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Energy Strategy Reviews 39 (2022) 100789

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

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ARTICLE INFO

Keywords:
MCDA
PV adoption
Belief network
Sensitivity analysis
Agent-based model

ABSTRACT

Multi-Criteria Decision Analysis (MCDA) is a sub-discipline of operations research that aims to solve multi-objective optimization problems by evaluating competing factors in decision-making. MCDA supports multidimensional decision-making processes through the analysis of diverse inputs at several levels of description, e.g. economic, technical, social, and environmental. The use of MCDA has been gaining momentum in the energy field, especially in endeavors that require evaluating the feasibility of different adoption scenarios for renewable energy technologies. The study presented in this paper investigates the combined use of multi-agent simulation, Bayesian modeling and sensitivity analysis for the development of a novel MCDA approach that supports the analysis of residential solar Photovoltaic (PV) adoption. The ensuing MCDA approach is evaluated alongside four popular MCDA methods (AHP, TOPSIS, SAW and ELECTREII) in a variety of tests aimed to assess overlap in criterion rankings and decision-making outcomes, covariation of criteria rankings in alternative scenarios, and the capacity to provide a model of correct decision-making. The comparative evaluation with AHP, TOPSIS, SAW and ELECTREII shows that overall ABM-BN-SA is well correlated with most of other MCDA methods and provides the best performing model of decision-making, with reference to the PV adoption use case under analysis. TOPSIS shows the closest fit with ABM-BN-SA, as expected since it used a ranking approach considerably closer to ABM-BN-SA as compared to the other MCDA treatments. ELECTREII yields the lowest degree of ranking overlap with ABM-BN-SA. All the reviewed methods have been illustrated and evaluated within our residential solar Photovoltaic (PV) adoption decision support system. In general, these methods enable a user to select an optimal solution out of a set of plausible alternatives according to multiple criteria and assist him in the design and exploration of the decision space. The ensuing decision-making methodology can be applied not only by Solar PV panel purchasers but also by stakeholders in other industries to logically and straightforwardly model and simulate the adoption decision-process of the public based on their individual preferences, behavioral rules, and interaction within a social network, with specific reference to a consumer utility function.

1. Introduction

The adoption and selection of renewable energy strategies is a multi-dimensional decision-making process involving a variety of economic, technological, societal, policy, and environmental factors. As a method for solving complex decision problems, Multi-Criteria Decision Analysis (MCDA), also known as Multi-Criteria Decision Making (MCDM),[1] provides an ideal approach for the evaluation of renewable energy strategies. By enabling the analysis of associations between elements that affect decision-making in renewable energy adoption, MCDA emerges as a most suitable tool to evaluate the relative impact of factors and explore alternative options. Such an analysis is needed to provide technical and scientific support to guide decision-making in the field of renewable energy[1].

While technology costs are a paramount concern in choosing among alternative energy sources, meteorological, environmental, energy safety and security factors, and ensuing economic outcomes play an increasingly important role. For example, the adoption of solar PV as a source of electricity generation is ideal in countries such as Qatar with a yearly average of nearly six peak sun hours per day, which is among the highest worldwide. Due to the extreme heat in the summer season, cooling represents the largest share of electricity demand during the

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[1] Henceforth, the term MCDA will be used to refer both to MCDA and MCDM.

https://doi.org/10.1016/j.esr.2021.100789
Received 1 November 2020; Received in revised form 21 November 2021; Accepted 1 December 2021
Available online 6 December 2021

summer months when there is greater sunlight, which solar PV can effectively harness to satisfy the cooling energy requirements[2].

The integration of distributed solar PV systems would contribute also help curtail infrastructural investments needed to keep the national power system in lockstep with ongoing economic and population grow. From 2010 to 2018, electricity demand in Qatar has grown at an annual average rate of about 6%, with peak loads going from 5090 to 7855 MW (see Table 1).

To ensure that electricity demand be met at peak load times, the capacity of the electricity grid needs to be constantly increased, even though maximum demand occurs only sporadically, at predictable times, e.g. summer afternoons due to high cooling demand, as shown in Fig. 1. Costs to upgrade the national electricity grid in Qatar for the period 2016–2020 may have reached $9bn in2020[3] and will continue to increase thereafter. These costs can be significantly cut by using distributed PV generation to reduce dependence on the grid during periods of peak consumption. In terms of grid security, the integration of distributed PV generation contributes to the modularity of the national power system, increasing the resiliency of the national electricity system in power outage emergencies and strengthening National Energy Security. From the economic and environmental perspective, the use of solar energy to produce electricity will yield significant savings of fossil fuels used for electricity production. For oil and gas rich countries, these savings can be repurposed for additional trade on the international gas market, used to develop a downstream industry based on gas-to-solid value-added products, or left untapped to extend the lifetime of the country's natural gas reserves and lower extraction costs. For countries which rely heavily of oil and gas imports for energy production, the use of solar energy would help reduce trade costs and increase energy independence. In either case, the use of solar energy in place of fossil fuels to generate electricity would lead to significant reduction in CO2 emissions [1]. For example, power plants operating in the US during 2018 generated on average 2.21 lb. of CO2 for each kWh of electricity produced with coal, 2.11 lb. of CO2 or each kWh of electricity produced with petroleum, and 0.92 lb. of CO2 or each kWh of electricity produced with natural gas.[4]With reference to technology costs, the situation has also been changing dramatically in the last decade. The average cost of residential PV in the US came down from $0.52/kWh in 2010 to $0.16/kWh in 2017 and is expected to reach $0.10/kWh in 2020 and $0.05/kWh in2020.[5]

Table 1
Electricity production and *max* and *min* demand in Qatar (source: KAHRAMAA [2]).

Year	*Total demand* [a]	*Max demand day* [b]	*Date*	*Min demand day* [b]	*Date*
2010	28,144	5090	14-Jul	1570	8-Feb
2011	30,730	5375	1-Aug	1785	13-Jan
2012	34,788	6255	6-Aug	1840	26-Jan
2013	34,668	6000	18-Jul	2046	16-Jan
2014	36,125	6740	7-Sep	2154	12-Feb
2015	41,499	7270	1-Sep	2320	24-Feb
2016	42,306	7435	3-Sep	2410	19-Jan
2017	43,800	7855	14-Aug	2600	25-Feb
2018	47,913	7875	12-Jul	2825	21-Jan

[a] *GWh.*
[b] *MW.*

To keep up with the complexity of decision making in the adoption and selection of renewable energy strategies, it is necessary to combine MCDA with simulation approaches that capture the dynamic aspect of alternative energy strategies. The approach described in this paper proposes to do so by using a Bayesian approach to MCDA to analyze simulation data generated via Agent-Based Modeling (ABM). The paper is organized as follow.

Section 2 provides a review of related MCDA work. Section 3 describes the novel approach developed in the study with specific reference to its basic components: ABM, Bayesian Networks, and sensitivity analysis (SA[6]). Section 4 provides a comparison of the novel MCDA approach with existing MCDA approaches. The results of the comparative evaluation in section 4 are discussed in section 5. Conclusive remarks and suggestions for further work are laid out in section 6.

2. Multi-Criteria Decision Analysis methods

Due to the multi-dimensional nature of sustainability objectives and the complexity of socio-economic systems, MCDA methods have become increasingly popular in sustainable energy decision-making [3]. One of the basic steps in MCDA models is the assignment of weights to criteria to determine the relative impact of criteria. MCDA researchers have proposed various methods to assign weights to criteria in solving different MCDA problems, see Ref. [4].

This section reviews some of the most well-known approaches.

- Choosing the optimal solution according to multiple criteria out of a potentially massive solution space is difficult due to several challenges, such as:
- Circumscribing the decision space from a multitude of criteria with reference to a decision output.
- Assigning weights to criteria for the dynamic ranking of decision candidates.
- Representing the solution space as an abstract construct that enables decision analysis and decision making in a user-friendly fashion.

Factors weighting methods are divided into three categories: subjective weighting, objective weighting, and combined weighting methods. Several methods based on weighted sum, priority setting, ranking, fuzzy set method and their combination can be used to address MCDA problems in renewable energy (RE) adoption. Many interactive methods have been proposed, and they are different from each other, for example, on how to express preferences and how to use preferences when using new solutions [5]. Fig. 2 provides a schematic summary of most used MCDA approaches. Some of these approaches have been applied to RE MCDA problems, such as the selection of Combined Cooling, Heating and Power (CCHP) alternatives [6], the comparisons of renewable energy plants and the DM of energy policy [7]. A description of some of these MCDA methods is provided below.

2.1. *Unique synthesizing criteria methods*

2.1.1. *AHP*

The Analytic Hierarchy Process (AHP) MCDA method [8] has been applied to a variety of domains including energy, social, economic, agricultural, industrial, ecological, and biological systems [9]. This

[2] "ABM-BN-SA" this term will be used to refer the developed method in this paper, it is the abbreviation of "Agent-based model-Bayesian Network-Sensitivity Analysis".
[3] Source: Arab Petroleum Investments Corporation (http://www.apicorp.org).
[4] https://www.eia.gov/tools/faqs/faq.phpid=74&t=11.
[5] https://www.energy.gov/eere/solar/sunshot-2030.
[6] The term SA will be used to refer to Sensitivity Analysis.

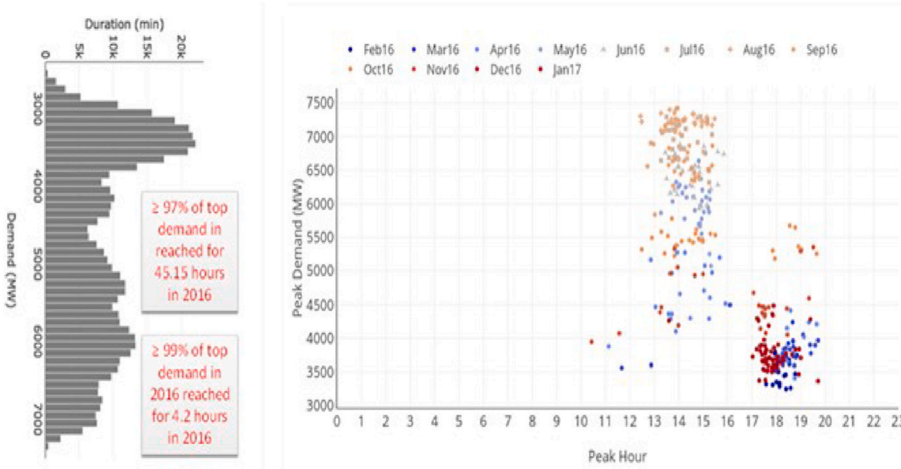

Fig. 1. Duration of demand levels and distribution of electricity peak demand by day in 2016 (adapted from Ref. [2]).

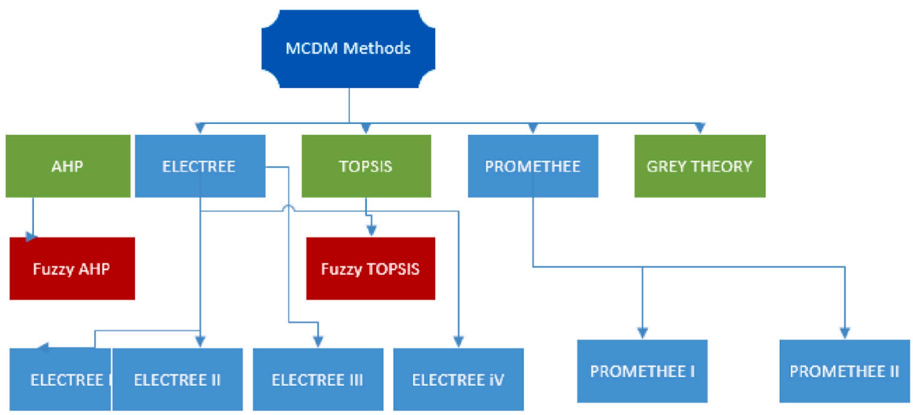

Fig. 2. A descriptive summary of the most commonly used MCDA methods.

descriptive decision analysis method computes the scaling importance of alternatives through pairwise comparison of evaluation criteria and alternatives.

AHP involves decomposing a complex decision into a hierarchy, where the goal (target) is at the top of the hierarchy, the criteria, sub-conditions are at the levels, and sub-levels of the hierarchy and the decision options are at the bottom of the hierarchy. AHP is a weighted sum method. The AHP method incorporates the following steps [10]:

a. *Define the problem:* this step aims to decompose the decision-making problem into different parts, as the highest-level problem target, intermediate-level standards (may be decomposed into lower-level sub-standards), and the lowest-level options.
b. *Build a pair-wise comparison matrix (weights):* according to Ref. [10], decision makers should answer questions such as" How important is criterion A relative to criterion B?". This must be performed for every pair of conditions. As the evaluation continues, the relative priority of each pairing criterion is determined by denoting 1 as" *equal importance*" and 9 as" *extreme importance*".
c. Judgment of Pair-wise comparison of options on each *criterion (scoring):* for each pair within each criterion a better choice will get a score again between 1 ("*equally good*") and 9 ("*absolutely better*"), and the other option in the pairing is assigned a rating problem goal.
d. *The final stage of AHP technology* is to calculate the inconsistency rate (*IR*)- a measure of the logical rationality of pairwise comparisons. If *IR* is less than 0.10, a pairwise comparison is generally considered acceptable. AHP assessment assumes that the decision maker is rational. For example, if A is compared to B, B is preferred, B is preferred to C, and A is preferred to C [11].

$$CI\mathrm{n} = \frac{\gamma max - n}{n - 1} \tag{1}$$

Where:

- n is Consistency Index
- γmax is the Eigenvalue and $\gamma max > n$, and
- n is number of comparisons

Next, $\gamma \mathrm{max} mustbecalculated : [Ax = \gamma maxx]$ where:

A is the comparison matrix of size $n \times n$, for n criteria, and x is the Eigenvector of size $n \times 1$.

$$CR_n = \frac{CIn}{RIn} \tag{2}$$

CR_n is Consistency Ratio which [8] concluded that if the value of the consistency ratio is less than or equal to 10%, the inconsistency is acceptable. If the consistency ratio is greater than 10%, the subjective judgment needs to be revised, and RIn Random Consistency Index which n is number of comparisons.

2.1.2. *TOPSIS*

TOPSIS is presented as a weighting strategy in the literature and can also be an MCDA method. TOPSIS [12] relies on the concept that the ideal alternative has the highest level of impact for all criteria, while in the worst alternative all criteria present the lowest impact [13]. The principle is simple: mathematically speaking, the elected best alternative should have the shortest distance from the positive ideal solution, and the longest distance from the negative solution.

This strategy assumes that each criterion has a monotonically expanding or diminishing utility. This makes it simple to find ideal and negative ideal solutions. TOPSIS uses probably the shortest Euclidean distance out of *the best solution* along with the farthest distance out of *the negative ideal solution* to establish the *worst* and *best* alternative. The TOPSIS strategy comprises the following steps:

(1) Normalize the decision matrix: the standardization of the decision matrix is done utilizing the below transformation for every nij:

$$n_{ij} = \frac{aij}{\sqrt{\sum_{i=1}^{m} aij^2}} \tag{3}$$

(2) Then, weights should be multiplied to normalized matrix [14].
(3) Determine the *positive* and *negative* ideal alternatives [14]:

$$A^{+} = \{v_1^{+}, v_2^{+}, \dots v_n^{+}\} = \{(max_i V_{ij} | j \in J), ((min_i V_{ij} | j \in J' | i = 1, 2, \cdots, m)\} \tag{4}$$

J = {j = 1, 2, …, n|j for negative attributes}

Where negative attributes are those with the worst attribute value. The formula in (4) is used to calculate the weighted normalized decision matrix: multiply the normalized decision matrix with its related weight. The weighted standardized value V_{ij} is determined as $V_{ij} = w_{ij} r_{ij}$ where w_j Indicates the weight of j^{th} attribute or condition.

The algorithms of the popular MCDM processes (AHP and TOPSIS) are well described and explained in Ref. [15]. This study identifies a listing of TOPSIS and AHP applications however it shows some of their limitations. For the original TOPSIS introduced by Ref. [16], input data should be numeric, definite, monotonically decreasing and increasing, and share a commensurate unit. This implies that this technique is unable to handle qualitative criteria that area unit troublesome to assess exactly, and it cannot tackle integrity and uncertainty of the assessment data. A review given in Ref. [17] found that AHP and TOPSIS are among the most popular methods employed to solve different selection problems.

2.1.3. Simple Additive Weighting (SAW)

Simple Additive Weighting (SAW) is one of the strategies used to solve multi-attribute decision problems. This strategy can be utilized to support Geographic Information System with overlay operations [18]. The fundamental idea of this technique is to find the weighted sums obtained from the performance ratings of each alternative on all criteria [19]. SAW requires normalizing the decision matrix (X) to a scale that may be compared with all present alternatives' ratings [20]. The method's evaluation criteria S_i is calculated by using equation (5):

$$S_j = \sum_{j=1}^{m} w_j \tilde{a}_{ij} \tag{5}$$

where ω_j is the weight of the *j-th* criteria and $\tilde{a}_{ij}$ is normalized by using equation (6), the value of the *j-th* criteria for the *i-th* alternative.

$$\tilde{a}_{ij} = \frac{rij}{\sum_{i=1}^{n} r_{ij}} \tag{6}$$

The Simple Additive Weighting (SAW) approach is an easy-to-use technique [18]. describes strong assumptions implicit in the SAW method (linearity and preferential independence).

An interesting work presented in Ref. [21] investigates the impacts of using relative weights in multiple criteria decisions making and presents a detailed description for the preferential independence condition of SAW.

2.2. The outranking methods

The basis of the outranking method is the construction and development of the ranking relationship introduced by Refs. [22,23]. The ranking relationship is the binary relationship S defined on the alternative set A, so that for any pair of alternatives A_i; A_k: $A_i S A_k$, if the preference of the decision maker is known, the evaluation quality of the alternatives and the nature of the problem considered, Then there are enough arguments to show that the alternative A_i is at least as good as the alternative A_k, but at the same time, there is no sufficient reason to reject this statement [24].

Compared with other multi-criteria evaluation methods, ranking methods have the feature of allowing incomparable alternatives. This feature is very important in situations where certain options cannot be compared for one reason or another.

2.2.1. Elimination and choice translating reality (ELECTREE)

This method was proposed by Benayoun, Roy and Sussman in 1966 [4,25,26], and was developed and improved by Roy in 1971. It consists of a pairwise comparison of alternatives, based on the degree to which in turn evaluations of the alternatives along with the preference weights ensure or even oppose the pairwise dominance connection somewhere between alternatives. It examines both the degree to which the preference weights agree with pairwise dominance relationships and the degree to which weighted evaluations differ from each other. These stages are based on a "concordance and discordance" set; hence, this method is also called concordance analysis [4].

There are several versions of the ELECTRE method, which provide improved versions of the initial method. There are two main stages for ELECTRE methods: (1) the construction of ranking relationships, and (2) the use of these relationships to obtain the final ranking of alternatives.

Different ELECTREE methods may differ in defining the ranking relationships between alternatives and how to apply these relationships to obtain the final ranking of alternatives. The ELECTREE method has evolved through several versions (I, II, III, IV, V). All variations are based totally on the identical fundamental concept however are operationally different. The ELECTREE I approach is designed for choice while ELECTRE II is used for ranking. In this study, the ELECTRE II approach will be used as a technique for figuring out the doubts of Qatar's residents to adopt residential solar photo-voltaic energy. ELECTREE II approach was chosen due to the fact of its capability in the current alternatives. So that this technique is very excellent to be used to search for the doubts of the public adopting solar energy.

3. MCDA with agent-based modeling, bayesian reasoning and sensitivity analysis

Most current MCDA methods help users design and explore the decision space, once the data that form the decision space have been procured. Our approach differs from these MCDA methods [27] in that it includes the automated generation of decision spaces via agent-based simulation to enable users to test and select alternative decision-making options with ease in an exhaustive and effective manner. Another novel aspect of the approach developed regards optimization.

While classical optimization theory deals with problems that aim to maximize or minimize a single criterion, most real-world decision-making problems [28], such as residential solar Photovoltaic adoption, require the optimization of multiple competing criteria. In using MCDA to evaluate alternative solar PV adoption scenarios generated via agent-based simulation, our strategy is to estimate the probability distribution of all criteria using a Bayesian reasoning approach [28].

Such a strategy provides both the expected value and uncertainty of the relevant criteria as an indication of their utility in the decision-making process. Factor ranking is performed by validating the probability variables of the Bayesian net by means of sensitivity analysis. The ensuing approach is compared with the TOPSIS, ELECTREE, SAW and AHP methods described in the previous section.

3.1. Proposed methodology

The novelty of the approach described in this paper is the automation of the entire MCDA process through the following steps (Fig. 3)[7]:

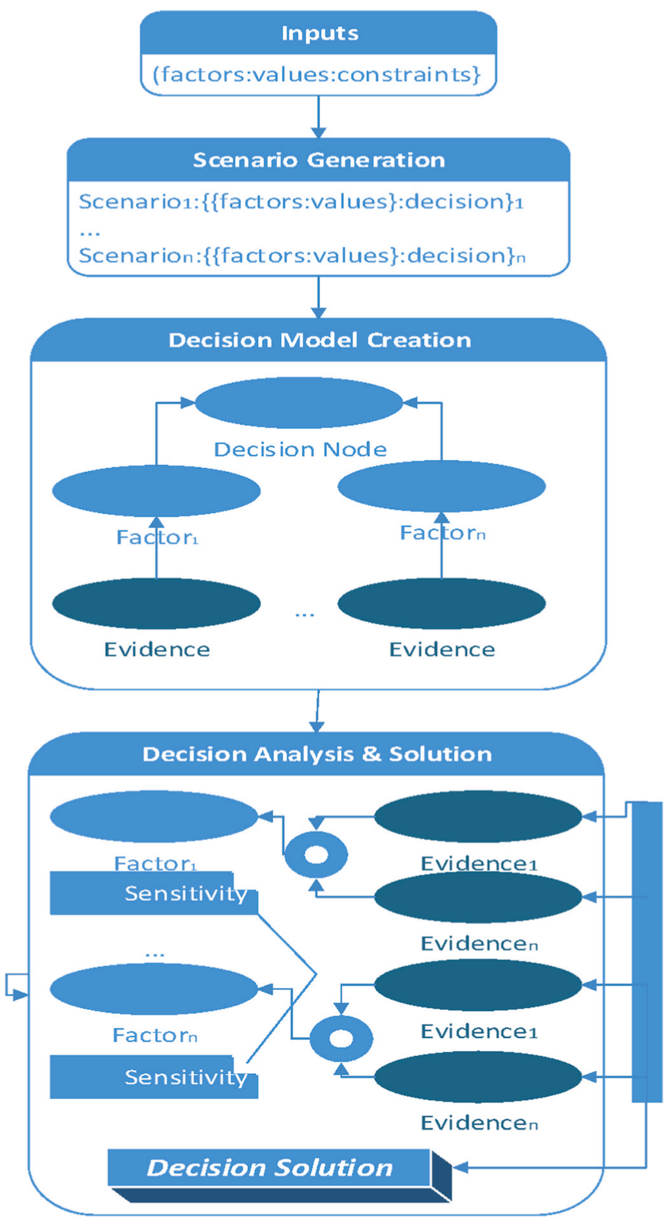

Fig. 3. Diagrammatic representation of the approach.

- Generate plausible scenarios to initialize the solution space
- Augment the solution space with alternative solution.
- Develop a classification model from the total solution space data to derive weights for all criteria.
- Construct an inference network using the classification model.

As described in Fig. 3, the input to the proposed MCDA system is a pair consisting of a list of factors (f) and a decision output variable (d), where each factor can take several values (v) within a certain range subject to number of constraints (c):

$$([(f_i : v_{ii}\vee, \ldots, \vee v_{in} : c_{ii}, \ldots, c_{in}), \ldots, (f_n : v_{ni}\vee, \ldots, \vee v_{nn} : c_{ni}, \ldots, c_{nn})], d_i]) \qquad (7)$$

The approach developed consists of three main components:

1. **Scenario Generation,** where most plausible mixture of factors leading to an agent PV adoption decision are instantly generated to derive a decision space dataset

$$\langle [(f_1 : v_{11}\vee, \ldots, \vee v_{1n}), \ldots, (f_j : v_{j1}\vee, \ldots, \vee v_{jn})], d_1 \rangle \qquad (8)$$

$$\langle [(f_k : v_{ki}\vee, \ldots, \vee v_{kn}), \ldots, (f_n : v_{ni}\vee, \ldots, \vee v_{nn})], d_n \rangle \qquad (9)$$

2. **Decision Model Creation,** where the decision space dataset is used as training data to derive a probabilistic belief network where nodes describe the PV adoption factors and PV adoption decision outputs and links the probabilities across the nodes.
3. **Decision Analysis Solution,** where factors are automatically ranked to help the user determine optimal decision making under diverse value assignments to criteria.

3.1.1. Scenario Generation-Agent-Based Modeling (ABM)

We used Agent Based Modeling [30] to generate residential PV adoption scenarios for a population of 65,536 households in Qatar during the course of 15 years in terms of five factors all expressed in US dollars per kilowatt-hour ($/kWh): (1) PV cost; (2) electricity tariff; (3) power gain resulting from the use of PV energy" *behind the meter*" (the estimated yearly Power$_{GAIN}$ in USD for 65,536 5 kW residential solar PV systems will vary as indicated in Fig. 4, with an average of 0.036 ¢/kWh); (4) a hypothetical carbon tax, and (5) the hypothetical reductions of gas and electricity subsidies [30]. We assume that PV cost would fall yearly due to technological maturity (Table .1) as detailed in Ref. [30] following [31].

A household's propensity to adopt solar energy in the model is determined by the logistic function in Equation.4, where L is a scaling constant, e is the natural logarithm, x is the cost of PV minus the *cost of electricity + carbon tax + power gain + gas/electricity subsidy reductions*,

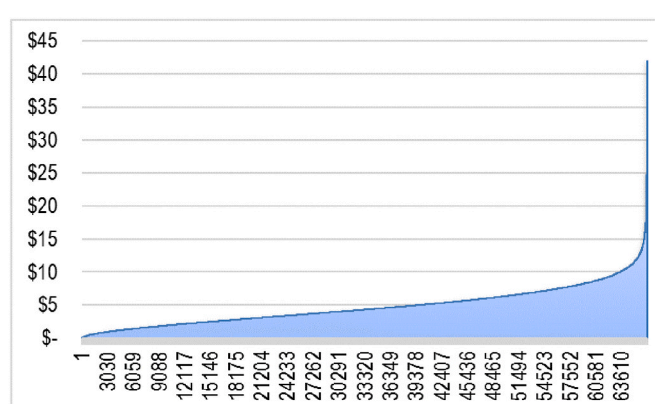

Fig. 4. Estimated yearly power gain in USD for 65,536 5 kW RPV systems (x-axis).

[7] The MCDA approach presented in this paper is based on a previous study described by the authors in Ref. [29].

and k is a parameter that determines the slope of the adoption curve.

We specify L = 1 to normalize the result of the logistic function as a probability. For the k parameter, we select a value that yields a PV market share of 2.5% at the end of the simulation in a scenario where the cost of PV stays constant through time. This market share is equivalent to the number of innovators in Rogers' innovation adoption curve [32], who by disposition are willing to adopt novel technology at a premium price.

$$n_{ij} = \frac{L}{1 + e^{-k*x}}, \tag{10}$$

The output of the logistic function in (10) is a probability that expresses cost-based propensity to PV adoption. At each simulation round, each household agent that has not adopted yet is presented with the opportunity of doing so. Adoption is set arbitrarily within regards to the output of the logistic function: an arbitrary probability pr might be generated, and in case the probability of adoption as estimated by the logistic function is over or even identical to pr, adoption comes up.

By running n simulation rounds, in addition to iterating every single round i times to smooth the impact of probabilistic adoption, we attain n*i adoption strategies, where every single solution could be represented, as shown in Table 2. For further details about this approach to the modeling of residential PV adoption, see Ref. [33].

3.1.2. Decision Model Creation-Bayesian Network (BN)

The dataset described in Table 2 is used as training material to derive a Bayesian Network (BN) (see Fig. 5) classifier that is capable of predicting the adoption decision of an agent ("YES" or "NO") according to a certain range of factor-value pairs, like those contained in Table 2. A BN represents a probability distribution.

$$p(\mathrm{U}) = \Pi_u \in \mathrm{U} p(u|parents(u)) \tag{11}$$

where U is the set of domain variables, and parents(u) denotes the parents of u. Within a BN approach to classification, the probability of a class variable C given a set of attribute variables X U is calculated as argmax_y p (C), where p (C X) = p(U)/p(X). The network structure of a BN and its parameters can be learned from a dataset such as the one described in Table 2 as detailed in Ref. [34].

Initially, a node does not have parents, and then parents are incrementally introduced to the node to take full advantage of the probability of the ensuing framework, before the probability of the ensuing network structure cannot be longer elevated with the inclusion of yet another parent. Once established structure of the BN, its parameters are learned using the empirical conditional frequencies from the data. The evaluation of the BN classifier trained from the data described in Table 3 using *precision, recall and F-Measure* [35] yields a high level of accuracy in the identification of PV *adopters* vs. *non-adopters*, as shown in Table 4.

3.1.3. Decision analysis & solution criteria assessment

As soon as the Bayesian network classifiers is created (Fig. 5) as part of the *Decision Model Creation component* from the datasets generated by means of ABM within the *Scenario Generation component*, the factors in the decision model are automatically ranked in the *Decision Analysis and Solution component* (Fig. 3).

These rankings assist the user in determining optimal value assignment alternatives to factors that can be used as user-driven input to the Bayesian net to generate decision-making choices as shown in Fig. 6.

Factor ranking is carried out by validating the probability parameters of the Bayesian network using sensitivity analysis [36], which evaluates the effect of small numerical changes of the probabilities related to factor nodes on output nodes. Extremely sensitive factor nodes impact output node much more drastically. Various methods for performing sensitivity analysis in Bayesian networks exists, as detailed in Refs. [36,37]. The present work assumes the approach described in Ref. [37].

Given a set of target nodes (e.g. ADOPTION CLASS), the sensitivity analysis algorithm calculates a complete set of derivatives of the posterior probability distributions over the target nodes for each of the numerical parameters of the Bayesian network (PV_{COST}, $\mathrm{ELECTRICITY}_{TARIFF}$, $\mathrm{ELECTRICITY}_{SUBSIDY}$, $\mathrm{GAS}_{SUBSIDY}$, $\mathrm{CARBON}_{T\ AX}$ and POWER_{GAIN}) (see Fig. 6).

These derivatives provide an indication of significance of accuracy of network numerical parameters for calculating the posterior probabilities of the goals. If the derivative is large for a parameter, then a small deviation in the parameter may lead to a large difference in the posteriors of the target node. If the derivative is small, consequently even significant deviations in the parameter produce little difference in the posteriors of the target node. See Ref. [37] for further details.

Fig. 7 shows a sample of sensitivity results for the Bayesian net described above, with reference to the impact of various factor-value pairs (e.g.PV_{COST}= *High/Medium/Low*, POWER GAIN = High/Medium/Low) on the target node (ADOPTION CLASS= Positive/Negative). In the present approach, sensitivity analysis is performed by changing the probabilities of all factor nodes by 10% and then observing how much change occurred in the probability the target node. For example, the probability of' ADOPTIONCLASS = Positive" left tornado graph in Fig. 7) goes from 0,443,792 to 0,459,527 when factor parameters are increased by 10%. Each factor can have a different impact on the output node in terms of strength (length of each bar in Fig. 4) and polarity (red bars indicate negative polarity, while green bars indicate positive polarity) (see Fig. 8).

For example, "PV_{COST} = *High*" is the strongest inversely correlated factor with positive PV adoption (left tornado graph in Fig. 7(a)) and directly correlated with negative PV adoption (left tornado graph in Fig. 7(a)). Analogous remarks apply to the remaining factor-value pairs in the two tornado graphs in Fig. 7. The user can now use the ranking provided through sensitivity analysis to compile diverse collections of optimal factor-values inputs for the Bayesian classifiers to receive as output the ensuing decision-making choices for each input, as shown in Table 5.

4. Comparative analysis and results

In this section, the MCDA approach developed in this study (henceforth *ABM-BN-SA*, short for Agent-Based-Modelling, Bayesian Net classification and Sensitivity Analysis) is compared with the MCDA treatments reviewed in section 2 (i.e. AHP, TOPSIS, SAW and ELECTREII) with reference to the contributing criteria and emphasis on criteria relevance weighting as described in Fig. 9. The degree of ranking overlap for criteria contributing to PV adoption across the different MDCA treatments is evaluated using diverse methods. The output data out of the simulation process described in section 3.1.1 are first used to rank MCDA criteria for Residential PV adoption (Fig. 9) with all MCDA treatments. Then, ABM-BN-SA rankings are compared against those obtained with TOPSIS, SAW, AHP and ELECTREII. The first comparison is based on Spearman rank-order correlation coefficient[8] and Kendall's coefficient concordance.[9] The second comparison uses Sensitivity analysis to measure the ranking overlap with alternative criteria settings. After comparing MCDA criteria, a comparison of the decision-making outcomes across the MCDA treatments under analysis is carried out. Finally, the capacity of each MCDA method to provide a model of correct decision-making for PV adoption is assessed.

[8] Spearman's rank correlation coefficient: A non-parametric measure of statistical dependence between two variables that assesses how well the relationship between two variables can be described using a monotonic function.

[9] Kendall's coefficient of concordance is a non-parametric statistic. It is a normalization of the statistic of the Friedman test, and may be employed for evaluating agreement among raters. Kendall W ranges out of 0 (no agreement) to 1 (complete agreement).

Table 2
Estimated Residential PV costs through 15 years.

Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PV Cost (¢/kWh)	11.68	10.22	8.76	7.3	5.84	5.61	5.37	5.14	4.91	4.67	4.44	4.2	3.97	3.74	3.5

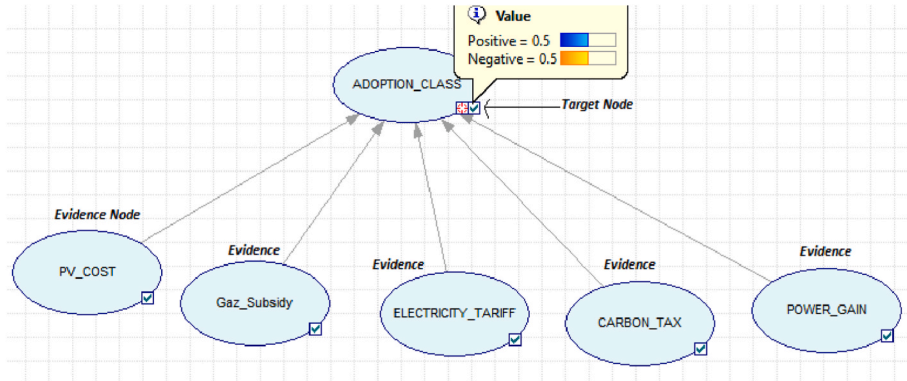

Fig. 5. Bayesian Network for the PV adoption decision-making scenarios with the GeNIe tool (Johansson Martenson, 2010).

Table 3
Sample data output from ABM simulation [33].

Year		Agent$_1$ values	Agent$_2$ values	..
Adopt Decision Variable	Adopt Class	Yes	No	…
Factor Variables	$^{PV}Cost$	4.44¢/kWh	5.84¢/kWh	…
	Electricity$_{Tariff}$	3.55¢/kWh	3.55¢/kWh	…
	Electricity$_{Subsidy}$	0.38¢/kWh	0.77¢/kWh	…
	$^{Gas}Subsidy$	0.21¢/kWh	0.42¢/kWh	…
	Carbon$_{Tax}$	0.040¢/kWh	0.005¢/kWh	…
	Power$_{Gain}$	0.036¢/kWh	0.011¢/kWh	…

Table 4
Evaluation results: C is the adoption class which can take two values (T = " True", F = " False") [33].

	TP Rate	FP Rate	Precision	Recall	F-Measure	C
Weighted Avg.	0.985	0	1	0.985	0.993	T
	1	0.015	0.953	1	0.976	F
	0.989	0.003	0.989	0.989	0.989	

4.1. TOPSIS, SAW, AHP and ELECTREII rankings

The computation procedure in ELECTRE II consist of three steps: (1) partition a set of variants; (2) build a complete pre- order, and (3) determine a full pre-order along with defining the partial pre-order.

For TOPSIS, the weighting vectors are computed by considering the distances to both the Positive and Negative Ideal Alternatives (PIA, NIA), in addition to a preference order that is ranked according to the relative closeness and a mix of these two distances measures. The best option in TOPSIS is the one that has the shortest distance from the PIA and the farthest distance to the NIA. The procedure used for SAW requires the normalization of the decision matrix to a scale similar to all current alternative ratings. AHP strategy incorporates a pair-wise comparison judgement of options on each criterion and a measurement of the logical rationality of pairwise comparisons (more details about each technique can be found in section 2).

4.2. Degree of criteria ranking overlap

The Spearman rank-order correlation coefficient r_s described in (12) was first used to quantify the correspondence between the ABM-BN-SA rankings with those obtained with SAW, TOPSIS, ELECTRE II and AHP MCDA. In (13), the value of r_s ranges from −1 to 1, d^2 is the sum of the squared differences between the pairs of ranks, and n is the number of comparison pairs.

Fig. 10 displays the degree of overlap of rankings between *ABM-BN-SA* and SAW, TOPSIS, ELECTRE II and AHP in terms of the r_s coefficient. TOPSIS shows the closest fit with *ABM-BN-SA* (r_s = 0.83), as expected since it used a ranking approach considerably closer to *ABM-BN-SA* as compared to the other MCDA treatments. ELECTREII yields the lowest

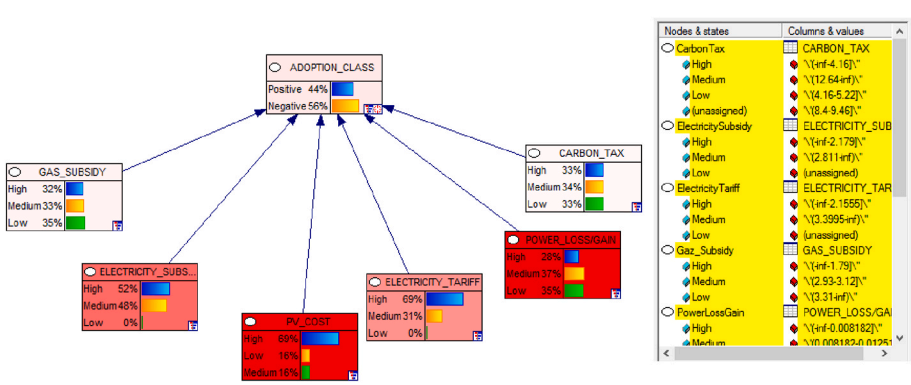

Fig. 6. Sensitivity Analysis conducted using the created BN: Bayesian Network with the order of preference of criteria influencing the PV adoption decision-making problem, Target nodes influencing the PV adoption decision-making.

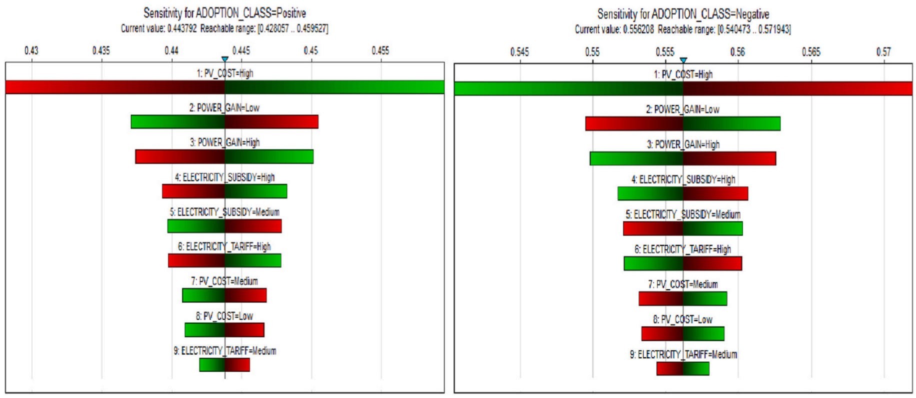

Fig. 7. Sensitivity Analysis conducted using the created BN-Tornado diagram of diverse criteria influencing Residential PV adoption decision-making.

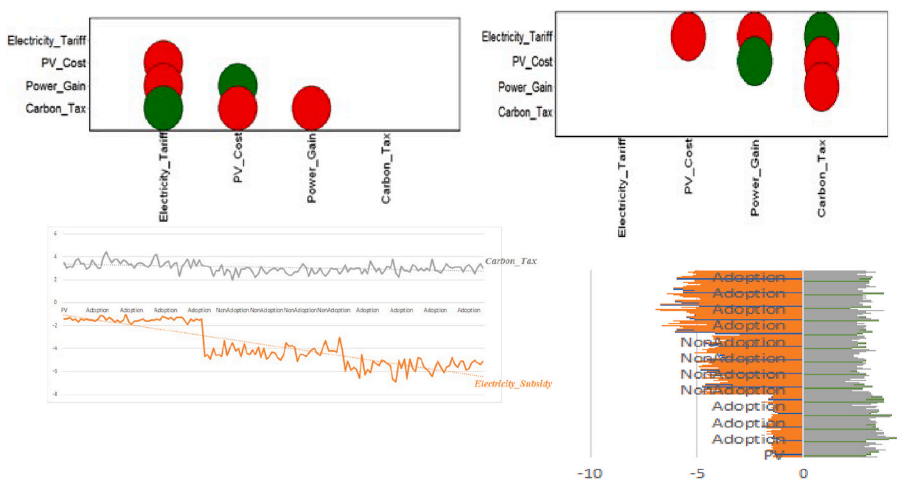

Fig. 8. Sensitivity Analysis conducted using the created BN-Correlation between diverse criteria influencing the PV adoption decision-making.

Table 5
Input/output sample for classifier model.

Factor	$Input_1$	$Input_2$
PV_COST	4.44¢/kWh	5.84¢/kWh
ELECTRICITY_TARIFF	3.55¢/kWh	3.55¢/kWh
ELECTRICTY_SUBSIDY	0.38¢/kWh	0.77¢/kWh
GAS_ SUBSIDY	0.21¢/kWh	0.42¢/kWh
CARBON_TAX	0.040¢/kWh	0.005¢/kWh
POWER_GAIN	0.036¢/kWh	0.011¢/kWh

→

ADOPTION_CLASS	
Output 1	Output 2
yes	no

degree of ranking overlap with *ABM-BN-SA* ($r_s = 0.33$).

$$r_s = 1 - \frac{6\sum d^2}{n(n^2-1)} \tag{12}$$

In the second comparison, the degree of criteria ranking overlap across all MCDA treatments was evaluated using Kendall's coefficient of concordance. As shown in Table 5, TOPSIS, SAW and *ABM-BN-SA* display the highest concordance (0.762–0.583). TOPSIS yields the highest concordance with *ABM-BN-SA* (0.762), closely followed by SAW (0.673). AHP has a lower degree of concordance with all other methods than TOPSIS, SAW and *ABM-BN-SA* (0.290–0.201). This may be due to AHP's "Decision Maker" strategy according to which criteria ranking is performed through pairwise criteria comparisons. One of the primary concerns of this strategy regards the degree of consistency required to generate efficient results. When the strategy is not consistent enough, resulting scores and weights values become questionable. ELECTREEII is the least correlated method to all others in terms of concordance.

The criteria ranking overlap results discussed in this section (Fig. 10 and Table 5) indicate that ranking order may differ considerably across MCDA strategies.

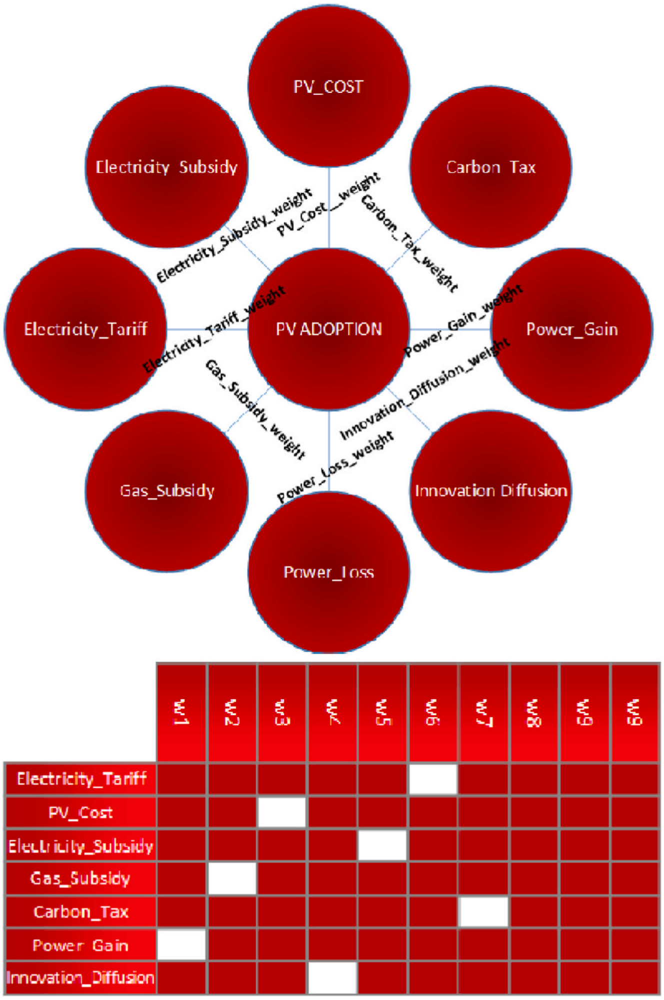

Fig. 9. MCDA criteria in Residential PV adoption.

4.3. Ranking disagreement through sensitivity analysis

The stability of the rankings produced by the five MCDA treatments under analysis was assessed through sensitivity analysis. The six criteria in Table 6 and the two target decision alternatives (adoption vs. no adoption) served as the parameters of this analysis. The six criteria were associated with weighting vectors from the simulation data described in section 3.1.1 (Table 7).

In the first sensitivity analysis test Experiment$_1$, the six criteria were assigned the same weight. In the second test, Experiment$_2$ the criteria weights were changed by using the mean of weights from the simulated dataset. In the next two tests, all weights were first set to the same value (0.1) and the weight for Electricity$_{Tariff}$ and PV$_{Cost}$ were reduced by 50% in Experiment$_3$ and Experiment$_4$ respectively. The rest of rest of criteria were considered as equally important. Table 7 summarizes all the experimental scenarios used in the sensitivity analysis evaluation.

Notes:

- $c_{i\ (0<i<7)}-$ PV$_{\text{Cost}}$, Electricity$_{\text{Tariff}}$, Carbon$_{\text{Tax}}$, Gas$_{\text{Subsidy}}$, Electricity$_{\text{Subsidy}}$, Power$_{\text{Gain}}$
- E_1- Same weight: all criteria are equally important for all MCDA methods.
- E_2- Average weight: the weights of the criteria were obtained from the dataset.
- E_3- "Electricity$_{\text{Tariff}}$" reduced by 50%.
- E_4- "PV_Cost" reduced by 50%.
- The asterisk character (*) indicates that scores are equal in the same experiment across all 200 iterations.

Fig. 11 provides a sampling of the criteria rankings for the MDCA treatments under analysis in the four experiments scenarios described in Table 6. This sampling was obtained by performing the sensitivity analysis within a numerical ranking system from 1 (*top rank*) to 7 (*lowest possible rank*) over 200 iterations and taking the average of all iterations as the final result.

The sensitivity analysis indicates that there is a fair amount of similarity across the five MCDA methods in all experimental scenarios. For example, the first three criteria (Electricity$_{Tariff}$, Carbon$_{Tax}$ and PV$_{Cost}$) consistently show higher ranking across MCDA methods and scenarios, while the last three criteria (Gas$_{Subsidy}$, Electricity$_{Subsidy}$, Power$_{Gain}$) are associated with lower rankings. This distribution corroborates *ABM-BN-SA* results.

4.4. Overlap in decision making outcomes

Overlap in the decision to adopt or not across the five MCDA methods was computed by averaging alternatives adoption rates for each MCDA technique across the 200 iterations (see Fig. 12). Not all iterations yielded an adoption decision results. The results in Fig. 13 show that there is agreement in that all MCDA methods have higher adoption than non-adoption.

As observed in the analysis of the degree of criteria ranking overlap (4.2), *ABM-BN-SA* and TOPSIS show the highest overlap with reference to adoption. As compared to the other MCDA methods, *ABM-BN-SA* displays the lowest "*no adoption*" rate, and is in the mid-range with

Table 6
Degree of criteria ranking overlap with Kendallâs coefficient of concordance.

	SAW	TOPSIS	AHP	ELECTREEII	ABM-BN-SA
SAW	1.000				
TOPSIS	0.583	1.000			
AHP	0.290	0.275	1.000		
ELECTREEII	−0.086	0.112	0.210	1.000	
ABM-BN-SA	0.673	0.762	0.201	−0.095	1.000

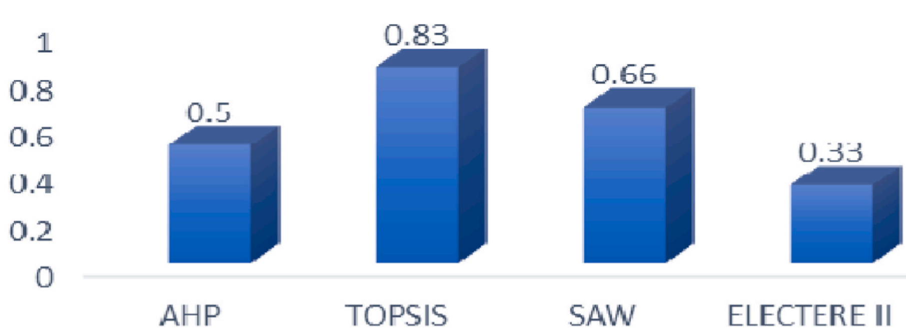

Fig. 10. Average r_s correlation between the ABM-BN-SA rankings with the rankings calculated by the SAW TOPSIS, ELECTRE II and AHP MCDA methods.

Table 7
Obtained criteria weights.

Criteria Experiment	Experiment$_1$	Experiment$_2$	Experiment$_3$	Experiment$_4$
	Weight 0 < i < 7	Weight 0 < i < 7	Weight 0 < i < 7	Weight 0 < i < 7
PV_Cost	0.142857142857	0.331	0.1	0.5
Electricity_Tariff	0.142857142857	0.25	0.5	0.1
Carbon_Tax	0.142857142857	0.31	0.1	0.1
Gas_Subsidy	0.142857142857	0.038	0.1	0.1
Electricity_Subsidy	0.142857142857	0.016	0.1	0.1
Power_Gain	0.142857142857	0.055	0.1	0.1
Sum ($\sum$)	1.0	1.0	1.0	1.0

c_i	*SAW*				*ELECTRE 2*				*AHP*				*TOPSIS*				*ABM-BN-SA*			
	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4
c_1	1	1	3	1	1*	1*	3	1	2	1	3	1	1	1	1*	1	1	1	1	1
c_2	2	2	1	2	1	2	2	2	2	2	1	2	2	2	1	2	2	2	2	1
c_3	3	1*	2	3	2	2	2	1	3	3	2	3	3	3	3	3	3	3	3	2
c_4	3	4*	4	5	3*	4	3	4	4	4	4	4	6	6	6	6	6	6	6	5
c_5	3	5	5	3	5*	4*	3*	3	5	5	5*	4*	4	5	5	5	4	5	5	4
c_6	5	6	5*	5	5*	4	5	5	6	6	5*	6	5	4	4	4	5	4	4	6

Fig. 11. Criteria ranking for the four experiments (E_1,…,E_4) calculated as the average weight for each of the six criteria in Table 6 (c_1, …,c_6) by MCDA technique over 200 iterations.

ELECTRICITY_TARIFF	PV_COST	ELECTRICITY_SUBSIDY	GAS_SUBSIDY	POWER_LOSS/GAIN	CARBON_TAX	Pr	ADOPTION_CLASS
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(6.772-7.59]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.574-0.645	TRUE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.503-0.574	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(10.044-10.862]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.787-0.858	TRUE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.432-0.503	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.432-0.503	FALSE
"\(-inf-2.1555]\"	"\(8.408-9.226]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.645-0.716	TRUE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(4.318-5.136]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(6.772-7.59]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.574-0.645	TRUE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.361-0.432	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(-inf-4.318]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(-inf-0.361]\"	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.503-0.574	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.432-0.503	FALSE
"\(-inf-2.1555]\"	"\(5.136-5.954]\"	"\(2.811-inf)\"	"\(2.93-3.12]\"	"\(0.042815-inf)\"	"\(12.64-inf)\"	"\(0.432-0.503	FALSE

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Fig. 12. Sample of training data for Bayesian net classifier. Feature values have been discretized.

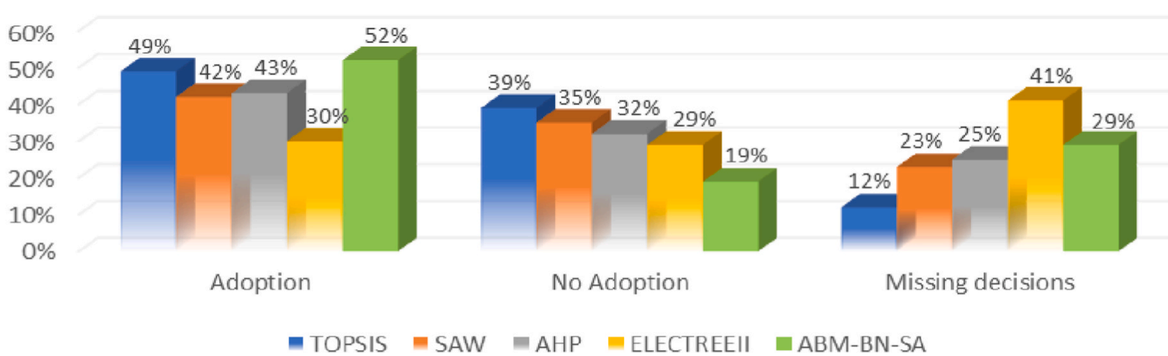

Fig. 13. Adoption decision rates across MDCA methods.

Table 8
Accuracy in the identification of adoption decisions across MDCA methods.

Alternative	TOPSIS	SAW	AHP	ELECTRE	ABM-BN-SA
Adoption	81.67%	79.43%	47.02%	32.89%	89.14%
No Adoption	18.33%	20.57%	52.98%	67.11%	10.86%

reference to missing decisions, where TOPSIS shows the lowest rates, and ELECTREII the highest.

4.5. Accuracy

The final test aimed at evaluating the capacity of each MCDA method to provide a model of correct decision-making for PV adoption. To do so, a training dataset was created for each MCDA method where each row contains a sequence of values for the six relevant adoption criteria (Table 8) and the associated adoption decision, as shown in Fig. 13.

A Bayesian net classifier was then used to predict adoption class as a function of the associated criterion values. The classifier was trained on 65% of the training data and tested on the remaining 35% using the accuracy metric shown in (13). As shown in Table 8, *ABM-BN-SA*, SAW and TOPSIS are the top-performing methods, with *ABM-BN-SA* showing a clear lead (89.14% vs 81.67 and 79.43%). AHP and ELECTRE display significantly lower accuracy.

$$\text{Accuracy} = \frac{|True\ Positives(TP) + TrueNegatives(TN)|}{|TP + TN + FP + FN|} \tag{13}$$

5. Discussion

As discussed in Section 4, the ABM-BN-SA approach developed in this study was evaluated alongside four popular MCDA methods (AHP, TOPSIS, SAW and ELECTREII) with reference to overlap in criteria ranking and decision making, and the capacity to provide a model of correct decision-making for PV adoption.

First, Spearman's correlation and Kendall's concordance were used to assess the overlap in criteria weighting and ranking. The Spearman and Kendall coefficients show that ABM-BN-SA is strongly correlated with TOPSIS and SAW, has a mild correlation with AHP, and exhibits the least overlap with ELECTRE II. Then, the covariation of criteria rankings in alternative scenarios is assessed across the five MCDA methods through sensitivity analysis. The sensitivity analysis indicates that the five MCDA methods exhibit similar criterion-ranking responses to changing criteria weightings in diverse experimental scenarios.

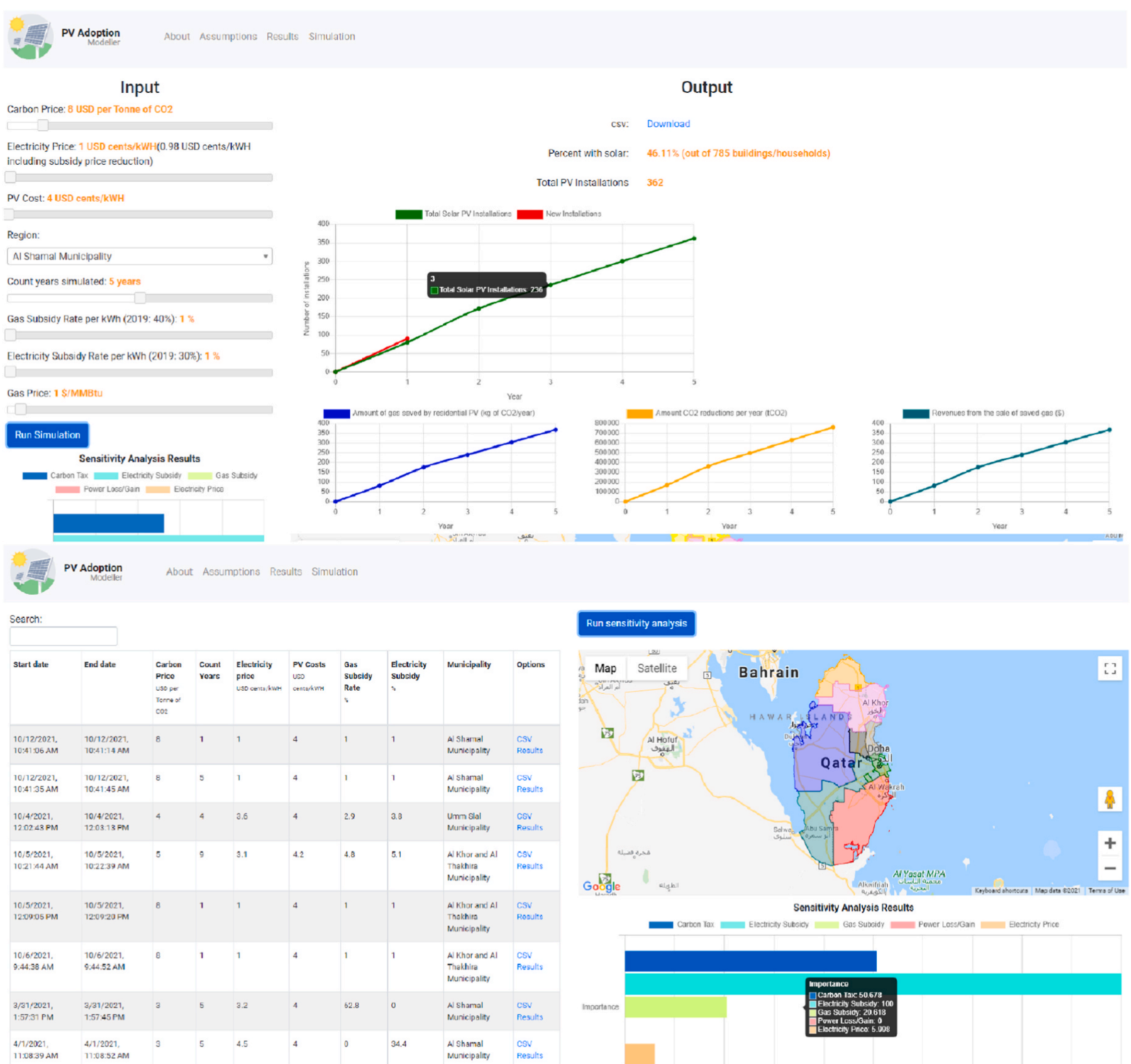

Fig. 14. Snapshots of the developed residential solar PV decision-support platform. The Online Platform for PV adoption connecting all implemented components: Database, Agent-based Model, Bayesian network and the sensitivity analysis component.

Next, the overlap in decision-making is computed across the five MCDA methods by comparing rates of adoption decisions across the five MCDA techniques. ABM-BN-SA shows the highest overlap with TOPSIS on the decision to adopt, displays the lowest "no adoption" rate, and is in the mid-range with reference to missing decisions, where TOPSIS shows the lowest rates, and ELECTREII the highest.

The final test evaluates the capacity of each MCDA method to provide a model of correct decision-making for PV adoption.

Results show that ABM-BN-SA, SAW and TOPSIS are the top-performing methods, with ABM-BN-SA showing a clear lead. Overall, the results of this comparative evaluation show that ABM-BN-SA is well correlated with the other MCDA methods and provides the best performing model of decision-making, with reference to the PV adoption use case under analysis.

6. Conclusion

The study presented in this paper focuses on the development of a novel MCDA method, using decision-making in residential solar PV adoption as use case. The novel MCDA method, ABM-BN-SA, combines multi-agent simulation to enable automated scenario generation, Bayesian modeling to assign weights to criteria, and sensitivity analysis to validate the relative impact of criteria.

The application of *ABM-BN-SA* to the use case exemplifies how a dataset of residential PV adoption scenarios generated through multi-agent simulation can be harnessed to derive a probabilistic belief network where PV adoption criteria are automatically weighted and ranked. The ensuing rankings are then evaluated through sensitivity analysis to verify their covariation in alternative scenarios. This application of sensitivity analysis enables the user to interact dynamically with criteria ranking by altering criteria weights to explore alternative scenarios in" *what-if"* games.

The comparative evaluation with AHP, TOPSIS, SAW and ELECTREII shows that overall *ABM-BN-SA* is well correlated with most of other MCDA methods and provides the best performing model of decision-making, with reference to the PV adoption use case under analysis.

The proposed method and its associated data and analytics components are made available as web application based on a Software as a Service (SAAS integration platform that provides data integration, predictive modeling, data analytics and visualization as services, and enables cloud and high performance computing.

The high-level graphical user interface (GUI) has been implemented as a web browser (see Fig. 14) provides a flexible way of interacting with the front-end part of the app and the back-end app. The user will be able to pose a range of queries from very simple (such as a simple value of the electricity subsidy for example) to complex (such as the results of one or more models) that take input from the analysis of data collection over a long period of time.

The developed application provides a decision support system to study and analyze which is the best combination of incentives and regulations to promote the adoption of solar energy systems by residents, businesses and utility companies in Qatar and identify the investments necessary to maintain the reliability and stability of the electricity system.

The ensuing decision-making methodology can be applied not only by Solar PV panel purchasers but also by stakeholders in other industries to logically and straightforwardly model and analyze the acceptance decision-process of the consumers based on their individual preferences, behavioral rules, and interaction within a social network, with specific reference to a consumer utility function.

The system is based on a modular approach that can be used to characterize residential solar Photovoltaic (PV) adoption in other GCC countries and worldwide through the reconfiguration of model parameters and model input data. The ensuing platform provides a computer implementation of the techno-economic analysis framework that together with the insights developed by the green energy roadmap and regulatory framework provides an evaluation of alternative green energy strategies. Future work will be devoted to the improvement of MCDA through the development of a hybrid method that combines the best aspects of each of the MCDA methods reviewed in this study.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Antonio Sanfilippo reports financial support was provided by Qatar National Research Fund. Dr. Ameni Boumaiza reports a relationship with Qatar Environment and Energy Research Institute that includes: employment.

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