Ann Oper Res (2016) 245:121–135
DOI 10.1007/s10479-015-1828-2

An extended goal programming model for site selection in the offshore wind farm sector

Dylan F. Jones · Graham Wall

Published online: 19 March 2015

Abstract This paper presents an application of extended goal programming in the field of offshore wind farm site selection. The strategic importance of offshore shore wind farms is outlined, drawing on the case of the United Kingdom proposed round three sites as an example. The use of multi-objective modelling methodologies for the offshore wind farm sector is reviewed. The technique of extended goal programming is outlined and its flexibility in combining different decision maker philosophies described. An extended goal programming model for site selection based on the United Kingdom future sites is then developed and a parametric analysis undertaken at the meta-objective level. The results are discussed and conclusions are drawn.

Keywords Multiple objective programming · Extended goal programming · Offshore wind · Renewable energy

1 Introduction

Following the energy crisis in 1973, western countries have been making great efforts to secure their energy supplies. In addition, growing concerns about atmospheric environmental pollution and climate change has provided the catalyst to harness a larger proportion of energy from renewable sources (e.g. wind, solar and biomass). It has also provided an opportunity to generate a number of new ‘green’ jobs. However, these renewable energy sources need to be able to compete economically with conventional energy sources (e.g. gas, coal and oil) in the medium to long term or otherwise be reliant on government subsidy.

Taking the United Kingdom (UK) as an example, under the EU 2008 Renewables Directive, the UK Government set a national target for 15 % of its total energy consumption to come

D. F. Jones (✉) · G. Wall
Department of Mathematics, Centre for Operational Research and Logistics, University of Portsmouth, Lion Terrace, Portsmouth PO1 3HF, UK
e-mail: dylan.jones@port.ac.uk

G. Wall
e-mail: graham.wall@port.ac.uk

from renewable sources by 2020. It is expected that wind energy will make the largest contribution to reach this target. Although the onshore sector is much more established, the UK government is driving forward the offshore sector given its excellent offshore wind resource and the fact that offshore wind farms avoid many of the issues that have led to public opposition to onshore wind farms (e.g. noise, visual intrusion, land take and subsequent lengthy planning permission periods). The Crown Estate (the organisation with responsibility for management of UK offshore territorial waters up to 12 nautical miles from the coast) have granted development rights in three rounds; round 1 was awarded in 2001 and consisted of 18 sites (1.5 GW), round 2 was awarded in 2003 and consisted of 3 strategic areas (7 GW) and round 3 was awarded in 2010 and consisted of nine zones (31 GW). During this time, the offshore wind farms that have been granted permission have been progressively larger in terms of area and therefore the number of turbines installed as well as being located in deeper waters further from the coast. By June 2012, there was approximately 5 GW of operational onshore wind capacity compared to 1.9 GW for offshore (Renewable 2012).

Since the mid-2000s, UK electricity generation costs have risen considerably. Between 2006 and 2010, gas, coal, nuclear, onshore wind and offshore wind has increased by 90, 219, 111, 33 and 51 % respectively (offshore wind up from £99/MWh in 2006 to £149/MWh in 2010; inflation adjusted) (Heptonstall et al. 2012).

The capital expenditure (CAPEX) for offshore wind farms rose sharply from £1.5 m/MW in 2004 to £3.0 m/MW in 2009 (Heptonstall et al. 2012). This has been due to a number of factors such as rising materials, commodities and labour costs, currency fluctuations and rising turbine costs due to supply chain constraints. Other factors include increased installation and foundation costs as well as rising operation and maintenance costs due to the increase in depth and distance of the turbines offshore. In addition, supply chain constraints with regards to vessels, ports and planning delays have also had an impact on cost (Heptonstall et al. 2012). The UK Government has set out an objective that offshore wind should reach a levelised cost of energy (lifetime cost of the project per unit of energy generated) of £100/MWh. The UK offshore wind cost reduction pathways study carried out in 2012 identified and quantified cost reduction opportunities in order to see costs reduced from the present £140/MWh (in 2011) to £100/MWh by 2020 (Crown Estate 2012) .

The cost reductions required lead to the need for greater levels of efficiency throughout the life-cycle of the offshore wind-farm. The offshore wind sector clearly has a strategic need to maximise its energy production whilst minimising its cost of generation. This must be done whilst considering the needs of other maritime stakeholders such as the fishing, container shipping and leisure/tourism communities. Positive environmental impacts of wind farms should be maximised whilst negative ones minimised. The opportunities for local economic regeneration afforded by offshore wind should also be maximised. Any road or rail disruption caused by transportation during the construction phase should be minimised. The above concerns clearly point to offshore wind as a sector involving decision making problems with multiple conflicting objectives and multiple stakeholders.

This paper examines the current state-of-the-art in multiple objective modelling for the offshore wind sector and proposes directions for future research, giving a demonstrative case study based on the authors' work in the 2OM (Pertin 2013) project. The remainder of the paper is divided into three sections. Section 2 overviews the current state-of-the-art and suggests areas of the offshore wind farm that would benefit from the development of multi-objective models. Section 3 details the extended goal programming methodology used in this paper. Section 4 then formulates, solves and discusses the result of a multi-objective location selection model based on the UK future Round 3 sites. Finally, Sect. 4 draws conclusions and gives suggestions for future research.

2 Multi-objective modelling for the wind sector

As detailed in Sect. 1, the offshore wind sector presents a complex decision environment where decisions have to be taken on both the strategic and operational level at various stages of the life-cycle of the wind farm. This has led to the development of various types of multi-objective decision making models arising. The major types detailed in the literature are categorised in this Section, and subsequent conclusions as to topics where further models could be developed are drawn.

2.1 Energy mix modelling

The first multi-objective to arise on a strategic energy planning level is what percentage of electricity in a network should be generated by wind (offshore, onshore or both dependent on the particular network being modelled). This can exist on a macro (national, regional) or on a micro (specific system) level. A range of other energy sources are considered dependent on the specific situation. Recent papers on this topic are described as follows: Koroneos et al. (2013) discuss the optimal mix of renewable energy types (wind, solar, and biomass) on the Greek Island of Lemnos. They consider environmental impact, energy demand satisfaction, energy cost, and resource availability as objectives. Stein (2013) uses the fuzzy Analytical Hierarchy Process (FAHP) to rank a range of energy sources including conventional and renewable. When considered against financial, technical, environmental and socio-economic-political objectives renewable sources in general, and wind energy in particular, were highly ranked under a range of possible decision maker weighting scenarios. Mourmouris and Potolias (2013) present a regional level decision support framework that considers wind, solar, biomass, geothermal, and hydro renewable sources. They apply their framework to the island of Thassos, Greece. Sampaio et al. (2013) present a goal programming city-level model which is applied to Guaratinguetá, Brazil. Their model considers hydro-electric, biogas, natural gas, and wind power sources. Deviations from goals relating to energy generation and environmental targets are considered. Gitizadeh et al. (2013) give a multi-objective model that considers the objectives of maximising economic returns, minimising fuel price rise risk and minimising emissions.

2.2 Offshore wind farm location modelling

The issue of where to locate and layout wind farms is another decision problem involving multiple stakeholders and multiple objectives. The issue of either selecting a set of wind farm sites to develop or ranking a number of potential sites is concerned with the large-scale strategic level decision making aspects of this issue. Mavrotas et al. (2003) combine a discrete multi-criteria (ELECTRE III) and continuous (integer programming) technique to produce a decision support system for selecting wind-farm sites in from amongst candidate applications in Greece. Kang et al. (2013) use the fuzzy AHP to rank the performance of existing wind farms in Taiwan and hence provide future policy planning suggestions.

Several heuristic methods have been proposed for the problem of optimally locating individual turbines within a wind farm. These include ant-colony optimisation (Eroglu and Seckiner 2012); genetic algorithms (Kusiak and Song 2010); evolutionary algorithms (Saavedra-Moreno et al. 2011); extended pattern search (Du Pont and Cagan 2012); and particle swarm optimisation (Wan et al. 2012). Chen and MacDonald (2012) propose a genetic algorithm based method that considers landowners preferences and willingness to sell land.

2.3 Engineering and design modelling considerations

There are several important multi-objective modelling issues arising in the engineering and design aspects of the design of wind farms and their components. The use of optimisation methods for several of the engineering aspects of wind farm operation is detailed in a survey by Banos et al. (2011). A particular area that has received attention is that of reactive power planning, the problem of how energy produced by wind farms is fed into wider electricity grids. This includes technical issues such as voltage control as well as pricing and regulation considerations. Key recent papers in this area include (Niknam et al. 2012) who use a combination of non-linear programming and a interactive fuzzy satisfying method to deal with the daily voltage control problem. Zare and Niknam (2013) use a bacterial foraging algorithm for a similar purpose. Qiao et al. (2006) use goal programming to optimise reactive power flow in a wind generation integrated system. Bevrani and Daneshmand (2012) present a fuzzy logic based model for optimising the Load-frequency control problem. Alonso et al. (2012) develop a multi-objective genetic algorithm for reactive power planning that considers voltage stability, voltage and power loss and cost. Kargarian and Raoofat (2011) also present a reactive power model based on non-linear multi-objective programming that considers market payments and voltage security. Zhang and Wirth (2010) construct a heuristic designed to deal with the variation of power from a wind turbine by optimising the use of a battery.

Multi-objective models that deal with the design or various components of the wind turbines are beyond the scope of this paper; however several authors deal with design and life-cycle issues at a strategic wind farm level. (Sareni et al. 2009) use a multi-objective genetic algorithm to consider the effects of a low cost passive structure wind turbine. (Ortegon et al. 2013) discuss the issues involved in dealing with the end-of-life of wind turbines including dismantling issues, recycling and the reverse supply chain.

2.4 Conclusions

It can be seen from the literature review undertaken in this section that some parts of the wind farm sector have been well treated from a multi-objective decision making perspective. This is particularly true of the energy mix and reactive power problems which consider how much offshore wind farms should contribute to an overall energy strategy and how they interact with the rest of the grid system. However, most of the papers consider on-shore or generic wind farms and there are few works dedicated specifically to offshore wind farms. This is possibly due to their relative newness compared to on-shore wind farms. There is also a lack of papers relating to the multi-objective decisions arising in the logistics and supply chains of wind farms, especially in the offshore wind sector. A good selection of multi-objective methods can be seen in the papers reviewed with discrete and continuous multi-criteria methods and meta-heuristic and exact solution methods all represented. The need remains to continue to develop multiple objective models to cover all parts of the offshore wind sector that include the realities of its multi-stakeholder environment.

3 Extended goal programming

This section details the technique of extended goal programming, the technique that is used to model the example developed in Sect. 4. Extended goal programming is chosen as a modelling tool due to its ability to combine the multiple underlying philosophies of satisficing, optimising and balancing in a multi-objective environment (Jones and Tamiz 2010). The classic extended goal programming formulation (Romero 2004) extended to four meta-objectives (Jones and Jimenez 2013) is chosen as the decision maker also wishes to consider the number of goals achieved and some of the preferences are given as pairwise comparisons. The non-lexicographic version is used as the decision maker does not have a natural order in which they wish to satisfy their goals. The algebraic form of the generalised four meta-objective model is given as:

$$Min\,a = \alpha\lambda + \beta\left\{\sum_{i\in Q_1}\frac{u_i n_i}{k_i} + \sum_{i\in Q_2}\frac{v_i p_i}{k_i}\right\} + \gamma\left\{\sum_{i\in Q_1}\mu_i s_i + \sum_{i\in Q_2}\nu_i t_i\right\}$$
$$+\,\delta\left\{\frac{1}{|Q_3|}\sum_{(i,j)\in Q_3}^{q}\left(N_{ij} + P_{ij}\right)\right\}$$

Subject to:

$$\frac{u_i n_i}{k_i} \le \lambda \quad i \in Q_1$$
$$\frac{v_i p_i}{k_i} \le \lambda \quad i \in Q_2$$
$$f_i(x) + n_i - p_i = b_i \quad i = 1, \ldots, q$$
$$f_i(x) + Ms_i \ge b_i \quad i \in Q_1$$
$$f_i(x) - Mt_i \le b_i \quad i \in Q_2$$
$$\frac{u_i}{u_j}\frac{n_i}{k_i} - \frac{n_j}{k_j} + N_{ij} - P_{ij} = 0 \quad i, j \in Q_1 \quad i < j$$
$$\frac{u_i}{v_j}\frac{n_i}{k_i} - \frac{p_j}{k_j} + N_{ij} - P_{ij} = 0 \quad i \in Q_1, \quad j \in Q_2$$
$$\frac{v_i}{v_j}\frac{p_i}{k_i} - \frac{p_j}{k_j} + N_{ij} - P_{ij} = 0 \quad i, j \in Q_2 \quad i < j$$
$$x \in F$$
$$n_i, p_i \ge 0 \quad n_i p_i = 0, i = 1, \ldots, q;\ N_{ij}, P_{ij} \ge 0 \quad i, j = 1, \ldots, q\ |i < j$$
$$s_i, t_i\ binary\ i = 1, \ldots, q$$

The model is defined as having q objectives. $f_i(x)$ is a function of decision variable set x giving the achieved value of the i'th objective which has an associated target value of b_i. Deviational variables n_i and p_i denote the negative and positive deviations from the i'th target value respectively. The maximal weighted deviation from amongst the set of unwanted deviations is denoted by λ. The weights u_i and v_i are associated with the relative level of importance associated with the per unit minimisation of the negative and positive deviational variables from the i'th target value respectively. Unwanted deviations are given a positive weight and deviations which are not desired to be minimised are given a zero weight. s_i is a binary variable that takes the value 1 if the achieved value of the i'th goal is less than the target value and 0 otherwise. t_i is a binary variable that takes the value 1 if the achieved value of the i'th goal is greater than the target value and 0 otherwise. The s_i and t_i variables thus represent whether the goals have been met for the cases of unwanted negative and positive deviations respectively. μ_i and υ_i are the relative weights representing the penalty applied for not meeting the i'th goal in the negative and positive direction respectively. M is a large positive constant. F is a set of hard constraints that must be satisfied in order to make the solution feasible. The normalisation constant of the i'th objective is given by k_i. N_{ij} and P_{ij}

are the deviations from the decision maker expressed pairwise comparison of the i'th and j'th unwanted deviational variables respectively. Q_1 is the ordered set of the indices of the unwanted negative deviational variables. Q_2 is the ordered set of the indices of the unwanted positive deviational variables and Q_3 is the set of pairs of unwanted deviational variables indices defined by:

$$Q_3 = (i, j \in Q_1 \mid i < j) \cup (i \in Q_1, j \in Q_2) \cup (i, j \in Q_2 \mid i < j)$$

The four meta-objective extended goal programming model contains four parameters $\alpha, \beta, \gamma, \delta$. Theses have the significance (with the underlying L_p distance metrics given in brackets where appropriate):

α: represents the relative importance of the meta-objective "Minimisation of the normalised (L_∞) maximum unwanted deviations from the set of goals "

β: represents the relative importance of the meta-objective "Minimisation of the normalised (L_1) weighted sum of unwanted deviations from the set of goals"

γ: represents the relative importance of the meta-objective "Minimisation of the number of unmet goals (L_0) from the set of goals"

δ: represents the relative importance of the meta-objective "Minimisation of the discrepancy between the expressed pairwise preferences of the decision maker and the actual preferences indicated by the solution"

Jones and Jimenez (2013) suggest that some form of formal or informal search heuristic is used to explore the resulting three-dimensional meta-objective parameter space given by $\alpha, \beta, \gamma, \delta \mid \alpha + \beta + \gamma + \delta = 1$.

4 Example: wind farm location modelling

This Section develops an extended goal programming model for offshore wind farm site selection. As such, the model developed belongs under the category of multi-objective offshore wind farm models described in Sect. 2.2. Four meta-objective extended goal programming is used to allow for the combination of balancing, optimising, satisficing, and goal-achieving philosophies of the decision-maker to be effectively modelled. The model built is hypothetical but based on real-world characteristics of locating offshore wind farms investigated by the 2OM research project (Pertin 2013).

4.1 Problem description and formulation

The case study presented relates to the selection of a suitable subset of the proposed UK round three sites for the development of wind farms. These nine sites, detailed in Table 1, have been shortlisted by the UK Crown Estate as potential new wind farm sites. A variety of operators will apply for licences for the nine sites. The purpose of the case study is to determine which subset(s) of sites are most attractive under different parameter settings of an extended goal programming model that considers a relevant set of multiple objectives and balances between underlying philosophies.

4.1.1 Selection of objectives

The primary purpose of the development round three sites is to enhance electricity production from offshore wind, a key renewable energy source for the UK, in the period 2020–2050. Therefore the generation of sufficient amounts of electricity from the round 3 sites is the first objective to be considered. This is subdivided into four seasonal objectives as the UK has different energy consumption needs and offshore wind generation capacity across different seasons. As the energy from offshore wind farms must be generated at as a competitive cost as possible, the minimisation of total lifecycle cost forms the fifth objective. As offshore wind farms also have considerable impact on other maritime users the remaining three objectives reflect this fact. The negative impact on the fishing industry, leisure industry, and environment are chosen as objectives six to eight.

4.1.2 Collection of data

The energy needs of the United Kingdom are taken from the figures published by the Department of Energy and Climate Change (DECC 2014), from which the target energy generation by season and importance of seasonal generation are set in Sect. 4.1.3. The estimated generation of electricity at each of the Round 3 sites, split by season, is derived from (Forewind 2012). This data is given by Table 1.

The cost of generation at each Round 3 site is based upon the estimated cost per turbine from Greenacre et al. (2010), reduced to reflect future expected cost efficiencies as the industry matures, with scaling factors relating to the distance from shore [an increase of 2.18 % per kilometre beyond the closest to shore of the round 3 sites, estimated from electrical infrastructure costs in Ernst and Young (2009)] and water depth [an increase of 7.62 % per metre beyond the shallowest of the round 3 sites, estimated from the foundation costs from Ramboll Offshore Wind (2010). The effect of economies of scale for larger wind farms has not been included as Dismukes and Upton (2013)] found that there was not yet sufficient evidence to statistically prove its existence. In practice, many of these sites are been developed in stages and may not utilise the whole area which will result in lower costs (for example the developers of the Dogger Bank site are currently planning to only utilise 80 % of the zone).

The negative effects on the fishing industry are estimated from landings data per ICES rectangle given by Marine Maritime Organisation (2013). The negative effects on the leisure industry are estimated from tourism data from Oxford Economics (2013) which gives the

Table 1 Energy generation by season

	MW	Winter (31 %)	Spring (26 %)	Summer (15 %)	Autumn (28 %)
1.Moray Firth	1500	465	390	225	420
2. Firth of Forth	3465	1074	901	520	970
3. Dogger Bank	9000	2790	2340	1350	2520
4.Hornsea	4000	1240	1040	600	1120
5. East Anglia	7200	2232	1872	1080	2016
6. Southern Array (Rampion)	665	206	173	100	186
7. West of Isle of Wight (Navitus Bay)	1200	372	312	180	336
8. Atlantic Array	1500	465	390	225	420
9. Celtic Array	4185	1297	1088	628	1172
Total	32,715	10,141	8506	4908	9160

Sources DECC (2014), Flood (2012)

Table 2 Cost and negative stakeholder effects

Location	Cost (£Billions)	Fishing impact	Leisure impact	Environmental impact
1. Moray Firth	5.879	2	5	4
2. Firth of Forth	17.863	7	3	2
3. Dogger Bank	127.783	6	4	5
4. Hornsea	18.310	4	5	7
5. East Anglia	35.822	6	7	9
6. Southern Array (Rampion)	1.329	5	7	6
7. West of Isle of Wight (Navitus Bay)	4.971	8	8	9
8. Atlantic Array	4.971	9	9	7
9. Celtic Array	16.218	4	6	5

Sources Greenacre et al. (2010), Ramboll Offshore Wind (2010), Ernst and Young (2009), Marine Management Organisation (2013), Oxford Economics (2013), DEFRA (2014)

share of employment in the tourism industry per local authority in 2012. The negative environmental effects are estimated by data from the Department for Environment, Food and Rural Affairs regarding Marine protected areas in the UK (DEFRA 2014). The summary of the estimated data for cost and negative stakeholder effects is given by Table 2.

4.1.3 Parameter setting

The relevant basic parameters to be set in a goal programme are the weights to be associated with the penalisation of unwanted deviation variables and the goal target values (Jones and Tamiz 2010). The goal target values for electricity generation by season from the Round 3 sites are set at 10 % of the UK's demand from DECC (2014), in accordance with the UK government's stated aims for generation of electricity from renewable sources. The total cost goal target is set at a challenging level of the total life cycle costs of 2 median cost wind farms. The three stakeholder negative effects goal targets are set at the level of 20 % of the total effects from all the round 3 wind farms. These targets are empirically set at sufficient challenging levels to ensure that all goals cannot be simultaneously achieved and hence Pareto Inefficient solutions will not occur (Jones and Tamiz 2010).

When assigning weights, energy generation and the four other factors are of equal importance, so 50 % of the weight is assigned to each category. The division amongst the energy generation goals is not equal, as more importance is given to generating electricity in the winter than in the summer, with intermediate values given to spring and autumn generation. Following this logic and taking into account the seasonal energy consumption of the UK (DECC 2014), as well as with knowledge gained on working on multiple European projects relating to offshore wind, the authors have formed the seasonal pairwise comparison matrix given by Table 3.

The Eigenvalue method is used to produce the first four weights to be used in the extended goal programming achievement function. The consistency level is an acceptable 1.45 %. The full set of weights is given as:

$$u_1 = 0.261, \quad u_2 = 0.100, \quad u_3 = 0.039, \quad u_4 = 0.100, \quad v_5 = 0.125,$$
$$v_6 = 0.125, \quad v_7 = 0.125, \quad v_8 = 0.125$$

Table 3 Pairwise comparison matrix for seasonal energy generation goals

Season	Winter	Spring	Summer	Autumn
Winter	1	3	5	3
Spring	1/3	1	3	1
Summer	1/5	1/3	1	1/3
Autumn	1/3	1	3	1

4.2 Model formulation

The decision variables are defined by the set of possible locations:

$$x_i = \begin{cases} 1 & if\, a\, wind\, farm\, is\, to\, be\, constructed\, at\, location\, i \\ 0 & otherwise \end{cases} \qquad i = 1, \ldots, 9$$

The four seasonal requirements for energy lead to the set of the first four goals:

$$\begin{aligned}
&465x_1 + 1074x_2 + 2790x_3 + 1240x_4 + 2232x_5 + 206x_6 \\
&\quad + 372x_7 + 465x_8 + 1297x_9 + \underline{n_1} - p_1 = 8976 \\
&390x_1 + 901x_2 + 2340x_3 + 1040x_4 + 1872x_5 + 173x_6 \\
&\quad + 312x_7 + 390x_8 + 1088x_9 + \underline{n_2} - p_2 = 8406 \\
&225x_1 + 520x_2 + 1350x_3 + 600x_4 + 1080x_5 + 100x_6 \\
&\quad + 180x_7 + 225x_8 + 628x_9 + \underline{n_3} - p_3 = 7340 \\
&420x_1 + 970x_2 + 2520x_3 + 1120x_4 + 2016x_5 + 186x_6 \\
&\quad + 336x_7 + 420x_8 + 1172x_9 + \underline{n_4} - p_4 = 7976
\end{aligned}$$

The total life cycle cost (In £Billions), fishing community impact, leisure community impact, and environmental impact goals are formulated as the respective set of four goals below:

$$\begin{aligned}
&5.879x_1 + 17.863x_2 + 127.783x_3 + 18.310x_4 + 35.822x_5 + 1.329x_6 \\
&\quad + 4.971x_7 + 4.971x_8 + 16.218x_9 + n_5 - \underline{p_5} = 32.436 \\
&2x_1 + 7x_2 + 6x_3 + 4x_4 + 6x_5 + 5x_6 + 8x_7 + 9x_8 + 4x_9 + n_6 - \underline{p_6} = 15 \\
&5x_1 + 3x_2 + 4x_3 + 5x_4 + 7x_5 + 7x_6 + 8x_7 + 9x_8 + 6x_9 + n_7 - \underline{p_7} = 16 \\
&4x_1 + 2x_2 + 5x_3 + 7x_4 + 9x_5 + 6x_6 + 9x_7 + 7x_8 + 5x_9 + n_8 - \underline{p_8} = 16
\end{aligned}$$

where n_i is a deviational variable that represents the negative deviation from the i'th goal and p_i is a deviational variable represents the positive deviation from the i'th goal. Table 4 details the context of the goals and which deviations are unwanted and hence will be penalised in the achievement function. Unwanted deviational variables are also underscored in their respective goal equation.

4.2.1 Formation of achievement function and complete goal programme

The Jones and Jimenez (2013) methodology has a parametric four meta-objective achievement function of the form:

$$MIN\, a = \alpha L_1 + \beta L_\infty + \gamma L_\infty + \delta L_{pc}$$

where L_1 represents a weighted sum of unwanted deviations and is hence associated with optimisation. L_∞ represents the minimisation of the maximal weighted unwanted deviation

Table 4 Significance of goals and deviational variables to be penalised

Goal	Significance	Deviational variable to be penalised
1	Energy generation—winter	Negative
2	Energy generation—spring	Negative
3	Energy generation—summer	Negative
4	Energy generation—autumn	Negative
5	Cost	Positive
6	Fishing community impact	Positive
7	Leisure community impact	Positive
8	Environmental impacts	Positive

and is hence associated with achieving a balance between goals. L_0 represents the number of unmet goals and is hence associated with goal seeking behaviour, and L_{pc} represents the distance from the decision makers expressed pairwise comparisons and is hence a measure of consistency with preferences α, β, γ, δ being parameters that control the respective amount of L_1, L_∞, $L_{0,} L_{pc}$ weighting in the achievement function. Using this representation yields the following algebraic formulation of the extended goal programming model:

$$
\begin{aligned}
Min\, a = \alpha\lambda + \beta & \left(\frac{0.261n_1}{8976} + \frac{0.1n_2}{8406} + \frac{0.039n_3}{7340} + \frac{0.1n_4}{7976} + \frac{0.125p_5}{32.436} + \frac{0.125p_6}{15}\right. \\
& \left. + \frac{0.125p_7}{16} + \frac{0.125p_8}{16}\right) + \gamma\left(\frac{0.261s_1}{8976} + \frac{0.1s_2}{8406} + \frac{0.039s_3}{7340} + \frac{0.1s_4}{7976}\right. \\
& \left. + \frac{0.125t_5}{32.436} + \frac{0.125t_6}{15} + \frac{0.125t_7}{16} + \frac{0.125t_8}{16}\right) + \frac{\delta}{6}\sum_{i,j=1,\ldots,4,i<j}\left(N_{ij} + P_{ij}\right)
\end{aligned}
$$

Subject to,

$$
\begin{aligned}
& 465x_1 + 1074x_2 + 2790x_3 + 1240x_4 + 2232x_5 + 206x_6 + 372x_7 + 465x_8 \\
& \quad +1297x_9 + \underline{n_1} - p_1 = 8976 \\
& 390x_1 + 901x_2 + 2340x_3 + 1040x_4 + 1872x_5 + 173x_6 + 312x_7 + 390x_8 \\
& \quad +1088x_9 + \underline{n_2} - p_2 = 8406 \\
& 225x_1 + 520x_2 + 1350x_3 + 600x_4 + 1080x_5 + 100x_6 + 180x_7 + 225x_8 \\
& \quad +628x_9 + \underline{n_3} - p_3 = 7340 \\
& 420x_1 + 970x_2 + 2520x_3 + 1120x_4 + 2016x_5 + 186x_6 + 336x_7 + 420x_8 \\
& \quad +1172x_9 + \underline{n_4} - p_4 = 7976 \\
& 5.879x_1 + 17.863x_2 + 127.783x_3 + 18.310x_4 + 35.822x_5 + 1.329x_6 + 4.971x_7 \\
& \quad +4.971x_8 + 16.218x_9 + n_5 - \underline{p_5} = 32.436 \\
& 2x_1 + 7x_2 + 6x_3 + 4x_4 + 6x_5 + 5x_6 + 8x_7 + 9x_8 + 4x_9 + n_6 - \underline{p_6} = 15 \\
& 5x_1 + 3x_2 + 4x_3 + 5x_4 + 7x_5 + 7x_6 + 8x_7 + 9x_8 + 6x_9 + n_7 - \underline{p_7} = 16 \\
& 4x_1 + 2x_2 + 5x_3 + 7x_4 + 9x_5 + 6x_6 + 9x_7 + 7x_8 + 5x_9 + n_8 - \underline{p_8} = 16 \\
& \frac{0.261n_1}{8976} \le \lambda, \quad \frac{0.1n_2}{8406} \le \lambda, \quad \frac{0.039n_3}{7340} \le \lambda, \quad \frac{0.1n_4}{7976} \le \lambda \\
& \frac{0.125p_5}{32.436} \le \lambda, \quad \frac{0.125p_6}{15} \le \lambda, \quad \frac{0.125p_7}{16} \le \lambda, \quad \frac{0.125p_8}{16} \le \lambda
\end{aligned}
$$

$$n_i - Ms_i \leq 0 \quad i = 1, \ldots, 4$$

$$p_i - Mt_i \leq 0 \quad i = 5, \ldots, 8$$

$$\frac{u_i}{u_j}\frac{n_i}{b_i} - \frac{n_j}{b_j} + N_{ij} - P_{ij} = 0 \quad i, j = 1, \ldots, 4 \quad i < j$$

$$x_i = 0\, or\, 1 \quad i = 1, \ldots, 9; \quad n_i, p_i \geq 0 \quad i = 1, \ldots, 8; \quad s_i = 0\, or\, 1 \quad i = 1, \ldots, 4;$$

$$t_i = 0\, or\, 1 \quad i = 5, \ldots, 8; \quad \lambda \geq 0, \quad n_i p_i = 0 \quad i = 1, \ldots, 8$$

where λ is the maximal weighted, unwanted deviation. s_i is a binary variable that takes the value 1 if the negative deviational variable of the i'th goal takes a positive value and value 0 otherwise. t_i is a binary variable that takes the value 1 if the positive deviational variable of the i'th goal takes a positive value and value 0 otherwise. The s_i and t_i variables thus act as indicators as to whether a goal has been met or not. All unwanted deviational variables, as well as the s_i and t_i variables have been normalised by the target value of the associated goal (*i.e.* $k_i = b_i$) in the achievement function in order to reflect their relative importance as this is deemed appropriate in the context of this application. The variables N_{ij} and P_{ij} represent the respective negative and positive deviation from the decision makers desired pairwise comparison between the i'th and j'th objectives. Unwanted deviational variables are underscored in their respective goal equation.

4.3 Experimentation and discussion of results

The Jones (2011) weight sensitivity analysis algorithm is used in meta-weight $(\alpha, \beta, \gamma, \delta)$ space in order to investigate the effect varying the mix of underlying philosophies will have on the location decision and to produce a diverse range of potential solutions. The input parameters of the algorithm are set as $T_{Max} = 2$ (vary at most two simultaneously) and Maxlevel = 2 (perform at most two bisections in each search direction). No further restrictions are placed on the values of $(\alpha, \beta, \gamma, \delta)$ other than the normalising $\alpha + \beta + \gamma + \delta = 1$ constraint in order to ensure a wide range of solutions. The equal meta-weight solution $\alpha = \beta = \gamma = \delta = 0.25$ is used as the starting point for the algorithm and minimum values for each meta-weight are set at 0.025 rather than 0 to ensure inefficiency does not occur in meta-weight space. The resulting 25 extended goal programming models are solved using LINGO 14 (LINDO 2014), each taking less than a second on a standard desktop PC. Eleven distinct solutions are found by the algorithm. These are listed in Table 5 in decision and objective space, along with the first set of meta-weights at which the solution was found.

4.3.1 Discussion of results

The algorithm has shown to be effective in producing a range of results, with varying location decisions and levels of goal achievement dependent on which set of meta-objectives are given importance. The problem as posed is seen to be truly multi-objective in nature, the challenging goal levels set have ensured that at most three goals are completely achieved by any solution, with the ambitious energy generation goals never being completely met by any of the generated solutions. Considering the meta-objectives in turn, the equal weights solution (A) produced a reasonable balance between factors as expected but did not meet any goals. Increasing the balance meta-objective led to solutions (B) and (C) which lowered cost but at the expense of worse energy generation. Increasing the efficiency meta-weight led to the less balanced solution (D) that did not produce so much energy but had significantly less cost and met the stakeholder goals. Increasing the number of goals meta-weight led to a similar but slightly less extreme solution (E). Solutions (D) and (E) had a relatively low number of wind

Table 5 Results of the (Jones 2011) algorithm

Solution	Variable	A	B	C	D	E	F	G	H	I	J	K
L_∞	α	0.25	0.925	0.625	0.025	0.025	0.025	0.188	0.475	0.475	0.375	0.313
L_1	β	0.25	0.025	0.125	0.925	0.025	0.025	0.188	0.475	0.025	0.125	0.188
L_0	γ	0.25	0.025	0.125	0.025	0.925	0.025	0.188	0.025	0.025	0.125	0.188
L_{AHP}	δ	0.25	0.025	0.125	0.025	0.025	0.925	0.438	0.025	0.475	0.375	0.313
Locations	$\underline{x}$	2459	12,489	259	149	125	123,589	13,459	249	12,456,789	124,589	12,459
Winter	n_1	3113	4415	4353	5954	5185	633	932	5345	1605	2183	2648
Spring	n_2	3505	4597	4545	5888	5243	1425	1676	5377	2240	2725	3115
Summer	n_3	4512	5142	5112	5887	5515	3312	3457	5592	3782	4062	4287
Autumn	n_4	2689	3874	3818	5264	4570	458	728	4714	1336	1858	2278
Cost	p_5	223	123	150	32	109	704	686	80	291	267	247
Fish	p_6	6	11	2	0	0	19	7	0	30	17	8
Leisure	p_7	5	12	0	0	0	18	11	0	34	19	10
Environ	p_8	7	9	0	0	0	16	14	0	33	18	11
Goals Met		0	0	3	3	0	0	3	3	0	0	0
Max Dev	λ	0.215	0.129	0.144	0.174	0.151	0.679	0.661	0.156	0.28	0.257	0.238

farms. Increasing either the consistency with AHP meta-weight (which is concerned with the subset of goals relating to energy), either alone producing solutions (F) and (G) or with balance producing solutions (I), (J) and (K) leads to the building of more wind farms which improves the energy situation but at the expense of extra costs and stakeholder dissatisfaction. Solutions (F) and (G) are particularly extreme in terms of cost increase whereas solution (I) is extreme in terms of stakeholder dissatisfaction increase. Finally, solution (H) is produced by increasing balance and efficiency meta-weights and shows a solution that is low cost and meets stakeholder goals, but at the expense of energy generation.

With regards to the locations chosen in decision variable space, it is first important to note that every solution chose to build at least three wind farms, with a maximum of 8 of the 9 in solution (I). Another important fact to note is that every wind farm is chosen in at least one of the eleven solutions. The most commonly chosen wind farms across all solutions are 9-Celtic Array, 2-Firth of Forth, 1-Moray Firth, 4-Hornsea and 5-East Anglia. Less commonly chosen are 6-Southern Array and 7-West Isle of Wight. It is hypothesised that this is because of the large stakeholder impacts relative to the energy production levels at this sites. Also not commonly chosen, although for a different reason, is 3-Dogger Bank. This is not commonly chosen because of its huge estimated cost compared to other wind farms via the methodology used in this paper. It should be noted, however, that future technological advances and learning curve effects may well lower the future estimated cost of this, and other, wind farms.

5 Conclusions and future research

A use of four meta-objective extended goal programming has been presented in this paper for a site-selection problem typical of those arising in the offshore wind farm sector. The model developed serves to demonstrate the multi-criteria, multi-stakeholder nature of decision making in the offshore wind farm sector. Economic, technical, sociological, and environmental considerations all play a part in determining the optimal course of action. The ambitious future offshore wind strategy of the United Kingdom, as encapsulated by the future Round 3 sites has been shown to have strong trade-offs between the energy generation, cost, and stakeholder impacts considered. Extended goal programming has been shown to be an appropriate technique to use due to its flexibility in combining different underlying philosophies and hence its ability to produce solutions that reflect the full range of underlying criteria. It is noted that excluding any of the four meta-objectives used in the case study in Sect. 4 would have led to less diverse range of potential solutions.

The literature review in Sect. 2 demonstrates the need to develop multiple objective models specifically for the offshore wind sector that are able to reduce unit energy costs by identifying efficiencies and technical improvements, whilst still considering and optimising social-economical and environmental objectives. In particular, the application of multiple objective techniques to the general field of the logistics and supply chain of on-shore or off-shore wind farm modelling is still a field in its infancy in terms of scientific publications.

The model developed in Sect. 4 is designed as a base level model to identify the trade-offs that occur. As further information becomes available due to the maturing of the offshore wind sector the data can be revisited in order to investigate if the solutions and trade-offs produced are changing. Other goal programming variants such as fuzzy or stochastic constrained goal programming could also be investigated in order to take into account the uncertainty around some of the model data, although the number of parameters to be set when combined with the four meta-objective extended goal programming framework could make this a challenging combination in terms of parameter setting and sensitivity analysis.

Acknowledgments The authors would like to thank the European Union Interreg IV A (Channel) programme for their funding of this research under the 2OM: Offshore Operations and Maintenance Mutualisation project and the two anonymous referees whose comments have helped enhance the paper.

References

Alonso, M., Amaris, H., & Alvarez-Ortega, C. (2012). A multiobjective approach for reactive power planning in networks with wind power generation. *Renewable Energy*, *37*, 180–191.

Banos, R., Manzano-Agugliaro, F., Montoya, F. G., Gil, C., Alcayde, A., & Gomez, J. (2011). Optimization methods applied to renewable and sustainable energy: A review. *Renewable & Sustainable Energy Reviews*, *15*, 1753–1766.

Bevrani, H., & Daneshmand, P. R. (2012). Fuzzy logic-based load-frequency control concerning high penetration of wind turbines. *IEEE Systems Journal*, *6*, 173–180.

Chen, L., & MacDonald, E. (2012). Considering landowner participation in wind farm layout optimization. *Journal of Mechanical Design*, *134*, 084506.

Crown Estate. (2012). *Offshore wind cost reduction pathway. Document from Crown Estate*. www.thecrownestate.co.uk. Accessed July 7, 2013

Dismukes, D., Upton, G. (2013). *Economies of scale, learning effects and offshore wind development costs*. Presented at 32nd USAEE/IAEE North American Conference. http://www.usaee.org/usaee2013/submissions/Abs/Dismukes%20Upton%202013.pdf. Accessed on July 10th, 2014

DECC. (2014). *Energy trends section 5: Electricity*. UK Department of Energy and Climate Change Report. https://www.gov.uk/government/publications/electricity-section-5-energy-trends. Accessed June 6th, 2014

DEFRA. (2014) *Marine protected areas in the UK*. UK Department for Food, Environment and Rural Affairs Report. http://jncc.defra.gov.uk/page-5201. Accessed June 6th, 2014

Du Pont, B. L., & Cagan, J. (2012). An extended pattern search approach to wind farm layout optimization. *Journal of Mechanical Design*, *134*, 081002.

Ernst & Young. (2009). *Cost of and financial support for offshore wind*. Ernst & Young report for the Department of Energy and Climate Change, DECC, London. http://webarchive.nationalarchives.gov.uk/+/http:/www.berr.gov.uk/files/file51142.pdf. Accessed on January 16, 2015

Eroglu, Y., & Seckiner, S. U. (2012). Design of wind farm layout using ant colony algorithm. *Renewable Energy*, *44*, 53–62.

Flood, D. (2012). *Round 3 offshore wind farms*. UK Future Energy Scenarios seminar 2012. Forewind Report. http://www.google.co.uk/url?url=http://www2.nationalgrid.com/WorkArea/DownloadAsset.aspx%3Fid%3D10466&rct=j&frm=1&q=&esrc=s&sa=U&ei=W5yRU5_ZCNKg7AbEyYDIAw&ved=0CEkQFjAH&sig2=oTA_83U-_31DgsFrH7RRZw&usg=AFQjCNGuw68f1p1qjXYeoYF1TDyFHwbk2A. Accessed June 6th, 2014

Gitizadeh, M., Kaji, M., & Aghaei, J. (2013). Risk based multiobjective generation expansion planning considering renewable energy sources. *Energy*, *50*, 74–82.

Greenacre, P., Gross, R. & Heptonstall, P., (2010). *Great expectations: The cost of offshore wind in UK waters*. UK Energy Research Centre, London. https://spiral.imperial.ac.uk/bitstream/10044/1/12649/6/Great%20Expectations%20-%20The%20cost%20of%20offshore%20wind%20in%20UK%20waters.pdf. Accessed on January 16, 2015

Heptonstall, P., Gross, R., Greenacre, P., & Cockerill, T. (2012). The cost of offshore wind: Understanding the past and projecting the future. *Energy Policy*, *41*, 815–821.

Jones, D. F., & Jimenez, M. (2013). Incorporating additional meta-objectives into the extended lexicographic goal programming framework. *European Journal of Operational Research*, *227*, 343–349.

Jones, D. F., & Tamiz, M. (2010). *Practical goal programming*. New York: Springer.

Jones, D. F. (2011). A practical weight sensitivity algorithm for goal and multiple objective programming. *European Journal of Operational Research*, *213*, 238–245.

Kang, M. S., Chen, C. S., Ke, Y. L., Lee, A. H., Ku, T. T., & Kang, H. Y. (2013). Applications of FANP and BOCR in renewable energy-study on the choice of the sites for wind farms. *IEEE Transactions on Industry Applications*, *49*, 982–989.

Kargarian, A., & Raoofat, M. (2011). Stochastic reactive power market with volatility of wind power considering voltage security. *Energy*, *36*, 2565–2571.

Koroneos, C., Xydis, G., & Polyzakis, A. (2013). The optimal use of renewable energy sources: The case of Lemnos Island. *International Journal of Green Energy*, *10*, 860–875.

Kusiak, A., & Song, Z. (2010). Design of wind farm layout for maximum wind energy capture. *Renewable Energy*, *35*, 685–694.

LINDO. (2014). *Lingo 14.0—Optimization modeling software for linear, nonlinear and integer programming*. Lindo Systems Ltd. http://www.lindo.com/index.php?option=com_content&view=article&id=2&Itemid=10. Accessed July 17th, 2014

Marine Management Organisation. (2013). *UK sea fisheries statistics 2012. A national statistics report*. http://www.marinemanagement.org.uk/fisheries/statistics/documents/ukseafish/2012/final.pdf Accessed 6th June 2014

Mavrotas, G., Diakoulaki, D., & Capros, P. (2003). Combined MCDA-IP approach for project selection in the electricity market. *Annals of Operations Research*, *120*, 159–170.

Mourmouris, J. C., & Potolias, C. (2013). A multi-criteria methodology for energy planning and developing renewable energy sources at a regional level: A case study Thassos, Greece. *Energy Policy*, *52*, 522–530.

Niknam, T., Zare, M., Aghaei, J., & Azizipanah-Abarghooee, R. (2012). Interactive multiobjective daily volt/var control of distribution networks considering wind power and fuel-cell power plants. *Journal of Renewable and Sustainable Energy*, *4*, 033120.

Ortegon, K., Nies, L. F., & Sutherland, J. W. (2013). Preparing for end of service life of wind turbines. *Journal of Cleaner Production*, *39*, 191–199.

Oxford Economics. (2013). *Tourism: Jobs and growth. The economic contribution of the tourism economy in the UK*. http://www.visitbritain.org/Images/Final%20proof%2015%20Nov_tcm29-39296.pdf. Accessed June 6th, 2014

Pertin, E. (2013, October). 2OM project. http://www.2om-project.eu/the-2om-project/. Accessed June 6th, 2014

Qiao, J. G., Min, Y., & Lu, Z. X. (2006). Optimal reactive power flow in wind generation integrated power system. *IEEE International Conferenc Proceedings on Power Systems Technology: POWERCON*, *1–6*, 928–932.

Ramboll Offshore Wind. (2010). *Focus on foundations: Offshore wind conference. Larger wind power stations further offshore & avoid costly delays*. Wind Power Monthly, London.

Renewable, U.K. (2012). *Wind energy in the UK: State of the industry reports 2012*. http://www.renewableuk.com/en/publications/reports.cfm/SOI2012. Accessed on January 16, 2015

Romero, C. (2004). A general structure of achievement function for a goal programming model. *European Journal of Operational Research*, *153*, 675–686.

Saavedra-Moreno, B., Salcedo-Sanz, S., Paniagua-Tineo, A., Prieto, L., & Portilla-Figueras, A. (2011). Seeding evolutionary algorithms with heuristics for optimal wind turbines positioning in wind farms. *Renewable Energy*, *36*, 2838–2844.

Sampaio, H. C., Dias, R. A., & Balestieri, J. A. (2013). Sustainable urban energy planning: The case study of a tropical city. *Applied Energy*, *104*, 924–935.

Sareni, B., Abdelli, A., Roboam, X., & Tran, D. H. (2009). Model simplification and optimization of a passive wind turbine generator. *Renewable Energy*, *34*, 2640–2650.

Stein, E. W. (2013). A comprehensive multi-criteria model to rank electric energy production technologies. *Renewable & Sustainable Energy Reviews*, *22*, 640–654.

Wan, C., Wang, J., Yang, G., Gu, H., & Zhang, X. (2012). Wind farm micro-siting by Gaussian particle swarm optimization with local search strategy. *Renewable Energy*, *48*, 276–286.

Zare, M., & Niknam, T. (2013). A new multi-objective for environmental and economic management of Volt/Var Control considering renewable energy resources. *Energy*, *55*, 236–252.

Zhang, L., & Wirth, A. (2010). Wind energy management with battery storage. *Journal of the Operational Research Society*, *61*, 1510–1522.