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Sustainable resource allocation for power generation: The role of big data in enabling interindustry architectural innovation

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Abstract

Economic, social and environmental requirements make planning for a sustainable electricity generation mix a demanding endeavour. Technological innovation offers a range of renewable generation and energy management options which require fine tuning and accurate control to be successful, which calls for the use of large-scale, detailed datasets. In this paper, we focus on the UK and use Multi-Criteria Decision Making (MCDM) to evaluate electricity generation options against technical, environmental and social criteria. Data incompleteness and redundancy, usual in large-scale datasets, as well as expert opinion ambiguity are dealt with using a comprehensive grey TOPSIS model. We used evaluation scores to develop a multi-objective optimization model to maximize the technical, environmental and social utility of the electricity generation mix and to enable a larger role for innovative technologies. Demand uncertainty was handled with an interval range and we developed our problem with multi-objective grey linear programming (MOGLP). Solving the mathematical model provided us with the electricity generation mix for every 5 minutes of the period under study. Our results indicate that nuclear and renewable energy options, specifically wind, solar, and hydro, but not biomass energy, perform better against all criteria indicating that interindustry architectural innovation in the power generation mix is key to sustainable UK electricity production and supply.

Keywords

energy innovation; interindustry architectural innovation; sustainable energy; fuel mix; grey TOPSIS, grey linear programming

1. Introduction

Energy supply is one of the most important elements of any economy. High quality and timely energy supply is necessary to meet demand in a growing range of operations. In this context, uninterrupted energy supply feeds into the production, value enhancement and retail of all commodities and even services (Bhattacharya et al, 2017). However, energy production, transformation and consumption are often delivered by large-scale industrial processes which are responsible for severe environmental damage (Kaldellis et al, 2004; Wang and Song, 2014; Mazzanti and Rizzo, 2017). Change to more sustainable systems and processes has been slowed by technological lock-in, which tends to maintain the status quo and competitiveness of incumbent organisations (Unruh, 2000; Foxon; 2002). Recent advances in renewable energy and energy storage systems, however, set the scene for a forthcoming complex energy system that enables deep decarbonisation (Rode et al, 2017). In this context, interindustry architectural innovation (Jaspers et al., 2012) offer a better approach in the energy sector. Architectural innovations are reconfigurations of existing products and systems, created through new interfaces between existing components, but where the technological basis of the components remains largely unchanged (Henderson and Clark, 1990). Interindustry architectural innovation is defined as the novel configuration of existing technologies from different industries or sectors. This approach integrates different mature technologies and incremental innovations to produce higher efficiency under reduced risk (Zhang et al., 2013) and presents less challenge than developing and integrating new radical innovations. Configuration approaches put the emphasis on optimising or incrementally improving existing solutions through the application of novel integration strategies (Hyard, 2013), leading to significantly different and innovative solutions (Kern, 2012; Negro et al., 2012).

To achieve interindustry architectural innovation and adopt a novel integrating approach, there is an increasing need for the efficient use of high frequency, large-scale data (Song et al, 2016) to address existing and forthcoming challenges in the energy sector (Chalvatzis and Rubel, 2015; Ulnicane, 2016). In this process, large-scale data hold the promise of unlocking opportunities for interindustry architectural innovation, particularly focused on the complex issues of sustainability (Etzion and Aragon-Correa, 2016). For this research we develop a novel multi-objective model that enables addressing conflicting challenges for sustainable power supply by using high-frequency demand and fuel mix data to fine-tune its operation. We argue that this approach promotes the sustainability of power supply system and facilitates interindustry architectural innovation.

There is a wide range of available energy resources, the supply of which can be optimised (Chalvatzis and Ioannidis, 2017a; 2017b), however in this research we call for a focus on electricity. Unlike other energy types, electricity can be used flexibly to support almost every energy need in the built environment (Darby, 2017), transportation (Canzler et al, 2017) and industrial processes (Zafirakis et al, 2014; Pappas and Chalvatzis, 2017). Moreover, electricity is potentially the only form of energy that can be produced and consumed with negligible environmental emissions (Kalkuhl et al, 2012; Jakob et al, 2014), meaning that electricity is an attractive proposition for meeting the ambitious challenge of economy-wide decarbonisation. Moreover, electricity is a secondary form of energy which can be produced from a variety of resources and resource combinations, depending on regional availability (Chalvatzis, 2009).

Electricity generation is not without challenges, not least with regards to optimal resource allocation (Malekpoor et al, 2017), demanding sustainability constraints and issues of social adjustment (Zafirakis, 2013; Messner, 2015). Policies at international, regional and national levels focus on the electricity sector to address multiple environmental issues. Climate change mitigation and air pollution control are strongly linked to emission from power generation (Spyropoulos et al. 2005; Heard et al, 2017), achieved by substituting fossil fuels for renewable energy sources and nuclear energy for power generation. The reduction of toxic urban air pollution that is responsible for respiratory and other health impacts, has also been an important environmental issue (Giles-Corti et al, 2016). It is expected that the substitution of internal combustion engine vehicles with electric vehicles and the electrification of domestic heating can significantly reduce urban pollution.

Power sector management is therefore highly complex. Addressing the sustainability challenges of electricity production and distribution requires the diffusion of new technologies that add to this complexity (Bompard et al, 2015). Considering the complexities within the electricity industry and the existence of multiple attributes involved with production planning, researchers have applied Multi-Criteria Decision Making techniques to evaluate and optimize the electricity generation mix and deliver a solution to sustainable electricity planning. Linares and Romero (2000) proposed a multi objective linear optimization approach to simultaneously minimize the cost and emissions related to electricity production in Spain. Unsihuay-Vila et al. (2011) proposed a Multi-Objective model for long-term expansion planning of electricity generation and transmission by applying mixed integer programming for economic and environmental criteria. However, social factors, an important basis of sustainable development, were omitted by this previous research. Arnette and Zobel (2012) made an effort to develop a regional generation mix for the USA. Applying a bi-objective optimization model, which aims to reduce the costs of generation and minimize the greenhouse gas (GHGs) emissions, they proposed a model to determine the optimal generation mix of wind, solar and coal generation systems. Perrera et al. (2013) developed an optimization model to design a hybrid electrification system for standalone grids. Applying non-linear multi-objective optimization, levelized cost of energy, unmet load fraction, wasted renewable energy and fuel consumption were considered as objectives and by applying TOPSIS the obtained Pareto frontier was assessed for optimal solutions. More recently, Pratama et al. (2017) developed a bi-objective optimization model to find the best scenarios for electricity generation in Indonesia for 2050. The results were assessed through a simple normalization aggregation process considering eleven economic, environmental and social criteria to select the best possible solution.

The development of low cost renewable energy technologies and the proliferation of renewable energy sources is adding large-scale intermittent output from wind and solar farms and thousands of micro power plants on house roofs. The expected popularity of electric vehicles will add millions of electricity consumption points as well as potential mobile power stations that can inject energy back into the grid (Haddadian et al, 2016). In addition to the enormous growth of power market participants their unpredictability brings forward the requirement for supply security mechanisms such as the capacity markets and the emergence of increased frequency market settlement to 5 and even 1-minute intervals (Dowling et al, 2017). In this context, attempting to describe the electricity market operation requires high frequency, large-scale data that capture the detailed role of each type of power generation.

Nevertheless, the use of large-data even though necessary and promising (Karpatne et al, 2017), poses new methodological and contextual challenges. Heterogeneity, redundancy and incompleteness (Yuan et al, 2017) are the main problematic features that result in unpredictable relationships between attributes. To this end, the interrelation of sustainability and big data has been explored and applied in various fields of supply chain performance (Hazen et al, 2016; Mani et al, 2017; Dubey et al, 2017; Badiezadeh et al, 2017), manufacturing (Rehman et al, 2016; Xu et al, 2016; Zhang et al, 2017), risk management (Janke et al, 2016; Choi et al, 2017) and marketing and prediction of business success (Li et al., 2015, Fan et al., 2015, Erevelles et al., 2016). One of the prominent features of energy system complexity is the behaviour of consumers and their relation to technology (Pothitou, 2016; 2017) and Diamantoulakis et al (2015) introduced dynamic energy management as a two-way flow between the grid and its users. Acknowledging the potential of big data, researchers have developed load scheduling and power dispatching smart power grid applications (Guo et al, 2016) and classification and assignment methods of customer energy loads for serving (Biscarri et al, 2017). There have been few applications of big data in demand prediction. Rahman et al. (2016) applied machine learning techniques to data collected for the past 20 years by the USA power management sector to develop a demand forecasting system. This aggregation of machine learning and big data analytics achieved a forecasting rate equal to 99% of the actual demand.

This body of literature shows that improved understanding and knowledge extraction from big data offers numerous opportunities for sustainability performance (Mukred and Jianguo, 2017). Sustainability challenges are often cited as the main driver for innovation in resource and knowledge based view approaches (Jelinek and Bergey, 2013). However, there have been few attempts to explain the role of big data in enabling innovation to address sustainability challenges. Wu et al (2016) provide a comprehensive review of conceptual approaches to big data for sustainability, but conclude that electricity sector sustainability is yet to be addressed. In their analysis they highlight the role of sustainable energy mix complexity as a hindrance for innovation.

Following this introductory section, Section 2 explains the context of our case study in the UK and the goals this paper achieves. The methodological framework and the detailed structure of the problem are presented in Section 3. The results are presented in Section 4 alongside figures that highlight our findings and a comprehensive discussion that facilitates contextualisation. Finally, we conclude with future research suggestions and limitations in Section 5.

2. The UK Case Study and Flow Diagram

For our case study we focus on the UK, because it combines several unique features that define its energy sector and contextualises the role of big data in enabling the diffusion of innovation for sustainability. The UK has a long-term commitment to energy decarbonisation (Sithole et al. 2016), manifested with the Climate Change Act (UK Government, 2008) and updated with consecutive Carbon Budgets, leading the country to a trajectory to reduce its total emissions by 80% in the period 1990-2050. It is anticipated that the UK electricity sector will be largely decarbonised significantly earlier than 2050, with 2030 cited as a target (Climate Change Committee, 2010).

The UK must achieve this ambitious plan of deep power sector decarbonisation against the backdrop of a fragile balance of supply and demand (Newbery, 2016). Specifically, underinvestment in new generation capacity in the UK electricity sector makes it increasingly difficult to meet demand. Capacity is being removed faster than it is replaced, with coal power stations being retired due to emissions quota and nuclear power stations reaching the end of their lifespans (Royal Academy of Engineering, 2013). The UK power sector is regularly at the centre of political discourse and public debate (Lilliestam and Hanger, 2016), with repeated suggestions for price caps and market control (BBC 2013; 2017) and unstable regulation. Within this environment power utilities do not innovate, but instead use alternative approaches to retain customers (Rutter et al, 2017).

Identifying the difficulties for UK's power sector the Government has recently uncovered a plan to support innovation in new energy technologies (UK Government, 2017), specifically with a focus on energy storage (Zafirakis and Chalvatzis, 2014) and smart metering. Part of this agenda aims to enable wide technology diffusion for demand side management putting consumers in the centre of the changes, an agenda that matches the EU Clean Energy Package (2016). Energy sector innovation, with the examples of energy storage and big data, was in the UK Coalition Government's Great Innovations as early as 2013 (UK Government, 2013).

In this manuscript we propose an electricity generation mix optimisation framework that satisfies sustainability requirements for high time frequency big electricity demand data. The sustainability performance of each generation option has been evaluated against technical, economic, environmental and social criteria. The inherent uncertainty in these evaluations and the use of linguistic terms for qualitative criteria has been modelled using grey TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). The objective functions have been established by using the TOPSIS scores for each generating system. Electricity demand has been considered within a specified range to cover for uncertainty and unexpected events; thus, the optimization problem was converted to interval multi-objective optimization type. Multi-objective grey linear programming (MOGLP), a reliable approach to deal with interval linear programming, has been used to solve the developed model (Figure 1).

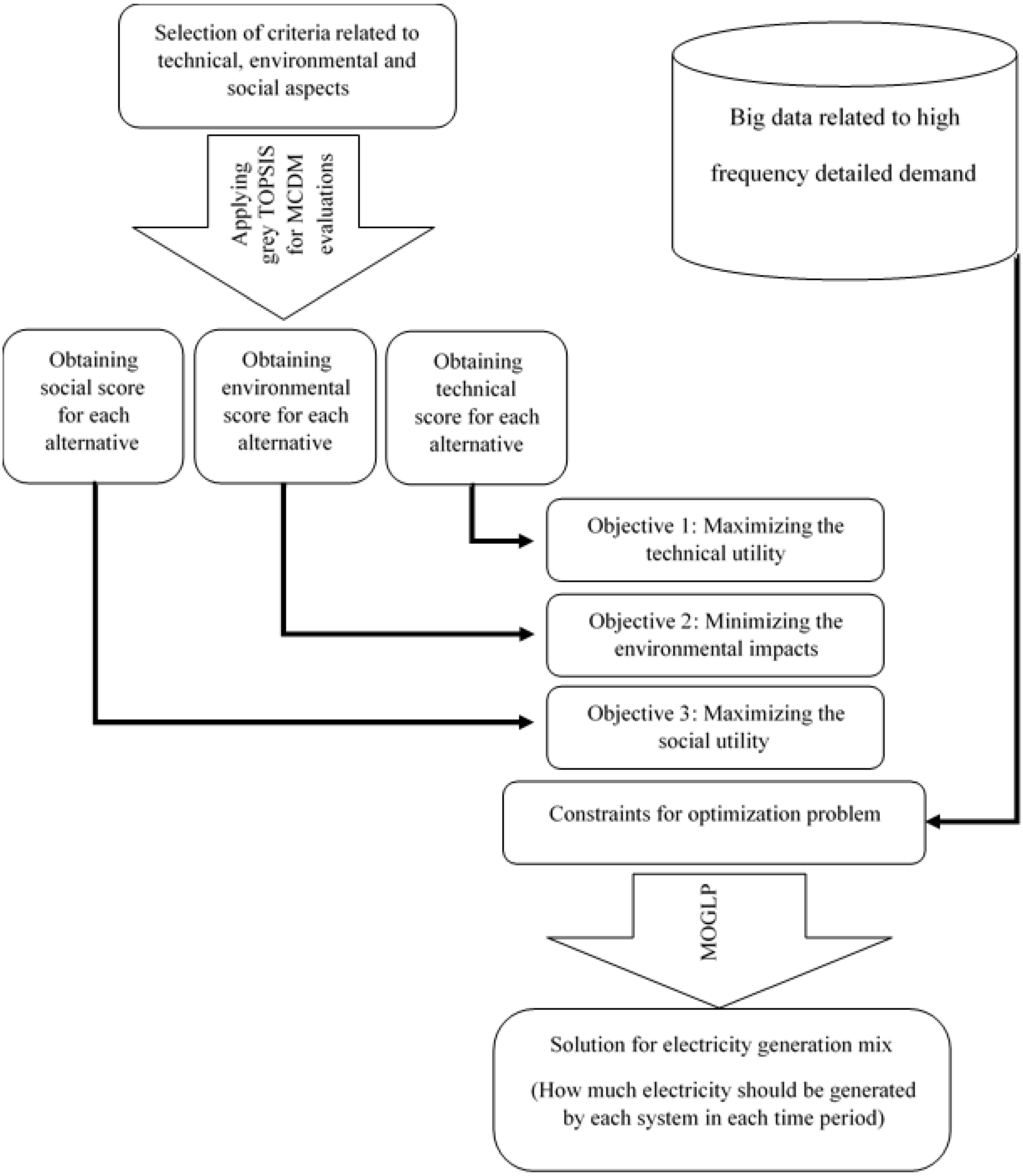


Figure 1: Overall solution procedure for obtaining the optimal electricity generation mix

3. Methodology

In real life decision making problems, decision makers (DMs) need to evaluate the performance of alternative options. For complex problems it is necessary to consider multiple parameters which are not straight-forward to process and quantify; therefore, it is preferable for DMs to occasionally apply qualitative linguistic terms instead of exact crisp values for a decision making problem. With the availability of large-scale data there is a degree of uncertainty for some factors which cannot be represented with a single value and require a range of values. Thus, we need to use methods capable of handling interval valued information.

3.1 Grey numbers

Grey number is a concept derived from the grey theory system, proposed by Deng (1982), which is well equipped to deal with insufficient, redundant, qualitative and interval information. A grey system is defined as a system capable of covering uncertain information presented by a grey number and a grey variable. For defining a grey number, let X be the universal set and $x \in X$. Then a grey set G of X is defined by its two mappings in equations 1 and 2:

$$\bar{\mu}_G(x): x \rightarrow [0,1] \quad (1)$$

$$\underline{\mu}_G(x): x \rightarrow [0,1] \quad (2)$$

In equations (1) and (2), $\bar{\mu}_G(x)$ and $\underline{\mu}_G(x)$ are upper and lower membership functions respectively. Generally grey numbers are expressed as:

$$\otimes G = G|_{\underline{\mu}}^{\bar{\mu}} \quad (3)$$

The lower and upper memberships can be estimated and an interval valued grey number with lower and upper bound can be defined as:

$$\otimes G = [\underline{G}, \overline{G}] \quad (4)$$

If we assume $\otimes G_1 = [\underline{G_1}, \overline{G_1}]$ and $\otimes G_2 = [\underline{G_2}, \overline{G_2}]$ two Grey interval numbers then, the main operations on grey numbers are done through following:

$$\otimes G1 + \otimes G2 = [\underline{G1} + \underline{G2}, \overline{G1} + \overline{G2}] \quad (5)$$

$$\otimes G1 - \otimes G2 = [\underline{G}1 - \overline{G2}, \overline{G1} - \underline{G2}] \quad (6)$$

$$\otimes G1 \times \otimes G2 = [\min(\underline{G1}\,\underline{G2}, \underline{G1}\,\overline{G2}, \overline{G1}\,\underline{G2}, \overline{G2}\,\overline{G1}), \max(\underline{G1}\,\underline{G2}, \underline{G1}\,\overline{G2}, \overline{G1}\,\underline{G2}, \overline{G2}\,\overline{G1})] \quad (7)$$

$$\otimes G1 \div \otimes G2 = [\underline{G1}, \overline{G1}] \times [\frac{1}{\underline{G2}}, \frac{1}{\underline{G2}}] \quad (8)$$

Also the lengths of a grey number can be calculated as follows:

$$L(\otimes G) = |\overline{G} - \underline{G}| \quad (9)$$

In order to find the distance between two grey numbers, we refer to Euclidian distance between two triangular fuzzy numbers (TFN). Grey numbers can be considered as a certain type of TFN. A TFN number can be shown as $\tilde{A} = (A_1, A_2, A_3)$ and we can transform it to a grey number by considering the range of it as $\otimes A = [A_1, A_3]$ (Oztaysi 2014). Applying fuzzy literature and based on Chen's (2000) definition of the distance between two TFN numbers, we define the distance between two grey numbers of $\otimes A = [\underline{A}, \overline{A}]$ and $\otimes B = [\underline{B}, \overline{B}]$ as follows:

$$Dis\,(\otimes A, \otimes B) = \sqrt{\frac{1}{2}[(\underline{A} - \underline{B})^2 + (\overline{A} - \overline{B})^2]} \tag{10}$$

If we consider a set of m alternatives $(y_1, y_2, \cdots, y_m)$ and a set of n criteria $(c_1, c_2, \cdots, c_n)$, we can build the grey decision matrix as follows:

$$DM = \begin{bmatrix} \otimes d_{11} & \otimes\ d_{12} & \cdots & \otimes d_{1n} \\ \otimes d_{21} & \otimes d_{22} & \cdots & d \otimes_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \otimes d_{m1} & d \otimes_{m2} & \cdots & \otimes d_{mn} \end{bmatrix} = [\otimes d_{ij}]\ for\ \ i = 1,2,\cdots,m;\ and\ \ j = 1,2,\cdots,n \tag{11}$$

Where $\otimes d_{ij} = [\underline{d}_{ij}, \overline{d}_{ij}]$ is the value of the ith alternative against the jth criterion.

TOPSIS is based on the idea that the solution or alternative with the shortest distance to the ideal solution and furthest distance from the worst solution is the best option among its peer alternatives. The solution procedure for grey TOPSIS is the following:

Step 1. Normalizing the decision matrix so the values lie between 0 and 1 based on equation 12 and 13.

$$\otimes N_{ij} = \frac{\otimes d_{ij}}{\max(\otimes d_j)} = \left[\frac{\underline{d}_{ij}}{max(\overline{d}_j)}, \frac{\overline{d}_{ij}}{\max(\overline{d}_j)}\right] if\ criterion\ \boldsymbol{j}\ belongs\ to\ benefit\ criteria \tag{12}$$

$$\otimes N_{ij} = 1 - \frac{\otimes d_{ij}}{\max(\otimes d_j)}$$

$$= \left[1 - \frac{\underline{d}_{ij}}{max(\overline{d}_j)}, 1 - \frac{\overline{d}_{ij}}{\max(\overline{d}_j)}\right] if\ criterion\ \boldsymbol{j}\ belong\ to\ cost\ criteria \tag{13}$$

This normalization converts all criteria to benefit criteria.

Step 2. Determining the positive and negative ideal solutions (PIS and NIS) based on equations (14) and (15) respectively:

$$PIS = \left\{\max_i \overline{N}_{ij} \,\middle|\, j = 1,2,\cdots,n\right\} = \{PIS_1, PIS_2, \cdots, PIS_n\} \tag{14}$$

$$NIS = \left\{\min_i \underline{N}_{ij} \,\middle|\, j = 1,2,\cdots,n\right\} = \{NIS_1, NIS_2, \cdots, NIS_n\} \tag{15}$$

Step 3. Calculating the distance between each alternative and the positive and negative ideal solution, Dis^{+} and Dis^{-} respectively, based on equations (16) and (17).

$$Dis_i^{+} = \sqrt{\sum_{j=1}^{n}(PIS_j - \underline{N}_{ij})^2 + (PIS_j - \overline{N}_{ij})^2} \quad for\ i = 1,2,\cdots,m \tag{16}$$

$$Dis_i^{-} = \sqrt{\sum_{j=1}^{n}(NIS_j - \underline{N}_{ij})^2 + (NIS_j - \overline{N}_{ij})^2} \quad for\ i = 1,2,\cdots,m \tag{17}$$

Step 4. Finally, relative closeness coefficient is obtained by equation (18) and alternative with the highest coefficient ranked as the best solution.

$$C_i^{*} = \frac{Dis_i^{-}}{Dis_i^{-} + Dis_i^{+}} \tag{18}$$

Figure 2 shows the necessary steps for execution of a grey TOPSIS evaluation.

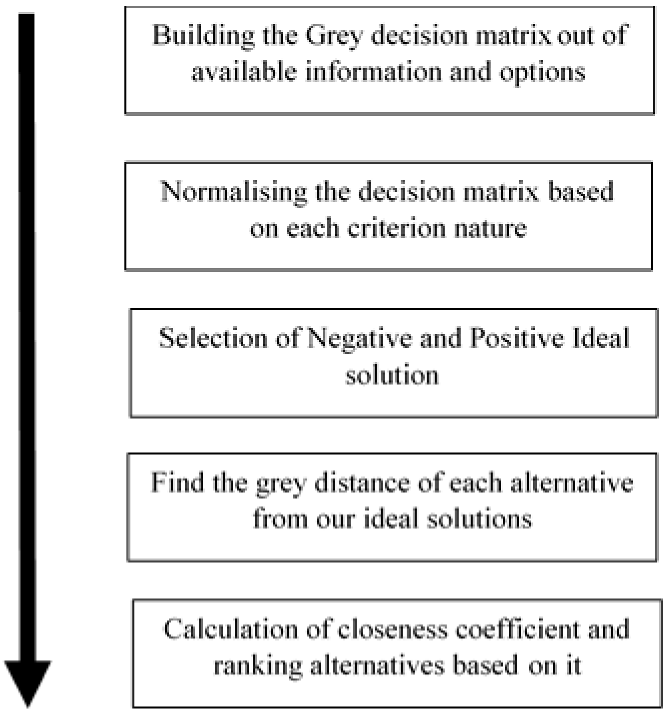


Figure 2: Grey TOPSIS procedure

3.2 Multi-Objective Grey Linear Programming (MOGLP)

Grey Linear Programming (GLP) is an optimization approach developed by Haung et al. (1992). In the presence of interval values, whether as coefficients of objective function or in the constraints of a linear problem, the problem cannot be solved by classical linear programming approaches. Model (1) introduces a typical GLP mathematical model.

$$max\ f: \otimes C \otimes X$$

Subject to:

$\otimes A \otimes X \leq \otimes B$ Model (1)

$\otimes X \geq 0$

Where $\otimes C = \{\otimes (c_1), \otimes (c_2), \cdots, \otimes (c_n)\}$ is a vector of coefficients for the objective function: $\otimes B^T = \{\otimes (b_1), \otimes (b_2), \cdots, \otimes (b_m)\}$ are the values of the left hand side of the constraints. Variables in $\otimes X^T = \{\otimes (x_1), \otimes (x_2), \cdots, \otimes (x_n)\}$ are our design variables and $\otimes A = [\otimes a_{ij}]$ for $i = 1,2,\cdots,n$ and $j = 1,2,\cdots,m$ is a matrix with the values of design variables on the right hand side of the constraints. Since all of the parameters in the model are in interval grey form, the optimal solution will also be in interval grey form as $\otimes f = [\underline{\otimes} f, \overline{\otimes} f]$ is the optimal value of the objective function and $\otimes X^* = [\otimes (x_1^*), \otimes (x_2^*), \cdots, \otimes (x_j^*)]$ where $\otimes (x_j^*) = [\underline{\otimes} x_j^*, \overline{\otimes} x_j^*]$ are the optimal values of the design variables.

To solve Model 1, Huang et al. (1992) proposed a two steps method (TSM). The principle of the method was to divide the problem into two sub problems and by solving each of them, the optimal values for lower and upper bounds of the design variable were found. Fan et al. (2011) improved the methodology by separating the positive and negative values of the objective function coefficients and guaranteeing that the solution would not violate the best-case constraints. If both the lower and upper bounds of the objective function ($f^{\pm}$) and right hand side of the constraints ($b^{\pm}$) are positive and for n interval coefficients in model (1), k of them be positive ($c_j^{\pm} \geq 0\ ;\ j = 1,2,\cdots,k$) and $n - k$ of them be negative ($c_j^{\pm} \leq 0\ ;\ j = k+1, k+2, \cdots, n$), then the first sub-model for obtaining the lower bounds can be shown as follows:

$$\max f^- = \sum_{j=1}^{k} c_j^- x_j^- + \sum_{j=k+1}^{n} c_j^- x_j^+$$

Subject to:

$$\sum_{j=1}^{k} a_{ij}^+ x_j^- + \sum_{j=k+1}^{n} a_{ij}^+ x_j^+ \leq b_i^- \ \ for\ i = 1,2,\cdots,m, \qquad Model\ (2)$$

$$x_j^- \geq 0 \ \ for\ j = 1,2,\cdots,k,$$

$$x_j^+ \geq 0 \ \ for\ j = k+1, k+2, \cdots, n.$$

By solving model (2) lower bounds for optimum value of $x_{j,opt}^{\pm}\ ;\ j = 1,2,\cdots,k$ and upper bounds for optimum value of $x_{j,opt}^{\pm}\ ;\ j = k+1, k+2, \cdots, n$ can be obtained. After solving model (2) the second sub-model for the main problem can be proposed as model (3) and by solving it the upper bound for objective function can be achieved.

$$\max f^{+} = \sum_{j=1}^{k} c_j^{+} x_j^{+} + \sum_{j=k+1}^{n} c_j^{+} x_j^{-}$$

Subject to:

$$\sum_{j=1}^{k} a_{ij}^{-} x_j^{+} + \sum_{j=k+1}^{n} a_{ij}^{-} x_j^{-} \leq b_i^{+} \quad for\ i = 1,2,\cdots,m,$$

$$\sum_{j=1}^{l_{i1}} a_{ij}^{-} x_j^{+} + \sum_{j=l_{i1}+1}^{k} a_{ij}^{-} x_{jopt}^{-} + \sum_{j=k+1}^{l_{i2}} a_{ij}^{-} x_j^{-} + \sum_{j=l_{i2}+1}^{n} a_{ij}^{-} x_{jopt}^{+} \leq b_i^{+} \quad for\ i = 1,2,\cdots,m,$$

$$x_j^{+} \geq x_{j,opt}^{-} \ for\ j = 1,2,\cdots,k, \qquad Model\ (3)$$

$$x_j^{+} \leq x_{j,opt}^{-} \ for\ j = k+1, k+2,\cdots,n,$$

$$x_j^{+} \geq 0 \ for\ j = 1,2,\cdots,k,$$

$$x_j^{-} \geq 0 \ for\ j = k+1, k+2,\cdots,n,$$

where:

$$a_j^{\pm} \geq 0 \ \ j = 1,2,\cdots,l_{i1};\ j = l_{i2}+1, l_{i2}+2,\cdots,n,$$

$$a_j^{\pm} \leq 0 \ \ j = l_{i1}+1, l_{i1}+2,\cdots,k;\ j = k+1, k+2,\cdots,l_{i2}.$$

In the aforementioned model, $x_{j,opt}^{-}$ and $x_{j,opt}^{+}$ are the optimum values for decision variables after solving model (2).

The initiation stage for a multi-objective optimization problem is to find the optimized value for each of the objective functions separately. Thus, by applying models (1) to (3), the optimal solution for each objective function should be obtained. Assuming the optimal objective function value for the l[th] objective function is $f_l^* = [\underline{\otimes} f_l^*, \overline{\otimes} f_l^*]$, a membership function for each minimization or maximization objective function can be obtained by equations (19) and (20) respectively:

$$\mu_l(x) = \begin{cases} 1 & if\ f_l(x) \leq \underline{\otimes} f_l^*, \\ \frac{\overline{\otimes} f_l^* - f_l(x)}{\overline{\otimes} f_l^* - \underline{\otimes} f_l^*} & if\ \ f_l(x) \geq \underline{\otimes} f_l^*. \end{cases} \tag{19}$$

$$\mu_l(x) = \begin{cases} 1 & if\ f_l(x) \geq \overline{\otimes} f_l^*, \\ \frac{f_l(x) - \underline{\otimes} f_l^*}{\overline{\otimes} f_l^* - \underline{\otimes} f_l^*} & if\ \ f_l(x) \leq \overline{\otimes} f_l^*. \end{cases} \tag{20}$$

Figure 3 demonstrates the objective function memberships.

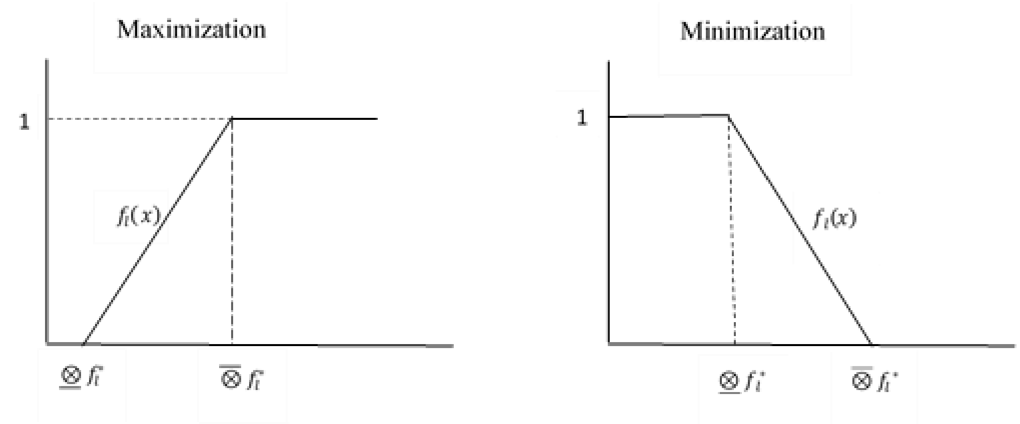


Figure 3: Minimization and Maximization of membership functions

Decreasing $f_l(x)$ leads to increasing the membership function in the minimization problem and on the contrary, an increase on the value of $f_l(x)$ increases the membership function for the maximization problem. Thus, lower amounts in minimization and higher amounts in maximization achieve higher values of membership function. The solution to the multi objective problem can be achieved through maximizing all the membership functions and by solving the model (4):

$$\max \sum_{l=1}^{p} w_l \mu_l\,(x)$$

Subject to:

$$\mu_l(x) \leq 1$$

$$\otimes A \otimes X \leq \otimes B, \qquad \text{Model (4)}$$

and $\otimes X \geq 0$.

Where $\mu_l(x)$ are the membership functions; w_l is the weight assigned to each objective function to emphasize the importance of the objectives based on DMs' opinion; and values for $\otimes A$ and $\otimes B$ are the same as the values applied in each objective problem. The above model is a grey linear programming problem and can be solved through steps (1) to (3).

3.3 Problem design

<u>3.3.1 MCDM evaluation</u>

As explained in Section 3.2, the coefficients for our objective functions are based on MCDM evaluations and specifically the closeness coefficient calculated by grey TOPSIS for each of the technical, environmental and social criteria. Defining the related criteria is one the most important steps in designing a comprehensive evaluation. An extensive literature review revealed the following criteria for the evaluation process (Tables 1,2,3).

Table 1: Technical Criteria for grey TOPSIS evaluation.

Criteria	Description and measuring unit	Reference
Evaluation of native resources	The extent to which the natural environment, natural resources and technological advances of a country support the generation system (Linguistic terms)	(Kabak and Dagdeviren, 2014)
Decreasing dependency on imported fuel	Effectiveness of the generation system in reducing the fuel imports and decreasing the dependency (Linguistic terms)	(Kabak and Dagdeviren, 2014)
Reliability of energy supply	Supplying sufficient electricity to the grid is a significant issue. Intermittent energy sources can be difficult to predict or control and thus provide a source of liability (linguistic terms)	(Sengul et al, 2015)
Levelized cost of generation	The average cost of the lifetime of the plant per MWh of electricity generated.	(Lazard, 2017)
Capacity factor	The Capacity factor of a power plant is the ratio of the electrical energy produced by a generating unit for a period of time: to the electrical energy that could have been produced at continuous full power operation during the same period (crisp numbers in percentages)	(Stein, 2013)

Table 2: Environmental Criteria for grey TOPSIS evaluation

Criteria	Description and measuring unit	Reference
Heavy metal emissions	Amount of emitted heavy metals to the environment due to fuel combustion of a power plant (Interval value, g/MWh)	Experts opinion
Water consumption	The amount of water withdrawals used for cooling conventional power plants (crisp number, m^3/GWh)	(Macknick et al, 2012)
Effect on global Warming	Impacts of certain generation systems based on GHG emissions on global warming (Linguistic terms)	(Streimikiene et al, 2012)
Land use	The environment and landscape are affected directly by the land occupied by energy systems (Interval value, m^2/MWh)	(Wang et al, 2009)
Disturbance of ecological balance	Extent of the negative impacts a power plant can have on the ecological system of the region due to land occupation, noise generation and wastes	(Garni et al, 2016)

	(Linguistic terms)	
Particulate matter PM_{10} and Particulate matter PM_{25}	Particulate matter emissions have been considered separately for PM10 and PM2.5. Particulate matter emissions pose significant risks for human health depending on size, distribution, microstructure and chemical composition (Interval value, kg/GWh)	(Streimikiene et al, 2012)
Special wastes (nuclear, …,)	Nuclear power plants, depending on the technology, produce 2.7 g of nuclear waste per MWh of electricity generation (Interval value, g/MWh)	(Brand and Missaoui, 2014)

Table 3: Social criteria for grey TOPSIS evaluation

Criteria	**Description and measuring unit**	**Reference**
Job creation	Levelized number of employees involved in the construction and operation phases of a power plant	(Maxim, 2014)
Social acceptability	The overview of opinions related to energy systems by the local population regarding the hypothesized realization of the projects under review from the consumer point of view, also known as potential for conflict generation (Linguistic terms)	(Wang et al, 2009)
Health costs associated with the technology	Electricity generation systems can damage human health. Emissions, toxicity, noise creation and radioactive effects are among the contributors of the externalities.	(Santoyo-Castelazo and Azapagic, 2014)

Regarding the criteria chosen for this research, where the precise information about the criterion is available, crisp numbers have been chosen as the unit. For cases with uncertainty in their values, interval values are used and where experts' opinions can best describe the criteria, linguistic terms have been applied to gather the best possible combination of information about all of the criteria.

3.3.2 Multi objective optimization model

In this section we present and explain the mathematical models used for the objective functions, decision variables (design variables) and constraints for this research. The goal of our model is to find the most sustainable electricity generation mix. The 8 sources of electricity generation, including Coal, Gas, Nuclear, Oil, Wind, Hydro, Solar and Biomass, compete with each other to gain a share of generation and to maximize the technical, environmental and social utility. Equations (21) to (28) show the multi-objective optimization model.

$$max\ Environmental\ score: \sum_{i=1}^{m}\sum_{k=1}^{T} Escore_i X_{ki}, \tag{21}$$

$$max\ Technical\ score: \sum_{i=1}^{m}\sum_{k=1}^{T} Tscore_i X_{ki}, \tag{22}$$

$$max\ Social\ score: \sum_{i=1}^{m}\sum_{k=1}^{T} Sscore_i X_{ki}, \tag{23}$$

Subject to:

$$X_{ki} \leq \widetilde{De}_k (1+S) LSC_i \quad for\ i = 1,2,\cdots,m, \tag{24}$$

$$\widetilde{De}_k (1+S) \leq \sum_{i=1}^{m} X_{ki} \leq \widetilde{De}_k (1.01+S) \qquad for\ \ k = 1,2,\cdots,T, \tag{25}$$

$$X_{ki} = 0 \qquad for\ \ i = 7 \quad and \quad k \in NS \tag{26}$$

$$X_{ki} = \tilde{P}_k \widetilde{De}_k (1+S) LSC_i \qquad for\ i = 7 \quad and \quad k \notin NS \tag{27}$$

$$X_{ki} \geq 0 \tag{28}$$

Where X_{ki} is the decision variable and it shows the rate of electricity generation (MWh) for generation option i in time period k.

$\widetilde{De}_k$ is the demand rate (MWh) for time period k and it is a grey interval variable.

$Escore_i$, $Tscore_i$ and $Sscore_i$ are the objective function coefficients and are obtained through grey TOPSIS evaluations.

LSC_i is the maximum percentage allowance of generation for system i.

S is the slack coefficient and is used as a reliability coefficient determining the confidence level for generating more electricity than demand, in case energy demand is higher than anticipated. This coefficient is a percentage.

$\tilde{P}_k$ is the solar capacity coefficient which limits the availability of the solar system generation in the time period of k and is a grey interval variable. Lower bound of $\tilde{P}_k$ is ratio of the minimum solar electricity generation at period k to maximum solar electricity generation for the total time periods of the last year and upper bound of $\tilde{P}_k$ is ratio of the maximum solar electricity generation at period k to maximum solar electricity generation for the total time periods of the last year. The variables for the model can also be seen in nomenclature section, appendix 1.

Equations (21) to (23) are the objective functions and aim to maximize the technical, environmental and social scores of the generation mix. Equation (24) is the constraint which guarantees diversity among the generation options. Equation (25) guarantees demand satisfaction in each time period. The total electricity generation through the system must satisfy electricity demand to prevent black outs. Equation (26) prevents the model from assigning any share to solar system during time periods belongs to NS where there is no solar radiation available and Equation (27) limit the generation of solar electricity proportionate to availability of solar radiation during the day. Equation (28) is a technical constraint to make sure there are no negative values in the solutions.

4. Results

The first step in our approach is to obtain the Technical, Environmental and Social scores through the multi-criteria evaluation of 8 mainstream generation options (i=1,2,⋯,8; respectively for Coal, Gas, Nuclear, Oil, Wind, Hydro, Solar and Biomass). The experts' opinions, statistical data and information about the criteria mentioned in Section 3.3.1 form the evaluation tables (Tables 4, 5 and 6). The importance weights of all of the criteria have been considered equal, as the consensus among the experts was that all of the criteria had a similar significance.

Table 4: Evaluation against technical criteria.

Criteria / Systems	Evaluation of native resources	Decreasing dependencies on imported fuel	Reliability of energy supply	Capacity Factor	Levelised cost of generation
Coal	**Medium High**	**Medium**	**Medium High**	**85**	**[124 153]**
Gas	**Medium**	**Medium**	**Very High**	**85**	**[56 58]**
Nuclear	**Low**	**Low**	**Medium High**	**85**	**[82 121]**
Oil	**Low**	**Very Low**	**High**	**85**	**[163 216]**
Wind	**Very high**	**Very High**	**Medium**	**24**	**[78.5 108.5]**
Hydro	**Medium High**	**Very High**	**Medium High**	**50**	**[58 68]**
Solar	**Medium**	**Very High**	**Low**	**20**	**[71 94]**
Biomass	**Low**	**Low**	**Medium High**	**83**	**[85 88]**

Table 5: Evaluation against environmental criteria.

Criteria / Systems	Heavy metal per g/GWh	Water Consumption m^3 / GWh	Global warming (tons CO_2 / GWh)	Land use (m^2/MWh)	Disturbance of ecological balance	Particulate Matter PM_{10} kg/GWh	Particulate Matter $PM_{2.5}$ kg/GWh	Nuclear waste
Coal	**[666.83 806.17]**	**2405**	**Very High**	**[360 440]**	**Very High**	**[175.5 210.98]**	**[65.44 146.25]**	**0**
Gas	**[115.11 139.31]**	**1480**	**Medium High**	**[36 44]**	**Medium High**	**[5.67 7.06]**	**[5.67 7.06]**	**0**

Nuclear	0	2405	Very low	[9 11]	Medium	0	0	[2.5 2.9]
Oil	[4322.98 5247.98]	2405	High	[36 44]	Very high	[203.5 246]	[147.25 178.25]	0
Wind	0	0	Very low	[632 948]	Medium	0	0	0
Hydro	0	0	Very low	[104 156]	Medium	0	0	0
Solar	0	0	Very Low	[110 130]	Low	0	0	0
Biomass	[2103.66 2573.66]	2271	medium	[11.3 13.9]	Low	[335.6 403.41]	[291.16 350.16]	0

Table 6: Evaluation against social criteria.

Criteria / Systems	Job Creation (Job years/GWh)	Social Acceptability	External Costs Associated with Health €/GWh
Coal	0.11	Low	[10200 76500]
Gas	0.11	Medium	[2000 8000]
Nuclear	0.14	Low	[1640 5740]
Oil	0.11	Medium	[2000 8000]
Wind	0.17	High	[340 1680]
Hydro	0.55	High	[200 6700]
Solar	0.87	High	4380
Biomass	0.21	Medium	1700-42500

Linguistic terms were converted into grey numbers. The lower and upper bounds of the grey numbers have been tuned in consultation with experts to best reflect their qualitative opinions (Table 7).

Table 7: Linguistic terms conversion to grey numbers.

Interval Term	Grey Value
Very High	[9 10]
High	[7 9]
Medium High	[5 7]
Medium	[3 5]
Low	[1 3]
Very Low	[0 1]

The evaluation process is done through steps 1 to 4 in Section 3.1. The closeness coefficients obtained for each generation alternative is entered directly into the objective functions of the mathematical multi-objective model. The demand data required for the optimization problem has been collected from the UK National Grid ("Data Explorer | National Grid") which provides high frequency demand in 5 minute intervals throughout 2017. To demonstrate the methodology, we single out the week with the highest demand in 2017, the 18th to 24th of January. The slack coefficient (S) was considered at 2% and the demand interval was presumed between the actual demand (ADe) and 3% above the actual demand ($\otimes\ De = [ADe, 0.03 \times ADe]$).

All of the systems have been limited to 20% of the generation mix share, except the gas generation system which was given the limitation of 30%. The choice of these specific figures is arguably arbitrary but it serves model functionality in a range of ways. First, it does allow for a fuel mix to be developed rather than for the best option to substitute all others. Second, it delivers a diverse fuel mix which increases robustness of supply security. Third, it maintains focus on electricity planning that acknowledges the existing UK infrastructure. In this context, given the rapid growth of renewable energy sources and the role for natural gas as the last fossil-fuel remaining in the UK power sector these constraints provide a balanced approach. Specifically, natural gas is given a higher role than other energy sources because of its large-scale existing infrastructure and its capacity to provide energy on demand at times when renewable energy sources are not productive.

($LSC_2 = 0.3\ and\ LSC_i = 0.2\ for\ i = 1,3,4,5,6,7,8$).

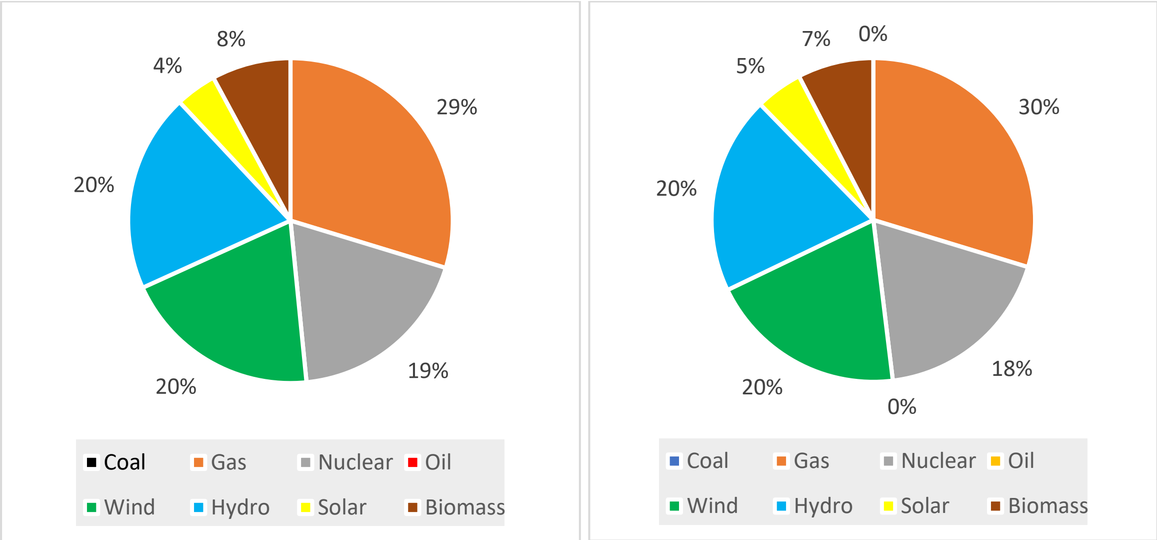
The grey TOPSIS evaluation final results show a higher closeness coefficient value as an indication for higher suitability of the options (Table 8).

Table 8: Grey TOPSIS evaluation results.

Systems / Scores	Coal	Gas	Nuclear	Oil	Wind	Hydro	Solar	Biomass
Technical scores	**0.5600**	**0.6365**	**0.4669**	**0.4238**	**0.6056**	**0.6813**	**0.4866**	**0.4730**
Environmental scores	**0.4866**	**0.7212**	**0.6163**	**0.4432**	**0.7141**	**0.9226**	**0.9278**	**0.4986**
Social scores	**0.0813**	**0.4743**	**0.4390**	**0.4743**	**0.6173**	**0.7874**	**0.8329**	**0.4344**

Similar to other large-scale datasets, the dataset provided by the grid-watch suffers from missing data points and redundant data throughout the year. For the selected highest demand week, we had 1,976 five-minute periods available (instead of 2,016) and the optimization process was run for these periods. A total of 15,808 decision variables exists in each of the objective functions. The problem was solved by Linear Programming function on CPLEX 12.0 which provides a reliable platform for large scale optimizations with a core i7 3.5 GHz CPU.

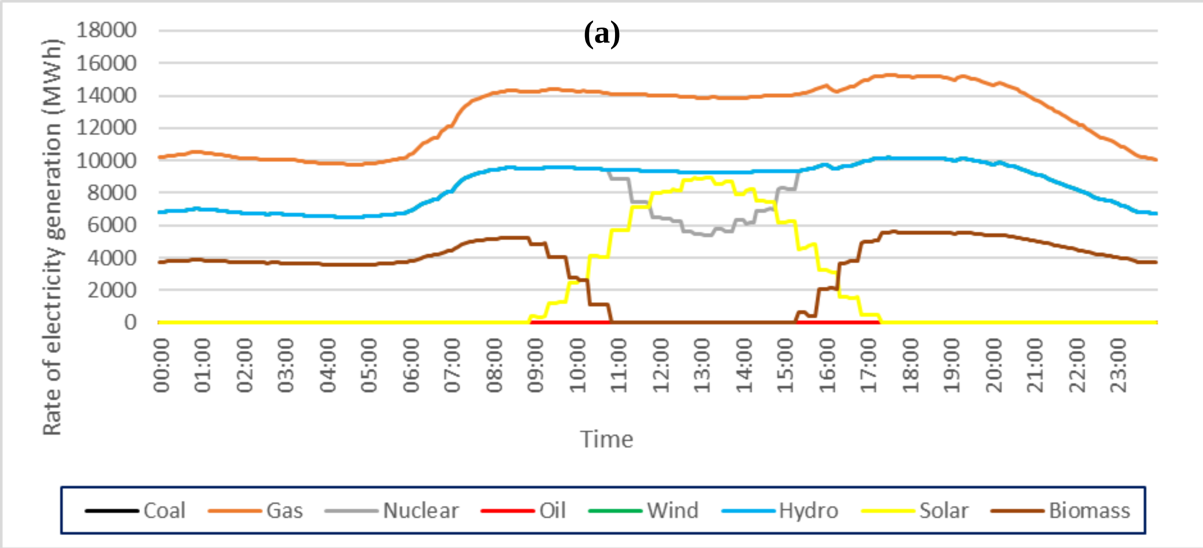
The optimised generation mix across all objective functions, as an average weekly snapshot, promoted low carbon energy resources as the best options (Figure 4a and b). Specifically, wind and hydro are rated at their maxima permitted (by the model) share of 20%. Coal and oil are virtually scheduled for zero generation, which fits with the forthcoming UK power plan to eliminate coal power stations that are not fitted with carbon capture and storage by 2025 (UK Government, 2015). Solar energy is overshadowed by other options which perform better in the UK and are better supported by the current policy instrument mix.



a b

Figure 4: Optimised generation mix of the selected week for lower (3a) and upper (3b) bound of generation

Figure 5 demonstrates the optimised use of generation options throughout the variable intraday demand for 18th January 2017. The contribution of wind and hydro is at all times equal (exactly at their cap of 20% of demand) for the 2 systems due to their satisfactory performance across the evaluation stages. Gas and nuclear contribute all of the non-renewable energy to the system. When, there is no solar radiation available, biomass is making up for the required demand of electricity, however, when solar starts the generation, biomass is the first option that is reduced and sometimes when solar production is high, biomass is eliminated. These results demonstrate how the examined energy supply sources would behave according to the criteria that have been set for their performance and their availability based on historical environmental patterns.



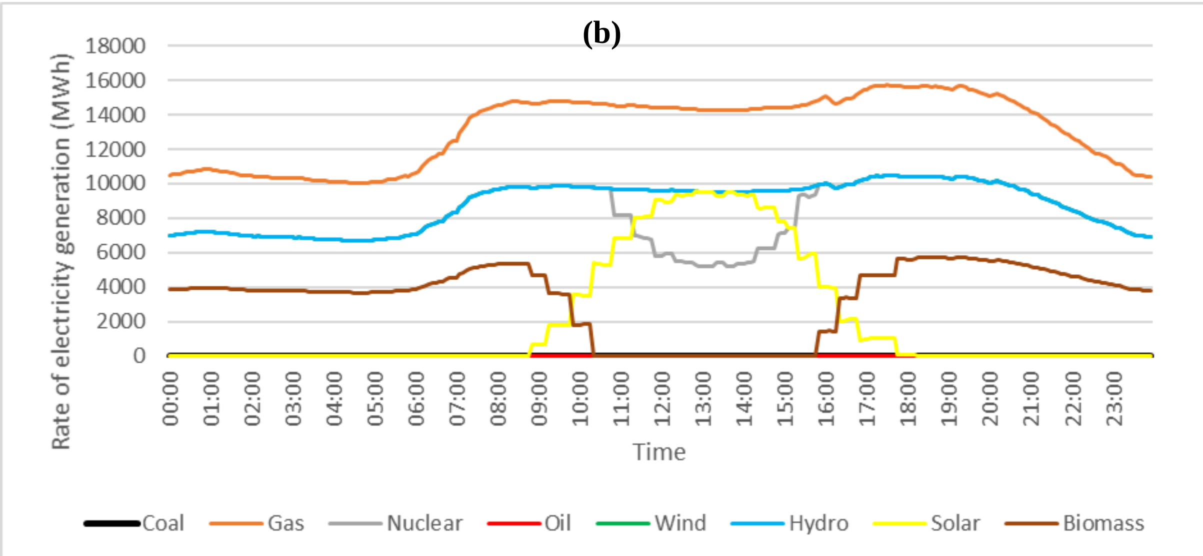


Figure 5: Intraday 5-minute interval generation for 18th January (a) Lower bound (b) Higher bound.

While the focus on a single optimal solution is an attractive proposition, the benefit of our recommended approach is its capacity to open up various viewpoints and demonstrate value propositions when a certain set of criteria is prioritised. To this end, we can demonstrate the specific performance of the generating options only against technical (Figure 6), environmental (Figure 7) or social (Figure 8) criteria without the "distortion" of all criteria having an impact at the same time.

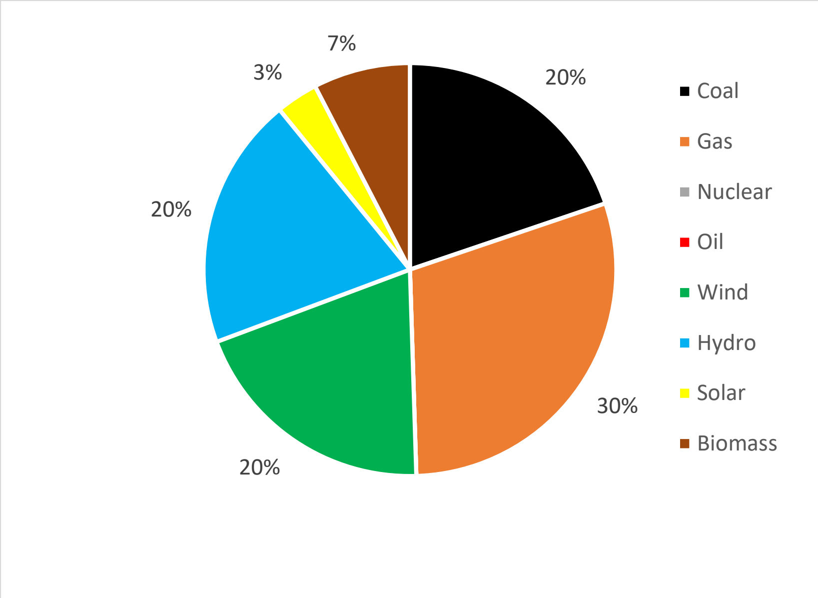


Figure 6: Optimal generation mix based on upper bound production of technical criteria

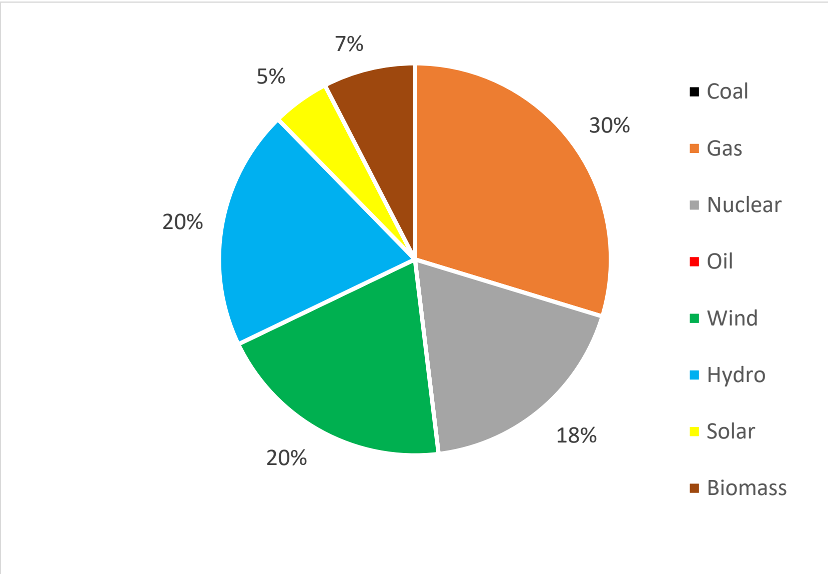


Figure 7: Optimal generation mix based on upper bound of environmental criteria

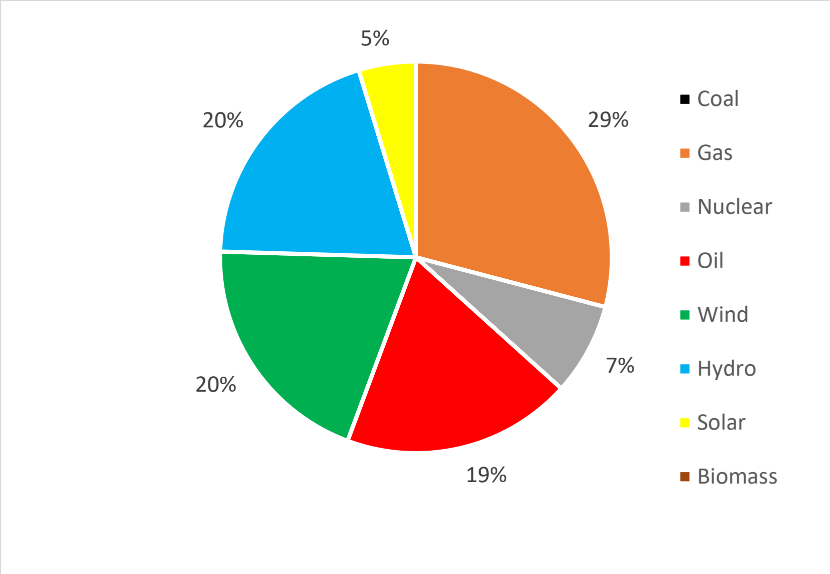
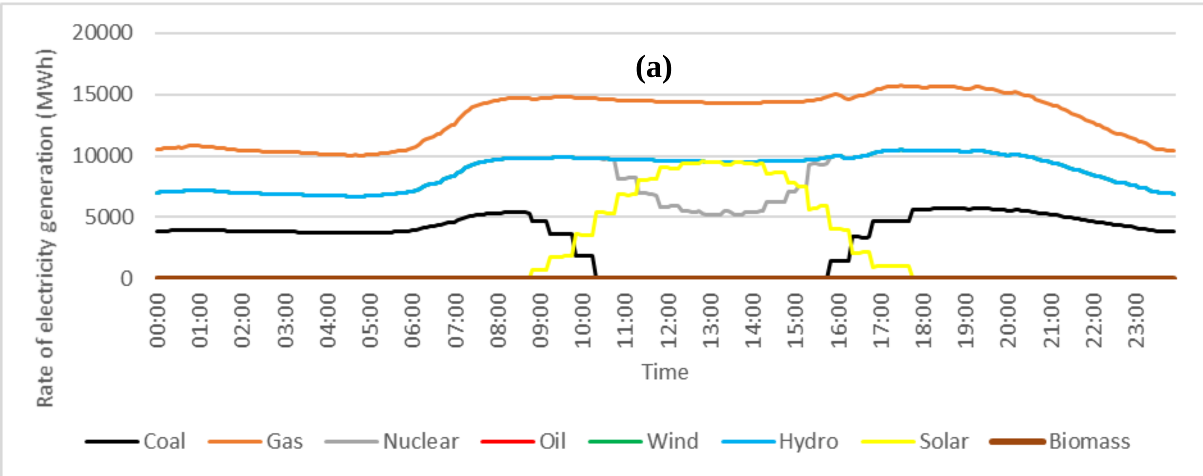


Figure 8: Optimal generation mix based on upper bound of social criteria

Specifically, the variable sets of criteria used for our objective functions deliver significantly different results. Coal is generally not considered to be an acceptable generation option, especially for new investment, but it performs well when it comes to technical criteria (Figure 6). The main reason for that is its long-term reliability in power generation. However, it is not featured in any of the other sets of criteria. Oil only performs well for social criteria and mainly for its role in skilled employment; however, it is completely eliminated against all other criteria. Biomass is the second solid fuel among our generation options, and it performs similarly to coal against technical criteria, but its high air pollution emissions and social costs eliminate it against all other criteria. The criteria-specific approach allows for the biomass, oil and coal options to be examined in the areas in which they perform well, allowing a more complete view of this evaluation exercise.



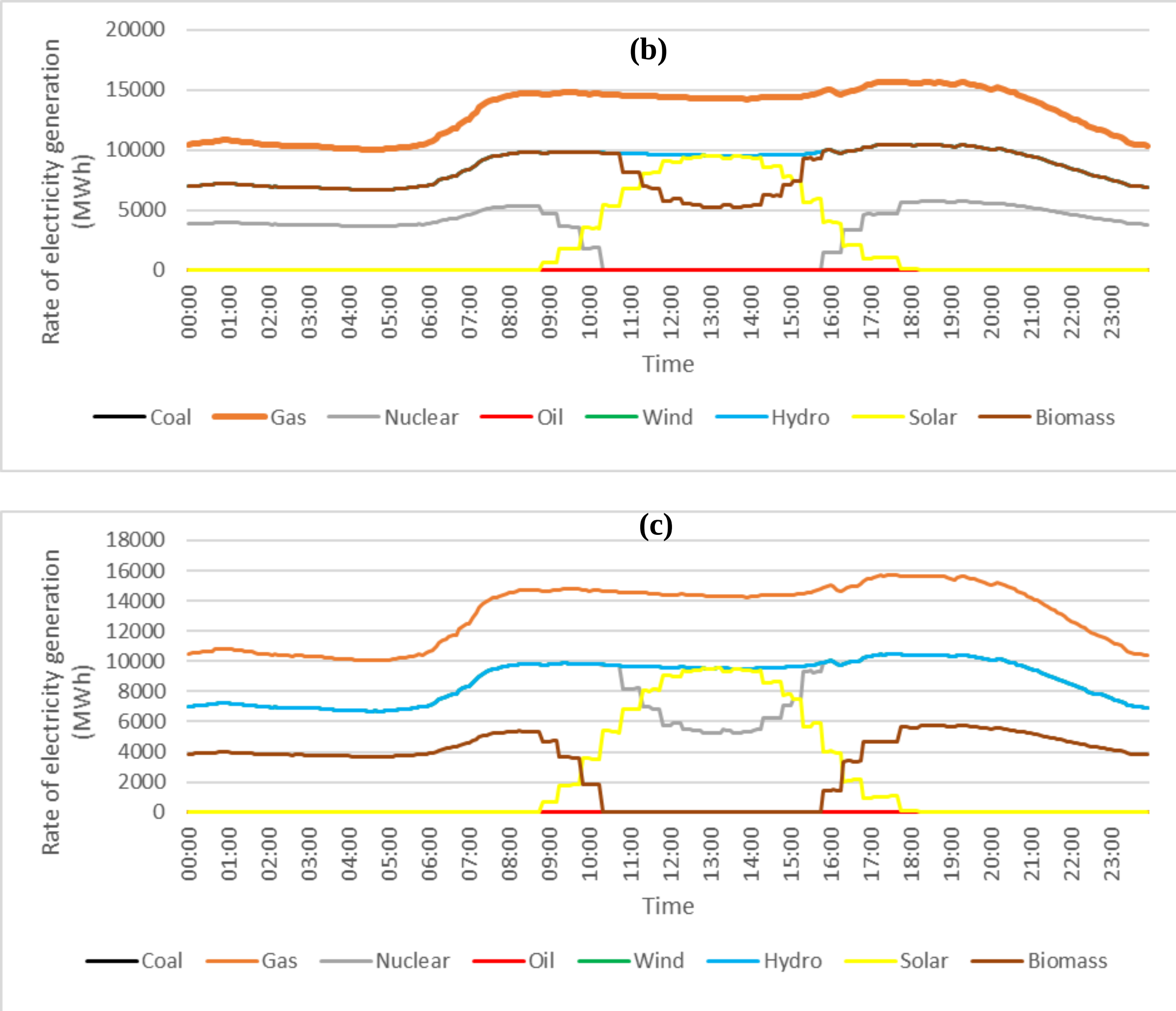


Figure 9: Generation rate in absence of social (a), environmental (b) and technical (c) criteria

Reviewing the results by eliminating each of the objective function can give us a good overview of the sensitivity of the results to the removed objective function. In figure 9 the results have been calculated, each time based on only two of the objective functions. As the share of generation for different systems based on lower and upper bound of generation is not significantly different, only upper bounds of the electricity generation have been presented. Due to satisfactory performance of the wind and hydro systems against all the sustainability criteria, these systems keep their generation at their maximum allowance by the diversity coefficient, at 20 percent of the generation mix in each time period. Furthermore, the solar system is also filling up its maximum share based on availability of the solar radiation. Eliminating social objective function allows coal to contribute and moreover, it allows nuclear energy systems to maximize production during the day. This shows the vulnerability of these two generation systems to social aspects of electricity generation. However, when solar power reaches its maximum generation capacity, coal fired generation becomes zero and nuclear production level reduces approximately by half.

In absence of environmental criteria, the generation share of biomass increases and this can be an indicator of a need for development of this technology regarding environmental measures. This might particularly important as biomass energy carbon capture and sequestration (BECCS) is often discussed as a possible carbon negative technology. The generation of electricity with oil system remains zero during all three scenarios. showing significant shortages against all criteria.

5. Conclusion

The rapid expansion of intermittent renewable energy will continue owing to both collapsing costs and decarbonisation targets. At the same time, energy innovations such as energy storage, demand side management systems, sensors and transmitters must play a role in ensuring the sustainable and secure supply of energy, but need the application of novel integration strategies through an interindustry architectural innovation approach. Controlling and integrating these innovations requires extracting knowledge about their interoperability from large-scale data. Overcoming the challenges inherent to large-scale data, such as redundancy and uncertainty can deliver promising results for sustainable planning across a wide range of applications and sectors (Song et al, 2017).

Our case study focuses on the UK electricity sector where we use high frequency, large-scale, detailed electricity demand data to develop a generation mix optimisation process. In this deterministic approach, we employ objective functions that maximise the environmental, technical and social utility to achieve optimum sustainability. We find that generation mix innovation is necessary for the UK to achieve its ambitious deep decarbonisation targets. Our results support the current UK strategy to completely remove coal from its power fuel mix by 2025. At the same time, nuclear capacity will be reduced because of power stations reaching the end of their life-span. Interindustry architectural innovation will be necessary to substitute coal and nuclear power stations with renewable energy sources. Our analysis indicates that wind, solar and hydro energy provide the optimal benefits for the UK electricity mix. To this end we suggest that subsidizing biomass might not be appropriate, in terms of overall sustainability, even if it allows the UK to achieve greenhouse reduction targets based on zero emission assumptions.

Apart from these final results, we argue that the transformation of the traditional utilities to a new disaggregated model is a case of interindustry architectural innovation which gradually appears to be feasible. This transitional decarbonisation phase requires fine tuning to a scale that was never previously necessary; therefore, with this work we contribute a robust methodological approach to integrate detailed large datasets for resource allocation in sustainable electricity production. Our approach is helpful to policy makers and utility managers because it allows an exploratory view of results with a separate focus on distinct technical, environmental and social objectives. In this context, decision makers can adjust their attention based on the specificities of the area they examine, ensuring the transferability of our method. We expect the implications of our work to be significant in enabling interindustry architectural innovation in the power sector. The use of large datasets to inform and fine tune this transition is essential and will promote sustainable resource allocation.

As with all modelling work, our approach comes with limitations. The main limitation is data quality. In addition, we do not control for the possibility of the rapid diffusion of new innovations, such as electromobility, that could have substantial interactions with the power sector. Future work should focus on a more meaningful understanding of innovation spill-over effects, particularly for example with the role of electric vehicles to provide grid services. Furthermore, future work should model energy diversity by accurately optimising the selected constrains for the selected energy mix options.

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Appendix 1: nomenclature

$Escore_i$	Environmental score for generation system type i
$Sscore_i$	Social score for generation system type i
$Tscore_i$	Technical score for generation system type i
X_{ki}	Generation level of system i at time period of k
$\widetilde{De}_k$	Range of electricity demand at time period of k
LSC_i	Maximum allowance of generation mix share for system i
$\tilde{P}_k$	Capacity coefficient of solar system at time period k
NS	Set of time periods k with no solar radiation available
S	Slack coefficient to reduce the risk of electricity interruption

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