitz and Hedman [32] study the unit commitment problem under the uncertainty of solar radiation. The scenarios are generated through Monte Carlo simulations and calculates the amount of reserve needed for each moment of the day.

Osório et al. [33] applied a scenario generation-based method for the unit commitment problem including power generation from wind. The scenarios were obtained from the probability density functions for wind values and are reduced by k-means clustering. The priority list method was applied to obtain the probability of solutions and then the solutions with a high percentage of occurrence were selected. Wu et al. [34], studied electricity generation considering the uncertainties in the wind speed. The stochastic scenarios were generated from a Weibull distribution function. They applied scenario-based and interval optimization approaches for security constraint unit commitment. They conclude that the scenario-based method provides more stable solutions but requires a higher computational time compared to the interval optimization approach. Wang et al. [35] studied the influence of wind forecasting on the schedule and reserve requirements concluding that wind uncertainties severely affect the operating costs and the reliability of the system. By comparing deterministic and stochastic solutions, they suggested that stochastic optimization should be adopted by operators as the decision-making tool. In the study conducted by Ji et al. [36], a large number of wind scenarios generated through Latin Hypercube Sampling was reduced with the backward reduction scenario technique. This technique provides a small number of scenarios to reduce the computational burden but with similar accuracy. They applied the improved gravitational search algorithm in order to solve the unit commitment problem including the uncertainty of wind power.

Generating scenarios that accurately represent the historical data is not trivial. Papavasiliou et al. [37] proposed a clustering method for scenario reduction. Lagrangian relaxation was applied to solve the transmission-constrained stochastic unit commitment with renewable energy. The reduced number of scenarios yielded comparable answers to previous problems with a larger number of scenarios. Hreinsson et al. [38] study stochastic security constrained unit commitment and non-spinning reserve allocation with performance guarantees. They applied mixed integer programming and a rule-based method. They concluded that the former requires a longer solution time but yields more robust results. Bai et al. [39] applied interval optimization for optimization of gas-electricity integrated energy systems networks. They considered demand response and wind uncertainty and studied the implications of wind forecast on the integrated network including the demand response. Nasrolahpour and Ghasemi [40] studied stochastic security constrained unit commitment model for reconfigurable networks with high wind power penetration. Monte Carlo simulation was used to generate a large number of scenarios which was then reduced to 15. They applied bi-level optimization. A master problem is solved first and a sub problem considering the wind uncertainty is then solved and fed to the master problem. Pandžić et al. [41] compared the three methods of stochastic, robust and interval optimization in order to solve the unit commitment problem considering the uncertainties in wind speed. It was found that the stochastic approach gives the more realistic objective value but has a higher computational cost as compared to the other two approaches. Shukla and Singh [42] applied K-means clustering, hierarchical clustering and the backwards reduction technique in order to reduce a large number of historical data. The PSO method was found to be comparatively effective in solving unit commitment problem with wind power uncertainty. They also conclude that including energy storage reduces the operating cost and the risk. Chandrasekaran et al. [43] used a metaheuristic algorithm called the Firefly algorithm in order to address the security constrained unit commitment problem (SCUC) for an integrated power generation system including solar farms and thermal power plants. The uncertainties in the solar radiation were assumed to have a normal distribution and energy storage was considered in order to compensate the fluctuations caused by discontinuous solar power. Aien and Fotuhi [44] carried out a probabilistic unit commitment with different penetrations of solar and wind power. A higher share of renewable energy in the generation mix means a lower operation cost but with a higher standard deviation in the total generation. Pappala et al. [45] applied Particle Swarm Optimization (PSO) to reduce the number of scenarios studied and to solve the unit commitment problem under demand and wind uncertainty. The deterministic and stochastic solutions were compared and the stochastic solution was found to be superior in the day-ahead scheduling due to the fact that all possible realizations of uncertainties were taken into account. Chaiamarit and Nuchprayoon[46] studied the economic dispatch problem. The historical wind and demand uncertainties were sampled in order to generate the stochastic scenarios. They found Newton´s method to be effective in solving the unit commitment problem. It is observed that as the degree of uncertainty rises, the mean objective value remains the same but there is a larger spread of objective values of each stochastic scenario. Delarue et al. [47] compared the

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enhanced priority list method solution time with a MILP solution time for the unit commitment problem and found the proposed priority list method was faster.

Ruddy [48] studied the optimal scheduling problem under uncertainty in the wind power, solar power and demand and their effects on costs. These author used the two-point estimation method to generate scenarios with different uncertainty percentages. Genetic algorithm was used for optimization.

Quan et al. [49] developed a computational framework for uncertainty integration in stochastic unit commitment with intermittent renewable energy resources. Demand, solar and wind scenarios were generated by using Monte Carlo simulation based on a fitted curve of prediction intervals. Using a genetic algorithm, the unit commitment problem is solved for deterministic and stochastic cases, where it is found that stochastic simulation provides a more robust solution. In a further study [50], the authors compared the implication of power reserve and risk for the unit commitment problem in the presence of uncertainties.

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Table 1
The research in the field of design and operation of integrated renewable energies

Authors	Scope	Case study	Solar	Wind	Uncertainties	Storage	Transmission constraints	Solving method
Kornelakis and Koutroulis [11]	Design	Crete grid	Yes	No	No	No	No	Genetic Algorithm
Kornelakis [12]	Design	Crete grid	Yes	No	No	No	No	Particle Swarm Optimization
Mondol et al. [13]	Design	Several locations in Europe	Yes	No	No	No	No	TRNSYS software[51]
Hernández et al. [14]	Design	37 bus and 837 kW grid in California	Yes	No	No	No	Yes	Power flow software
Zebarjadi and Askarzadeh[15]	Design	Six homes in Iran	Yes	No	No	Yes	No	Harmony search
Cetinay et al. [16]	Design	3000MW grid in Turkey	No	Yes	No	No	No	LP solved with MATLAB
Pereira et al. [17]	Design	Portuguese grid	No	Yes	No	Yes	No	Multiobjective optimization solved with CPLEX
Carapelluci and Giordano [18]	Design	4000kW grid in Italy	No	Yes	Random generation of diurnal model parameters	No	No	Genetic algorithm
Wang et al. [19]	Design	118 bus test system	No	Yes	Average and severe wind scenario	No	Yes	Semi-definite optimization solved with CPLEX
Alsayed et al. [20]	Design	200 kW grid	Yes	Yes	No	No	No	Multicriteria Decision Analysis
González et al. [21]	Design	700 kW grid in Spain	Yes	Yes	365 days of demand, wind and solar data are used as input	No	No	Controlled Elitist Genetic Algorithm
Mitchell et al. [22]	Design	17 kWh house in Australia	Yes	Yes	No	Yes	No	In-house program in Excel
Dufo-López et al.[23]	Design	Small location in Spain	Yes	Yes	No	Yes	No	GRHYSO software[52]
Wang and Singh[24]	Design	800 kW grid in Lebanon	Yes	Yes	No	Yes	No	Particle Swarm Optimization
Torrent-Fontbona and López [25]	Design	57 bus system and 14 bus system	Yes	Yes	No	Yes	No	Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing

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Table 1 (Continued)

Authors	Scope	Case study	Solar	Wind	Uncertainties	Storage	Transmission constraints	Solving method
Türkay and Telli [26]	Design	160 kW grid in Turkey	Yes	Yes	Graham algorithm (Solar) and Weibull probability distribution (Wind)	Yes	No	HOMER software [27]
Mazhari et al. [29]	Design and Operation	US grid	Yes	No	From historical data, calculate for each month the percentage with respect to maximum solar radiation month.	Yes	No	Combination of Scatter Search, Tabu Search and Neural Networks
Pineda et al. [30]	Design and Operation	24 bus power system	No	Yes	Random sampling of probability distribution function of wind speed forecast error	No	Yes	MILP solved with CPLEX
Kayal and Chanda [31]	Design and Operation	28 bus power system in India	Yes	Yes	Beta (Solar) and Weibull (Wind) probability distributions	No	Yes	Particle swarm optimization
Hytowitz and Hedman [32]	Operation	1996 reliability test system	Yes	No	100 scenarios using Monte Carlo simulation from solar forecast model	No	Yes	MILP solved with Gurobi
Osório et al. [33]	Operation	10 generating units	No	Yes	Latin Cube Hypersampling and Cholesky Decomposition of Gaussian distribution of wind power	No	No	Priority list
Wu et al. [34]	Operation	118 bus test system	No	Yes	Variation of +/- 20% of wind speeds	No	No	MIP solved with CPLEX and interval optimization
Wang et al. [35]	Operation	10 generating units	No	Yes	Random sampling of Gaussian distribution of wind speed forecast errors	No	No	MILP solved with CPLEX
Ji et al. [36]	Operation	11 generating units	No	Yes	Latin Cube Hypersampling and Cholesky Decomposition of normal distribution of wind forecast errors and subsequent backwards scenario reduction	No	No	Binary gravitational search algorithm
Papavasiliou et al. [37]	Operation	225 bus test system	No	Yes	Importance sampling of Monte Carlo simulation	No	Yes	Lagrangian relaxation
Hreinsson et al. [38]	Operation	30 bus test system	No	Yes	Determined set of scenarios which contain a certain probability a level of uncertainty	No	Yes	MIP solved with Gurobi
Bai et al. [39]	Operation	118 bus test system	No	Yes	Variation of +/- 20% of wind speeds	No	Yes	In-house optimization algorithm
Nasrolahpour and Ghasemi [40]	Operation	118 bus test system	No	Yes	Variation of +/- 20MW of expected capacity	No	Yes	Benders decomposition

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Table 1 (Continued)

Authors	Scope	Case study	Solar	Wind	Uncertainties	Storage	Transmission constraints	Solving method
Pandžić et al.[41]	Operation	118 bus test system	No	Yes	Statistical approach to scenario reduction	No	Yes	Benders decomposition, robust and interval optimization
Shukla and Singh [42]	Operation	14 generating units	No	Yes	Clustering of scenarios generates through Monte Carlo simulation	Yes	No	Weight-Improved Crazy Particle Swarm Optimization
Chandrasekaran et al. [43]	Operation	24 bus test system	Yes	No	Normal distribution of solar radiation sampling	Yes	Yes	Firefly algorithm in MATLAB
Aien and Fotuhi [44]	Operation	6 bus test system	Yes	Yes	Wind, Solar	No	No	Mathpower software
Pappala et al. [45]	Operation	7 generating units	No	Yes	PSO to find set of most representative scenarios from forecasted demand and wind	Yes	No	Particle Swarm Optimization
Chaiamarit and Nuchprayoon[46]	Operation	5 generating units	No	Yes	Sampling of uniform (demand) and Normal (wind) distributions	No	No	Newton´s method
Delarue et al. [47]	Operation	10-100 generating units	Yes	Yes	Demand, generic renewable	No	No	MATLAB for Enhanced Priority List and MILP solved with CPLEX
Reddy [48]	Operation	30 bus test system	Yes	Yes	Weibull distributions of solar and wind power	No	No	MILP solved in MATLAB
Quan et al. [49]	Operation	12 generating units	Yes	Yes	Normal distribution (Demand), Monte Carlo sampling of prediction interval distribution (Wind, Solar)	Yes	No	Genetic algorithm
Quan et al. [50]	Operation	12 generating units	Yes	Yes	Normal distribution (Demand), Monte Carlo sampling of prediction interval distribution (Wind, Solar)	Yes	No	Genetic algorithm

As discussed earlier, researchers in the field have focused on either the design of renewable energy systems or their integration and operation with the electricity grid. Seldom have design and operation of the integrated system been considered simultaneously. However, similar to other industrial processes, design and operation of electricity networks share important decisions [53]. This is of particular interest to the integrated renewable energy systems, due to the associated large degree of uncertainties. If their stochastic behaviour is not considered at the design stage, it will be difficult to accommodate their stochastic behaviour in the operational stages. More importantly, the current energy infrastructure is mostly based on thermal and nuclear power generation systems. Achieving a high degree of renewable energy penetration requires a holistic framework in which the design and operation of these novel technologies are considered in conjunction with the design and operation of the existing infrastructure. The present research aims at developing the desired framework. The novel contributions of the research are:

- A comprehensive mixed integer optimization program is developed for the design and operation of smart electricity grids that includes the uncertainties in power demand, as well as wind and solar availability, potentials for energy storage and transmission constraints.
- The problem complexity is managed by piece-wise linearization of the constraints. In addition, realistic scenarios representing uncertainties are generated from historical wind and solar data using the k-means clustering method.
- The developed framework was demonstrated on the realistic case of retrofitting the UK national grid for the minimum of 50% renewable power generation by 2030.
- The results of the optimization include the optimal location and capacity of the new generation sites, as well as the optimal operational scheduling of the overall electricity grid.
- The study also includes comparisons between the deterministic and the stochastic solutions, as well the implications of the level of stochasticity by including different numbers of scenarios in terms of the problem size, solution time and the economic significance.

The rest of the paper is organized as follows. Section 2 presents the research methodology. In Section 3, the results will be reported and discussed in detail. Finally, the paper will conclude by summarizing the key observation and findings. In order to maintain the paper brevity, the details of the case study and extensive visualization of the results are presented in the accompanying Supplementary Material (SM).

1.1. Problem statement

The present research addresses the problem of retrofitting the existing electricity grid in the United Kingdom so that 50% of the electricity generated in 2030 is renewable [6]. Currently the grid uses a mix profile of power plants based on fossil fuels (e.g., natural gas and coal), in addition to nuclear power plants. The UK government aims to retire all the coal power plants by 2025 [54]. All existing nuclear power plants will be also retired by 2030. However, the government plans to commission new nuclear power generation sites [55]. All these considerations are included in the demonstrating case study.

The design challenge is that renewable resources such as wind speed and solar radiation involve a high degree of uncertainty. Furthermore, the electricity demand has regular hourly, daily, and seasonal variations, as well as stochastic variations for example due to local events or extreme weather conditions. Such uncertainties are often accommodated by designing extra capacity in the power plants or investing in energy storage systems. The present research addresses the aforementioned challenges by considering the design and operation of the smart grid simultaneously. The given parameters include the existing or planned power generation capacities in terms of gas-fired power plants and nuclear power plants in addition to the existing electricity transmission systems. The unknown variables include the location and capacity of wind and solar farms, the location and capacity of electricity storage systems, and the required modification to the existing transmission system. It is also required to identify the optimal operational schedule for the smart grid for the set of representative scenarios of the electricity demand, as well as the availability of solar and wind energy. Considering the design (retrofit) and operation of the smart grid at the same level ensures that the grid remains flexible and economically optimal over a wide range of uncertainties.

1.2. Scope of Study

The objective of this study is to retrofit the UK existing grid to achieve 50% renewable energy generation. The study takes into account the uncertainties in the electricity demand and in the wind and solar power generation. This results in a very computationally demanding problem. Without loss of generality and in order to manage the computational complexity, certain aspects of this very intricate problem were prioritised and other aspects were not studied for simplification purposes and can be the scope of a further study.

- The optimization function only considers the economic performance. This assumption could be relaxed in future studies for example to include multi-objective optimization of environmental impacts.
- The time frame for this study was a day divided into 24 hourly intervals. This applies to both the operational scheduling and the uncertainties in demand, solar and wind power. Although smaller intervals of time produce more detailed results, the computational time would increase intractably.
- The uncertainties in economic parameters where not considered in this study.

2. Methodology

The research methodology is based on stochastic mixed integer (piece-wise) linear programming. In order to manage the size of the stochastic formulation, a big-data analytical method, called k-means clustering, was used for generating the representative stochastic scenarios that sufficiently describe the historical data.

2.1. Model formulation

In the following section, the optimization objective function, constraints, variables and parameters are presented and discussed. The electricity grid was modelled as a number of nodes connected by electricity transmission lines. At each node, there is a certain electricity demand, a certain generation capacity, and the potential for installation of renewable generation sites, and energy storage.

2.1.1. Objective function

The objective function aims to minimize the cost of the electricity grid and is formulated as:

$$Total\ Objective = \sum_{s=1}^{S} prob_s \times obj_s \tag{1}$$

Where obj_s is the cost of each scenario and is formulated as:

$$obj_s = \sum_{t=1}^{T} \sum_{g=1}^{G} cc_{s,g}(t) + fc_{s,g}(t) + oc_{s,g}(t) + vc_{s,g}(t) \tag{2}$$

The objective function represents the total hourly costs (£/h) of electricity generation and is the summation of the capital costs, fixed costs, operating costs, and variable costs over all the generation sites and technologies, G, and considering all the time periods T. The right-hand side terms are:

- Capital costs (£/h), $cc_{s,g}$, that are calculated by multiplying the required investment of a typical unit (£/MW installed) by the unit's capacity (MW). This number is then divided by the expected life of the unit (years) and the total hours of a year period (8760 h/year times the capacity factor of each generator).
- Fixed costs (£/h), $fc_{s,g}$, (e.g., employee salaries) do not depend on the generation hours and are calculated by multiplying the fixed cost of a typical unit (£/MW installed and year) by the unit's capacity (MW) and dividing by the total hours of a year period (8760 h/year times the capacity factor of each generator).
- Operating costs (£/h), $oc_{s,g}$, depend on the hourly generation. They are calculated as the operation cost of a typical unit (£/MWh) multiplied by the power generated (MW) in time period *t*.
- Variable costs (£/h), $vc_{s,g}$, (e.g., Fuel costs) are similar to operating costs in that they depend on the hourly generation. They are calculated as the operation cost of a typical unit (£/MWh) multiplied by the power generated (MW) in time period *t*.

2.1.2. Electricity balance constraints

Each node, represented by the index n, includes the electricity consumers, the existing power plants, and the options for investing in renewable generators and storage capacity. The energy balance between the generated power, the consumed power and the power lost in transmission are considered in the following constraints:

$$\sum_{i=1}^{IN} PT_{s,n,i}(t) + \sum_{k=1}^{KN} PN_{s,n,k}(t) + PW_{s,n}(t) + PS_{s,n}(t) + \eta_p PP_{s,n}(t) + PSt_{s,n}(t) + \sum_{l=1}^{LN} (f_{s,l}(t) - 0.5 q_{s,l}(t)) = D_{s,n}(t) \tag{3}$$

In this equation, the total energy produced from all generators in a node, added to the flow in the lines connected to the node and the loss per line is equal to the demand in the node.

The following constraint ensures that the new installed renewable capacities will supply at least a percentage (e.g. 50%) of the demand.

$$\sum_{n=1}^{N} \left(PW_{s,n}(t) + PS_{s,n}(t) \right) = (Ren\%) \times \sum_{n=1}^{N} D_{s,n}(t) \tag{4}$$

2.1.3. Constraints associated natural gas power plant model

The model of natural gas power plants was adapted from [56] as follows.

$$PT_{n,i_{min}} x_{s,n,i} \leq PT_{s,n,i}(t) \leq PT_{n,i_{max}} x_{s,n,i} \qquad x_{s,n,i} \in [0,1] \tag{5}$$

$$PT_{s,n,i}(t) - PT_{s,n,i}(t-1) \leq RUT_{n,i} \tag{6}$$

$$PT_{s,n,i}(t-1) - PT_{s,n,i}(t) \leq RDT_{n,i} \tag{7}$$

The first constraint sets the minimum and maximum amount of power that an existing plant can deliver. The lower bound represents the minimum stable generation level. This is the minimum throughput that power plant is able to generate due to technical limitations such as excessive pressure drop throughout the system and the turndown ratio of the major process equipment such as turbines. The binary variable $x_{s,n,i}$ indicates if the plant is functioning in that particular scenario. The second and third constraints limit the ramping rate, or the rate of change of power generation between one hour and the next, in order to protect process equipment.

There is an additional constraint that describes the reduction in the conversion efficiency when the power plant operates away from the nominal operating point. The following constraint calculates the fuel required depending on the power generated. To maintain model linearity form, this calculation is approximated through a linear equation [57].

$$fuel_{s,n,i}(t) = a_{n,i} P_{s,n,i}(t) + b_{n,i} \tag{8}$$

2.1.4. Constraints associated with the nuclear power plant model

Nuclear power plants tend to have slow start-ups [58]. The slow dynamics limit the option for flexible operation of nuclear power plants. Therefore, power generated is at either the full capacity or total shutdown as denoted by a binary variable $y_{n,k}$. Hence, in our model, there are no ramping constraints for nuclear power plants.

$$PN_{s,n,k}(t) = PN_{n,k_{max}} y_{n,k} \tag{9}$$

$$y_{n,k} \in [0,1] \tag{10}$$

2.1.5. Wind power constraints

Wind power output is calculated by multiplying the wind power generated by each wind turbine unit at each point in time, by the installed wind capacity. The amount of installed wind capacity is an integer decision variable to be determined by the optimization program.

$$PW_{s,n}(t) = WP_{s,n}(t) \times IWC_n \tag{11}$$

2.1.6. Solar power constraints

Similarly, solar power is calculated as the solar power created using a solar panel unit multiplied by the installed solar capacity. The amount of installed solar capacity is an integer decision variable.

$$PS_{s,n}(t) = SP_{s,n}(t) \times ISC_n \tag{12}$$

2.1.7. Storage constraints

In the present research, pumped hydroelectric systems were considered for electricity storage. The first constraint limits the rate at which power can be pumped at any certain hour. The second constraint limits the rate at which power can be stored at any certain hour.

$$PP_{s,n}(t) \leq IPC_n \tag{13}$$

$$PSt_{s,n}(t) \leq IPC_n \tag{14}$$

The following constraint provides a storage balance for any period. At a certain period of time, the stored electricity is the summation of the stored electricity in the previous period and the incoming electricity power minus the outgoing electricity power. The incoming power is multiplied by an efficiency coefficient in order to consider the conversion losses.

$$ES_{s,n}(t) = ES_{s,n}(t-1) + \eta_P PSt_{s,n}(t) - PP_{s,n}(t) \tag{15}$$

The maximum power that can be stored is bounded by the capacity of the reservoir.

$$ES_{s,n}(t) \leq ES_{n,max} \tag{16}$$

As storage is highly important for the secure operation of electricity grids and especially when renewable energy is present, the model includes the possibility of installing new additional storage capacity. The total capacity is calculated as the sum of the old storage capacity and the new storage capacity.

$$IPC_n = EN_n + EO_n \tag{17}$$

Furthermore, an energy conservation constraint for balancing the stored electricity is included in the model. This balance ensures that the energy supplied from a storage unit equals the stored energy. Given that some days due to a surplus of the generated energy, it will have to be stored and other days due to a lack of energy generated, energy will have to be extracted from storage, the balance is carried out over all scenarios.

$$\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{n=1}^{N}(\eta_P PSt_{s,n}(t) + PP_{s,n}(t)) = 0 \tag{18}$$

2.1.8. Electricity transmission constraints

The electricity flow between the grid nodes was modelled as a linear power flow and included the energy losses. The first equation relates the flow in a transmission line with the difference between the angles of the nodes connected to that line. This flow is limited by the line capacity and can be positive or negative depending on the direction of flow between the nodes.

$$f_{s,l}(t) = B_{s,l}\left(\theta_{s,NF}(t) - \theta_{s,NT}(t)\right) \tag{19}$$

$$-f_{l.max} \leq f_{s,l}(t) \leq f_{l,max} \tag{20}$$

Node 1 was set as the reference angle:

$$\theta_{s,N=1}(t) = 0 \tag{21}$$

Losses are calculated as the multiplication of the conductance of the line and the cosine of the difference between node angles. The losses are limited by the line capacity and are considered to be positive.

$$q_{s,l}(t) = 2G_l(1 - \cos\left(\theta_{s,NF}(t) - \theta_{s,NT}(t)\right)) \tag{22}$$

$$0 \leq q_{s,l}(t) \leq f_{l,max}(l) \tag{23}$$

The cosine function is not linear and was approximated by the following piecewise linearization.

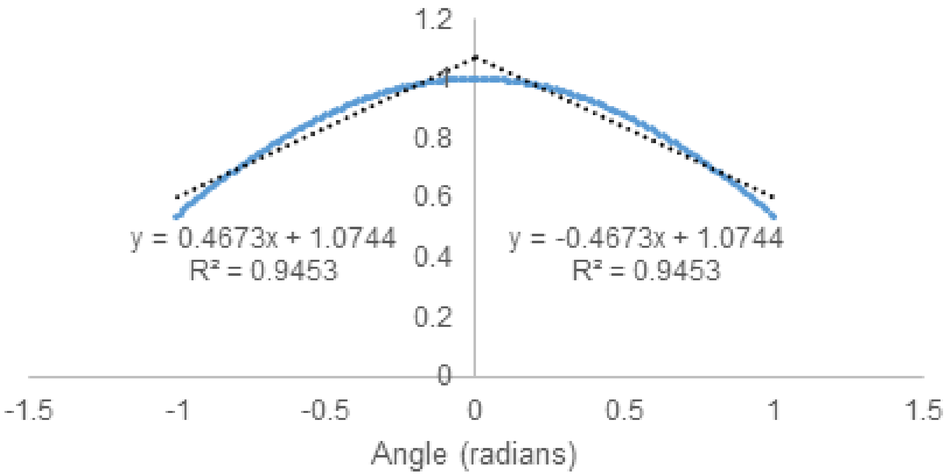

Fig. 1. Piecewise linearization of cosine function in equation (23)

The difference between the node angles was divided into two segments. For each segment, a linear function that approximates the cosine function was calculated.

$$\theta_{s,NF}(t) - \theta_{s,NT}(t) = \delta_{1_s}(t) + \delta_{2_s}(t) \tag{24}$$

$$\delta_{1_s}(t) \leq 1, \delta_{2_s}(t) \leq 1 \tag{25}$$

2.2. *Stochastic scenarios*

The stochastic optimization considers different scenarios that are concerned with the variability in the demand, wind speeds and solar irradiance. The applied method is scenario-based optimization under uncertainty, which was formulated as mixed-integer (piecewise) linear optimization program. In the approach, the hourly uncertainties in the demand, solar radiation and wind speed are captured using representative scenarios. For each scenario, the value of the objective function is multiplied by its likelihood in order to calculate the aggregated value of the total objective function. The optimization variables can be classified into two groups: design decisions and operational decisions. The design optimization variables such as the number of renewable generation sites, storage capacity and transmission lines have a physical realization. The implication is that when these design variables are decided, their value is fixed and cannot be changed without costly modifications. However, there are operational decisions such as the rate of electricity generation in each element of the grid and the rate charging or discharging electricity storages that can be adjusted in order to counteract the negative effects or potentially take advantages of the positive realization of uncertainties in demand, wind and solar. Since the uncertainties realize themselves over the time horizon, a multi-stage framework is adapted in which the design decisions are constant. However, the operational decisions are adjusted in each time interval in order to optimize the overall economic performance.

2.3. *Scenario generation*

In order to generate realistic scenarios for stochastic optimization programming, historical data of demand, wind speed and solar radiation were collected [59,60].

Since the wind speed has a nonlinear correlation with power, the following piecewise linearization was applied and the generated power was calculated instead.

$$WP = \begin{cases} WP = 0 & v \le v_{ci}, v \ge v_{co} \\ WP = \alpha v^3 + \beta WP_{max} & v \le v_r \\ WP = WP_{max} & v \ge v_r \end{cases} \tag{26}$$

Where α and β are multiplication factors that can be calculated as:

$$\alpha = \frac{WP_{max}}{v_r^3 - v_{ci}^3} \tag{27}$$

$$\beta = \frac{v_{ci}^3}{v_r^3 - v_{ci}^3} \tag{28}$$

In above equations, v is the wind speed, v_r is the rated wind speed and v_{ci} is the cut in wind speed, v_{co} is the cut out wind speed, WP is the wind power and WP_{max} is the maximum wind power that can be generated by the wind turbine. The solar power data was calculated from the solar irradiance data using the following equation:

$$SP = \eta_s \times R \times A_C \tag{29}$$

In the above equation, SP is the solar power generated by the solar panel, η_s is the power generation efficiency, R refers to solar radiation and A_C is the area of the solar panel.

The effect of temperature on the solar power generation was not considered in this study for two reasons. Firstly, temperature varies from hour to hour, day to day and season to season. This means that considering temperature for the calculation of solar power would introduce a fourth uncertain variable that would exponentially increase the computational cost. Secondly, the solar power output is not very sensitive to the ambient temperature. For instance, the power generated by Sunpower E20-435 solar panel chosen in this study, varies only 0.3%/°C [61]. This is significantly less than the magnitude of the solar power uncertainty (86%) in the programmed stochastic optimization. Similarly, the effects of panel tilt angle or tracking method was not considered in the present study.

In order to check solar power generation, the software HOMER [27] which uses models with more parameters, was used to compare results from scenario data. It was found that there was only a 17% difference in power generation results, which is well within the range of variability covered in the different scenarios. A 10% difference was found in the case of wind power and the uncertainty considered in the stochastic wind scenarios was 150%.

Considering five years of data for wind power, solar power and electricity demand would result in an intractably large formulation. Therefore, in the present study, an optimization-based method for scenario reduction was applied in which the k-mean value of various scenario clusters is calculated in order to minimize the error between the historical data and the predictions of k-means clusters for each source of uncertainties. The method of k-means clustering aggregates those time-series that are similar. The number of historical data sets associated with each cluster gives a good estimation of the likelihood of that scenario. The following algorithm was applied:

1. Choose an initial set of k clusters and calculate cluster means (i.e., centroids).
2. Calculate the Euclidean distance from each observation (each time-series) to the centroids.
3. Assign each observation to the nearest centroid.

4. Recalculate clusters’ averages.

5. Repeat steps 2-4 until cluster means do not change.

Cluster probability is calculated as the ratio between number of observations assigned to the cluster and the total number of observations.

Different combinations of each demand, wind power and solar power scenarios were created to generate the overall scenario tree (Fig. 2). The probability of each final scenario was calculated as the weighted average of the probability of the demand scenario, the wind power scenario and the solar power scenario, and their summation is equal to one.

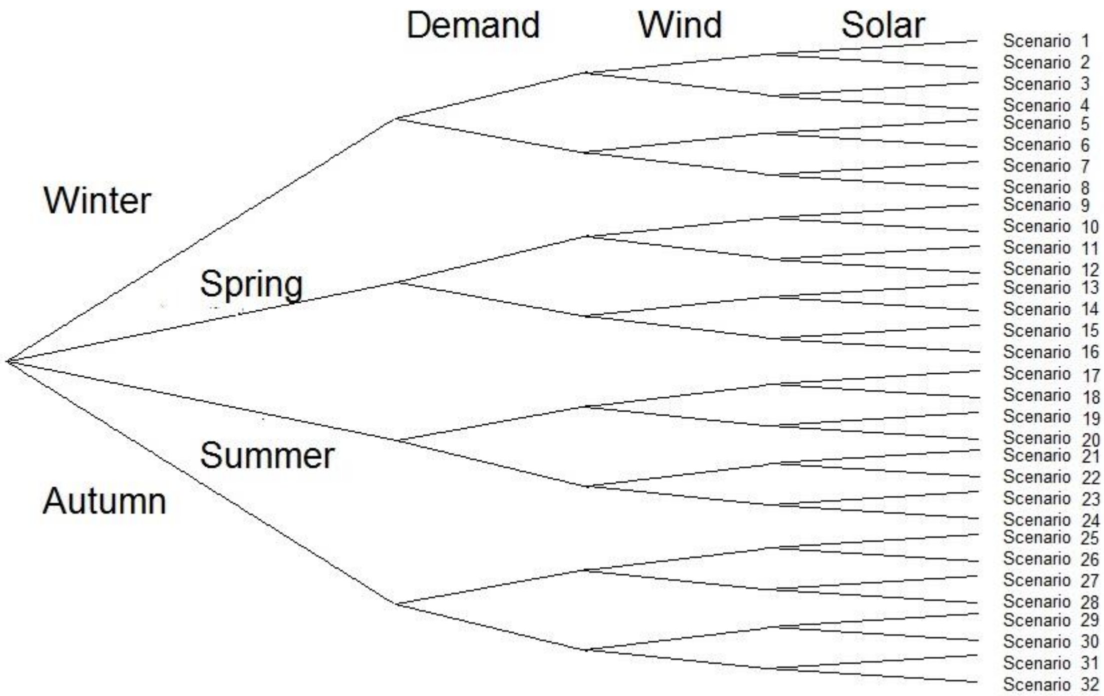

Fig. 2. Scenario construction for 32 stochastic scenario case

2.4. Stochastic and deterministic optimization studies

In the present study two stochastic optimization programs were developed. In the first stochastic program, the seasonal variations in the wind speed, solar radiation and electricity demand were considered. In the second stochastic optimization, two levels (high/low) were considered for the solar radiation, wind speed and demand in each season. Furthermore, in order to enable comparisons with the stochastic optimization studies, three deterministic optimizations were programmed. The first deterministic scenario was the average of all the historical data. The second and third deterministic programs were concerned with the worst and best values of the stochastic parameters (demand, solar power and wind power) were considered.

3. Case study

The present research addresses the case of retrofitting and decarbonizing the existing electricity grid in the United Kingdom. The optimization is constrained by a minimum 50% renewable electricity objective by 2030. A realistic representation of the electricity grid was adapted from [62] which consists of 29 nodes and 99 transmission lines that connect the nodes. The generation technologies included were 33 natural gas power plants, 7 nuclear power plants and existing renewable generation sites. Each generation site has its maximum and minimum generation capacities. The storage technology considered was hydroelectric pumped storage. Currently four pumped hydro-storage plants are in use in the UK [63].

The stochastic scenarios of wind speed and solar irradiance values were extracted from the data acquired from the British Atmospheric Data Centre MIDAS database for the years 2010-2014 [48]. As the territory covered by the grid is large it is safe to assume that these measurements will vary noticeably from north to south. To mimic these patterns, the UK map was divided into three zones and data was collected from three MIDAS stations within these zones. To calculate wind power and solar power, specifications for a Vestas V90 wind turbine unit [64] and an E20-435 solar panel unit [61] were used. The generated scenarios can be found in Supplementary Material (SM).

4. Results

In the following, the results of the optimization programming are presented and discussed. The features of interest include the economic performance of the smart grid, the configuration of the retrofitted grid, and the generation schedule for various operational durations.

4.1. Economic performance

The objective function measures the total hourly capital and operational costs and is listed for various deterministic and stochastic scenarios in Table 2. The main factor that contributes to the optimized objective values is the difference between the capital expenditure, required for the installation of renewable energy. The first column shows the objective function for the most optimistic scenario when the electricity demand is low and the availabilities of solar and wind are high. The last column shows the objective function value for the most pessimistic scenario when the demand is high and the availabilities of wind and solar power are low. The average scenario stands between theses extremes. There are two stochastic scenarios which represent the seasonal uncertainties as well as stochastic behaviour of wind and solar radiation. The differences are in the type of uncertainties and the considered level of each uncertainty variable. The key observation is that while the stochastic scenarios are more realistic and practical, they are not necessarily very expensive. Both stochastic scenarios have objective values closer to the optimistic deterministic scenario. The implication is that due to a large number of the degrees of freedom regarding the design and operation of the smart grid, the optimizer (i.e., smart operation control system) has the opportunity to minimize the costs, by counteracting the negative realization of uncertainties and taking advantage of the positive scenarios.

Table 2
Objective function and computational values for various deterministic and stochastic scenarios.

	Optimistic deterministic scenario	**Average deterministic**	**Stochastic 4 scenarios [a]**	**Stochastic 32 scenarios [b]**	**Pessimistic deterministic scenario**
Total daily cost (£/day)	23,987,702.11	44,673,440.39	29,050,004.12	31,894,371.21	77,716,723.26
Number of variables	25,350	25,350	101,122	808,318	25,350
Number of constraints	50,007	50,007	200,023	1,600,163	50,007
Computational time [c]	00:00:00:17	00:00:00:14	00:00:07:16	01:16:15:22	00:00:00:14

Note: [a] seasonal variation (4 levels: spring, summer, fall, winter), **[b]** seasonal variation (4 level), demand variation (2 levels), solar variation (2 levels) and wind variation (2 levels), **[c]** the computational time is in the form of “days:hours:minutes:seconds”.

4.2. Design of the electricity grid

In the following sections, we will discuss the design and operational decisions of the optimization program for various deterministic studies as well as the stochastic study with seasonal variations. The results of the stochastic study with 32 scenarios is presented in the Supplementary Material (SM), for the sake of brevity. The discussions include the design decision variables concerned with retrofitting the existing grid structure such as the number of new wind power units, solar power units, potential close down of the nuclear power plants and the capacity of new energy storage facilities that need to be installed. Operational decisions are concerned with scheduling of the electricity grid. They are the production of each generator, transmissions of electricity between nodes and the amount of electricity sent or extracted from storages in each time period.

4.2.1. Installation of renewable solar and wind power generators

Fig. 3 shows the location of the new power generation sites in the UK, for various stochastic and deterministic scenarios. These correspond to the retrofit of the existing electricity grid with renewable generators. In the following firstly the common features of these solutions are discussed and then, the main differences are highlighted.

As a common feature, the allocation of new renewable power plants is influenced by several factors. The north of the UK has different meteorological conditions compared to the south. In the north, there are wind streams with higher speeds, providing the opportunity for installation of new wind power stations. Similarly, to take advantage of the higher solar radiation, the new solar farms are located in the southern nodes. Additionally, the allocation of new power generation sites also depends on the demand intensity (e.g., proximity to large cities) of each area. For instance, new renewable power generators are allocated to the nodes near Greater London area in order to supply the needed power at a lower operational cost. Furthermore, new renewable generation sites are allocated to remote areas with insufficient generation capacity in order to minimize the transmission losses.

There are several important differences between the electricity grids shown in Figs. 3. For instance, Fig. 3a shows that in the average deterministic scenario, no solar power is installed. Wind power is preferred over solar power because of its higher availability during the day and night. However, it can be seen in Fig. 3b that for the most pessimistic scenario, a large number of renewable generators and storage sites are installed. The aim is to accommodate very high demands despite very low availability of wind and solar radiation. Conversely, the optimistic design in Fig. 3c requires the minimum number of generators. A comparison between stochastic studies also shows that in the most comprehensive optimization with 32 scenarios (Fig. 3d), there are more renewable generators and they are more geographically dispersed in order to accommodate extreme scenarios.

4.2.2. Storage

The allocation of storage to a node can be mainly due to two reasons. The first reason could be that there is a high renewable capacity installed at the node. The storage is thus installed at these nodes in order to dampen the variations caused by renewable power. The second reason could be that the total generation installed capacity at the node is much lower than the demand at that node. When the demand is high, the storage aids in providing the power needed. Consequently, the new storage capacity increases with the severity of the case studied. Furthermore, some common points can be found between cases. For example, node 24 requires new storage capacity both in the deterministic and the stochastic cases studied, which is due to the presence of solar power in this node. During nights and in the absence of solar power the stored energy is discharged to meet the demand.

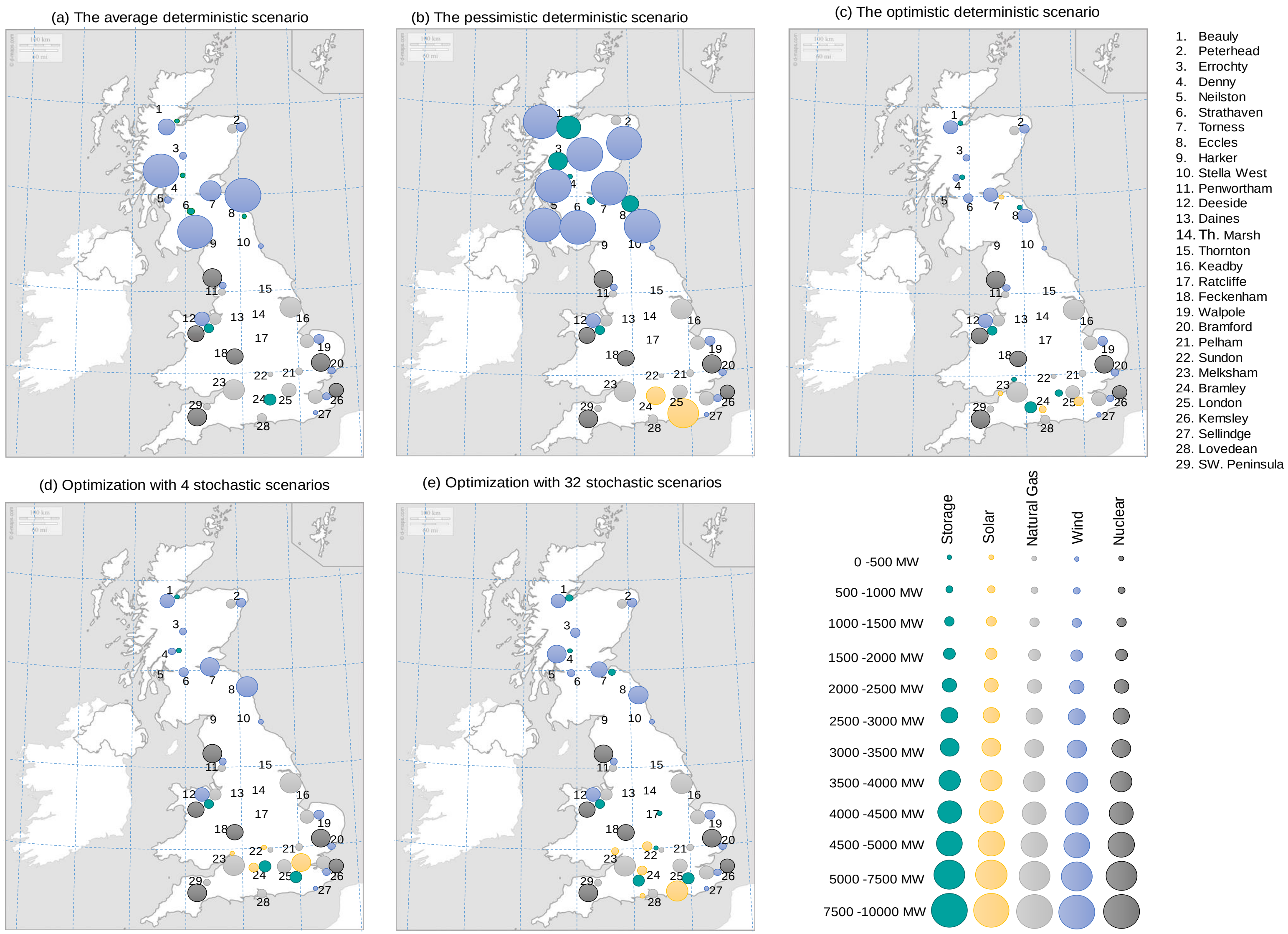

Fig. 3. The geographical allocation of new renewable power generation sites in combination with existing electricity grid

4.2.3. Operational Scheduling

The main operational decision is the scheduling of power generation. As proposed in the Methodology Section, the time period of 24 hours was studied for the representative days of the four seasons. The aim was to minimize the generation costs by assigning the optimal mixe of power generation in order to accommodate uncertainties in the demand, as well as the availability of wind and solar power. In the following, several important scenarios are discussed in order to illustrate the key factors that influence the power generation.

In Fig. 4, a scenario in which the demand, solar and wind uncertainties are close to their expected mean values is presented. Several important trends can be observed from this figure. The first observation is that since the operational costs of renewable generators are lower, they are fully exploited and the generation from natural gas is maintained at the lowest possible levels. Furthermore, the generated surplus power is stored and is used when demand is highest in the evening.

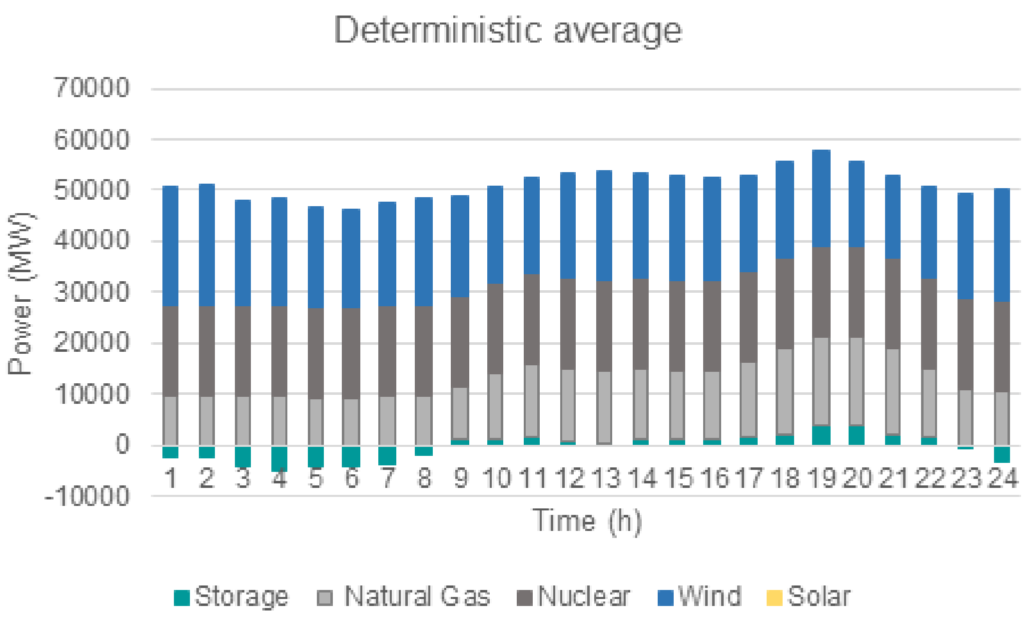

Fig. 4. The operational schedule of the average deterministic scenario

Fig. 5 presents the schedule optimized for the most pessimistic scenario during the winter day. In this scenario, the demand is at its highest level and available renewable power is very low. Despite the low available renewable power, the renewable power contribution to the total power supply is high because of the large wind capacity installed. The natural gas power plants are operated flexibly to balance the changes in the demand. The large amount of wind power produced in the early hours of the day is stored and is later used in the afternoon.

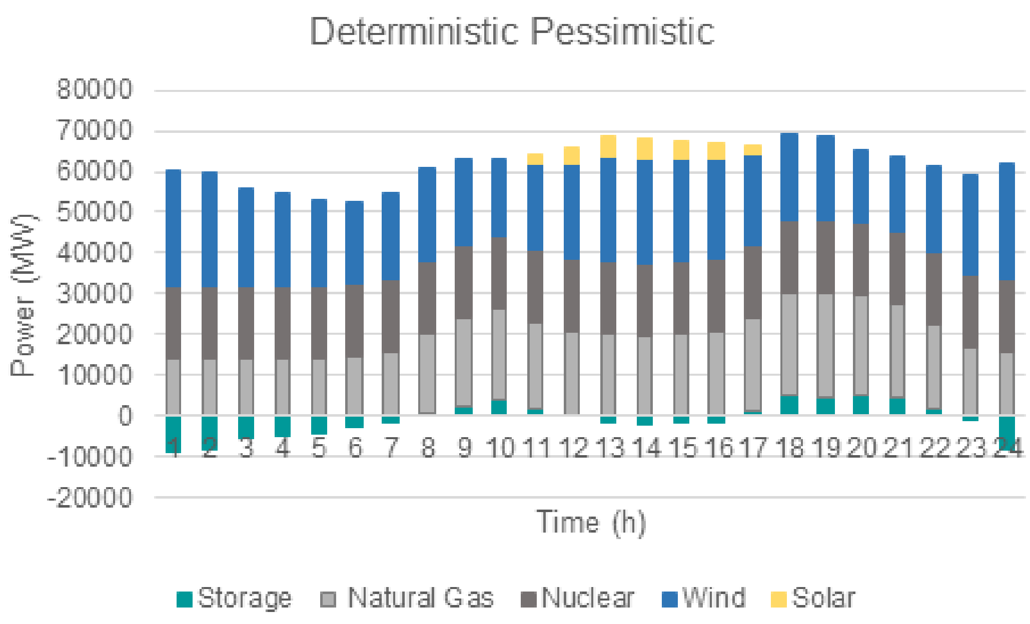

Fig. 5. The operational schedule of the pessimistic deterministic scenario

In Fig. 6, the most optimistic scenario is shown when, the demand is low and the renewable resources are abundant, which is during a summer day. The figure shows that a large percentage of the demand is supplied by the nuclear power plants and that the contribution of natural gas generation is low. Again, all of the renewable capacity was exploited due to lower operational costs. Compared to the other deterministic cases, there is more solar power generated because of the higher solar power availability. As can be appreciated in this figure, the storage output changes depending on the changes in the demand.

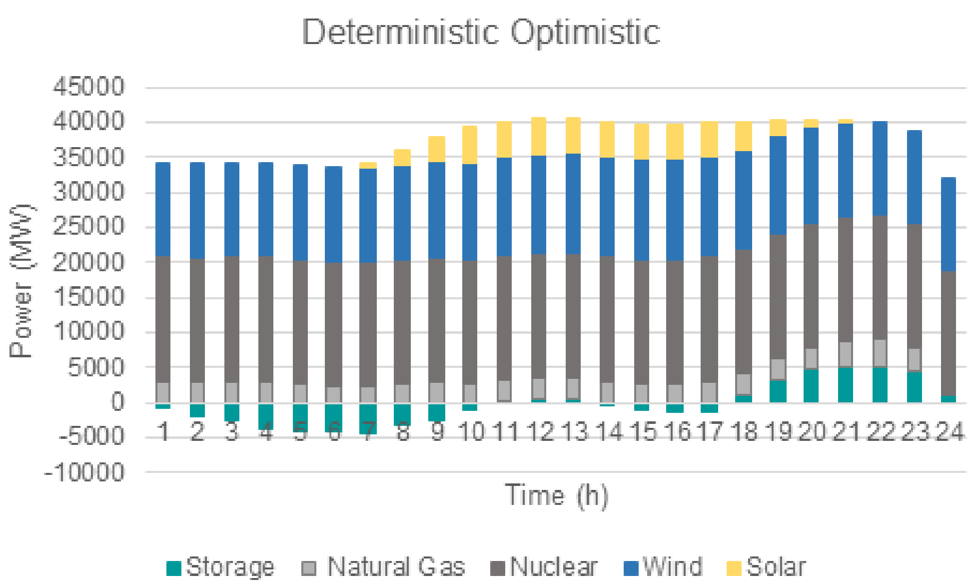

Fig. 6. The operational schedule of the optimistic deterministic scenario

Fig. 7 shows the scheduling for the stochastic case with seasonal variations (4 scenario). During spring and summer, more solar power is generated. Consequently, less natural gas power is needed for the supply of electricity. Furthermore, seasonal energy storage patterns emerge for different seasons. The excess of power generated caused by the high solar power available in spring and summer creates the need for energy to be stored during the middle hours of the day. Conversely, in the middle hours of the day during winter and fall, the stored energy is supplied to the grid. As a consequence, when the solar availability is high, the natural gas power plants could be operated at lower capacities or be totally shut-down. However, given the low variable cost of nuclear power generation and their inflexible operation, they remain in full operation for all studied cases.

Similar seasonal and hourly traits can be seen in the scheduling of stochastic scenarios with more variability in demand and in renewable energy available. The scheduling of the scenarios of the 32 scenario stochastic case can be found in the Supplementary material.

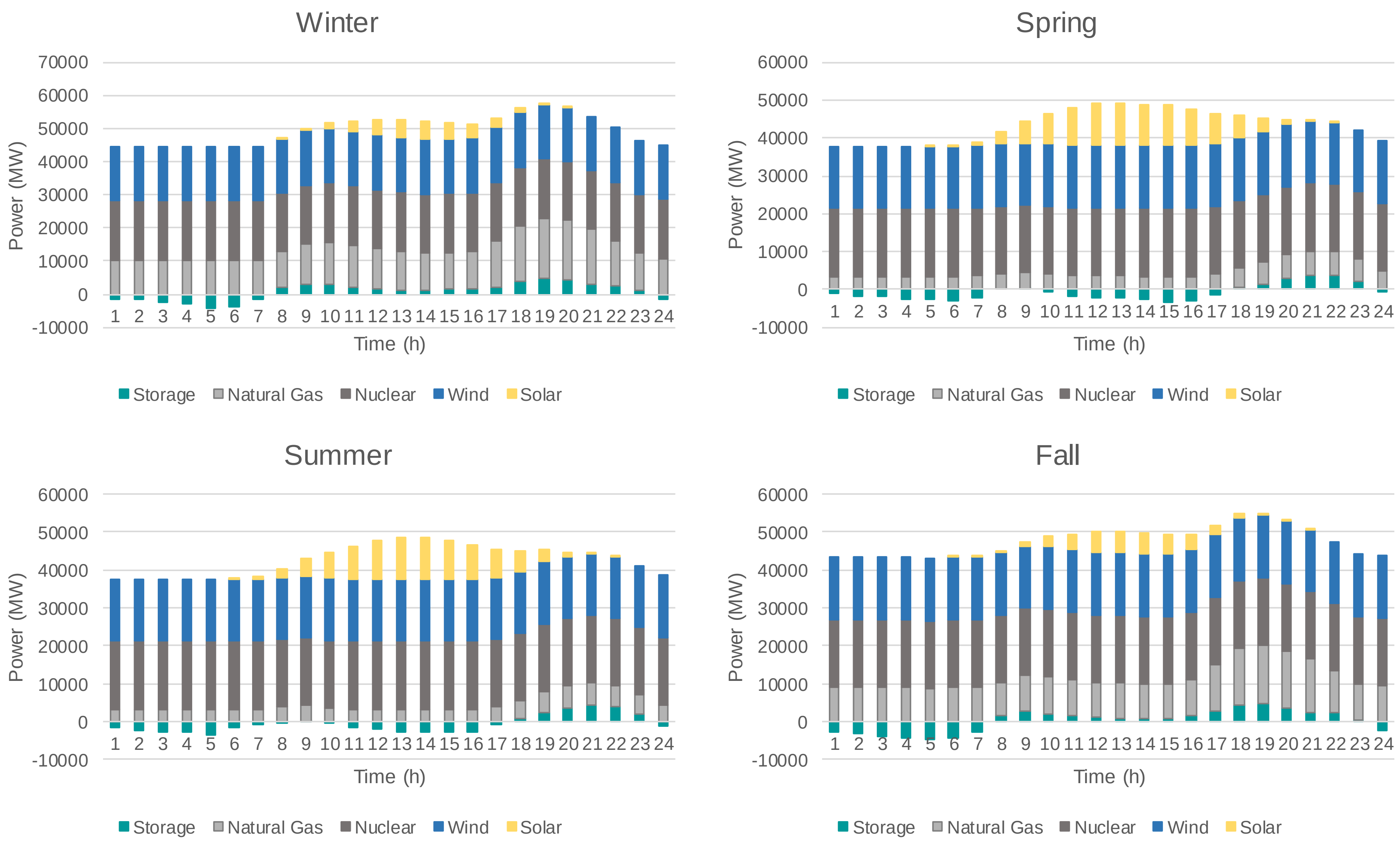

Fig. 7. The operational schedule of the stochastic optimization with seasonal uncertainty in demand, as well as wind speed and solar radiation

4.2.4. Power transmission

Fig. 3 suggests that renewable solar and wind power generators are located closer to where there is a higher availability of renewable resource. The new wind farms are generally allocated to the north sites and the solar panels are to be installed in the south farms. Therefore, electricity has to be transmitted from these sites to where it is demanded. The solution shows that the costs of transmission and transmission losses are compensated by the extra generation of renewable power. Similar observations were made by Lamy et al [65].

A high degree of variability in the electricity transmission was observed for various scenarios at different time periods. The transmitted electricity from node to node changes according to the changes in demand and renewable power generation. For the sake of brevity, the network configuration is not presented for all scenarios. An example snapshot of the network at t=6 for the best deterministic case is presented in Fig. 8. The main features are discussed in the following.

Fig. 8. Electricity flow in the best deterministic case at t=6.

Figs. 9.a. and b. show two parts of the grid for different time intervals (t=6 and t=20, respectively) for an example stochastic scenario (scenario 12 in Fig. S6b of the online Supplementary Material).

The thickness of the lines represents the amount of electricity transmitted. At t=6, the lines are thicker than at t=20 because more electricity is being transmitted. This is due to the high renewable generation at t=20 in node 25, which results in less electricity needing to be transmitted from nodes connected to node 25.

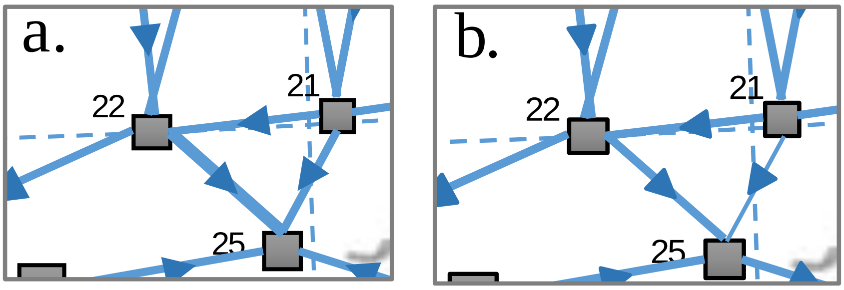

Fig. 9. Example of amount of electricity transmitted at two different time intervals

Figs. 10a. and b. show another part of the grid for the same scenario presented for the time intervals t=6 and t=18, respectively. The difference between time periods is that at t=18 there is no electricity transmitted between nodes 14 and 16. Considering the power loss during transmission, there are time periods where transmission between a given pair of nodes may be inexistent due to a better balance of electricity.

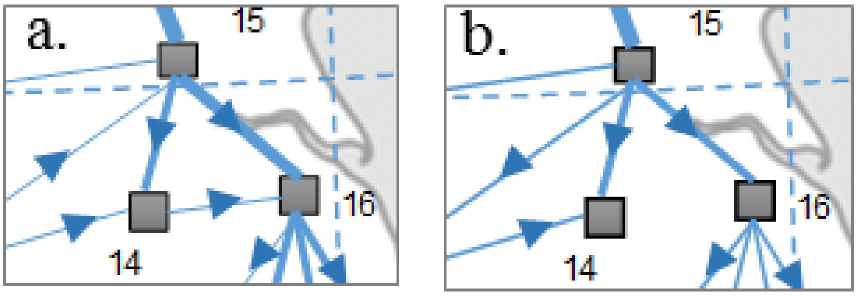

Fig. 10. Example of stopping of transmission between two nodes

Figs. 11a. and b. show two parts of the grid for the example stochastic scenario at t=6 and t=13, respectively. There is a change in direction of the electricity flow from node 23. This observation is due to an increase in the demand. There is a large natural gas capacity installed in node 23 and the electricity generated at this node is transmitted to surrounding nodes when the demand is high.

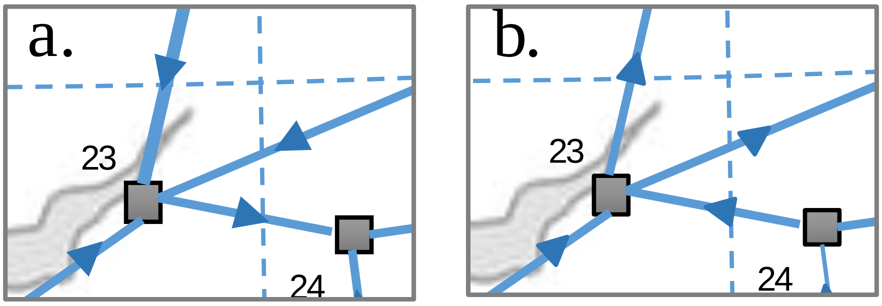

Fig. 11. Example of direction of electricity transmission at two different time intervals

A difference in direction and amount of energy transmitted can also be observed from scenario to scenario. This is due to the difference of renewable energy generated in the nodes for the different scenarios. Fig. 12 shows a part of the grid at t=6 for scenario 5 (high demand, low renewable) and scenario 12 (average demand, average renewable) of Fig. S6b. As can be seen, more electricity is transmitted in the example scenario as there are higher wind speeds, generating more wind power, in comparison to the worst scenario.

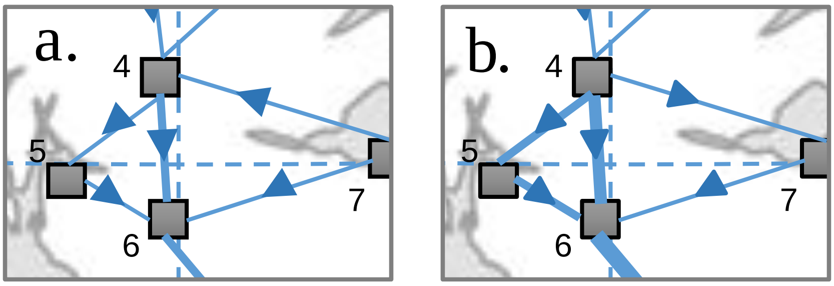

Fig. 12. Example of the change in the electricity transmission in two different scenarios

5. Conclusions

Renewable resources such as wind and solar provide unprecedented opportunities for decarbonization of the electricity grid. However, seamless integration of renewable power generation systems into existing electricity grid poses an important challenge; renewable power generation is intermittent and subject to high degrees of uncertainties in the availability of wind and solar energy. The present research proposes a systematic framework based on mixed-integer stochastic optimization programming and clustering techniques, in which design and operation of the integrate electricity grid is considered simultaneously.

To this end, several models were developed to realistically address the problem. Solar and wind power were modelled using simple (piece-wise linear) but accurate equations. Furthermore, the grid was modelled considering different power generation units, energy storage and interconnecting power flow transmission network. The model also took into account the power losses and variation in the energy conversion efficiencies in power plants.

Additionally, the variable nature of renewable power and demand is considered when including different scenarios into the optimization. The scenarios were generated from past data using k-means clustering as this method is often used for wind speeds and solar irradiance scenarios. Each scenario for the optimization was generated through the combination of demand, wind and solar power scenarios. This in turn produces results that can be used for any scenario, thus resulting in a reliable and flexible electricity grid. The realistic case of retrofitting the existing UK grid for 50% penetration of renewables was studied in order to demonstrate the effectiveness of the research methodology.

The optimization results demonstrated that flexibility is the key enabler for adaptation of the renewable power generation technologies. It was observed that it is essential to create electricity storage capabilities in order to accommodate the uncertainties in the demand, wind and solar. Furthermore, it is essential to manage the electricity transmission system according to an optimal scheduling in order to maximize the exploitation of the renewable resources and minimize the potential undesirable stochastic behaviours. The comparison between the deterministic and stochastic scenarios suggested that the economic performance of the stochastic (i.e., more realistic) model is superior to the average deterministic scenario. The important implication is that it is possible to integrate renewable generation technologies into conventional electricity grid and overcome the uncertainties in the both supply and demand sides, provided that such uncertainties are taken into account in the design of the electricity grid and the grid operational decisions are optimized in real-time.

6. References

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