[Postprint version, please cite as] Ishizaka A, Siraj S, Nemery P, Which energy mix for the UK? An evolutive descriptive mapping with the integrated GAIA-AHP visualisation tool, Energy, advance online publications, doi: 10.1016/j.energy.2015.12.009

Which energy mix for the UK? An evolutive descriptive mapping with the integrated GAIA-AHP visualisation tool

Alessio Ishizaka[1], Sajid Siraj[1,2,3], Phillipe Nemery[4]

[1]Centre for Operational Research and Logistics, Portsmouth Business School, University of Portsmouth, Portsmouth PO1 3DE, United Kingdom
Alessio.Ishizaka@port.ac.uk

[2]COMSATS Institute of Information Technology, The Mall, Wah Cantonment, Pakistan

[3]Centre for Decision Research, Leeds University Business School, Leeds, United Kingdom

sajidsiraj@gmail.com

[4] SAP BeLux, Avenue des Olympiades 2, 1140 Brussels, Belgium

pnemery@gmail.com

Abstract: Although Multi-Criteria Decision Making methods have been extensively used in energy planning, their descriptive use has been rarely considered. In this paper, we add an evolutionary description phase as an extension to the AHP method that helps policy makers to gain insights into their decision problems. The proposed extension has been implemented in an open-source software that allows the users to visualise the difference of opinions within a decision process, and also the evolution of preferences over time. The method was tested in a two-phase experiment to understand the evolution of opinions on energy sources. Participants were asked to provide their preferences for different energy sources for the next twenty years for the United Kingdom. They were first asked to compare the options intuitively without using any structured approach, and then were given three months to compare the same set of options after collecting detailed information. The proposed visualization method allows us to quickly discover the preference directions, and also the changes in their preferences from first to second phase. The proposed tool can help policy makers in better understanding of the energy planning problems that will lead us towards better planning and decisions in the energy sector.

Keywords: Multi Criteria Decision making; Energy planning; Group judgments; AHP; GAIA; Visualization.

1 Introduction

Energy planning is an important process that has long-range implications but unfortunately, the process is not trivial as it involves many stakeholders with different backgrounds, and has to be analysed in many contexts including the social, economic, environmental and technical contexts. To facilitate this process, multi-criteria decision making (MCDM) methods have been extensively used to prioritize available options after assessing and synthesizing all the individual preferences [1]. However, the aggregative approaches like Analytic Hierarchy Process (AHP) have low explanatory power and results are often not enough to reach to a consensual decision by stakeholders, especially when they have divergent views [2]. It is therefore necessary to identify the points of agreements and disagreements before initiating a negotiation process. In response to this need, Graphical Analysis for Interactive Aid (GAIA) [3] was developed to capture different views of DMs with respect to many criteria and to display them graphically. The GAIA method was initially proposed to complement PROMETHEE which is widely used in strategic decision making [3]. GAIA has recently been combined with Geographical Information Systems [4] and FlowSort [5].

In this paper, we propose to combine the GAIA method with AHP and show its usefulness in the area of energy policy making. We investigate the visualization of preferences and their evolution in situations where additional information is acquired during the decision making process. The proposed combination (AHP-GAIA) displays a graphical representation that can easily highlight the presence of any like-minded decision makers/agents or opposite minds, and can also reflect changes in their preferences over time. This hybrid method has been applied in a two-phase experiment. In the first phase, participants were asked to rank seven energy sources in the United Kingdom for the next 20 years. Each participant compared the options in pairs without any specific tool. For the second phase, the participants were informed about the widely-used criteria to evaluate the energy sources, and were asked to produce a documented report on how well the energy sources were fulfilling these criteria. Three months later, the participants submitted their reports that showed their analyses of the seven energy sources with the help of AHP. The adapted GAIA approach was then used to visualize the change in participants' preferences. In both phases, the solar energy has been found to be the most preferred choice, while coal remained the least preferred. Interestingly, the dispersion of the opinions decreased in the second phase i.e. more participants were found in agreement with each other after performing the detailed analysis of the selected energy sources.

The proposed technique of AHP-GAIA has been implemented in an open-source software tool - called PriEsT - that helps visualize all the preferences of multiple stakeholders in a single plot. We believe that the proposed technique can help policy makers towards understanding the preferences of each stakeholder and therefore can help towards better justification, better communication and even towards better ways for negotiation.

The remaining paper is structured as follow: Section 2 reviews the literature on energy planning with multi-criteria methods. Section 3 introduces the AHP and GAIA methods; Section 4 then proposes the use of GAIA in AHP group decision making. Section 5 presents the experimental analysis and their results; and Section 6 concludes the paper with possible future work.

2 Literature review

Energy planning is becoming more and more complex as demands are increasing for more energy while at the same time, challenges like environmental impact, safety, security, and economic viability are all pressing for a need to have better technology and tools in the field of energy production and planning. Although several methods have been proposed to assist the energy planning process, the two most widely-used techniques found in literature are the use of simulation and multi-criteria decision making techniques.

2.1 Simulation

Simulation can be defined as the imitation of an operation or set of operations that helps understanding a real-world process or system. To have a proper simulation results, one must construct a model with the key representation of the process. However, due to practical limitations, models are often simplified with a number of assumptions. For example, Ma et al. [6] examined the present energy structure in Hong Kong and modelled three different scenarios representing three different types of energy mix (i.e. combination of different energy production mechanisms to meet the overall demand) to assess the situation by 2020. Similarly, the possibility and the challenges in Macedonian [7] and Hungarian [8] energy production have also been investigated using simulation tools like EnergyPLAN. They assessed the use of renewable energy sources to reduce their dependence on energy-related imports. There exists a number of such studies based on simulations for different countries, for example, Serbia [9], China [10], and Korea [11].

As several scenarios are possible, simulation in itself is often not sufficient to take a decision. It provides support and information but not a definitive answer. Therefore multi-criteria methods have been largely used in this respect, as described in the next section.

2.2 Multi-Criteria Decision Making

Multi-criteria decision making methods help decision-makers to take a single or group decision. These methods involve a set of incommensurable quantitative and qualitative criteria to assess a set of alternatives. The MCDM methods have been recognised to be well suited for solving energy planning problems [1] and have been extensively used in the literature. Table 1 summarizes the most widely used MCDM methods that have been published in the energy policy making literature. According to the surveyed literature, AHP and PROMETHEE are the two most widely used methods. Another recent trend is to use hybrid methods to overcome weaknesses of one method by the strength of another method. The method proposed in the next section also belongs to the same family where we propose a hybrid approach combining the AHP and GAIA methods.

Table 1 The use of MCDM methods for energy policy making

Single Method	Acronym	References
Analytic Hierarchy Process	AHP	[2, 12-23]
Analytic Network Process	ANP	[24, 25]
Data Envelopment Analysis	DEA	[26, 27]
ELimination Et Choix Traduisant la REalité	ELECTRE	[28]
Multi-attribute Utility Theory	MAUT	[2, 22, 29-31]
Ordered Weighted Averaging	LOWA	[32, 33]
Preference Ranking Organization METHod for Enrichment of Evaluations	PROMETHEE	[2, 22, 23, 34-39]
Technique for Order of Preference by Similarity to Ideal Solution	TOPSIS	[40-43]
VIseKriterijumska Optimizacija I Kompromisno Resenje	VIKOR	[42]
Novel Approach to Imprecise Assessment and Decision Environments	NAIADE	[2]
Fuzzy logic		[44]
Grey Relational Analysis	GRA	[45]
Simple Additive Weighting	SAW	[42]
Choquet integral		[33]
Multi-Objective Optimization by Ratio Analysis	MULTIMOORA	[43]
Measuring Attractiveness by a Categorical Based Evaluation TecHnique	MACBETH	[46]
Additive Ratio Assessment	ARAS	[42]

Hybrid Method	References
AHP- (Additive Ratio Assessment Method) ARAS	[47]
Fuzzy AHP	[46, 48-56]
Fuzzy TOPSIS	[57]
ELECTRE- NSGA-II	[58]
Fuzzy Multi-Objective Optimization by Ratio Analysis (MULTIMOORA)	[59]
AHP-VIKOR	[60]
AHP-Fuzzy VIKOR	[61, 62]

Complex Proportional Assessment (COPRAS)-AHP	[42]
Probabilistic forecasting – ELECTRE III	[63]
Probabilistic forecasting – weighted sum method	[63]
Fuzzy Axiomatic Design	[56]

In all these studies, a very static view of decision making has been taken as the decision analysis in these studies does not take into account any change in the environment. For example, the Fukushima disaster has completely changed the energy policy of Japan and many other countries and therefore, it is important to have tools to visualize changes in preference directions over time.

2.3 State of the art analysis

Recent studies show that simulation and MCDM are the two techniques that are widely used in energy policy making. Simulation has the advantage that it allows temporal modelling of a dynamically changing environment, however a number of assumptions are generally taken into account due to the use of simplified models. Different assumptions lead to different scenarios and therefore the final decision generally does not remain straightforward.

On the other hand, unlike simulations, the MCDM methods do not offer analyses of decisions in a dynamic environment. As energy policy making and planning is not a static procedure and changes need to be taken into account, we construct a hybrid multi-criteria decision making method that can be used to track modifications happening due to changes in the external environment. For this reason, there is a need to develop a descriptive tool that should display the preference changes over time. Such a descriptive tool will prove highly useful that can help policy makers to communicate their analysis easily to all the stakeholders. The literature shows that such a tool is highly desirable and yet currently missing [2]. In this paper, we address this weakness by complementing the AHP method with a visual analytic tool, GAIA, for describing the preferences of each stakeholder and the evolution of these preferences with time as well.

We briefly discuss the AHP method below first to justify its use and how it can be extended with a visual analytic capability.

3 Analytic Hierarchy Process

3.1 Basics on AHP

AHP is a widely-used MCDM technique with the following two important features as compared to other MCDM methods [64]:

- The decision problem in AHP can be decomposed into a multi-level hierarchical structure of criteria. The criteria at the lowest level of the hierarchy are considered 'atomic' in a sense that they could not be decomposed further. The alternatives are then placed below these 'atomic' criteria.
- All the evaluations are provided through pairwise comparisons and priorities are derived for every criterion at each level of hierarchy. These priorities are then aggregated to generate an overall prioritization score for each alternative.

In AHP, the decision-maker is usually asked to compare alternatives and criteria on a linear scale of 1 to 9, where 1 implies indifference, 9 implies extreme preference, and all the intermediate values are equally spread between these two extremes. Although several other scales exist, the use of 1 to 9 scale dominates all the other scales [65]. AHP has therefore the advantage of not requiring explicitly a table of scores and/or a utility function.

For larger problems, the number of pairwise comparisons increases significantly, and as most of these comparisons appear redundant, the process of pairwise comparison appears to be a less productive task. However, these apparently redundant comparisons help us detect and measure the level of inconsistency in the respondent's judgments. A high inconsistency may indicate an error or a random filling of the evaluations. Several inconsistency indexes have been developed [66] and several methods have been proposed to automatically improve the consistency in pairwise comparison judgments (Cao et al. 2008, Siraj et al. 2012). However, some empirical results show that automatically improving the consistency may decrease the quality of the decision [67].

From the comparison matrix, several methods have been proposed for calculating the priorities [68]. The two most used methods are the Eigenvector method [69] and the Geometric Mean method [70]. The estimated priorities are normalised ($\sum_i p_i = 1$) in order to aggregate them. This commensurability of priorities is useful for using GAIA (discussed in Section 4).

3.2 AHP for group decision making

As described earlier, the important feature of AHP is to decompose the decision problem into a hierarchy of criteria. This idea of decomposition can easily be extended for group decision making as well by simply adding another layer for participants (i.e. decision makers) in the hierarchy above the criteria [71]. In this case, each decision maker is asked to solve independently the problem and then their priorities are aggregated to generate the overall scores.

However, a mere aggregation of all the scores may lose important information content and sometimes may even produce a misleading result. For example, if one decision maker considers Solar energy to be the most preferred and another considers it to be the least preferred; the average of the two decision makers may place 'Solar' energy in the middle of the preference scale, which does not satisfy both. Although, this can be seen as a logical compromise, the final outcome does not depict faithfully the preference of any of the two decision makers.

To effectively analyse and communicate the results, it is advantageous to offer the prioritization results in a tool where decision-makers can clearly visualize the underlying preference structure. This visualization may appear a simple task when there are few decision makers and few alternatives but it becomes a serious issue as the numbers increase. Therefore, in the, next section will explain how the entire information can be visualised within two or three dimensions.

4 AHP-GAIA – A visualization aid for AHP

4.1 Constructing the GAIA plan

The idea of GAIA is to represent multidimensional information in a low dimensional space with as much information as possible. For example, a decision problem that involves six criteria will have six-dimensional scores assigned to each alternative, which is impossible to visualize in a conventional Euclidean space. This is sometimes referred to as "curse of dimensionality". To solve this problem, GAIA borrows the idea of dimensionality reduction from principle component analysis – a widely used technique to find and sort axes of maximal variance.

Consider the priority decision matrix M with n alternatives ($A_i |\ i = 1,2, \dots , n$) and m decision makers ($D_j |\ j = 1, 2, \dots , m$), where s_{ij} is the priority of alternative i for decision-maker j.

$$\mathrm{M}_{n\times m} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1j} & \cdots & s_{1m} \\ s_{21} & s_{22} & \cdots & s_{2j} & \cdots & s_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ s_{i1} & s_{i2} & \cdots & s_{ij} & \cdots & s_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ s_{n1} & s_{n2} & \cdots & s_{nj} & \cdots & s_{nm} \end{bmatrix}$$

This matrix has the property to be unit less due to the fact that the priorities are calculated from pairwise ratio comparisons (section 3.1). The relative scores are calculated with the additional constraint of normalization i.e. $\sum_i s_{ij} = 1$. Therefore, the data can be represented in an m-dimensional space with n vectors. Each dimension in this space represents one of the m decision makers. The n alternatives are located in this space according to their relative scores given by the m decision makers.

As an illustration, we consider a simple case of having only two decision makers with the following priority decision matrix:

$$
M = \begin{array}{cc} \text{DM1} & \text{DM2} \end{array}
\begin{array}{l} \\ \end{array}
$$

$$
M = \begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \end{array}
\begin{array}{cc} \text{DM1} & \text{DM2} \\ \left[\begin{array}{cc} 0.40 & 0.05 \\ 0.10 & 0.10 \\ 0.05 & 0.40 \\ 0.05 & 0.25 \\ 0.25 & 0.05 \\ 0.20 & 0.05 \\ 0.05 & 0.20 \end{array}\right] \end{array}
\begin{array}{l} \\ \text{Gas} \\ \text{Nuclear} \\ \text{Solar} \\ \text{Wind} \\ \text{Coal} \\ \text{Oil} \\ \text{Tidal} \end{array}
$$

With only two decision makers, it is easy to visualize their preferences, as shown graphically in Figure 1. The first decision maker prefers conventional sources of energy (Gas, Coal and Oil while the second one is inclined towards the renewable energy alternatives (Solar, Wind and Tidal). The combined view shows that the 'Nuclear' alternative has a central location but ranked very low by both decision-makers.

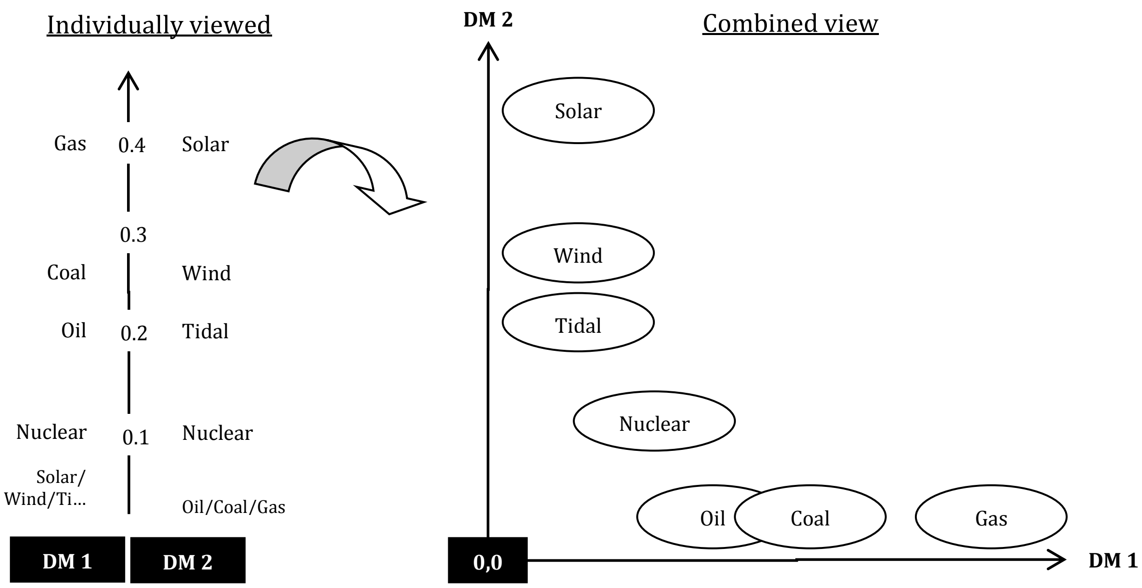

Figure 1 Visualization of the two decision makers' preferences

The same visualisation for three decision makers can be plotted in a three-dimension space. However, the visualization becomes difficult for more than three decision makers.

In the case of many decision makers, we can use the dimensionality reduction technique of the principal component analysis, as pointed out earlier. In order to display the maximal information, we display the data on a plane with the two axes having the maximal and next-to-maximal dispersions. These two axes correspond to the first two principal components.

In order to map the decision table on first two principal components, we compute the co-variance matrix C, C = $M^T M$, where Φ^T denotes the transposition of M. The eigenvalues $\lambda_j(j = 1, \dots n)$ of C represent the amount of information contained in each principal component and their respective eigenvectors represent the direction of the principal component.

The two eigenvectors u and v with the highest eigenvalues correspond to the first two principal components. The coordinates of each alternative *i* in the (u, v) plane are given by $(u_i, v_i) = \left(M_i{}^T * u, M_i{}^T * v\right)$, where M_i is the i^th^ row of M.

As the decision makers were represented along each axis in the original space, their translation in the(u, v) plane represents the preference direction of each decision maker. This can be calculated as the projection of the original axes on the (u, v) plane i.e. $(e_k{}^T u \, , e_k{}^T v)$ where e_k is the unit vector direction of the k^{th} decision maker in the original space.

The overall preference direction can also be calculated in a similar fashion by taking projection of the original weight vector on the (u, v) plane i.e. $(w^T u \, , w^T v)$, where w is the weight vector given to the decision makers. This is also known as the decision stick in the PROMETHEE context.

In the projection, some information is lost. The amount of preserved information is calculated with:

$$\delta = \frac{\lambda_1 + \lambda_2}{\sum_{j=1}^{q} \lambda_j}$$

where λ_1 and λ_2 are the highest two principal eigenvalues.

This idea of extending GAIA for AHP have been programmed and tested in PriEsT [72] which is an open source software tool available online.

4.2 Interpreting the GAIA plane

An illustrative example of a GAIA plane with more than two DMs is given in Figure 2, where the preferences of four decisions makers are represented by four vectors (see arrows DM1, DM2, DM3, and DM4 emanating from centre) and the alternatives are represented by dots. The decision stick (labelled as DMG) represents the compromise decision direction amongst all the decision makers. The reading is done by projection on the relevant arrow. For example, we can thus notice by projection on DMG, that alternative A3 is the compromise alternative for the given group of decision makers. For DM4, alternative A1 is the best.

An angle between two vectors represent the degree of consensus between the two decision makers i.e. the smaller the angle between two arrows, the similar their preferences are. For example, DM1 and DM2 in Figure 2 have similar preferences but DM3 and DM4 have almost opposite (conflicting) preferences. Finally, if alternatives are close, it means that they are similarly ranked by the decision makers (e.g. A2 and A4).

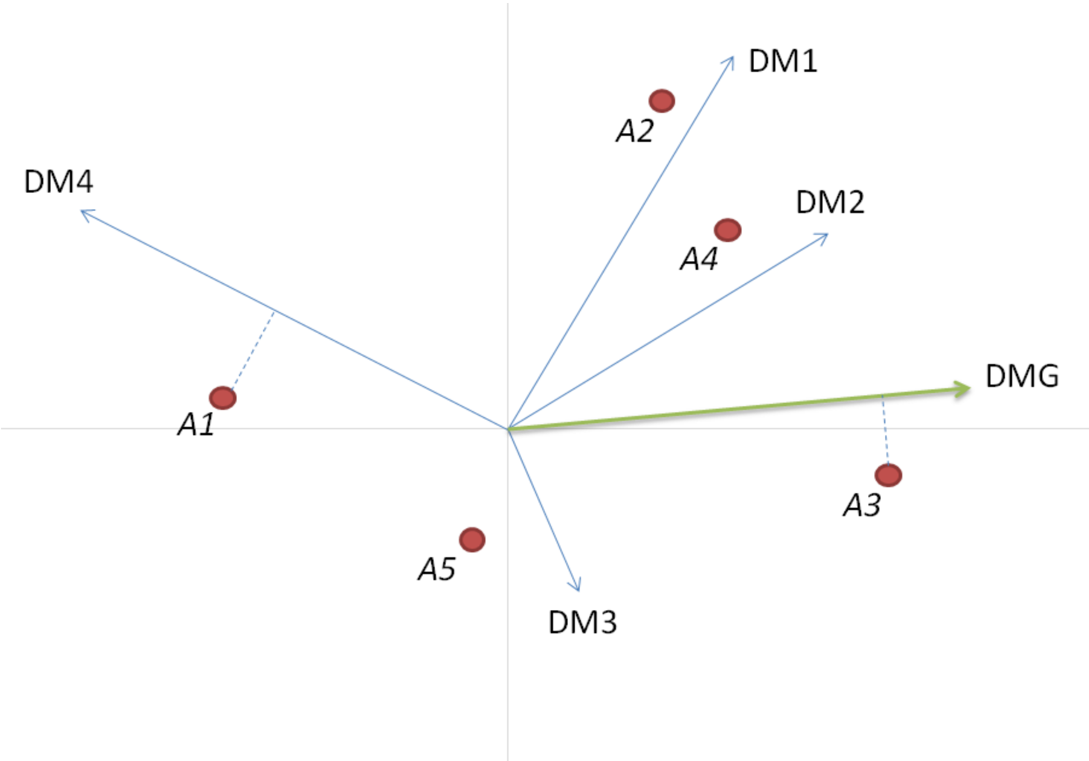

Figure 2 Example of the obtained AHP-GAIA graph

5 Case study

The GAIA-AHP hybrid group decision making method and visualisation has been used in a two-phase experiment to investigate the difference of intuitive versus informed and structured decision in the energy sector. Postgraduate students in the Portsmouth Business School were asked to estimate the importance of seven sources of energy production (coal, gas, nuclear, oil, solar, tidal and wind) for the next twenty years for the United Kingdom. Students are an important voting class and it is important to know their opinion. Furthermore, students belong to the next generation of policy makers and are the most open to new methodologies and technologies. The data were collected from participants in two distinct and successive ways. In the first phase (intuitive approach), each participant compared the seven alternatives in pairs intuitively, without first decomposing the problem into multiple criteria. In the second phase (investigative approach), the participants were given three months to explore and investigate the topic before submitting their final reports and using a structured approach. The detailed description and results of these two phases are described below.

5.1 Intuitive decision making

The participants were educated to use AHP. They received a three hours lecture on AHP and case studies solved with the method. No information is given on the energy sector. Immediately after, each participant filled a self-administered questionnaire in class. They were asked to pairwise compare on a 1-9 scale the overall importance of the seven energy sources in next twenty years, without breaking the problem into multiple criteria. We call this phase intuitive because the participants provided their judgements based only on their current knowledge on the topic. See Appendix A for the questionnaire provided to the participants for this phase.

Out of the total of 82 participants, 45 participants managed to fill in all the 21 pairwise comparisons correctly (e.g. some did not fill the whole questionnaire, or they gave evaluations outside the 1-9 scale, or they provided two different judgements for one comparison).

Out of these 45 matrices, only 15 matrices were found acceptable according to the consistency threshold of CR<0.1. However, instead of rejecting the 30 inconsistent matrices, we also analysed the preferences generated by these matrices and compared them with the consistent ones. The mean and variance energy priorities for these two groups and the combined two groups (i.e. for all participants) are given in Table 2. As discussed in section 3.1, the AHP method allows the decision makers to be inconsistent and to have priorities calculated. Therefore, our testing hypothesis is that both the consistent and inconsistent comparison matrices bear equally useful preference information. To verify our hypothesis, we performed an F-test to investigate whether consistent and inconsistent data acquired from the decision makers have similar characteristics.

The bottom part of Table 2 provides the F-values and p-values showing analysis of variance between inconsistent and consistent data obtained from the participants. The results show that the consistent and inconsistent data were not significantly different from each other, with an exception of the data for "Coal". As the two groups were not significantly different, we treat them indifferently as a single group of respondents. The exception of "Coal" was not investigated as it was not the main reason of this research. Nonetheless, this could be an area of further investigation.

Table 2 Preference scores elicited from the intuitive approach (the first step). F-test for comparing consistent and inconsistent data (F_crit(1, 29) = 2.05, α = 0.05)

	Solar	Wind	Nuclear	Tidal	Gas	Oil	Coal
Inconsistent data	19.9±1.4	15.4±0.5	16.1±1.2	11.6±1	15.1±0.9	11.6±1.2	10.4±0.8
Consistent data	21.9±1.0	16.2±0.7	15.4±1.1	16.0±1.1	11.6±0.8	11.2±1.1	7.8±0.3
Combined data	21.2±1.1	15.9±0.6	15.6±1.1	14.5±1.1	12.7±0.8	11.3±1.1	8.7±0.5
F-value	1.285	0.660	1.105	0.886	1.081	1.096	2.286
p-value	0.274	0.207	0.394	0.419	0.412	0.400	**0.029**

The preferred solution by the participants was the 'Solar' energy based power production, followed by the 'Wind' energy. However, the average preference of all the participants does not give much information. Therefore, a detailed analysis, the preferences of the 45 decision makers can be visualized with GAIA as a two-dimensional plot wherein each alternative is shown as a circle. Each decision maker is represented as a vector pointing towards his/her direction of preference. For example, the participant with label 'W' can be seen as a vector in Figure 3 that points downwards toward the 'Wind' and 'Tidal' alternatives (and in the opposite direction of nuclear and oil). This means that this participant prefers the former alternatives. Similarly, the participant with label 'Q' has a vector pointing towards 'Oil' implying that this participant is in favour of Oil-based power production. Another interesting observation on this plot is that the alternatives are grouped according to their similarity. It can be seen that 'Oil', 'Coal', and 'Gas' form a distinct cluster that clearly shows that participants considered the three alternatives similar to each other. Similarly, 'Wind' and 'Tidal' were considered closer to each other.

The plot also shows the combined preference of all the decision makers (considering them all equally important). The overall preference direction is shown as a vector with label 'D0'. In this case study, the combined preference of the participants is clearly in favour of the 'Solar' alternative, followed by the 'Nuclear' alternative.

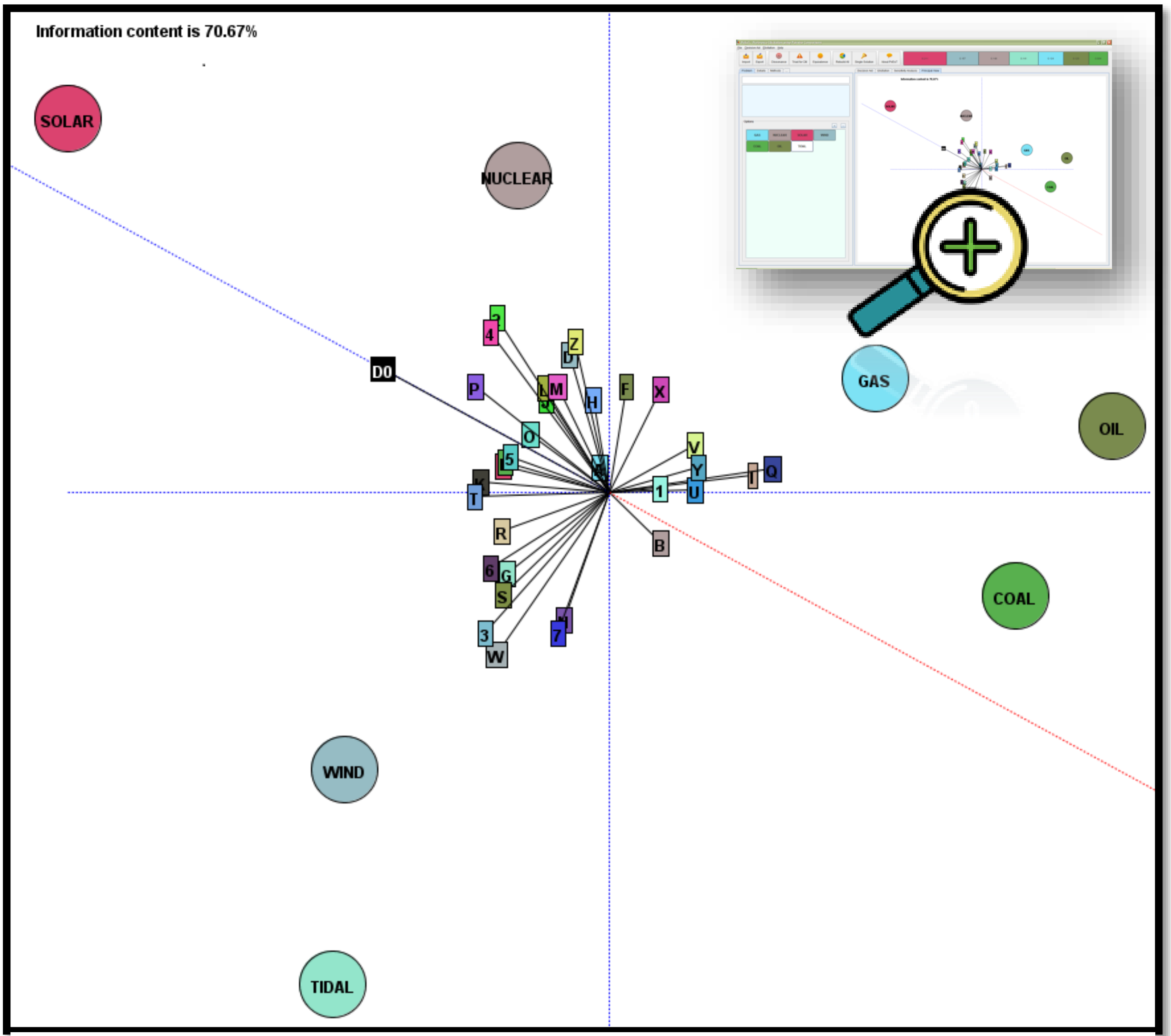

Figure 3 Visualizing the alternatives and decision makers in PriEsT for the intuitive approach

It's worth noting that the information content in the plane is 70.67% (as shown on the top-left of the plot in Figure 3) which is the amount of information captured by the first two principal components.

5.2 Investigative decision making

In the second phase, the participants were asked to explore and investigate the same seven alternatives while considering technical, economic, environmental, and social aspects. The participants had three months to write a small report, which was a graded assignment. Therefore, they had a clear incentive to seek information. The participants were asked to submit a two-part report (see Appendix-B); the first part containing a literature review on the seven energy sources and describing how these sources are fulfilling the four given criteria. The students were advised to further decompose these four criteria if deemed necessary, and were also advised to read the sub-criteria listed by [1]. The second part of the report was to present their energy source evaluations with AHP as regards to the four main criteria.

Among the valid 45 participants of the first phase, 41 took part at the second phase. 8 of these submissions were not included in the analysis because their submitted reports were inappropriate (too weak literature review or AHP energy problem not solved), therefore only 33 participants have completed all the research procedure correctly and were analysed.. The results of the second phase are given in Table 3.

Table 3 Energy source preference scores

	Solar	Nuclear	Wind	Gas	Oil	Tidal	Coal
Mean ± variance	19.9±1.4	16.1±1.2	15.4±0.5	15.1±0.9	11.6±1.2	11.6±1	10.4±0.8

As in the previous phase, a GAIA plane is constructed (Figure 4). The information content in the plane is shown on top-left as 85%. In this plane, as in the first phase, the alternatives 'Gas', 'Coal', and 'Oil' are again forming a cluster. Similarly, 'Wind' and 'Tidal' remain close to each other as well. The intra-cluster distance is reduced which implies that after investigating the seven alternatives, the participants considered the conventional alternatives of 'Gas', 'Coal', and 'Oil' much closer to each other, and similarly the two renewable energy alternatives of 'Wind' and 'Tidal' closer to each other as well. However, interestingly, the alternative of 'Nuclear' has been considered closer to the conventional form of energy production, which was previously considered closer to the 'Solar' alternative and away from the 'Coal', 'Oil' and 'Gas' alternatives. Recall that the overall preference vector 'D0' was previously pointing towards the 'Solar' alternative, which is now tilted towards the 'Wind' and 'Tidal' alternatives. In other words, the participants have reported the two renewable energy alternatives to be of higher importance after investigating the issue in more detail.

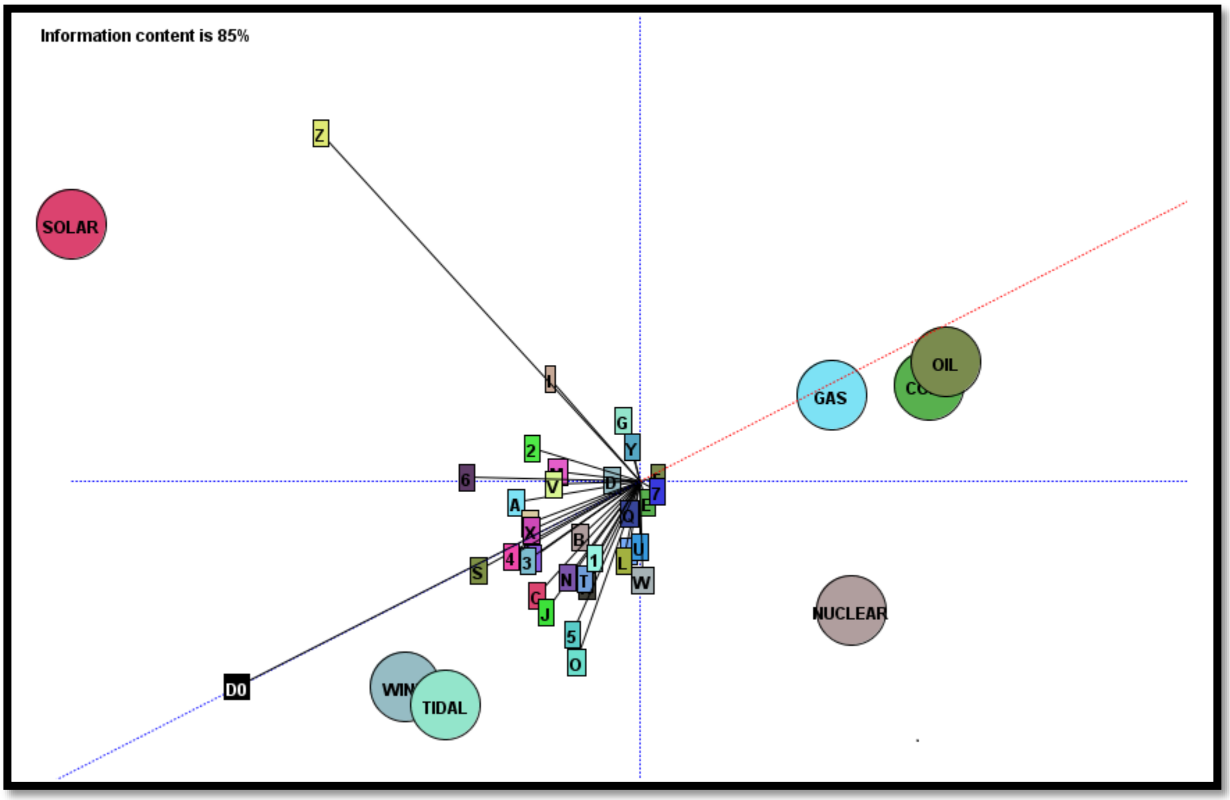

Figure 4 Visualizing the options and decision makers in PriEsT for the investigative approach

In the previous case, all the vectors representing individual decision makers were scattered around the origin. However, in this case, almost all the vectors have shifted away from the conventional means of energy production (and also nuclear energy).

5.3 Visualizing the shift in preferences

From the analysis of the two phases, it is evident that the 'Solar' option remains to be the most preferred one; however, the overall preferences have slightly changed. The similarity and difference between the two phases is summarized in Table 4. The scores for Solar, Nuclear, Gas and Oil have gone down (on average), while the other three options (Wind, Tidal, and Coal) have moved slightly upwards. The positive correlation values for the Coal, Oil, and Tidal options suggest that the individual preferences remained similar. On the contrary, the DMs did change their opinions about the Nuclear and Gas options.

Table 4 Preference shift and correlation between initial and final phases

	Solar	Nuclear	Wind	Gas	Oil	Tidal	Coal
Mean difference	-2.24%	-2.05%	2.32%	-0.26%	-2.25%	3.05%	1.43%
Pearson's Correlation	0.0522	-0.1242	0.1709	-0.1280	0.3521	0.2429	0.5551

In order to better represent the evolutions in the decision makers' mind between the first and the second step, the two figures, Figure 3 and Figure 4, have been combined into a single graph (shown in Figure 5). Figure 5 represents a new developed GAIA-AHP Map which combines the GAIA-AHP map of Phase 1 (shown in circles with bold outline) with the GAIA-AHP Map of Phase 2 (shown in circles with thin outline). This has the advantage to show the evolution between the two situations. The figure is obtained as follows: the coordinates of all the points for Phase 1 (we term GM1) and for Phase 2 (we term GM2) are computed separately. Then, the angle between the decision stick of GM1 and GM2 is computed (while using the same origin for both planes). The options (circles) in GM2 are then rotated around the origin of the plane with amplitude defined by the calculated angle. Performing this rotation allows us to have the dots of the two different phases on a unique plane. The shift between the two phases is indicated by the distance between two alternatives. The comparison of two scenarios within one plane is a distinctive feature of the PriEsT software.

Figure 5 clearly highlights the change in preference direction - see the dashed lines for each alternative with arrows pointing from their old preference position to the new one. For example, the alternative 'Solar' has shifted rightwards depicting that the strength of its preference has reduced. By contrast, the 'Wind' and 'Tidal' alternatives have both gained their preference weights in the second phase of study. Also, the conventional alternatives of 'Gas', 'Coal', and 'Oil' came closer to each other in the second step. Last but not the east, the alternative 'Nuclear' has reduced its preference weight and has shifted closer to the conventional energy alternatives.

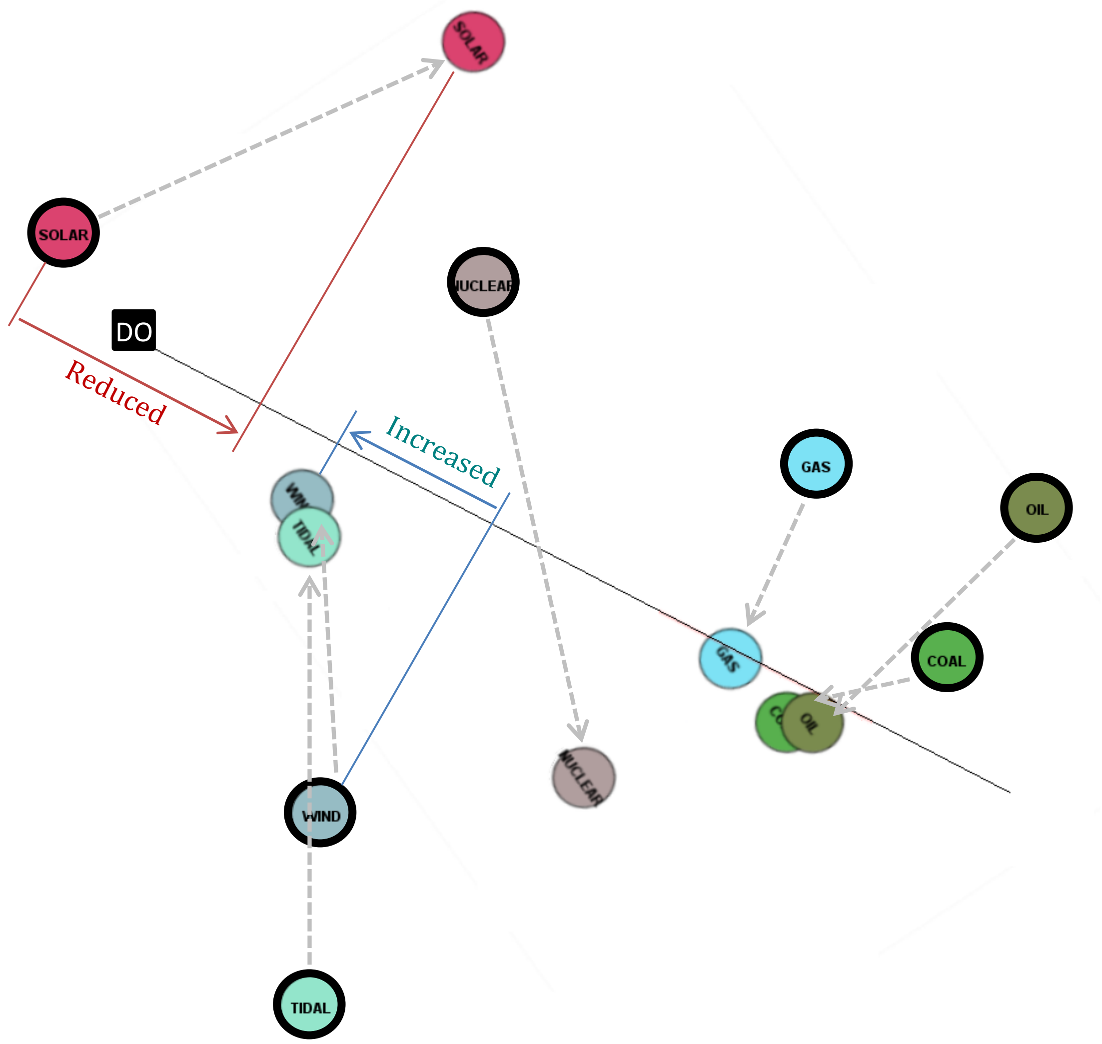

Figure 5 Combined view of results obtained from both the intuitive and the investigative decision making

We consider these plots highly useful to show the evolution of preferences and also to highlight any possible clustering of similar alternatives and/or the de-clustering process.

6 Conclusion

Energy planning is a complex problem that has been often solved with multi-criteria decision methods. These methods have the strength to incorporate technical and subjective conflicting appreciations. In this paper, we complement AHP with a visualisation tool in an open-source software tool that helps visualize the preferences of multiple stakeholders in a single plot. This descriptive feature allows policy makers to better understand the preferences of stakeholders, and has the ability to provide better justification, improved communication and negotiations.

We applied the combined AHP-GAIA software to understand the preferences of participants toward the different energy sources for producing electricity in next twenty years for the United Kingdom. We show the usefulness of the single two dimensional plot which helps toward gaining insights into the preference structure. Firstly, all the decision makers can be shown on this plot with their preference directions. Secondly, the alternatives are grouped according to their similarity. And thirdly, the overall preference direction can also be shown. In both stages of the conducted experiments, the participants rated solar energy as the most preferred alternative while the use of coal was least preferred. Overall, the preferences have only slightly changed between the two phases. This suggests that the participating students were well aware of the energy planning problems.

It can also be seen in the GAIA plane that the cohesion of the preferences increased in the second phase. This indicates that informed participants tend to have less dispersed preferences. Therefore, it somehow suggest the usefulness of sharing information among the stakeholders before any decision process. This confirms the good practice of some countries (e.g. Switzerland), that in their direct democracy process, include an accessible, objective and complete informative leaflet with the ballot paper for all votes, e.g. to accept to introduce a new tax on CO2 to support the green energy or to decide an embargo to nuclear energy.

The proposed hybrid tool has many future applications as it can help policy and decision-makers to establish more informed, consensual and improved complex energy planning. Also, it is to note that AHP-GAIA is generic enough to be used for many decision problems, thus opening up an avenue to a large range of applications. In a further development, we can imagine to have a continuous monitoring of opinions that can be used for marketing, information campaigns, etc.

Finally, although we have considered the AHP and the GAIA methods in this research, the descriptive components can be introduced and investigated for several other MCDM methods - another area for future research. .

References

[1] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews. 2009;13(9):2263-78.
[2] Buchholz T, Rametsteiner E, Volk T, Luzadis V. Multi Criteria Analysis for bioenergy systems assessments. Energy Policy. 2009;37(2):484-95.
[3] Brans J-P, Mareschal B. The PROMCALC & GAIA decision support system for multicriteria decision aid. Decision Support Systems. 1994;12(4-5):297-310.

[4] Lidouh K, De Smet Y, Zimanyi E. An adaptation of the GAIA visualization method for cartography. Conference An adaptation of the GAIA visualization method for cartography, Paris (France). 2011, p. 29-35.
[5] Nemery P, Ishizaka A, Camargo M, Morel L. Enriching descriptive information in ranking and sorting problems with visualizations techniques. Journal of Modelling in Management. 2012;7(2):130-47.
[6] Ma T, Østergaard P, Lund H, Yang H, Lu L. An energy system model for Hong Kong in 2020. Energy. 2014;68(15):301-10.
[7] Ćosić B, Krajačić G, Duić N. A 100% renewable energy system in the year 2050: The case of Macedonia. Energy. 2012;48(1):80-7.
[8] Sáfián F. Modelling the Hungarian energy system - The first step towards sustainable energy planning. Energy. 2014;69:58-66.
[9] Bjelic I, Ciric R. Optimal distributed generation planning at a local level - A review of Serbian renewable energy development. Renewable and Sustainable Energy Reviews. 2014;39:79-86.
[10] Zou H, Du H, Broadstock D, Guo J, Gong Y, Mao G. China's future energy mix and emissions reduction potential: a scenario analysis incorporating technological learning curves. Journal of Cleaner Production. 2015;advance online publication: doi:10.1016/j.jclepro.2015.08.012.
[11] Ahn J, Woo J, Lee J. Optimal allocation of energy sources for sustainable development in South Korea: Focus on the electric power generation industry. Energy Policy. 2015;78:78-90.
[12] Chatzimouratidis A, Pilavachi P. Technological, economic and sustainability evaluation of power plants using the Analytic Hierarchy Process. Energy Policy. 2009;37(3):778-87.
[13] Yi S-K, Sin H-Y, Heo E. Selecting sustainable renewable energy source for energy assistance to North Korea. Renewable and Sustainable Energy Reviews. 2011;15(1):554-63.
[14] Stein E. A comprehensive multi-criteria model to rank electric energy production technologies. Renewable and Sustainable Energy Reviews. 2013;22(0):640-54.
[15] Ozgur D. Evaluating the best renewable energy technology for sustainable energy planning. International Journal of Energy Economics and Policy. 2013;3:23-33.
[16] Scannapieco D, Naddeo V, Belgiorno V. Sustainable power plants: A support tool for the analysis of alternatives. Land Use Policy. 2014;36(0):478-84.
[17] Ahmad S, Tahar R. Selection of renewable energy sources for sustainable development of electricity generation system using analytic hierarchy process: A case of Malaysia. Renewable Energy. 2014;63(0):458-66.
[18] Karger C, Hennings W. Sustainability evaluation of decentralized electricity generation. Renewable and Sustainable Energy Reviews. 2009;13(3):583-93.
[19] Rosso M, Bottero M, Pomarico S, La Ferlita S, Comino E. Integrating multicriteria evaluation and stakeholders analysis for assessing hydropower projects. Energy Policy. 2014;67(0):870-81.
[20] Kurka T. Application of the analytic hierarchy process to evaluate the regional sustainability of bioenergy developments. Energy. 2013;62(0):393-402.
[21] Erol Ö, Kılkış B. An energy source policy assessment using analytical hierarchy process. Energy Conversion and Management. 2012;63(0):245-52.
[22] Pušnik M, Sucic B. Integrated and realistic approach to energy planning – a case study of Slovenia. Management of Environmental Quality: An International Journal. 2014;25(1):30-51.
[23] Ren H, Gao W, Zhou W, Nakagami K. Multi-criteria evaluation for the optimal adoption of distributed residential energy systems in Japan. Energy Policy. 2009;37(12):5484-93.
[24] Köne A, Büke T. An Analytical Network Process (ANP) evaluation of alternative fuels for electricity generation in Turkey. Energy Policy. 2007;35(10):5220-8.
[25] Kabak M, Dağdeviren M. Prioritization of renewable energy sources for Turkey by using a hybrid MCDM methodology. Energy Conversion and Management. 2014;79(0):25-33.

[26] Mallikarjun S, Lewis H. Energy technology allocation for distributed energy resources: A strategic technology-policy framework. Energy. 2014;72(0):783-99.
[27] Wang H. A generalized MCDA–DEA (multi-criterion decision analysis–data envelopment analysis) approach to construct slacks-based composite indicator. Energy. 2015;80(0):114-22.
[28] Grujić M, Ivezić D, Živković M. Application of multi-criteria decision-making model for choice of the optimal solution for meeting heat demand in the centralized supply system in Belgrade. Energy. 2014;67(0):341-50.
[29] Ribeiro F, Ferreira P, Araújo M. Evaluating future scenarios for the power generation sector using a Multi-Criteria Decision Analysis (MCDA) tool: The Portuguese case. Energy. 2013;52(0):126-36.
[30] Santoyo-Castelazo E, Azapagic A. Sustainability assessment of energy systems: integrating environmental, economic and social aspects. Journal of Cleaner Production. 2014;80(0):119-38.
[31] Maxim A. Sustainability assessment of electricity generation technologies using weighted multi-criteria decision analysis. Energy Policy. 2014;65(0):284-97.
[32] Doukas H, Marinakis V, Karakosta C, Psarras J. Promoting renewables in the energy sector of Tajikistan. Renewable Energy. 2012;39(1):411-8.
[33] Zhang L, Zhou D-Q, Zhou P, Chen Q-T. Modelling policy decision of sustainable energy strategies for Nanjing city: A fuzzy integral approach. Renewable Energy. 2014;62(0):197-203.
[34] Oberschmidt J, Geldermann J, Ludwig J, Schmehl M. Modified PROMETHEE approach for assessing energy technologies. International Journal of Energy Sector Management. 2010;4(2):183-212.
[35] Ghafghazi S, Sowlati T, Sokhansanj S, Melin S. A multicriteria approach to evaluate district heating system options. Applied Energy. 2010;87(4):1134-40.
[36] Tsoutsos T, Drandaki M, Frantzeskaki N, Iosifidis E, Kiosses I. Sustainable energy planning by using multi-criteria analysis application in the island of Crete. Energy Policy. 2009;37(5):1587-600.
[37] Madlener R, Kowalski K, Stagl S. New ways for the integrated appraisal of national energy scenarios: The case of renewable energy use in Austria. Energy Policy. 2007;35(12):6060-74.
[38] Terrados J, Almonacid G, Pérez-Higueras P. Proposal for a combined methodology for renewable energy planning. Application to a Spanish region. Renewable and Sustainable Energy Reviews. 2009;13(8):2022-30.
[39] Kowalski K, Stagl S, Madlener R, Omann I. Sustainable energy futures: Methodological challenges in combining scenarios and participatory multi-criteria analysis. European Journal of Operational Research. 2009;197(3):1063-74.
[40] Brand B, Missaoui R. Multi-criteria analysis of electricity generation mix scenarios in Tunisia. Renewable and Sustainable Energy Reviews. 2014;39(0):251-61.
[41] Doukas H, Karakosta C, Psarras J. Computing with words to assess the sustainability of renewable energy options. Expert Systems with Applications. 2010;37(7):5491-7.
[42] Yazdani-Chamzini A, Fouladgar M, Zavadskas E, Moini H. Selecting the optimal renewable energy using multi criteria decision making. Journal of Business Economics and Management. 2013;14(5):957-78.
[43] Streimikiene D, Balezentis T, Krisciukaitienė I, Balezentis A. Prioritizing sustainable electricity production technologies: MCDM approach. Renewable and Sustainable Energy Reviews. 2012;16(5):3302-11.
[44] Ren J, Fedele A, Mason M, Manzardo A, Scipioni A. Fuzzy Multi-actor Multi-criteria Decision Making for sustainability assessment of biomass-based technologies for hydrogen production. International Journal of Hydrogen Energy. 2013;38(22):9111-20.

[45] Liu G, Baniyounes A, Rasul M, Amanullah M, Khan M. General sustainability indicator of renewable energy system based on grey relational analysis. International Journal of Energy Research. 2013;37(14):1928-36.
[46] Ertay T, Kahraman C, Kaya İ. Evaluation of renewable energy alternatives using MACBETH and fuzzy AHP multicriteria methods: the case of Turkey. Technological and Economic Development of Economy. 2013;19(1):38-62.
[47] Sliogeriene J, Turskis Z, Streimikiene D. Analysis and Choice of Energy Generation Technologies: The Multiple Criteria Assessment on the Case Study of Lithuania. Energy Procedia. 2013;32(0):11-20.
[48] Kahraman C, Kaya I. A fuzzy multicriteria methodology for selection among energy alternatives. Expert Systems with Applications. 2010;37(9):6270-81.
[49] Liu G. Development of a general sustainability indicator for renewable energy systems: A review. Renewable and Sustainable Energy Reviews. 2014;31(0):611-21.
[50] Tasri A, Susilawati A. Selection among renewable energy alternatives based on a fuzzy analytic hierarchy process in Indonesia. Sustainable Energy Technologies and Assessments. 2014;7(0):34-44.
[51] Shen Y-C, Lin G, Li K-P, Yuan B. An assessment of exploiting renewable energy sources with concerns of policy and technology. Energy Policy. 2010;38(8):4604-16.
[52] Heo E, Kim J, Boo K-J. Analysis of the assessment factors for renewable energy dissemination program evaluation using fuzzy AHP. Renewable and Sustainable Energy Reviews. 2010;14(8):2214-20.
[53] Nieto-Morote A, Ruz-Vila F, Cánovas-Rodríguez F. Selection of a trigeneration system using a fuzzy AHP multi-criteria decision-making approach. International Journal of Energy Research. 2011;35(9):781-94.
[54] Huang W-C, Jhong C-H, Ding J-F. Key Factors Influencing Sustainable Development of a Green Energy Industry in Taiwan. Mathematical Problems in Engineering. 2013;2013:10.
[55] Deng Y, Xu J, Liu Y, Mancl K. Biogas as a sustainable energy source in China: Regional development strategy application and decision making. Renewable and Sustainable Energy Reviews. 2014;35(0):294-303.
[56] Kahraman C, Kaya İ, Cebi S. A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process. Energy. 2009;34(10):1603-16.
[57] Kaya T, Kahraman C. Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. Expert Systems with Applications. 2011;38(6):6577-85.
[58] Haydt G, Leal V, Dias L. A multi-objective approach for developing national energy efficiency plans. Energy Policy. 2014;67(0):16-27.
[59] Balezentiene L, Streimikiene D, Balezentis T. Fuzzy decision support methodology for sustainable energy crop selection. Renewable and Sustainable Energy Reviews. 2013;17(0):83-93.
[60] San Cristóbal J. Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. Renewable Energy. 2011;36(2):498-502.
[61] Asif A, Imtiaz A, Bal G. Integrated fuzzy VIKOR and AHP methodology for selection of distributed electricity generation through renewable energy in India. International Journal of Engineering Research and Applications. 2011;1(3):1110-3.
[62] Kaya T, Kahraman C. Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. Energy. 2010;35(6):2517-27.
[63] Hunt D, Bañares-Alcántara R, Hanbury D. A new integrated tool for complex decision making: Application to the UK energy sector. Decision Support Systems. 2013;54(3):1427-41.
[64] Ishizaka A, Labib A. Selection of new production facilities with the Group Analytic Hierarchy Process Ordering method. Expert Systems with Applications. 2011;38(6):7317–25.

[65] Ishizaka A, Labib A. Review of the main developments in the analytic hierarchy process. Expert Systems with Applications. 2011;38(11):14336-45.
[66] Brunelli M, Fedrizzi M. Axiomatic properties of inconsistency indices for pairwise comparisons. Journal of the Operational Research Society. 2014;66(1):1-15.
[67] Linares P. Are inconsistent decisions better? An experiment with pairwise comparisons. European Journal of Operational Research. 2009;193(2):492-8.
[68] Ishizaka A, Lusti M. How to derive priorities in AHP: a comparative study. Central European Journal of Operations Research 2006;14(4):387-400.
[69] Saaty T. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology. 1977;15(3):234-81.
[70] Crawford G, Williams C. A Note on the Analysis of Subjective Judgement Matrices. Journal of Mathematical Psychology 1985;29(4):387-405.
[71] Arbel A, Orgler Y. An application of the AHP to bank strategic planning: The mergers and acquisitions process. European Journal of Operational Research. 1990;48(1):27-37.
[72] Siraj S, Mikhailov L, Keane J. PriEsT: an interactive decision support tool to estimate priorities from pairwise comparison judgments. International Transactions in Operational Research. 2013;22(2):217–35.

[Postprint version, please cite as] Ishizaka A, Siraj S, Nemery P, Which energy mix for the UK? An evolutive descriptive mapping with the integrated GAIA-AHP visualisation tool, Energy, advance online publications, doi: 10.1016/j.energy.2015.12.009

APPENDIX-A

Participant no: ____________

PHASE-1 Intuitive ranking

<u>To compare **in your opinion** the importance of options for energy production in the UK in **20 year time**</u>

Presently, gas and coal-based plants are the major contributors towards the overall electricity production in the UK, followed by the nuclear power plants. However, renewable energy has attracted much attention in the recent years and is considered to be replacing the conventional power plants in next couple of decades.

You are asked to compare, according to your opinion, the importance of the following available options for the production of electricity in the UK in 20 year time:-

1. NATURAL GAS
2. NUCLEAR ENERGY
3. SOLAR ENERGY
4. WIND ENERGY
5. COAL ENERGY
6. OIL ENERGY
7. TIDAL and WAVE ENERGY

Fill in the following pairwise comparison matrix with your judgments. Please use the Saaty's scale of 1 to 9 (or the reciprocal values 1/2 to 1/9).

	GAS	NUCLEAR	SOLAR	WIND	COAL	OIL	TIDAL/WAVE
GAS							
NUCLEAR							
SOLAR							
WIND							
COAL							
OIL							
TIDAL/WAVE							

APPENDIX-B

PHASE 2

To investigate the options available for energy production in the UK

Introduction

This phase gives you a chance to practically apply Analytic Hierarchy Process (AHP) with Expert Choice to rank different options for the next electricity generation (i.e. in 20 year time) in the UK.

Objective

You are required to prioritize **according to your vision** the following available options for the production of electricity in the UK:-

1. NATURAL GAS
2. NUCLEAR ENERGY
3. SOLAR ENERGY
4. WIND ENERGY
5. COAL ENERGY
6. OIL ENERGY
7. TIDAL and WAVE ENERGY

Although there exists several ways to produce electricity, these methods have been carefully chosen for this assignment. In order to prioritize, you need to analyse these options with respect to the following criteria:-

1. Technical
2. Economic
3. Environmental
4. Social

Deliverables

Your report should have the following section:

- Introduction
- Brief literature review on energy
- Problem structuring in a hierarchical form with description of the model
- Problem solving with Expert Choice
- Analysis and discussion of the results, including details of the recommendations you would make to the decision maker sensitivity analysis
- Conclusion
- References to books, articles, etc. that you make use of.

The electronic file of Expert Choice and all matrices must be submitted in appendix.