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Constructing a Decision Tree for Energy Policy Domain Based on Real-Life Data

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Abstract: This manuscript aims to construct a decision support tool for the energy policymakers and energy providers to facilitate an analytical decision-making framework where the key drivers, motivators, and barriers are accounted for. The decision support system is designed in the format of a decision tree algorithm, integrating information about the key drivers, motivators, and barriers derived from the results of the ECHOES project and input from decision-makers based on their perceptions regarding the relevance, importance, potential impact, and probability of occurrence for each parameter, in each phase of the process. The input relies on the analysis of 67 in-depth interviews, 15 focus groups, and 12 case studies conducted in seven countries in the energy policy domain. It is exploited to construct patterns, rules, and scenarios as inputs to the decision tree algorithm. The algorithm can be utilized for evaluating the likelihood of success for a particular process or endeavour, conducting scenario analysis concerning various projections of the system under consideration, deciding which projects to prioritize, which schemes to select for implementation, or how to improve the risk management, and assessing the return on the efforts or investments to improve particular key drivers or motivators and alleviate particular barriers. The proposed algorithm also contributes to the alleviation of challenges associated with the exploitation of qualitative data for energy-related decision-making.

Keywords: decision tree; decision support system; policy-making

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1. Introduction

Energy policy-making has long been a high-priority item on the agenda of many countries. The policymakers need to decide on the energy portfolio, select the appropriate technologies to utilize and plan the supply and manage the demand on the country and regional levels. Accordingly, energy-related decision-making has also been a popular research topic, including subtopics such as selecting the energy portfolio, incorporating new technologies into the energy system, planning for energy supply, evaluating alternative energy sources, and policy-making in general [1]. Energy policy-making is not only bound to country-level frameworks. Policies derived through international agreements are adapted as national or regional level policies. These also impact energy policy-making on the local level. The comprehensive strategic policy package of the European Union (EU), for instance, involves a framework based on commitments regarding climate and environmental goals. Highlights of these EU policies involve targets for 2030 towards a 40% reduction in carbon emissions, achieving a share of 32% for energy supplied from renewables, 32% increase in energy efficiency [2], and increase in the share of cross-border interconnections to 15% of the installed capacity [3].

Although policy-making is in the domain of formal social units that act as policymakers and energy providers, which have more power and authority to impact energy-related decisions, policymakers need to target energy behaviours and relevant outcomes. More often than most policymaking spheres, energy-related behaviours and their outcomes are realized outside of the control of the central governments. Regarding the case of demand management, for instance, even though the governments may develop policies towards demand management as an integral part of energy supply planning, utility companies, local communities, and consumers are more likely to influence the extent to which the associated policy targets are achieved [4]. Hence, enhancing the real-life effects of energy policies requires a more explicit consideration of the energy systems, stakeholders, and key drivers of energy-related endeavours. In this sense, the concepts of consumer behaviour, socioeconomic and socio-technical factors, and innovative approaches should be prioritized over political considerations [5,6].

The impacts of policies on the social, economic, and cultural domains also need to be considered. Taxing schemes or regulations on greenhouse gas emissions, for example, contribute to achieving environmental and sustainability goals, but on the other hand, may hinder the adoption of new technologies, bring about economic burdens to households and companies, or provoke a perception of unfair treatment of different segments of the society, e.g., those who can benefit from incentives versus those who cannot [7–11]. Given this trade-off between a myriad of factors pertaining to a spectrum of economic to environmental factors, a systematic assessment of these factors and their impacts along with the design, implementation, and monitoring phases of policy-making becomes more important. The policy implementation is further impeded by failing to properly address these interdisciplinary aspects [12,13].

Although qualitative data have been more widely utilized to reveal insights in energy research, few studies in the literature focus on utilizing qualitative data from stakeholders in energy policy-making [14]. Such an approach would contribute to energy and climate policies by incorporating the behavioural, social, and cultural factors [15]. One promising advancement in this respect is the EU's Joint Research Centre (JRC) mission statement, which involves providing evidence-based support for EU policies.

On the other hand, qualitative evidence is exploited mainly through a theoretical discussion of the energy policies [16–18]. In addition, several studies perform quantitative assessments of policies regarding wind power [18], renewable energy policies [19–21], and the impacts of non-governmental organizations, the political environment, and the consumers' perceptions on the effectiveness of energy policies [22].

The endeavours undertaken within the context of energy transition further increase the extent and significance of relevant policy-making, bringing in restructuring and redefinition of energy systems for decreasing greenhouse gas emissions, improving the energy security of countries, securing the affordable supply of energy, and achieving a common interconnected energy market among other objectives of energy transition [23]. Although the underlying motive is not likely to be so, such policies designed to support energy transition imply significant changes to the processes regarding sourcing, distribution, and consumption of energy and, hence, to how the energy system stakeholders design, implement, and control their processes [24,25].

To this end, the objective of this manuscript is to construct a decision tree that will be utilized as a decision support tool for energy-related policy-making. The decision tree algorithm presented in this manuscript aims to provide an operational tool in an attempt to contribute to the alleviation of challenges associated with the exploitation of qualitative data for energy-related decision-making. Towards these objectives, the decision-tree algorithm is utilized for evaluating the potential for success concerning cases or endeavours associated with energy transition. Although the intended potential users are the policymakers and energy providers (i.e., the formal social units), decision-makers at various levels can use the algorithm. The decision tree algorithm utilizes the results of the ECHOES project [26–28]. The input data for constructing the algorithm are derived from the qualitative inquiry that concentrates on three focal areas of the ECHOES project. These are smart energy systems, e-mobility, and buildings. These pillars of the energy transition enhance a comprehensive coverage for the constituents of policy-relevant decisions. The qualitative inquiry identified the main drivers of the energy systems, including barriers, motivators, key factors, best practice, and successful implementation. This information is further exploited to construct the patterns, rules, and scenarios as inputs to the construction of the decision tree algorithm to be utilized as a decision support tool for energy policy-making. Identifying the main drivers of the energy-related decision-making process for policy-making also reveals significant aspects of successful implementation as emerging themes. These main drivers are associated with internal decision-making frameworks, including top-down mechanisms in the decision-making process, bottom-up mechanisms, relevant formal constructs, and policy-making and governance frameworks. As they might fit well into the formal description of the associated decision-making process, these drivers sometimes conflict with and hence augment and redefine the presumed decision-making process, mostly through the analysis of the various case studies.

The rest of the manuscript is organized as follows: In Section 2, a review of the relevant literature is presented. Section 3 describes the methodology utilized for the construction of the decision tree algorithm. Section 4 provides the details of the decision tree structure and the computations of the decision tree. Section 5 provides concluding remarks and suggestions for future work.

2. Literature Review

Decision trees are represented and processed as root nodes and branches of the tree. Within this representation, every branch of the tree emanates from a leaf node and corresponds to a subset of characteristics, patterns, or decisions pertaining to the system under consideration. The terminal node of the decision tree stands for the final decision or classification for the system [29].

In order to quantitatively assess the outcomes of the characteristics or patterns in a classification, probabilities or weights can be incorporated in the construction of the decision tree [30–33]. Furthermore, if the variables used for classification in the decision tree are continuous, an optimal threshold value can be identified for classification [29].

Decision tree algorithms are instances of learning algorithms. Such algorithms exploit the existing information base about the system under consideration to identify rules or patterns concerning the system. These rules and patterns are then used to make estimates or assessments, which, in turn, aid decision-making [34–36]. Thus, it can be argued that learning algorithms analyse available information on examples and learn from them to structure rules. Then, these rules can be evaluated to estimate the outcomes for scenarios or similar circumstances that may arise in the future. Learning algorithms are also employed in the contemporary implementations of artificial intelligence (AI) to fine-tune the model parameters for the AI algorithm to mimic the real system behaviour as close as possible.

Since by construct learning algorithms derive conclusions about a system utilizing existing information, the performance of a learning algorithm is very much dependent on the available data and their properties. In this sense, two significant metrics are the availability of data representing an extensive range of possible inputs and the ability of these inputs to involve a comprehensive scope of the system response in terms of possible outputs. Given the inputs, the design quality of the learning algorithm is a key determinant in how well the model simulates the system's behaviour under consideration, reflecting the impacts of users/stakeholders. Decision tree algorithms model the system behaviour using real system data on inputs and outputs for training and identifying decision rules to predict the categories of outputs [37–39]. One other distinctive feature of decision tree algorithms is that they can be designed as supervised learning algorithms. That is, decision tree algorithms can be utilized to make assessments about systems in the presence of uncertainty. These assessments can be in terms of regressions [40–46].

Analysis of the earlier research reveals that decision tree algorithms have been utilized in various areas of energy systems. For instance, Nie et al. [47] utilize decision tree methodology in order to forecast the electricity consumption of buildings. The methodology is also used for simulating the electricity consumption. Similarly, Ramos et al. [48] utilize decision trees to compare the two most feasible algorithms, one based on machine learning and the other based on neighbourhood search, to forecast the energy consumption of a building. Moutis et al. [49] use decision trees for optimizing and balancing community microgrids. Hou et al. [50] consider the planning problem of microgrids and propose a decision tree algorithm for optimizing the dispatch rule for microgrids. Saleh and Ayad [51] utilize decision trees to identify internal and external fault zones in microgrids, based on component measurements. Barbier et al. [52] consider a hybrid system that is optimized through the use of decision tree algorithms. Shaik et al. [53] present a three-stage algorithm for an energy distribution system that relies on renewable energy. The decision tree methodology is implemented for the classification phase of the algorithm. Salman Saeed et al. [44] use a decision tree-based model that assists distribution system operators (DSOs) in determining categories for customers and assessing the likelihood of a customer to practice fraud in their electricity bill. The model uses the customers' consumption information, including seasonal differences in consumption, comparisons against threshold consumption values, and consumption variability. Namazkhan et al. [29] developed a decision tree model to determine the factors affecting residential gas demand in the Netherlands. Out of the four factors considered, building-related, socio-demographic, and psychological parameters are demonstrated to be effective determinants of household gas consumption.

Jiale [54] presents decision tree-based energy systems planning. The proposed methodology involves using probabilities for ranking the variables of the energy system under consideration and improving the reliability, efficiency, and accuracy of the model. Another decision tree-based study seeks to identify the sustainability patterns and characteristics of a group of coal cities in China, whose energy portfolio and economies are dominated by coal and its side industries [55]. The study develops an indicator for representing and measuring coal cities' sustainability and identifying the impacts of the resource curse and resource blessing on these cities. The authors also point out the strength of decision tree analysis over other data mining approaches in terms of their ability to identify new sustainability characteristics and sustainability patterns. Lei et al. [56] consider regional energy systems which involve significant uncertainties regarding loads and prices and construct a multi-stage scenario-based decision tree algorithm for such systems. Bugaje et al. [57] employ decision trees in dynamically determining how secure the responses of power systems are to internal and external disturbances.

Tomczak et al. [58] utilize decision trees to compare the financial performances of companies operating in the photovoltaic (PV) industry against companies that are not in the PV industry. In doing so, the study utilizes decision tree methodology and questions whether PV sector companies can be identified using the developed indicators and ratios. In addition, the article tests the predictive power of the decision tree algorithm in identifying which of the two classes a particular company belongs to, through financial indicators and patterns. Ganti et al. [59] designs a hybrid algorithm which is a combination of a decision tree algorithm and sparrow search algorithm in order to optimize the efficiency of photovoltaic systems.

3. Methodology

This manuscript follows decision tree methodology to construct a decision-support tool for evaluating the potential for success concerning cases or endeavours associated with the energy transition. Decision trees utilize past data from the observations of a system to address classification problems or make predictions about the system, mimicking human decisions based on rules derived from past data.

Decision tree algorithms exploit the tree structure to provide analytical insights into a system and make predictions regarding the outcomes of the system, using evidence from the past modes of the system [60,61]. The tree structure allows for the simpler representation of complex systems, where the required computations can also be performed more easily by dividing the overall analytical effort to the internal nodes of the tree and integrating them in the terminal nodes.

The decision tree algorithm starts with the root node corresponding to all possible system states. Information to specify system characteristics is added through the internal nodes. As the internal nodes are accessed, the values or outcomes of associated characteristics or attributes are incorporated via partial information provided at each node. Values at each internal node may come from a discrete set of choices or a continuous set, an interval [62,63]. At the terminal nodes, a final value or a decision is reached. That is, the root nodes of the decision tree represent the generic system without any specific characteristics, the internal nodes represent the components of the system, phases of an operation, or steps of a process, and the terminal nodes correspond to a full specification of the system characteristics or a scenario. Hence, a path starting from the root node reaching a terminal node involves all possible parameters, according to a certain scenario. Evaluation of particular scenarios at the terminal (leaf) nodes demonstrates the system's potential outcomes (i.e., predictions) [60,61]. Figure 1 provides a representation of a generic decision tree algorithm.

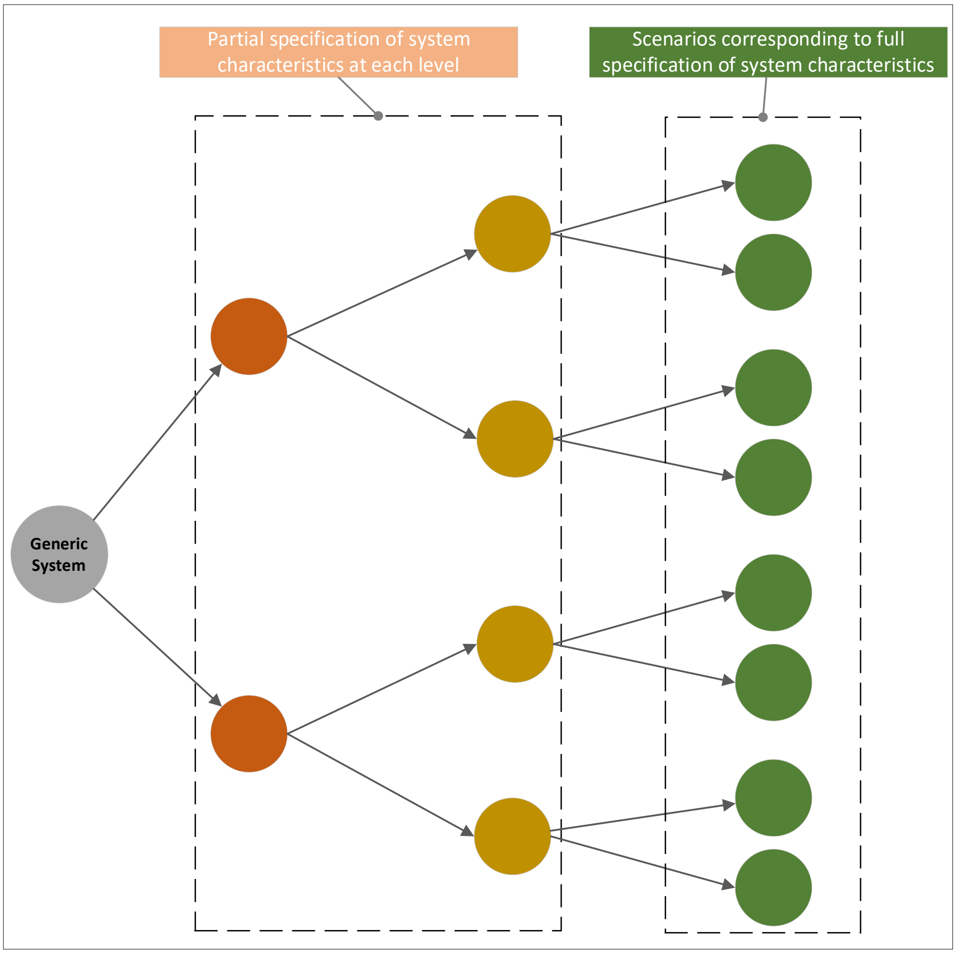

Figure 1. Generic decision tree representation.

The developed decision tree algorithm demonstrates the potential for success of the scenarios concerning the energy transition processes, utilizing the information concerning the key parameters, motivators, and barriers pertaining to the formal social units. The tree's root node corresponds to a generic case pertaining to the energy transition. When different factors can potentially trigger the same type of case, multiple root nodes are included to account for these different triggers. The parameters selected at each internal node correspond to the case's phase under consideration. The level of utility or disutility for each internal node is computed using the input from the user concerning the weights (levels of importance) and impacts of the motivators, barriers, and key factors at that phase of the case in terms of the success of the whole endeavour.

For each motivator, barrier, and key factor under consideration, the user is asked to specify the most suitable weight, impact, and probability of occurrence values among the possible alternatives presented. In order to achieve a high resolution for the results and the conclusions derived from the decision tree algorithm, five possible values for the weights of the values, five possible values for the impacts, and ten possible values for the probabilities of occurrence are defined. Hence, for each parameter, the decision tree algorithm constructed in this study presents a sufficiently large number of alternatives for an accurate assessment of the contribution of the particular parameter to the outcome of the case. The reason for using a discrete metric for the continuous variable probability is to ease the user process, where the user is likely to feel more comfortable selecting a value from among ten possible alternatives as opposed to setting a value from an infinite set within the interval [0, 1].

This research was undertaken as a part of Horizon 2020-funded ECHOES project's Work Package 6, coordinated by MEB (the lead author), and MHD (author) also contributed to D6.5. The decision tree algorithm presented in this manuscript uses the outputs of the H2020 ECHOES project [26–28], which identifies the processes, along with the associated variables, parameters, and key factors pertaining to the energy behaviours of different decision-making levels, including individuals, collectives, and formal social units. The roadmap for defining the decision-making process for different types of decision-makers and identifying the motivators, barriers, and key factors involved focus group studies, in-depth interviews implemented in Austria, Bulgaria, Finland, Norway, Spain, and Turkey, and case studies implemented in Austria, Bulgaria, Finland, Germany, Italy, Norway, Spain, and Turkey. In this context, a total of 15 focus groups, 67 in-depth interviews, and 12 case studies were conducted. The methodology for analysing the data from the in-depth interviews and focus groups was based on the framework provided by Kvale [64] and Corbin and Strauss [65]. The corpus text amounting to more than 1000 pages was coded by the authors to identify the key emergent themes. This analysis was performed through the steps of open coding, axial coding, and selective coding. The output of this process was the identification of the key drivers, motivators, and barriers derived from experiences associated with low carbon energy transition in Europe. Finally, the resulting emerging themes were compared and complemented with the themes obtained from a review of the existing literature. For detailed information on the analysis of the in-depth interviews and focus groups, please see: Biresselioglu et al. [66]).

Hence, for the construction of the decision tree, data from the literature review, in-depth interviews, and focus groups were utilized to establish the process mapping and identify the motivators, barriers, and key factors. The initial decision tree structure was extended and modified by analysing the cases representing best practice and successful implementation. This analysis also revealed the triggers specific to different processes and how the process components and key factors are interrelated, and whether this interrelation is positive or negative. Hence, the analysis of the cases enhanced the incorporation of field data in the decision tree design, with a better mapping of the energy-related processes and implementations. The extensive size of the sample for this study contributes to the predictive capability of the decision tree algorithm.

A two-stage methodological approach was employed to construct the decision tree algorithm. The first stage involved identifying process steps and the key factors relevant to energy-related decision-making. Then, based on the infrastructure constructed in the first stage, the second stage of the methodological framework identified the associated motivators and barriers and mapped them on the constructed infrastructure, utilizing the field data from case studies.

4. Decision Tree Algorithm

4.1. Structure of the Decision Tree

The structure of the decision tree algorithm is based on the classical perspective of the decision process mapping that involves the phases of problem identification, alternative selection, planning, implementation, and monitoring [67]. These phases are extended to incorporate an auxiliary leaf node that functions to compute the final utility (likelihood of success) score for the case or endeavour under consideration. Figure 2 below demonstrates the principal nodes of the decision tree with the augmented process mapping.

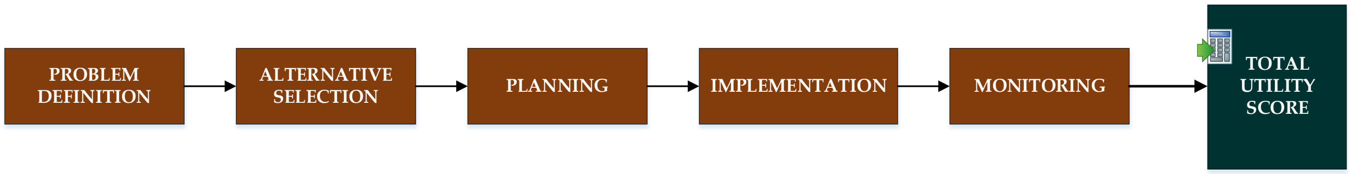

Figure 2. Augmented process mapping.

The construction of the decision tree is further extended to include two root nodes that correspond to the triggers of the process. For formal decision-making units, the triggers are "Signal from metrics", "External signal", "Problem-driven", and "Goal-driven", which mark the subsequent processes accordingly [28]. Furthermore, these root nodes are positioned adjacent to the initial root node "Problem Identification", making it an internal node of the extended tree. Figure 3 demonstrates the triggers for the decision-making process.

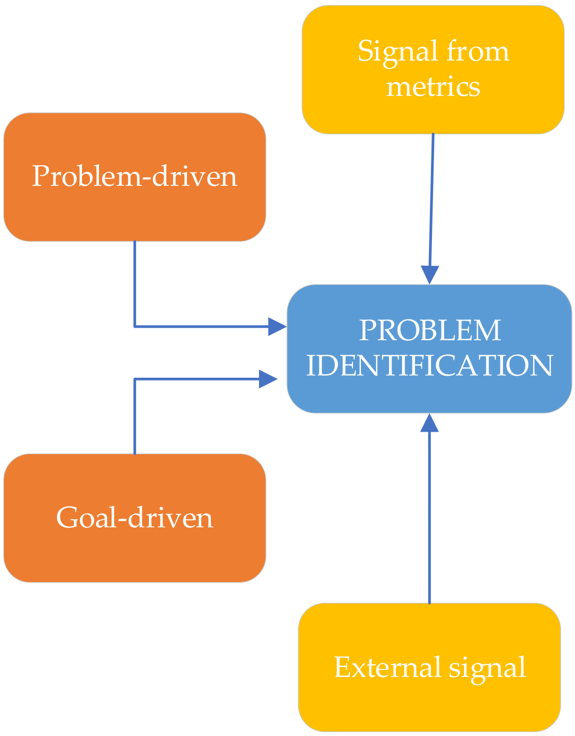

Figure 3. Triggers for the process (source: Biresselioglu et al. [28]).

The next step in constructing the decision tree is the inclusion of key drivers as terminal nodes. Each such node representing a key factor is connected to the node representing the process phase for which the key driver is effective [28].

As with the nodes for the key drivers, the decision tree is further extended to include nodes representing the motivators and barriers impacting the phases of the energy-related implementations. Similarly, the nodes representing motivators and barriers are added as terminal nodes connected to the node representing the associated process phase. For each process phase, one node representing the motivators and one node representing the barriers is added to stand for the joint effect of all motivators or barriers [28]. An alternative representation would be to use one separate node for each motivator and each barrier. However, it is not preferred since this representation would result in a more complicated visual.

The key drivers, motivators, and barriers are identified as demonstrated in Tables 1–3:

Table 1. Key drivers for formal social units (source: Biresselioglu et al. [28]).

Key Driver
Iteration of top-down and bottom-up mechanisms
Support from mid-level executives

Table 2. Motivators for formal social units (source: Biresselioglu et al. [28]).

Motivator	
Globalization	Good examples
Energy efficiency	Energy self-sufficiency
Energy savings	Prosumerism
Incentives	Local production
Tax benefits	Awareness
Climate concerns	Information
Environmental concerns	Communication
Cost savings	

Table 3. Barriers for formal social units (source: Biresselioglu et al. [28]).

Barrier	
Circumstances	Legal
	Financial
	Environmental
	Economic
Mismanagement	
Operational mistakes	
Lack of awareness	
Administrative barriers	Organizational
	Capacity
	Procedural
	Conflicts
	Trust and transparency
The perceived value of energy	
Social and individual barriers	Habits
	Resistance to change
	Status quo (inertia)
	Cultural norms
Uncertainty and risk	Technological
	Regulatory
	Political
	Legislation

The resulting structure for the decision tree is demonstrated below in Figure 4:

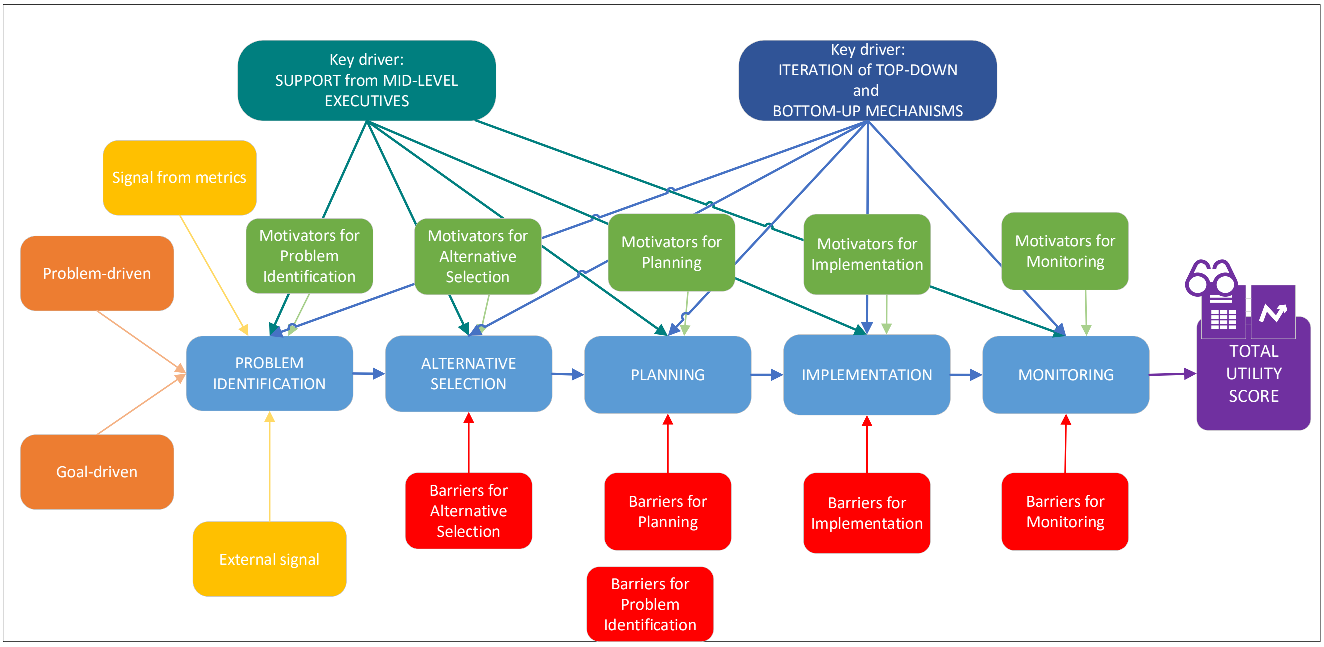

Figure 4. Decision tree structure for formal social units.

4.2. Computations for the Decision Tree

The decision tree is constructed to include the process phases and the key drivers, motivators, and barriers for the case or endeavour under consideration. The decision tree algorithm relies on the decision-maker's input to identify the total utility score for the overall process. This is achieved by first collecting contextual input from the decision-makers concerning the key drivers, motivators, and barriers. The decision tree algorithm follows an analytical approach in evaluating the impacts of the associated key drivers, motivators, and barriers. Moreover, this approach also drives the decision-makers into a more thorough consideration of these factors. The decision-makers are asked to input the weight, impact, and probabilities of occurrence or existence for each key driver, motivator, and barrier value. The weight value refers to the significance or relevance of the particular parameter (key driver, motivator, or barrier) for the process phase under consideration. The impact level corresponds to the magnitude of the parameter's effect in the scenario that it exists or is realized.

On the other hand, the probability value refers to the decision-makers' assessment of the likelihood of occurrence of the particular parameter in the associated process phase. Besides computing the total utility score, this information is valuable from two perspectives. First, it provides the decision-makers a list of significant parameters, including key drivers, motivators, and barriers, as derived from the field. Second, it incorporates the decision-maker's expertise in the particular process and allows them to utilize existing data, for instance, based on their earlier implementations.

For each parameter, the decision-makers are asked to select weight values from a Likert scale of 0 to 5, with 0 corresponding to not relevant/significant, 1 corresponding to low relevance/significance, 2 meaning slightly relevant/significant, 3 standing for moderately relevant/significant, 4 corresponding to relevant/significant, and 5 corresponding to highly relevant/significant. Similarly, the impact assessment also uses a 5-point Likert scale where 0 corresponds to no impact, 1 corresponds to impact not important, 2 corresponds to impact slightly important, 3 means impact moderately important, 4 stands for impact important, and 5 means impact very important.

Through a spreadsheet interface, the decision-makers are able to assess the relevant values by choosing from a drop-down menu of potential values. Along with the values, corresponding verbal expressions from the Likert scale are also included to enhance the decision-maker's choice. Hence, the decision-makers can convert their perceptions into numeric values. Since by definition the probability of occurrence varies from 0 to 1, for each parameter, the decision-makers are asked to select probability values from this range. For the comfort of the decision-makers, a discrete set of alternatives is provided to the decision-makers, rather than asking them to specify a value within the continuous interval [0, 1]. At this point, it is important to note that providing a large set of values might increase the time it requires for the decision-makers to make a choice, whereas providing a small set of possible values would decrease the accuracy of the process and the likelihood of reflecting the decision-makers' perceptions regarding probabilities of occurrence. For the decision tree under consideration, increments of 0.1 are used, that is, the decision-makers are provided with the alternatives 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0 for the probability of occurrence of a parameter.

Table 4 below represents a snapshot of the spreadsheet interface for receiving the input of the decision-makers concerning the motivators for the process phases of problem identification and alternative selection.

Table 4. Interface for selecting the weight, impact, and probability values.

Motivator	Weight	Impact	Probability
Globalization	3—moderately relevant/significant	4—important	0.4
Energy efficiency	2—slightly relevant/significant	2—slightly important	0.4
Energy savings	3—moderately relevant/significant	3—moderately important	0.3
Incentives	1—low not relevance/significance	3—moderately important	0.5
Tax benefits	4—relevant/significant	4—important	0.4
Climate concerns	3—moderately relevant/significant	1—not important	0.3
Environmental concerns	2—slightly relevant/significant	3—moderately important	0.5
Cost savings	2—slightly relevant/significant	2—slightly important	0.1
Good examples	3—moderately relevant/significant	3—moderately important	0.4
Energy self-sufficiency	5—highly relevant/significant	3—moderately important	0.3
Prosumerism	4—relevant/significant	1—not important	0.5

Upon receiving the input from the decision-makers, the decision tree algorithm computes the utility values for the key drivers and motivators and the disutility (negative utility) value for the barriers as follows.

The utility of a key driver is computed as the product of the associated weight, impact, and probability values assessed by the decision maker. For instance, if the decision-maker selects 3—moderately relevant/significant for the weight, 4—important for the impact, and 0.8 for the probability, the utility value would be ($3 \times 4 \times 0.8$) = 9.6. Similarly, the product of the weight, impact, and probability values is taken as the utility value for a motivator. The same formula is used for barriers, however, in this case, the product of the weight, impact, and probability values is interpreted as the disutility (negative utility) of the barrier. For instance, the disutility value for a barrier where the decision-maker selects 4—relevant/significant for the weight, 2—slightly important for the impact, and 0.3 for the probability would be ($4 \times 2 \times 0.3$) = 2.4.

After that, for each phase, the utility from the key drivers and motivators and the disutility from the barriers are computed as the averages of the utilities from the individual key drivers, motivators, and the average of disutilities from the barriers, respectively. Taking the average for each component is needed to normalize the overall effects of the key drivers, motivators, and barriers against one another. Alternatively, the total values of utilities and disutilities may also be used, or a weighing based on the decision makers' perceptions can also be utilized.

Using the average value approach, if a particular process phase has two key drivers, with utility scores of 5.8 and 3.6, respectively, the utility of key drivers for this phase would be (5.8/2) + (3.6/2) = 4.7. Similarly, considering a process phase with three motivators that have utility scores of 2.4, 2.4, and 6.3, the utility by motivators for this phase would be: (2.4/3) + (2.4/3) + (6.3/3) = 3.7. For the barriers, the average of disutility values is computed as the disutility for the phase. If the particular phase has three barriers, with disutility values calculated as 6.0, 3.5, and 4.9, respectively, the disutility by parries for this phase would be computed as (6.0/3) + (3.5/3) + (4.9/3) = 4.8.

The utility score of a particular process phase is, then, the sum of the utilities for key drivers and motivators minus the disutility of the barriers. That is, the disutility of the barriers is included as a negative utility value. For the previous example with a process phase where the decision-makers have identified the utility from key drivers as 4.7, utility from motivators as 3.7, and disutility from barriers equal to 4.8, the utility score of this phase is calculated as (4.7) + (3.7) − (4.8) = 3.6.

Finally, the utility score of the overall process is calculated as the minimum or the average/sum of the utility scores for the individual phases. Taking the minimum of the phase utility scores reflects the understanding that the overall process can be as successful as its least successful phase, whereas taking the average/sum reflects the assumption that the overall success is reflected by the average performance of the individual phases of the process.

Considering the five phases of a process, where the problem identification phase has a utility score of 5.2, the alternative selection phase has a utility score of 3.8, the planning phase has a utility score of 4.5, the implementation phase has a utility score of 4.2, and the monitoring phase has a utility score of 3.6, the minimum value method would assess an overall utility score of min {5.2, 3.8, 4.5, 4.2, 3.6} = 3.6, whereas the average value method would result in an overall utility value of (5.2 + 3.8 + 4.5 + 4.2 + 3.6)/5 = 4.26.

The design of the decision tree algorithm is flexible in the sense that it can incorporate various perspectives concerning the calculation of the utility of a phase or the overall utility of the process, for instance, using weighted sums, averages, or minimum values, simply by properly modifying the associated formula.

5. Conclusions

The decision tree algorithm is constructed utilizing a literature review, in-depth interviews, focus groups, and case studies conducted in the context of the ECHOES project [27,28]. For this purpose, data captured through the analysis of 67 in-depth interviews, 15 focus group studies, and 12 case studies conducted in 7 selected countries were utilized. These data are utilized to construct the decision tree and fed into the learning component of the decision tree algorithm. One of the important merits of learning algorithms is using existing information from the users' experience or past data to identify patterns for a process or a system. Learning algorithms such as decision trees then use this information to assess the system or support decision-making for similar situations. In this way, the decision tree algorithm relies on a large knowledge base; hence, it is expected to have a decent predictive capability. In order to enhance the implementability of the decision tree algorithm for a wide range of energy-related decision-making situations, a general process structure including the phases of problem identification, alternative selection, planning, implementation, and monitoring is utilized. These phases constitute the main infrastructure of the decision tree. The decision tree is further augmented by adding two types of nodes. One set of nodes corresponds to the various triggers of the process, whereas the other corresponds to the key drivers, motivators, and barriers for the process. The decision tree algorithm is executed following the reception of input from the decision-makers concerning the relevance/significance, magnitude of impact, and likelihood of occurrence for each parameter, including the key drivers, motivators, and barriers, for each process phase. This input is then utilized to compute the utility scores for the process phases and the total utility score for the overall process. The interface of the decision tree algorithm is designed so that the decision-makers can input their assessments by visualizing both the numeric scores of their choices for weight, impact, and probability and their linguistic counterparts. In this way, the decision-makers can more easily translate their perceptions into scores.

The resulting algorithm can be utilized as a decision support tool for evaluating the likelihood of success for a particular process or an endeavour. Moreover, the decision tree can also be used for scenario analysis, where each scenario would correspond to different perceptions for the relevance, significance, magnitude of impact, or the likelihood of occurrence/realization of associated key drivers, motivators, and barriers. The total utility scores for each scenario can be used as inputs in the decision-making and policy-making processes. The decision tree also measures the return on the efforts or investments to improve particular key drivers or motivators and alleviate particular barriers. Comparison of the utility scores for the scenarios with and without the designated investments or efforts demonstrates how justified these are. In this way, the allocation of resources can be performed as informed decisions. Scenarios may also be constructed to represent various projections concerning the future (e.g., base scenario reflecting the expected realizations of future events, optimistic or pessimistic scenarios representing positive or negative expectations, respectively) regarding the implementation of projects and the establishment of incentive schemes or campaigns for increasing awareness. Evaluating the utility scores under different scenarios helps the decision-makers decide which projects to prioritize, which schemes to select for implementation, or how to improve the risk management.

Moreover, different collections of policy tools can be tested using the decision tree to decide on a set of tailored policy tools for implementation. Another advantage of the developed decision tree algorithm is providing decision-makers with a structured perspective of the process under consideration, including the process phases and the associated key drivers, motivators, and barriers. This information enhances the decision-makers to establish a more insightful perspective and triggers a more thorough consideration of the process. Moreover, it allows the decision-maker to approach the process through an analytical framework by evaluating its interrelations and associated parameters. In this way, the decision-makers can reflect their expertise on the subject matter based on their roles and knowledge base associated with the particular process and transform this into quantitative evidence based on their perceptions or existing data.

Future research to address the shortcomings of the current decision tree algorithm may include pilot implementations and updating of the decision tree structure by incorporating new data that may become available through other projects and related research. Moreover, the existing decision tree algorithm assumes that the same set of key factors, motivators, and barriers are valid for each endeavour and for each decision-maker. The algorithm can be improved through future studies to incorporate geographical, contextual, and decision-maker-specific customization options.

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