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A fuzzy goal programming with interval target model and its application to the decision problem of renewable energy planning

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Abstract

Optimizing sustainable renewable energy portfolios is one of the most complicated decision making problems in energy policy planning. This process involves meeting the decision maker's preferences, which can be uncertain, while considering several conflicting criteria, such as environmental, societal, and economic impact. In this paper, rather than using existing techniques, a novel multi-objective decision making (MODM) model, named fuzzy goal programming with interval target (FGP-IT), is proposed and constructed based on recent developments and concepts in fuzzy goal programming (FGP) and revised multi-choice goal programming (RMCGP). The model deals with decision making problems involving a high level of uncertainty by offering decision makers a more flexible way to formulate and express their preferences, namely, fuzzy interval target goals. The proposed method is used to optimize a hypothetical sustainable wind energy portfolio in Algeria. The results show that the FGP-IT model is capable of assisting decision makers with uncertain preferences in making such complicated decisions.

Keywords Fuzzy goal programming · Multi-choice goal programming · Multi-criteria decision making · Renewable energy planning · Uncertainty modeling

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1 Introduction

The increasing complexity of today's world has forced us to change our approach to real-life problems to incorporate numerous perspectives—political, environmental, economic, and technological, among others—as described in 1984 by the physicist Moravcsik (1984):

> "In a nutshell, my point is that an overwhelming fraction of work in the science of science, and in fact in many other areas of inquiry, has been carried out in an implicitly or explicitly one-dimensional framework and therefore with a correspondingly one-dimensional methodology. It is my contention that this is a fundamentally incorrect way of looking at problems which, from the very outset, distorts reality and hence is unable to arrive at truly insightful conclusions. Instead, I claim, one must adopt a multi-dimensional model of reality and use a methodology befitting this model to achieve meaningful and functional understanding which then also has some predictive power."

From this perspective, sustainable development (SD) can be viewed as an approach that seeks to achieve the optimal balance between oftentimes competing multi-dimensional factors such as environmental, societal, and economic impact (WCED 1987). However, integrating a multi-dimensional approach into decision making and policy planning is far from an easy endeavor. The renewable energy (RE) sector provides a clear example of the conflicts of interest that can arise among different actors in a sector (Vakulchuk et al. (2020)). It is clear today that energy consumption has a positive impact on economic growth (Kraft and Kraft (1978), Stern (2004), Dogan (2015), and Mrabet et al. (2017)). That means surplus energy is key for nations to achieve their development goals and support economic expansion. However, providing highly reliable and affordable energy that is also sustainable is challenging because of the uncertainty surrounding related factors, such as regulations, technological progress, and climate change (Stock and Tatikonda (2008), Burke et al. (2015), and Barnett et al. (2020)). An example of regulatory uncertainty is the high potential that energy policy will change in the future—e.g., because of a global climate agreement—and affect markets and their participants (Hoffmann et al. (2009)). The risk of new compliance or pre-compliance regulations, the potential for litigation in emerging markets, and other related risks raise investor uncertainty and, in particular, reluctance to commit to multi-year agreements. Uncertainty about future prices and technological progress are also major obstacles to investment in the RE sector. Finally, the sector's close relationship to the environment and climate change add further complexity to the problem, as these factors are very difficult to control for or incorporate into investment planning. Uncertainty related to future climatic conditions plays a major role in decision making related to renewable technologies.

If decisions are to be made from a multi-dimensional perspective, policymakers will require more mathematical tools to tackle these types of decision problems (see, e.g., Hocine and Kouaissah (2019), Fischer (2019), Hussain et al. (2019) and Hocine et al. (2020)). In this context, determining the optimal sustainable RE portfolio is a key factor in energy policies and deserves study. The problem involves meeting the decision maker's (DM's) preferences while considering the indicators of sustainability. However, one of the main issues that make the formulation of this problem difficult is the uncertainty embedded in DM preferences. In real life, uncertain or fuzzy interval preferences arise in several situations. For example, in RE planning, DMs often make conservative initial estimates based on the available information and resource limitations. For instance, a DM might say, “Under our resource limitations, we suggest that the realization time of project ‘X’ will be between approximately 12 and 16 months.” Or they might say, “This project will cost around 350,500 to 400,500 euros.” DMs normally make conservative initial estimates because they anticipate problems in achieving these goals (e.g., an architect’s reluctance to change specifications or drawings, harsh weather, or errors in executing project activities). However, estimates using language like “between approximately” and “around … to …” are very difficult to model using the existing fuzzy goal programming (FGP) techniques.

Motivated by these concerns, this paper tackles the problem by proposing a novel model that can overcome this limitation. The model, named fuzzy goal programming with interval target (FGP-IT), has been formulated to solve fuzzy multi-objective problems with an interval target (or interval goal). In this respect, the novel approaches taken by this paper are as follows. From a theoretical point of view, this paper combines two important techniques—FGP and revised multi-choice goal programming (RMCGP)—to overcome their respective limitations. In particular, it allows FGP to consider interval target values and thereby be applied in more complicated scenarios. Moreover, it makes RMCGP suitable for addressing fuzzy type uncertainty problems. To achieve this aim, it formulates the aspiration levels on the right hand side (RHS) of the system constraints. It also considers the most common types of fuzzy membership functions that are generalized to account for interval target values. This model thus extends the capability of its building blocks to solve a wide range of real-world problems. To provide a practical perspective, the proposed approach is used to determine the optimal sustainable wind energy portfolio decision in Algeria. This not only validates the FGP-IT model but also provides useful insights for policymakers and contributes to the continuing debate on whether implementing the optimal RE portfolio is a key step toward SD.

The remainder of this paper is structured as follows. In Sect. 2, we present relevant literature on multi-criteria models using goal programming (GP) applied to the study of sustainability and RE. In Sect. 3, we describe the different approaches to modeling GP problems in uncertain or imprecise environments. Some of the concepts related to and types of fuzzy interval membership functions related to our proposed formulation are presented in Sect. 4. The proposed FGP-IT model is developed in Sect. 5. The application of FGP-IT to optimize sustainable wind energy portfolios in Algeria is laid out in Sect. 6. Finally, our conclusions and suggestions for future work are presented in Sect. 7.

2 A review of sustainability and renewable energy goal programming analysis

Though the literature on SD and RE features an abundance of applications of multi-attribute decision making (MADM), studies taking multi-objective decision making

(MODM) approaches were rather limited. This may be because it is relatively easy, and appears appropriate, to apply MADM methods to the selection process. However, when the problem involves not only conflicting criteria but also a deeply uncertain decision context (i.e., some preferential statements from the DMs that are deeply uncertain), taking the MODM approach would be a better choice. The importance of such models is confirmed by several remarkable modeling techniques that tackle problems under conditions of uncertainty. Furthermore, mature MODM methods have been used to construct tailored models to support decision making problems. In other words, investigating how the field of MODM can be applied to and potentially used to construct a mathematical model of a RE source selection problem involving conflicting criteria and an uncertain goal and goal target is a worthwhile research topic. For instance, San Cristóbal (2012) studied the problem of planning the expansion of a RE sector that involves an optimal mix of different types of energy on different Spanish lands, where each base type should be planted according to the different criteria imposed. In this work, the author used a basic GP method combined with network analysis. Later, Oliveira et al. (2014) reviewed different modeling approaches from the literature based on coupling input–output analysis with multi-objective models, which can be particularly useful for policymakers to assess the trade-offs between the economy-energy-environment-social pillars of SD, a relevant advantage in the current sluggish economic context. Jayaraman et al. (2015) applied a weighted GP (WGP) model that integrates optimal workforce allocation to simultaneously satisfy the 2030 targets for economic development, energy consumption, greenhouse gas emission reduction, and job growth for the United Arab Emirates (UAE). Zografidou et al. (2016) studied an optimal design of the Greek RE production network applying an integer-weighted GP model, taking into account environmental and economic criteria. Also for the UAE, Jayaraman et al. (2017a) developed a stochastic GP (SGP) model with a satisfaction function that integrates optimal resource (labor) allocation to simultaneously satisfy contradicting criteria related to economic development, energy consumption, workforce allocation, and greenhouse gas emissions. Jayaraman et al. (2017b) then introduced a WGP model involving the criteria of economic development (GDP), electricity consumption, greenhouse gas emissions, and total number of employees to establish the optimal labor allocation to various economic sectors. Zografidou et al. (2017) produced a RE map for the installation of solar power plants in Greece using social, financial, and power production aspects. A specific GP model is developed under the target and structural constraints, and all possible weight combinations are examined. Zhuang and Hocine (2018) treated the multi-criteria wind farm planning problem as a De Novo programming (DNP) problem and used meta-GP to allocate a large initial construction budget according to electricity generation guidelines determined based on several locations.

However, complex real-life situations have created grounds for debate as to the compatibility of these approaches in the presence of uncertainty. Several studies have attempted to address this issue: Lee et al. (2008) applied the FGP approach to evaluate the effects of carbon taxes on different industries and simultaneously find an optimal carbon tax scenario. Bravo and Gonzalez (2009) proposed a stochastic GP (SGP) model to water use planning. The authors developed a decision support model to help public water agencies allocate surface water among farmers and authorize the use of groundwater for irrigation. Ghosh et al. (2010) formulated a fuzzy non-linear GP model to optimize resources and maximize sales and profit. Daim et al. (2010) developed a FGP model for assessing the best RE portfolio. More recently, Ghouali et al. (2019) studied the efficiency of RE base plants in Algeria using a FGP approach. Zamanian et al. (2019) proposed a FGP model for optimizing the sustainable supply chain by focusing on environmental and economic costs and revenue. Yu et al. (2019) developed an optimal renewable electricity generation mix for China using a fuzzy multi-objective approach. Hocine et al. (2020) proposed a weighted-additive fuzzy multi-choice GP (WA-FMCGP) model established on a purely commensurable GP basis to aid in the decision of choosing a suitable location for wind farm expansion, when the decision involves several (types of) fuzzy yet multi-choice goals (i.e., FMCGs). However, none of these studies can solve decision making problems involving fuzzy interval targets. One attempt was proposed by Kouaissah and Hocine (2020), who used a fuzzy interval GP approach to optimize sustainable and RE portfolios. To fill this gap, this paper contributes to this literature stream and tries to extend the work presented by Hocine et al. (2018) and (2020) and develop a novel approach to solving decision making problems featuring fuzzy interval targets.

Based on these important studies, we conclude that the use of MODM methods in the RE selection process is so far limited to a few works. In particular, FGP is the primary GP approach that has been used so far for optimizing RE portfolios under uncertainty. Importantly, few studies focus on RE choices with preferences stated in terms of fuzzy interval targets or goals. Furthermore, as many previous researchers have noted (Kouaissah and Hocine (2020)), most existing FGP models support only a single target goal. These models cannot fully satisfy DMs measured by membership functions and are unable to optimize RE portfolios efficiently when the DM is hesitant about his/her target values. This, however, is the situation presented by many real-life applications, suggesting that the proposed FGP-IT model may be useful to solve various MODM problems under high levels of uncertainty and in imprecise environments.

3 Goal programming approaches in the uncertain or imprecise environment

Supported by a large number of studies, GP has been and still is one of the most widely used approaches to solving MODM problems. Based on a philosophy of 'satisfactory' or 'sufficient,' it is useful for tackling MODM problems that involve several conflicting objectives and, sometimes, incomplete or imprecise decision-relevant information. GP was originally proposed by Charnes and Cooper (1961) and developed further by several distinct works such as Lee (1972), Ignizio (1985), Romero (1991), and Tamiz et al. (1998), among others (Aouni et al. (2012)). The purpose of GP is to minimize the deviations between the achievement of goals and their aspiration levels. In general, it can be expressed as the following program (when the achievement function is in the 'WGP' form):Min $\sum_{i=1}^{K} w_i[(p_i + n_i)/T_i]$ under the condition that $(AX)_i + n_i - p_i = b_i; X \in C_s n_i, p_i \geq 0$ (for $i = 1,\ldots,K$), where b_i is the target level for the i-th goal;

variables n_i and p_i indicate, respectively, the positive and the negative deviations from/toward the DM-defined target value b_i; X is the decision vector to be determined; F denotes the feasible solutions set of constraints; and w_i and T_i are, respectively, the preferential weights and normalization constant of the i-th goal (see Jones and Tamiz (2010)).

Standard variants of the GP formulation consider the aspiration levels to be precise, deterministic, and well known. However, when there are multiple goals present, it is difficult to ask a DM what attainment is desired for each of the goals, and this is one of the major drawbacks when using GP (Lai and Hwang (1994)). In practice, there are many decision making situations in which the DM does not have complete information about some parameters and, in particular, the aspiration levels required for a GP model. To deal with this situation, several techniques have been proposed for modeling GP problems with uncertain and imprecise goals. Among those techniques are FGP, multi-choice GP (MCGP), and its revised version, RMCGP. As this study constructs the proposed model based on concepts from both RMCGP and FGP, these building blocks' models are reviewed.

3.1 Multi-choice goal programming

There is a large evolving literature surrounding the issue of uncertainty in MODM paradigms. One of the techniques dealing with uncertainties in the GP context is the MCGP model (Chang (2007)). With MCGP, a DM can consider several target values for each goal, and the model allows a DM to set multi-choice aspiration levels (MCALs) for each goal (i.e., many aspiration levels map to one goal). Doing so avoids underestimations (or overestimations) of the real level that a left hand side (LHS) criterion function can achieve. During the formulation, binary variables are used on the RHS to construct the multiplicative terms that can select 'a suitable choice out of the multiple choices of aspiration level' for each goal constraint. According to these, the mathematical form of a MCGP model is expressed as follows:

(MCGP)

$$\text{Min} \sum_{i=1}^{K} w_i(p_i + n_i)$$

s.t.

$$(AX)_i + n_i - p_i = \sum_{j=1}^{n} b_i\, S_{ij}(B) \quad i = 1, \ldots, K$$

$$n_i, p_i \geq 0 \quad i = 1, \ldots, K$$

$$S_{ij}(B) \in R_i(x) \quad i = 1, \ldots, K$$

$$X \in C_s$$

where w_i denotes the weight of the i-th goal; n_i and p_i are the negative and positive deviational variables; $S_{ij}(B)$ represents a function of binary serial number; $R_i(x)$ is the function of resource limitations; and Cs is an optional set of hard or soft constraints as also found in other mathematical programming approaches (Kwak et al. (2005)).

As mentioned previously, to express the MCALs of a goal, multiplicative terms of binary variables are involved in the MCGP model. However, this leads to difficult implementation (when the problem size gets large) and interpretation, i.e., it is not easily understood by the industrial participants. To tackle this problem, Chang (2008) proposed the RMCGP model. In the RMCGP method, on the RHS, those aggregated multiplicative terms controlled by the binary variables are replaced by an interval aspiration level delimited by the lower and upper bound of each objective function. As can be read in the abovementioned paper, the RMCGP model can be viewed as one final solution to the continuous versions of interval GP (IGP), where the aspiration level y_{i} is a continuous variable bounded the upper $g_{\mathrm{i,max}}$ and the lower $g_{\mathrm{i,min}}$ (i.e., $g_{\mathrm{i,min}} \le y_{\mathrm{i}} \le g_{\mathrm{i,max}}$). In other words, this approach is capable of solving the problem with a continuous, interval-based MCAL span on the RHS. Based on these concepts, the general form of a RMCGP model is expressed as follows:

(RMCGP)

$$\text{Min} \sum_{i=1}^{K} \left[w_i (p_i + n_i) + \alpha_i (e_i^+ + e_i^-) \right]$$

s.t.

$$(AX)_i + n_i - p_i = y_i \quad i = 1, \ldots, K$$

$$y_i - e_i^+ + e_i^- = g_{i,\min} \text{ or } g_{i,\max} \quad i = 1, \ldots, K$$

$$g_{i,\min} \le y_i \le g_{i,\max} \quad i = 1, \ldots, K$$

$$n_i, p_i, e_i^+, e_i^- \ge 0 \quad i = 1, \ldots, K$$

$$X \in C_s$$

where p_{i} and n_{i} are positive and negative deviations attached to the i-th goal, i.e., $|(AX)_i - y_i|$; e_i^+ and e_i^- are the positive and negative deviations attached to $|y_i - g_{i,\max}|$ or $|y_i - g_{i,\min}|$, respectively; α_{i} is the weight attached to the sum of the deviation $(e_i^+ + e_i^-)$; w_i is the weight attached to the sum of the deviations $(p_i + n_i)$; y_i is the continuous variable with a range of interval values $g_{\mathrm{i,min}} \le y_{\mathrm{i}} \le g_{\mathrm{i,max}}$; and $g_{\mathrm{i,max}}$ and $g_{\mathrm{i,min}}$ are the upper and lower bounds of the i-th goal, respectively.

3.2 Fuzzy goal programming

Initially, Narasimhan (1980) incorporated the fuzzy set theory to GP and proposed the FGP model. Since then, several works related to FGP have been presented in the literature. For more details about FGP, see the review by Aouni et al. (2009). To solve FGP problems, several models based on various approaches have been proposed. Recently, with the concept of 'tolerance,' Yaghoobi et al. (2008) proposed a more efficient formulation for solving FGP problems. This generalized model uses the most common linear fuzzy membership functions presented in most real-world problems. As we will formulate the proposed FGP-IT model partially based on this model, this FGP model is reviewed here.

Assume that the goals, identified by i, are divided into a number of i_0 right-sided membership functions, a number of i_0 left-sided membership functions, a number of $(j_0–i_0)$ triangular membership functions, and a number of $(K–j_0)$ trapezoidal membership functions. Then, a generalizable FGP model can be represented by the following algebraic formulations:

(FGP)

$$\text{Min} \sum_{i=1}^{i_0} w_i \frac{p_i}{\Delta_i^R} + \sum_{i=i_0+1}^{j_0} w_i \frac{n_i}{\Delta_i^L} + \sum_{i=j_o+1}^{K} w_i \left(\frac{n_i}{\Delta_i^L} + \frac{p_i}{\Delta_i^R} \right)$$

s.t.

$$(AX)_i - p_i \le b_i \quad i = 1, \ldots, i_o$$

$$(AX)_i + n_i \ge b_i \quad i = i_0 + 1, \ldots, j_o$$

$$(AX)_i + n_i - p_i = b \quad i = j_0 + 1, \ldots, k_o$$

$$(AX)_i - p_i \le b_i^u \quad i = k_0 + 1, \ldots, K$$

$$(AX)_i + n_i \ge b_i^l \quad i = k_0 + 1, \ldots, K$$

$$\mu_i + \frac{p_i}{\Delta_i^R} = 1 \quad i = 1, \ldots, i_o$$

$$\mu_i + \frac{n_i}{\Delta_i^L} = 1 \quad i = i_0 + 1, \ldots, j_o$$

$$\mu_i + \frac{n_i}{\Delta_i^L} + \frac{p_i}{\Delta_i^R} = 1 \quad i = j_0 + 1, \ldots, K$$

$$\mu_i, n_i, p_i \ge 0 \quad i = 1, \ldots, K$$

$$X \in C_s,$$

where w_i denotes the weight of the i-th fuzzy goal; μ_i is a model variable that determines the degree of membership function for the i-th fuzzy goal; n_i and p_i are the negative and positive deviational variables; and C_s is as defined previously.

It is obvious that FGP allows only one fuzzy goal target that should be achieved to satisfy the DM. However, in some cases, the DM is hesitant or reluctant to specify only one single target rather than a range of goal targets. In other words, under certain circumstances, DMs may face situations involving multiple or interval target goals. The authors believe that this scenario cannot be solved by current FGP approaches. The optimization process chooses the most suitable target goal from the range of interval goal targets that highly satisfy the DM. To achieve this aim, the next section will start with an examination of how the FGP model can be extended and improved by introducing the fuzzy interval number to the RHS of each fuzzy goal constraint, enabling the DM to express his/her preferences in terms of fuzzy interval goal targets and thus increase decision supportability. This will be followed by a discussion about how the above method can improve the existing fuzzy MCGP (FMCGP) models that consider MCGP modeling rather than its revised version. In summary, the content presented in Sect. 4 discusses and extends this section by setting the theoretical ground for subsequent modeling works. Moreover, in Sect. 4, we emphasize how the proposed model may improve upon those models that merge both FGP and MCGP.

4 Extended studies and the ground for the proposed model

4.1 Membership functions with fuzzy intervals

To express ambiguous or vague information in the decision making process, the fuzzy sets theory was first introduced by Zadeh (1965). Fuzzy sets have reasonable differences from crisp (classical) sets. Crisp set A in universe U can be defined by listing all of its elements denoted as x. Alternatively, a 0–1 valued membership function, $\mu_A(x)$, which is given below, can be used to define on x.

$$\mu_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases}.$$

Unlike crisp sets, a fuzzy set $\tilde{A}$ in universe U is defined by a membership function, $\mu_{\tilde{A}}(x)$, which takes values on interval [0,1]. Therefore, the definition of a fuzzy set can be viewed as an extended version of the crisp set. While the membership function takes a value of 0 or 1 from crisp sets, it can take any possible value on the [0,1] interval from a fuzzy set. In the context of GP, the DM will be asked by a standard GP model to specify a precise aspiration level for each of the objectives. But as known, in real-life problems, there are situations during a decision process wherein a DM is unable to specify all or part of the aspiration levels precisely. Therefore, the FGP method has been developed rightly for this purpose.

In studies of FGP, there are various ways to express and formulate *the base form of goal fuzziness*, each of which leads to a different fuzzy membership function. To the best of our knowledge, the first work to formulate the FGP problem by taking the membership function concept was Narasimhan et al. (1981). In subsequent works, including the listed (FGP) model which involves the 'tolerance' concept mentioned in Sect. 3.2, all these functions are defined on the interval [0,1]. That is, the membership function has a value of 1 when this goal is fully attained and the DMs are totally satisfied, or it has a value in the interval [0,1] otherwise. This should be a main and common property of the FGP models which use the membership function concept.

However, in reality, the expression and measurement of *the fuzziness of interval goal targets* should be another focus. When using FGP models such as (FGP), given his/her preference structure, a DM does not always feel it is easy to specify the parameters of 'the desired attainment' for a membership function, e.g., the b values set on the RHS of each fuzzy goal constraint in the (FGP) model. So, in at least some cases, using an interval value may better serve the purpose (Silva et al. (2013), Mouslim et al. (2014), Umarusman (2018), and Ho (2019)).

In this study, we consider the situation in which a DM determines his/her aspiration levels in a fuzzy interval manner and allow him/her a flexible way to express the fuzziness of interval goal targets in constructing a FGP model, as to obtain a better solution for decision making. In order to present this clearly, in the rest of this section, a semantic model of the encountered problem is introduced. The FGP-IT model will then be proposed in Sect. 5. Following symbolic conventions, in this study the following FGP problem with K fuzzy goals is considered, which encounters an extended version of the problem domain considered by the (FGP) model (which enables the 'fuzziness of interval targets'):

(Semantic Model)

OPTIMIZE

$$(AX)_i \tilde{\leq} [g_{i,\min}, g_{i,\max}] \quad i = 1, \ldots, i_0$$

$$(AX)_i \tilde{\geq} [g_{i,\min}, g_{i,\max}] \quad i = i_0 + 1, \ldots, j_0$$

$$(AX)_i \tilde{=} [g_{i,\min}, g_{i,\max}] \quad i = j_0 + 1, \ldots, K$$

$$X \in C_s,$$

where OPTIMIZE means finding an optimal decision vector X such that all fuzzy goals are satisfied;$(AX)_i$ is the matrix multiplication form of the criterion function for the i-th objective, which can be expanded as: $(AX)_i = \sum_{j=1}^{n} a_{ij} x_j$, $i = 1, \ldots, K$;. For $i = 1, \ldots, K$,$[g_{i,\min}, g_{i,\max}]$ represents a continuous span of multiple fuzzy aspiration levels for a goal in terms of a fuzzy interval number;C_s is an optional set of hard constraints as found in traditional LP; and the '~' symbol is the fuzzifier operator, representing the imprecise fashion in which the goals are stated.

We are interested in the form of the support of membership functions that allows the possibility of setting interval target values. The three types of fuzzy interval membership function involved here are defined below in Eqs. 1, 2, 3 and their respective shapes in Figs. 1, 2, 3 (Yaghoobi and Tamiz (2007)). Observe that in these figures, each y_i is an additional decision variable that plays the key role in providing the flexibility

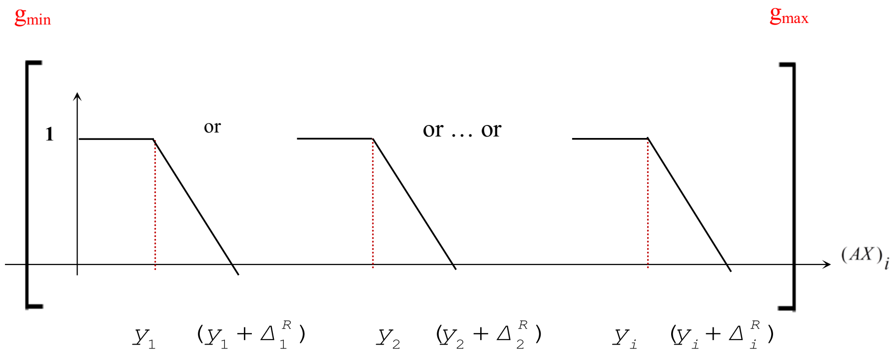


Fig. 1 Right fuzzy interval membership function

on the RHS of the corresponding fuzzy goal constraint. These formulations generalize the classic membership functions and allow DMs to set multiple target values.

$$\mu(AX)_i = \begin{cases} 1 & (AX)_i \le y_i \\ 1 - \frac{(AX)_i - y_i}{\Delta_i^R} & y_i \le (AX)_i \le y_i + \Delta_i^R \quad i = 1, \ldots, i_0 \\ 0 & (AX)_i \ge y_i + \Delta_i^R \\ \text{where } y_i \in [g_{\min}, g_{\max}] \end{cases} \tag{1}$$

$$\mu(AX)_i = \begin{cases} 1 & (AX)_i \ge y_i \\ 1 - \frac{y_i - (AX)_i}{\Delta_i^L} & y_i - \Delta_i^L \le (AX)_i \le y_i \quad i = i_0 + 1, \ldots, j_0 \\ 0 & (AX)_i \le y_i - \Delta_i^L \\ \text{where } y_i \in [g_{\min}, g_{\max}] \end{cases} \tag{2}$$

$$\mu(AX)_i = \begin{cases} 0 & (AX)_i \le y_i - \Delta_i^L \\ 1 - \frac{y_i - (AX)_i}{\Delta_i^L} & y_i - \Delta_i^L \le (AX)_i \le y_i \\ 1 - \frac{(AX)_i - y_i}{\Delta_i^R} & y_i \le (AX)_i \le y_i + \Delta_i^R \quad i = j_0 + 1, \ldots, K \\ 0 & (AX)_i \ge y_i + \Delta_i^R \\ \text{where } y_i \in [g_{\min}, g_{\max}] \end{cases} \tag{3}$$

4.2 Related studies

As discussed in Sect. 4.1, in FGP problems the goals are viewed as fuzzy sets, and it is assumed that their membership functions are known (Lai and Hwang (1994) and Mirzaee et al. (2018)). However, sometimes the DM may feel it is difficult to specify his/her membership function parameters and, in particular, those aspiration level parameters required in the traditional GP context. This should be true, although each FGP model proved its effectiveness in dealing with uncertainties in real-world decision problems. In some cases, using the MCAL technique may successfully resolve such a problem, and this is one of the main reasons to take the MCGP modeling

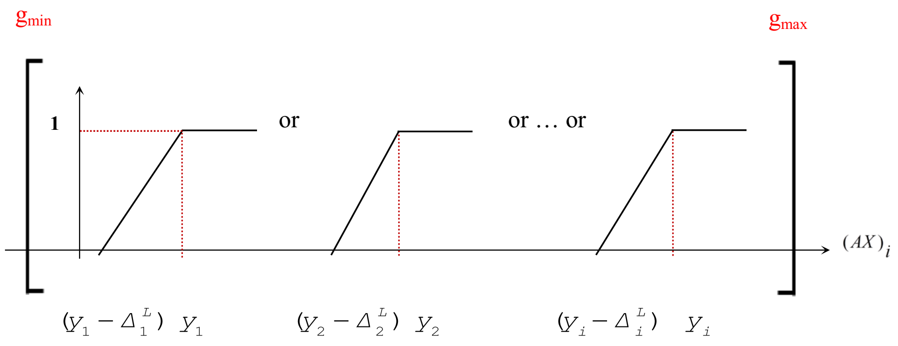


Fig. 2 Left fuzzy interval membership function

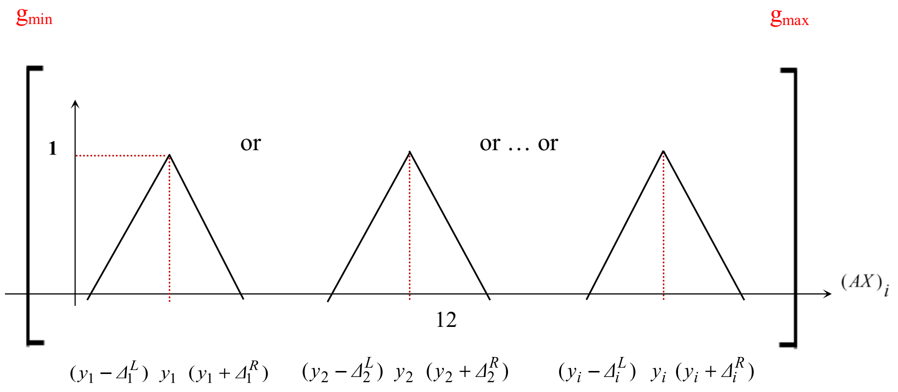


Fig. 3 Triangular fuzzy interval membership function

approach (Patro et al. (2018)). In the initial MCGP formulation, the possible MCALs from which a goal can be chosen are considered to be precise, deterministic, and well known. However, in many decision contexts, it is hard to determine the fixed values for these possible MCALs. Therefore, using interval numbers, the RMCGP model was proposed to 'glue-up' these possible MCALs (Chang (2008)), and, later, the utility-theory-based method involving piece-wised utility function slopes was established (Aalaei and Davoudpour (2016) and Attari et al. (2017)). Aside from Chang's works, Tabrizi et al. (2012) was the first research paper to formulate the fuzzy MCGP (FMCGP) approach. In their model, they adopted the max–min approach proposed by Zimmermann (1978) to solve the FMCGP problem based on only one type of membership function, which is the triangular membership function. However, before this model was proposed, such a monotonous treatment of membership functions was criticized by many articles, such as Chen and Tsai (2001) and Yaghoobi and Tamiz (2007). The second work that formulates the FMCGP problem was the model proposed by Mouslim et al. (2014), named FGP with Multi-Target-Level (FGP-MTL). This model obtains a solution by trying to maximize the degree of membership function.

These two FMCGP models are constructed based on the initial version of the MCGP model (i.e., Tabrizi et al. (2012) and Mouslim et al. (2014)). Unfortunately, that means the possible drawbacks of the MCGP formulation mentioned above are inherited (i.e., using the function of binary serial, making it hard to implement) by both models. Therefore, as can be seen from the semantic model in Sect. 4.1, this study learns the concept from the RMCGP model, while interval numbers are used to formulate the fuzziness around the fuzzy goal targets on the right hand side. In other words, such an approach not only provides alternative ways of conducting FMCGP-relevant research but also widens the application of the concept of RMCGP. With this modification, the fuzzy goal target in the FGP model becomes a moveable window that is automatically adjustable at the solution stage (when the base form of the model was a fuzzy model taking the membership function concept). This is why the proposed model is called the fuzzy goal programming with interval target (FGP-IT) model.

5 The proposed model: fuzzy goal programming with interval target (FGP-IT)

According to the concepts discussed in Sect. 4, the FGP-IT model is formulated and proposed as follows:

(FGP-IT)

$$\text{Min} \sum_{i=1}^{i_0} w_i \frac{p_i}{\Delta_i^R} + \sum_{i=i_0+1}^{j_0} w_i \frac{n_i}{\Delta_i^L} + \sum_{i=j_o+1}^{K} w_i \left(\frac{n_i}{\Delta_i^L} + \frac{p_i}{\Delta_i^R} \right) + \alpha_i (e_i^+ + e_i^-)$$

s.t.

$$(AX)_i - p_i \leq y_i \quad i = 1, \ldots, i_0$$

$$(AX)_i + n_i \geq y_i \quad i = i_0 + 1, \ldots, j_0$$

$$(AX)_i + n_i - p_i = y_i \quad i = j_0 + 1, \ldots, K$$

$$y_i - e_i^+ + e_i^- = g_{i,\min} \text{ or } g_{i,\max} \quad i = 1, \ldots, K$$

$$g_{i,\min} \leq y_i \leq g_{i,\max} \quad i = 1, \ldots, K$$

$$\mu_i + \frac{n_i}{\Delta_i^L} = 1 \quad i = 1, \ldots, i_0$$

$$\mu_i + \frac{n_i}{\Delta_i^L} = 1 \quad i = i_0 + 1, \ldots, j_0$$

$$\mu_i + \frac{n_i}{\Delta_i^L} + \frac{p_i}{\Delta_i^R} = 1 \quad i = j_0 + 1, \ldots, K$$

$$\mu_i, n_i, p_i, y_i \geq 0 \quad i = 1, \ldots, K$$

$$X \in C_s,$$

where all variables are defined as in FGP and RMCGP.

In summary here, the proposed FGP-IT model can be viewed as a continuous version of other FMCGP models, in which the fuzzy goal targets are not able to be fuzzified (Tabrizi et al. (2012), Mouslim et al. (2014), Ho (2019), and Mirzaee et al. (2018)) and which are thus discontinuous. Another possible advantage of the proposed model is suggested by recent trends in GP scholarship, which is moving to address several types of fuzzy goals for real-world problems. Thus, this extension of classical FGP has more support and resources to accommodate higher satisfaction levels. The following real-life application validates and demonstrates the usefulness of the proposed model.

6 Application

6.1 Background

Returning to the topic of renewable energy (RE), as discussed in Sect. 2, Algeria has recently launched an ambitious program—the National Renewable Energy Action Plan (NREAP (2017))—to develop RE by developing and expanding the use of inexhaustible resources, such as solar and wind power. According to the plan, which was adopted by the government of Algeria in February 2011, the country aims to produce about 27% of its national electricity from renewable sources by 2030. As wind power has been one of the fastest-growing RE sources worldwide, the government of Algeria plans to produce a large portion of its electric power from wind by 2030 and will thus operate many wind turbines in order to generate the required electricity. Hence the following question naturally arises: how can the government create the optimal energy portfolio from the three wind farms while satisfying SD restrictions? Wind farms must be built in areas with sufficient wind resources, in other words, where average wind speeds are sufficient. The Sahara desert is one of the windiest areas on the planet, especially on the western coast, where the Atlantic coastal desert runs through Western Sahara and Mauritania. According to the Algerian RE development center, Algeria's southwestern region has great potential, with speeds exceeding 4 m/s for the site of Timimoun, 5 m/s for the site of Tindouf, and even 6 m/s for the site of Adrar, as shown in Fig. 4. The set of three locations being considered to build wind farms are as follows: Tindouf, Adrar, and Timimoun, as marked in Fig. 5.

6.2 Modeling

In Algeria, the electricity market is headed almost entirely by the national company SONELGAZ. Suppose that to produce clean electricity, this company plans to build three hypothetical wind farms of 30 wind turbines, each one with a rated power of 1000 kW (30 MW in total) (Himri et al. (2008)), in three different locations in the southwestern region of Algeria, namely, Adrar (X_1), Timimoun (X_2), and Tindouf (X_3), which means the power generated for each station, as shown in Fig. 5. Also, assume that the material resources that will be used are the same in each region due to the homogeneous geological nature of the areas (desert nature) selected for the project.

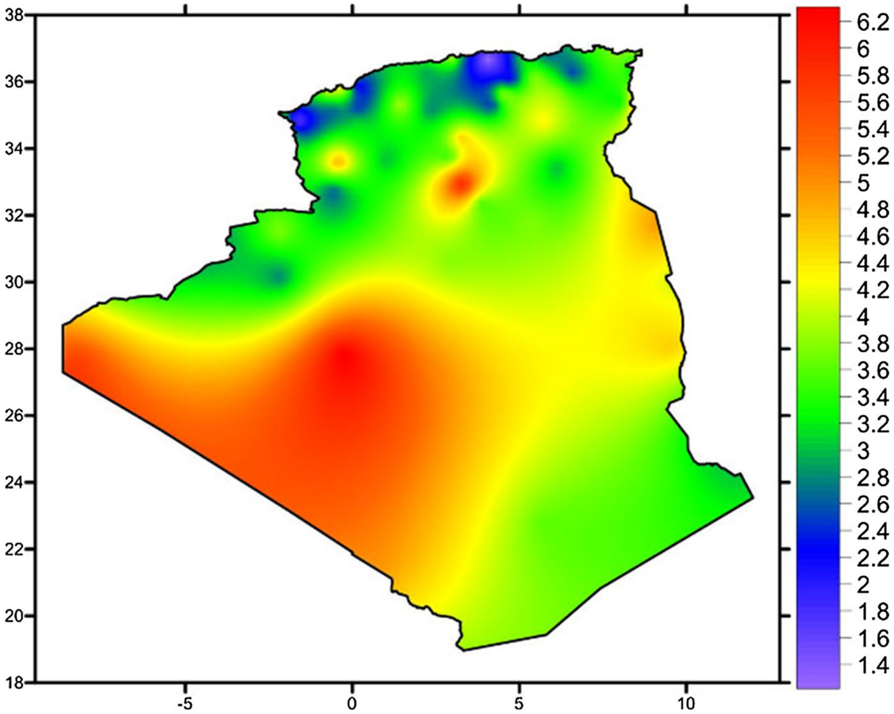
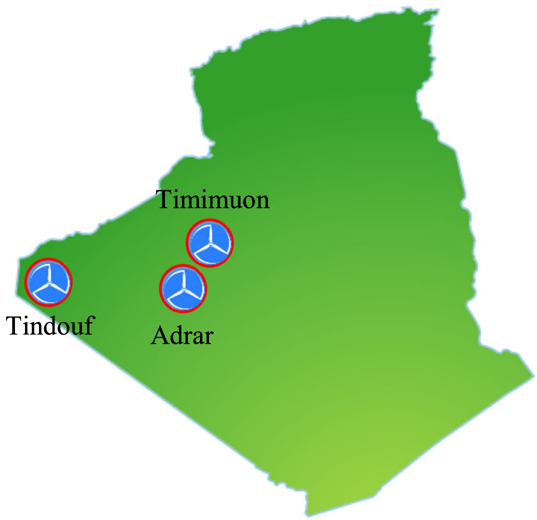


Fig. 4 Algeria's annual wind speed (https://www.cder.dz/spip.php?article1765)

Fig. 5 Potential locations of wind energy generation



In this study, since the FGP-IT model proposed in Sect. 5 is to be applied to select the optimal sustainable wind energy portfolio under an uncertain and imprecise decision environment, the criteria which will be used in the decision making process should be

Table 1 Data description of objective functions' coefficients Source: Himri et al. (2008)

Objectives (or goals)	Adrar	Timimoun	Tindouf
Plant capacity factor (PCF) (%)	38	30	21
Cost of energy (COE) ($/kWh)	0.0309	0.0430	0.0657
Net present value (NPV) ($)	76,125,725	48,843,997	19,712,439
Greenhouse gases avoided (GGA) (tons/year)	48,577	38,406	27,544
Social benefits	7	6.5	6.5

first determined. In reference to the discussion in Sect. 2, the constructs involved in evaluating the energy supply system here are: *technical*, *economic*, *environmental*, and *social*. Five criteria are considered as follows: Plant capacity factor (PCF) (%), Cost of energy (COE) ($/kWh), Net present value (NPV) ($), Greenhouse gases avoided (GGA) (tons/year), and Social benefits. These, together with the construct to which a criterion belongs, are summarized from the existing relevant literature (i.e., Haddah et al. (2017) and Hocine et al. (2018)).

Therefore, for the decision case, there are five objectives: plant capacity factor (PCF) (%), cost of energy (COE) ($/kWh), greenhouse gases avoided (GHG) (tons/year), net present value (NPV) ($), and social benefits. Each objective's parameters are presented in Table 1.

Therefore, a multi-objective programming model that considers these objectives and the observable resource constraints can be semantically expressed as follows:

(**M5**)

$$\text{Max } z_1 = 38\, X_1 + 30X_2 + 21X_3 \qquad PCF$$

$$\text{Min } z_2 = 0.0309\ X_1 + 0.0430\ X_2 + 0.0657\, X_3 \qquad COE$$

$$\text{Max } z_3 = 76\,125\,725\ X_1 + 48\,843\,997\, X_2 + 19\,712\,439\ X_3 \qquad NPV$$

$$\text{Max } z_4 = 48577\, X_1 + 38406\ X_2 + 27544\, X_3 \qquad GGA$$

$$\text{Max } z_5 = 7X_1 + 6.5X_2 + 6.5X_3 \qquad SB$$

$$\left.\begin{array}{r} X_1 \geq 95 \\ X_2 \leq 125 \\ X_3 \geq 70 \\ X_3 \leq 120 \\ X_1 + X_2 \geq 185 \\ X_1 + X_3 \geq 180 \\ X_2 + X_3 \geq 190 \end{array}\right\} \text{Strategic constraints.}$$

Table 2 The interval-based MCALs and goal types defined on the five fuzzy goal criteria

Goals	Type of fuzzy interval goals	Tolerance	Target levels
Plant capacity factor (PCF) (%)	Left	5	[40,70]
Cost of energy (COE) ($/kWh)	Right	40	[4000,6000]
Net present value (NPV) ($)	Left	10	[100,200]
Greenhouse gases avoided (GGA)(tons/year)	Left	5000	[50000,120000,30]
Social benefits	Left	2	[8,9]

Table 3 The results from solving the problem with FGP-IT model

Solutions	Item	Electricity generated from each station (MWh/year)
Decision	x_1	95
Variable	x_2	105
Values	x_3	85
Utility in terms of degree of MF	μ_1	1
	μ_2	1
	μ_3	1
	μ_4	1
	μ_5	1

6.3 Solving the decision-making problem utilizing FGP-IT model

Suppose that the DM has determined his/her preference-related parameters for the five fuzzy goal criteria as summarized in Table 1. As suggested by FGP-IT, these data should be given in a fuzzy interval fashion. As such, suppose that the two ends of a continuous MCAL span and the type of each goal as well as its 'tolerance' are described in Table 2.

Therefore, applying the proposed FGP-IT model with the given data set using LINGO (Schrage (2009)), the optimal solution set is obtained in Table 3.

As can be seen, the solution set satisfies the DM in terms of the degree of membership functions. All the goals are fully achieved with 100%. In addition, it is observed that according to this optimal solution set, the annual gross energy yield, without losses, from a hypothetical wind farm of 30 MW installed capacity at each of the three locations (Adrar, Timimoun, and Tindouf) would be 95, 105, and 85 MWh, respectively. Furthermore, the most important outcome of producing wind energy at these sites would be the avoidance of 48,577 tons of greenhouse gases (GHG) entering the local atmosphere of Adrar each year, and about 1214,425 tons over the lifetime of the wind power plant. Similarly, at Timimoun and Tindouf, a total of 38,406 and 27,544 tons of GHG emissions would be avoided. This results supports the social acceptability goal to achieve and reach the value of 100% of satisfaction. All of these results mean that the DM should be very satisfied with the choice suggested by the proposed model, because the strategic plan should be close to his ideal.

The proposed FGP-IT model, which uses the concept of fuzzy interval membership functions, should be more efficient and realistic than previous models that use discontinuous fuzzy membership functions (Tabrizi et al. (2012), Mouslim et al. (2014), Umarusman (2018), and Mirzaee et al. (2018)). According to the modeling results obtained using FGP-IT, the model may make it possible to achieve some goals more completely by adjusting the interval window on the RHS of each goal criterion automatically, which will consequently utilize the resources more appropriately and create a higher satisfaction level for the DM. Based on these observations, the proposed FGP-IT model should offer a superior solution to traditional FGP approaches.

7 Conclusion

The identification of the most suitable RE source for electricity generation is an important issue in the implementation of appropriate RE planning policies. To tackle this problem, in this study, a FGP-IT model is proposed to optimize the creation of a sustainable wind energy portfolio in Algeria when the decision context involves deep uncertainty and the overall aim is SD in the country. This was original motivation for the study. The uncertainty in this situation is deep because, in the decision problem, there are not only fuzzy goals but also fuzzy interval goal targets. Methodologically, a main advantage of the proposed model is its ability to deal with problems having continuous fuzzy MCALs, which cannot be expressed and formulated by current FMCGP techniques. At the very least, it provides an alternative way to formulate the FGP problem when the preferences of the DM are described using complex terms such as "between approximately." Another advantage of the proposed model is that it can be easily applied to handle the complexity of real-world decision making problems, where several main types of membership functions are considered and formulated. At least, this feature was important for the real-life application modelled and solved in Sect. 6. Furthermore, this has widened the application of FGP, in that this study has applied an MODM model for the optimization of a wind energy portfolio problem. In this sense, as a concluding remark here, we note that the proposed FGP-IT model should be more effective than other FMCGP formulations and that it has broadened the model application context of FGP. These promising results may inspire us to conduct further studies (e.g., sensitivity analysis, comparison of results with those from MADM models, etc.), or to apply it to solve other MODM problems, such as those in the fields of transportation, healthcare planning, supply chain management, and so on.

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References

Aalaei A, Davoudpour H (2016) Revised multi-choice goal programming for incorporated dynamic virtual cellular manufacturing into supply chain management. Eng Appl Artif Intell 47(1):3–15

Aouni B, Martel JM, Hassaine A (2009) Fuzzy goal programming model: an overview of the current state of-the art. J Multi Crit Decis Anal 16(1):149–161

Aouni B, Abdelaziz FB, La Torre D (2012) The stochastic goal programming model: theory and applications. J Multi Crit Decis Anal 19(1):185–200

Attari MYN, Pasandide HSZ, Agaie A, Niaki STA (2017) Presenting a stochastic multi choice goal programming model for reducing wastages and shortages of blood products at hospitals. J Ind Syst Eng 10(1):81–96

Barnett M, Brock W, Hansen LP (2020) Pricing uncertainty induced by climate change. Rev Financial Stud 33(3):1024–1066

Bravo M, Gonzalez I (2009) Applying stochastic goal programming: a case study on water use planning. Eur J Operation Res 196(3):1123–1129

Burke M, Dykema J, Lobell AB, Miguel E, Satyanath S (2015) Incorporating climate uncertainty into estimates of climate change impacts. Rev Econ Stat 97(2):461–471

Chang CT (2007) Multi-choice goal programming. Omega 35(4):389–396

Chang CT (2008) Revised multi-choice goal programming. Appl Math Model 32(12):2587–2595

Charnes A, Cooper WW (1961) Management models and industrial applications of linear programming. Wiley, New York

Chen LH, Tsai FC (2001) Fuzzy goal programming with different importance and priorities. Eur J Operation Res 133(1):548–556

Daim TU, Kayakutlu G, Cowan K (2010) Developing Oregon's renewable energy portfolio using fuzzy goal programming model. Comput Ind Eng 59(1):786–793

Dogan E (2015) Revisiting the relationship between natural gas consumption and economic growth in Turkey. Energy Sources Part B 10(1):361–370

Fischer MM (2019) Quantifying the uncertainty of variance partitioning estimates of ecological datasets. Environ Ecol Stat. https://doi.org/10.1007/s10651-019-00431-6

Ghosh S, Basu SC, Sengupta PP (2010) Improvement of financial efficiency and cost effectiveness in energy sector: a case study from Indian thermal power plant. In ICEMT 2010–2010 international conference on education and management technology proceedings (512–516)

Ghouali S, Guellil MS, Belmokaddem M (2019) Looking over the Horizon 2030: efficiency of renewable energy base plants in Algeria using fuzzy goal programming. In: Hatti M (ed) Smart energy empowerment in smart and resilient cities. Springer, New York, pp 329–337

Haddah B, Liazid A, Ferreira P (2017) A multi-criteria approach to rank renewables for the Algerian electricity system. Renew Energy 107(1):462–472

Himri Y, Rehman S, Draoui B, Himri S (2008) Wind power potential assessment for three locations in Algeria. Renew Sustain Energy Rev 12(1):2488–2497

Ho HP (2019) The supplier selection problem of a manufacturing company using the weighted multi-choice goal programming and MINMAX multi-choice goal programming. Appl Math Model 75(1):819–836

Hocine A, Kouaissah N (2019) XOR analytic hierarchy process and its application in the renewable energy sector. Omega. https://doi.org/10.1016/j.omega.2019.06.008

Hocine A, Kouaissah N, Bettahar S, Benbouziane M (2018) Optimizing renewable energy portfolios under uncertainty: a multi-segment fuzzy goal programming approach. Renew Energy 129(1):540–552

Hocine A, Zheng-Yun Z, Kouaissah N, Der-Chiang L (2020) Weighted-additive fuzzy multi-choice goal programming (WA-FMCGP) for supporting renewable energy site selection decisions. Eur J Operation Res. https://doi.org/10.1016/j.ejor.2020.02.009

Hoffmann VH, Trautmann T, Hamprecht J (2009) Regulatory uncertainty: a reason to postpone investments? not necessarily. J Manage Stud 46(7):1227–1253

Hussain T, Hassan SB, Chesneau C (2019) A new probability model with application to heavy-tailed hydrological data. Environ Ecol Stat 26(1):127–151

Ignizio JP (1985) Introduction to linear goal programming. Sage, Beverly, Hills

Jayaraman R, La Torre D, Malik T, Pearson YE (2015) Optimal labor allocation for energy, economic and environmental sustainability in the United Arab Emirates: a goal programming approach. Energy Procedia 75(1):2999–3006

Jayaraman R, Colapinto C, Liuzzi D, La Torre D (2017a) Planning sustainable development through a scenario-based stochastic goal programming model. Oper Res Int Journal 17(3):789–805
Jayaraman R, Colapinto C, La Torre D, Malik T (2017b) A Weighted Goal Programming model for planning sustainable development applied to Gulf Cooperation Council Countries. Appl Energy 185(1):1931–1939
Jones DF, Tamiz M (2010) Practical goal programming. Springer, New York
Kouaissah N, Hocine A (2020) Optimizing sustainable and renewable energy portfolios using a fuzzy interval goal programming approach. Comput Ind Eng. https://doi.org/10.1016/j.cie.2020.106448
Kraft J, Kraft A (1978) On the relationship between energy and GNP. J Energy Dev 3(2):401–403
Kwak NK, Lee CW, Kim JH (2005) An MCDM model for media selection in the dual consumer/industrial market. Eur J Operation Res 166(1):255–265
Lai YJ, Hwang CL (1994) Fuzzy multiple objective decision making: methods and applications. Lecture notes in economies and mathematical systems. Springer, New York
Lee SM (1972) Goal programming for decision analysis. Auerbach, Philadelphia
Lee CF, Lin SJ, Lewis C (2008) Analysis of the impacts of combining carbon taxation and emission trading on different industry sectors. Energy Policy 36(2):722–729
Mirzaee H, Naderi B, Pasandideh SHR (2018) A preemptive fuzzy goal programming model for generalized supplier selection and order allocation with incremental discount. Comput Ind Eng 122(1):292–302
Moravcsik MJ (1984) Life in a multidimensional world. Scientometrics 6(2):75–86
Mouslim H, Belmokaddem M, Benbouziane M, Melloul S (2014) A fuzzy goal programming formulation with multiple target levels. J Multi Crit Decis Anal 21(3–4):223–235
Mrabet Z, AlSamara M, Jarallah SH (2017) The impact of economic development on environmental degradation in Qatar. Environ Ecol Stat 24:7–38
Narasimhan R (1980) Goal programming in a fuzzy environment. Decision Sci 11(2):325–336
Narasimhan V, Huang RYM, Burns CM (1981) Effect of concentration and second polymer on elution volumes in gel permeation chromatography. J Appl Polym Sci 26(4):1295–1300
NREAP (2017) National Renewable Energy Action Plan (NREAP). Available at https://www.iea.org/policies/4838-national-renewable-energy-action-plannreap
Oliviera C, Coelho D, Antunes CH (2014) Coupling input-output analysis with multiobjective linear programming models for the study of economy-energy-environment-social (e3s) trade-offs: a review. Ann Oper Res 247(1):471–502
Patro KK, Acharya MM, Acharya S (2018) Multi-choice goal programming approach to solve multi-objective probabilistic programming problem. J Inf Optimization Sci 39(3):607–629
Romero C (1991) A handbook of critical issues in goal programming. Pergamon Press, Oxford
San Cristóbal JR (2012) A goal programming model for the optimal mix and location of renewable energy plants in the north of Spain. Renew Sustain Energy Rev 16(1):4461–4464
Schrage L (2009) Optimization modelling with LINGO. Lindo Syst Inc., Chicago
Silva AFD, Marins FAS, Montevechi JAB (2013) Multi-choice mixed integer goal programming optimization for real problems in a sugar and ethanol milling company. Appl Math Model 37(1):6146–6162
Stern DI (2004) Economic growth and energy. In: Cutler J (ed) Encyclopedia of energy: 2. Elsevier Cleveland, Philadelphia
Stock GN, Tatikonda MV (2008) The joint influence of technology uncertainty and interorganizational interaction on external technology integration success. J Operations Manag 26:65–80
Tabrizi BB, Shahanaghi K, Jabalameli MS (2012) Fuzzy multi-choice goal programming. Appl Math Model 36(4):1415–1420
Tamiz M, Jones D, Romero C (1998) Goal programming for decision making: an overview of the current state-of-the-art. Eur J Operation Res 111(1):569–581
Umarusman N (2018) Fuzzy goal programming problem based on minmax approach for optimal system design. Alphanumeric J 6(1):177–192
Vakulchuk R, Overland I, Scholten D (2020) Renewable energy and geopolitics: a review. Renew Sustain Energy Rev. https://doi.org/10.1016/j.rser.2019.109547
World Commission for Environment and Development (WCED) (1987) Our common future. Oxford University Press, Oxford
Yaghoobi MA, Tamiz M (2007) A method for solving fuzzy goal programming problems based on MINMAX approach. Eur J Operation Res 177(1):1580–1590
Yaghoobi MA, Jones DF, Tamiz M (2008) Weighted additive models for solving fuzzy goal programming problems. Asia PacJ Operational Res 25(5):715–733

Yu S, Zhou S, Zheng S, Li Z, Liu L (2019) Developing an optimal renewable electricity generation mix for China using a fuzzy multi-objective approach. Renew Energy 139(1):1086–1098
Zadeh LA (1965) Fuzzy sets. Inf Control 8(1):338–353
Zamanian MR, Sadeh E, Sabegh ZA, Rasi RE (2019) A fuzzy goal-programming model for optimization of sustainable supply chain by focusing on the environmental and economic costs and revenue: a case study. Adv Math Finance Appl 4(1):103–123
Zhuang ZY, Hocine A (2018) Meta goal programing approach for solving multi-criteria de Novo programing problem. Eur J Operation Res 265(1):228–238
Zimmermann HJ (1978) Fuzzy programming and linear programming with several objective functions. Fuzzy Sets Syst 1(1):45–55
Zografidou E, Petridis K, Arabatzis G, Dey PK (2016) Optimal design of the renewable energy map of Greece using weighted goal-programming and data envelopment analysis. Comput Oper Res 66(1):313–326
Zografidou E, Petridis K, Petridis NE, Arabatzis G (2017) A financial approach to renewable energy production in Greece using goal programming. Renew Energy 108(1):37–51

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