Planning sustainable development through a scenario-based stochastic goal programming model

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Abstract Most real-world optimization problems involve numerous conflicting criteria, imprecise information estimates and goals, thus the stochastic goal programming method offers an analytical framework to model and solve such problems. In this paper, we develop a stochastic goal programming model with satisfaction function that integrates optimal resource (labor) allocation to simultaneously satisfy conflicting criteria related to economic development, energy consumption, workforce allocation, and greenhouse gas emissions. We validate the model using sectorial data obtained from diverse sources on vital economic sectors for the United Arab Emirates. The results offer significant insights to decision makers for strategic planning decisions and investment allocations towards achieving long term sustainable development goals.

Keywords Multi-criteria decision making · Stochastic goal programming · Satisfaction function · Energy–environment–economic models

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1 Introduction

Multi-criteria decision analysis (MCDA) is an important branch of operations research which deals with modeling and analysis of problems involving several competing objectives suitably considering trade-offs and solution alternatives. Among the various solutions in the feasible set the decision maker (DM) chooses the one that simultaneously satisfies all criteria without under and/or over achieving the targeted goals. Over the years several solutions methods have been proposed to model and analyze multi-criteria problems including analytical hierarchy process (AHP), analytical network process (ANP), data envelopment analysis (DEA), technique for order of preference by similarity to ideal solution (TOPSIS), VIKOR, goal programming (GP), preference ranking organization method for enrichment of evaluations (PROMETHEE), elimination and choice expressing reality (ELECTRE), and multi-attribute utility theory (MAUT). The choice of a particular method varies widely based on the nature of the problem and the application domain. Typical MCDA problems consist of the desired goal value, DM's preferences, model criteria, decision alternatives and trade-offs. GP models are quite popular and well known technique. They offer the flexibility in solving decision problems involving competing objectives by minimizing the deviations between achieved and targeted values to explore potential tradeoffs. Standard GP models deal with deterministic goals that are precisely defined. Common variants to standard GP models include lexicographic GP (LGP), weighted GP (WGP), and polynomial GP (PGP). GP models has been widely used by economists and policy planners to study multi-criteria decision problems in a variety of application domains such as: agriculture (Prišenk et al. 2014; Ragkos and Psychoudakis 2009), energy (Zografidou et al. 2016; Jones and Wall 2015), environment (Brandenburg 2015), finance (Aouni et al. 2014; Zopounidis et al. 2015;), manufacturing (Yu et al. 2015), resources planning (Leung and Chan 2009), supply chain (Choudhary and Shankar 2014), and healthcare (Ben Abdelaziz and Masmoudi 2012) to name just a few. In several real-world problems goals, model parameters and decision variables are not precise or deterministic. In such cases stochastic formulation or more generally stochastic GP (SGP) models have received attention (see e.g. Aouni et al. 2012). Ballestero (2001, 2005) propose a mean–variance approach to SGP with standard expected utility for linear, WGP models under uncertainty. Aouni and La Torre (2010) study solution methods for stochastic multi-objective problems using GP models by solving the deterministic equivalent of the model and treating the resulting solution as a random variable to compute its probability distribution function.

Jayaraman et al. (2015a) develop a PGP model considering sustainability criteria on energy consumption and GHG emissions, a fuzzy GP model (Jayaraman et al. 2015b) and WGP model (Jayaraman et al. 2015c, d) to study economy, energy, environmental and sustainability related goals applied to the United Arab Emirates (UAE). In this paper we extend these previous works to develop a SGP model with linear satisfaction function applied towards sustainable development for optimal resource allocation considering the multiple criteria on economic development, energy consumption, and GHG emissions. We validate the proposed SGP model towards achieving year 2030 sustainability goals of the UAE. The UAE carries over 5.9 % of the worldwide oil reserves (BP Review 2013), and maintains a high GDP per capita, with a robust vision to diversify into a knowledge based economy and a strong commitment to preserve the environment through sustainable development policies (UAE Vision 2021, Abu Dhabi Economic Plan 2030). The growing economic prosperity and developments have brought significant challenges on energy consumption and population growth in turn contributing to increased GHG emissions (Omri 2013; Al-mulali et al. 2012). Electricity generation in the UAE is primarily through non-renewable sources such as natural gas and oil, with renewables (wind and solar) contributing to <0.1 % (Kazim 2007). During the years 2000–2010 the annual growth of electricity demand is 10.8 %, closely followed the trend of 11 % annual population growth (Mokri et al. 2013). Due to the growing electricity demand the overall GHG emissions in UAE are increasing at alarming rates. According to year 2013 estimates, 199.65 million tons of CO_2 and other greenhouse gases were released in environment (Ministry of Energy, UAE 2015). While the UAE's total GHG contribution to climate change may be insignificant, it still represents a very high per capita rate of 24.16 tons in comparison to global average of 7 tons per person.[1]

In the context of a growing body of literature, the motivation for our model stems from the increased concern about the relation between global population growth, energy consumption and GHG emissions and the effects on long-run sustainability. In order to develop comprehensive strategies policy makers rely on quantitative decision tools to model and study the underpinnings and causality among various sustainability criteria. The research community is paying attention to significant criteria such as: energy (electricity) consumption, population growth, GHG emissions, gross domestic product (GDP), labor allocation, interest rates and green taxation. The long-run dynamics of the sustainability criteria offers unique challenges and opportunities to better plan resource allocation, attract investments in important sectors to achieve stable economic growth and mitigate future risks.

In this paper we develop a multi-criteria model using SGP with linear satisfaction function for optimal resource allocation to simultaneously satisfy multiple criteria on GDP growth (F1), electricity consumption (F2), GHG emission (F3) and number of employees in each economic sector (F4). The results of the model can be used by policy makers and economists to explore long term policy options for planned investments towards increased energy efficiency, diversify electricity generation, explore new modes of transportation and indicative measures for long term (economic, energy and environmental) sustainability. The results provide quantitative insights for future investments in sustainable energy transition with a combination of renewables and non-renewables in energy portfolio for long term economic and environmental benefits.

The rest of the paper is organized as follows: in Sect. 2 we discuss the relevant literature on SGP models focusing on energy and environment applications, Sect. 3

[1] UAE released 200 m tons of greenhouse gases in 2013. URL: http://www.thenational.ae/uae/environment/uae-released-200m-tonnes-of-greenhouse-gases-in-2013.

introduces SGP with satisfaction functions. Section 4 describes the model formulation. Section 5 we validate the proposed model with application to the UAE and conclusions are presented in Sect. 6.

2 Literature review: goal programming and sustainability

MCDA using goal programming have been widely used in literature to determine optimal investments in energy production, economic sustainability and environment protection. GP formulations have shown their importance in balancing conflicting aspect of competing criteria: in particular when the probability distribution of uncertainty is known a stochastic GP might be efficiently utilized. A recent survey on GP applications to different areas is presented in Colapinto et al. (2015). During the past decades a variety of energy resources allocation models have been developed different multi-criteria and GP models based on weighted averages, priority setting, stochastic and fuzzy principles and their combinations have been proposed and employed for energy planning decisions. However, due to the complexity of model formulation, in literature only few contributions can be found on the application of SGP specific to environment and related issues. In this section we present the most recent work involving SGP models.

Li et al. (2014) propose a SGP model for groundwater remediation management under human-health-risk uncertainty. They study optimal design approach for groundwater remediation through incorporating numerical simulation, health risk assessment, uncertainty analysis and nonlinear optimization within a general framework. They introduce a SGP model to handle uncertainties in groundwater remediation systems in western Canada. Alikhani and Azar (2013) present a combined SGP model with fuzzy approach for gas resources allocation to different sub-sectors under uncertainty. Two significant bottlenecks that hinder the multi-criteria allocation problem are the system complexity and uncertainty. This method draws upon the existing chance constrained programming and fuzzy set approaches by allowing analysis on trade-offs among desirable value of objective functions and the risk of violating constraints that include uncertain parameters. Niknam et al. (2012) present an efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation. They propose a stochastic model for optimal energy management with the goal of cost and emission minimization where uncertainties related to the forecasted values for load demand, available output power of wind and photovoltaic units and market price are modeled by a scenario-based stochastic programming. Bravo and Gonzalez (2009) apply a SGP model to water use planning. The authors develop a decision support model to help public water agencies allocate surface water among farmers and authorize the use of groundwater for irrigation. Their model considers two goals, namely farm management and environmental impact using targets established by the environmental agency. They present a case study using year-to-year statistical information on available water over the period 1941–2005. André et al. (2009) develop a methodology using GP techniques incorporating environmental perspectives with macro-economic goals applied to Spanish economy. Al-Zahrani and Ahmad (2004) develop a SGP model for optimal blending of desalinated water with groundwater. Werczberger (1984) presents a planning model that applies versatility criterion to GP problems with uncertainty about the constraints assumed to be stochastic variables with a joint normal distribution, the solution maximizes the probability of satisfying all the constraints. The model was applied to land-use planning. The model proposed in this work explicitly integrates electricity consumption, economic growth and environmental pollution is an important addition to the literature. The SGP model considers the uncertainty in the real-world sustainable development. In addition the model employs economic sectors that reflect the peculiarities of an oil-based Middle East economy characterized by high population, increased electricity consumption and affluence.

3 General structure of the goal programming model

The first formulation of a GP models was presented by Charnes et al. (1955), Charnes and Cooper (1952), and further expanded by Lee (1973). We refer the readers to excellent books and state-of-the art survey articles (Ignizio 1976; Aouni et al. 1997, 2014; Romero 1991; Jones and Tamiz 2010; Colapinto et al. 2015). In the literature, GP models are typically used to:

- Determine the required resources to achieve a desired set of goals,
- Determine the degree of attainment of the goals with the available resources,
- Provide the best satisfying solution under resource constraints, goal priorities and uncertainties.

A positive aspect of the GP philosophy is its simplicity and ease of use that makes GP to be well-known and supported by a huge community of researchers and practitioners (Aouni and Kettani 2001). GP can hence handle relatively large numbers of variables, constraints and objectives and this ideally justifies the large number of GP applications in many and diverse fields. A negative limitation is the generation of non Pareto efficient solutions. However, there are several techniques in literature to detect when this occurs and transform the solution into a Pareto efficient solution in a suitable manner. Moreover, the GP formulation can be readily solved through some powerful mathematical programming software such as LINGO® and CPLEX®.

Given p different and competing criteria f_i, $i = 1, \ldots, p$ a set of p aspiration levels/goals g_i associated with each criterion f_i, and a feasible set $D = \{h_s(x) \leq 0,\ s = 1, 2, \ldots, m\}$, the standard mathematical formulation of the GP model (Charnes and Cooper 1952) is the following:

$$
\begin{aligned}
&\text{Min} && Z = \sum_{i=1}^{p} \delta_i^+ + \delta_i^- \\
&\text{Subject to:} && \begin{cases} f_i(x) + \delta_i^- - \delta_i^+ = g_i, & i = 1,\ldots,p \\ x \in \{h_s(x) \le 0, s = 1,2,\ldots,m\} \\ \delta_i^-, \delta_i^+ \ge 0, & i = 1,\ldots,p \end{cases}
\end{aligned} \tag{1}
$$

where δ_i^+ and δ_i^- are, respectively, the positive and the negative deviations with respect to aspiration levels g_i, $i = 1,\ldots,p$. The aspiration levels are double sided meaning that both positive deviation and negative deviation are undesired.

In the classical GP model (1) the decision variables and the aspirations levels are precise and deterministic. However in practical applications, there are several decision-making situations involving parameters that are subject to a certain level of uncertainty and the DM will not be able to assess them precisely. In these circumstances the DM might be able to provide some information regarding the probability distribution of parameter values which leads us to consider the SGP model. The SGP formulation is a natural extension of the classical deterministic GP model in stochastic context (Contini 1968; Aouni et al. 2012). The SGP model deals with the uncertainty related to the decision making situation and in its classical formulation the goals are assumed to be stochastic and follows a specific probability distribution. The general formulation of the SGP is as follows:

$$
\begin{aligned}
&\text{Min} && Z = \sum_{i=1}^{p} w_i^+ \tilde{\delta}_i^+ + w_i^- \tilde{\delta}_i^- \\
&\text{Subject to:} && \begin{cases} f_i(x) + \tilde{\delta}_i^- - \tilde{\delta}_i^+ = \tilde{g}_i, & i = 1,\ldots,p \\ x \in \{h_s(x) \le 0, s = 1,2,\ldots,m\} \\ \tilde{\delta}_i^-, \tilde{\delta}_i^+ \ge 0, & i = 1,\ldots,p \end{cases}
\end{aligned} \tag{2}
$$

where typically $\tilde{g}_i$ are normally distributed $N(\mu_i; \sigma_i^2)$. The complexity of a decision making problem involving stochastic parameters can be well understood when considering the fact that a point in the domain might be an optimal solution of the problem only when some realizations of the random parameters occur. The usual strategy to deal with stochastic decision making situation is to transform the stochastic formulation into a deterministic equivalent formulation. The negative counterpart of these transformations is the loss of information. To avoid such a situation, Aouni and La Torre (2010) propose a different formulation of a SGP model based on a scenario-based philosophy. In their formulation, the optimal solution is supposed to be a random variable and this assumption describes with much more details the complexity of the stochastic context.

More precisely, in this context for simplicity we suppose that the space of events $\Omega = \{\omega_1, \omega_2, \ldots, \omega_s\}$ is discrete. Associated with each event ω_j there is a probability p_j such that $\sum_{j=1}^{s} p_j = 1$. For each event $\omega_j \in \Omega$, let us consider the following scenario-based GP model

$$
\begin{aligned}
&\text{Min} && Z = \sum_{i=1}^{p} w_i^{+}\delta_i^{+}(\omega_j) + w_i^{-}\delta_i^{-}(\omega_j) \\
&\text{Subject to:} && \begin{cases} f_i\left(x(\omega_j), \omega_j\right) + \delta_i^{-} - \delta_i^{+} = g_i(\omega_j), & i = 1, \ldots, p \\ x(\omega_j) \in \{h_s(x) \leq 0, s = 1, 2, \ldots, m\} \\ \delta_j^{-}(\omega_j) \geq 0, & j = 1, \ldots, p \end{cases}
\end{aligned} \tag{3}
$$

For each $\omega_j \in \Omega$ the above model can be solved, thus generating an optimal solution $x(\omega_j)$: in other words, the optimal solution is then a discrete random vector defined on the probability space Ω. This is the fundamental difference between SGP and other classical formulations, that the solution is a random variable that still possesses all information related to the complexity of the decision making process. Abdelaziz (2012) propose various solution approaches for stochastic multiobjective problems and corresponding transformations. It is then possible to describe $x : \Omega \to R$ by means of its moments. The mean and the variance of x can be calculated as:

$$E(x) = \sum_{j=1}^{s} p_j x(\omega_j) \tag{4}$$

$$\sigma^2(x) = \sum_{j=1}^{s} p_j \left[x(\omega_j) - E(x)\right]^2 \tag{5}$$

In the next section we propose a modified scenario-based SGP model that explicitly incorporates the DM's preferences through the notion of satisfaction function. The notion of satisfaction function as a useful tool to model the DM preferences, was introduced by Martel and Aouni (1990) and employed by other authors in literature (Allouche et al. 2009; Aouni et al. 2005). Moreover Aouni et al. (2005) extend the notion of satisfaction function in the context of SGP model. This notion is equivalent to the notion of utility function and is well known in the economics literature. Several definitions of satisfaction function are available: in general a satisfaction function is a mapping $S : R_+ \to [0, 1]$ which satisfies the following properties:

- $S(0) = 1$
- $S(\delta) = 0, \quad \forall \delta \geq \delta_0$
- S is a decreasing function

In this paper we utilize the simplest notion of satisfaction function, namely the linear (Jayaraman et al. 2015e). The mathematical expression of $S(\delta)$ is given by:

$$S(\delta) = \begin{cases} 1 - \alpha\delta & 0 \leq \delta \leq \dfrac{1}{\alpha} \\ 0 & \delta \geq \dfrac{1}{\alpha} \end{cases} \tag{6}$$

For satisfaction function given in Eq. (6) the veto threshold is set to be equal to $\frac{1}{\alpha}$. When the notion of satisfaction function is introduced within the GP approach, the model reads as

$$\begin{aligned} &\text{Max} && Z = \sum_{i=1}^{p} w_i^+ S\left(\delta_i^+(\omega_j)\right) + w_i^- S\left(\delta_i^-(\omega_j)\right) \\ &\text{Subject to:} && \begin{cases} \mathrm{f}_i\left(x(\omega_j), \omega_j\right) + \delta_i^- - \delta_i^+ = g_i(\omega_j), & i = 1, \ldots, p \\ x(\omega_j) \in \{h_s(x) \leq 0, s = 1, 2, \ldots, m\} & \\ \delta_j^-(\omega_j) \geq 0, & j = 1, \ldots, p \end{cases} \end{aligned} \tag{7}$$

4 Model formulation

In the proposed model we suppose the decision maker has to deal with "n" economic sectors. For the jth sector, $j = 1, \ldots, n$, let X_j denote the number of workers represent the decision variables of the model. We consider raw labor in each sector, so that population size can be approximated by $\sum_{j=1}^{n} X_j$. A typical macroeconomic decision making situation considers several conflicting criteria related to sustainable development. In this context we consider the following criteria:

- F_1 = Sectorial gross domestic product (GDP), the monetary value of all the finished goods and services produced by the sector within a country's borders in a specific time period (typically 1 year)
- F_2 = Sectorial electricity consumption (in Giga watt hours)
- F_3 = Sectorial GHG emissions (in Giga gram equivalent of CO_2)
- F_4 = Total number of employees in each economic sector, and as we suppose there is no unemployment, the population size and the labor force perfectly coincide.

Each criterion is supposed to be linearly dependent on each of the above input variables X_j, $j = 1, \ldots, n$ where $i = 1, \ldots 4$ can be described as:

Table 1 Probability distribution of events

ω_k	ω_1	ω_2	ω_3	ω_4	ω_5
p_k	$p_1 = 0.1$	$p_2 = 0.2$	$p_3 = 0.4$	$p_4 = 0.2$	$p_5 = 0.1$

$$F_i(X_1, X_2, \ldots, X_n) = a_{i1}X_1 + a_{i2}X_2 + \cdots + a_{in}X_n$$

The coefficients a_{ij} are presented in the Sect. 5. For each of the above criteria F_i the DM has a random goal g_i whose outcomes are discrete and depends on the associated probabilities. In particular we assume an underlying discrete probability space $\Omega = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5\}$ where associated with each event ω_k there is a probability p_k as described in Table 1.

Each goal g_i will assume different outcomes depending on the realization of the event ω_k with probability p_k and leads to different possible scenarios for the macroeconomic objective functions F_i. The possible scenarios are obtained by projecting the current trends over long term, such estimations are of course affected by a certain level of uncertainty, which justifies the assumption that the goals are following a random distribution. The scenario-based SGP model with linear satisfaction function can be mathematically represented as

$$\begin{array}{ll} \text{Max} & \sum_{i=1}^{4} 1 - \alpha_i^+ \delta_i^+ + \sum_{i=1}^{4} 1 - \alpha_i^- \delta_i^- \\ \text{Subject to:} & \begin{cases} a_{11}X_1 + a_{12}X_2 + \cdots + a_{1n}X_n + \delta_1^- - \delta_1^+ = g_1(\omega_k) \\ a_{21}X_1 + a_{22}X_2 + \cdots + a_{2n}X_n + \delta_2^- - \delta_2^+ = g_2(\omega_k) \\ a_{31}X_1 + a_{32}X_2 + \cdots + a_{3n}X_n + \delta_3^- - \delta_3^+ = g_3(\omega_k) \\ a_{41}X_1 + a_{42}X_2 + \cdots + a_{4n}X_n + \delta_2^- - \delta_2^+ = g_4(\omega_k) \\ X_1 \geq \overline{X_1} \\ X_2 \geq \overline{X_2} \\ \cdots \\ X_n \geq \overline{X_n} \\ \delta_i^-, \delta_i^+ \geq 0, \ i = 1, \ldots, 4 \\ \delta_i^-, \delta_i^+ \leq \dfrac{1}{\alpha} \end{cases} \end{array} \tag{8}$$

The DM wishes to maximize his/her satisfaction by keeping the deviation values as small as possible. The values $\overline{X_i}$ represent the current number of employees per sector, and the inequalities take into account the DM's willingness to preserve the current level of employment. The optimal solutions of the above model will depend on the event ω_k with probability p_k that is all of them are discrete random variables defined on the space of events $\Omega = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5\}$. The DM can then decide the optimal allocation of labour forces across the sectors by using the highest probability criterion.

5 Case study: application to the UAE

5.1 Data analysis and source

The social accounting matrix (SAM) is a versatile tool that captures economic activity across various sectors. SAM represents flows describing consumption, investment, intermediate inputs, government deficit, and savings in a schematic way. To validate our model in Eq. (8), we use data from several sources. We use the eight sector SAM developed for the UAE by Vellinga (2006) consisting of eight economic sectors. The sector wise data on GDP and number of employees are obtained from the UAE Ministry of Economy's Annual Economic Report 2012. Electricity consumption data are obtained from the International Energy Agency (IEA) with reference to the year 2011. The IEA data provides aggregate numbers of electricity consumption for some sectors; to disaggregate we use the percentile contribution of GDP relative to each sector. GHG emissions data for the year 2005 (the most recent entry) are obtained from the United Nations Framework Convention on Climate Change 2012. Table 2 presents the per capita estimates of the criteria for the eight economic sectors. The year 2030 goals were estimated from the economic and developmental objectives laid out in the UAE Vision 2021 and Abu Dhabi Economic Vision 2030 are presented in Table 3.

Table 2 Sectorial indicators for the model criteria

Decision variable	Sector	GDP per capita[a]	Electricity consumption per capita[b]	GHG emissions per capita[c]	Number of employees[a]
X_1	Agriculture	0.03521739	0.00478696	0.01728696	230,000
X_2	Crude oil, natural gas and quarrying	4.69696970	0.05912121	1.71707576	66,000
X_3	Manufacturing and electricity	0.18134206	0.02502291	0.06629133	611,000
X_4	Construction and real estate	0.08385650	0.01873543	0.00267227	1,338,000
X_5	Trade and transport	0.17690457	0.01614274	0.00627506	1,247,000
X_6	Restaurant and hotels	0.08095238	0.00738571	0.00258095	210,000
X_7	Banking and financial Corporations	1.05138889	0.14509722	0.03349306	72,000
X_8	Government, social and personal services	0.09569444	0.00872083	0.00305000	720,000

Data source

[a] UAE Ministry of Economy Annual Economic Report, UAE National Bureau of Statistics

[b] International Energy Agency

[c] Third communication to UNFCCC

Table 3 Values and growth rate of goals

Goals	Value (growth rate)
G_1 (GDP)	2725 Billion (7 %)
G_2 (electricity consumption)	286,980 Gwh (8 %)
G_3 (GHG emissions)	284,739 Gg (2 %)
G_4 (number of employees)	9,452,000 (3.75 %)

Table 4 Scenarios and probability distribution

	$\omega_{-10\%}$	$\omega_{-5\%}$	ω_0	$\omega_{+5\%}$	$\omega_{+10\%}$
g_1	2,452,365	2,588,607	2,724,850	2,861,250	2,997,500
g_2	258,282	272,631	286,980	301,329	315,678
g_3	256,265	270,502	284,739	298,976	313,212.9
g_4	8,506,800	8,979,400	9,452,000	9,924,600	1.04E + 07
p_k	$p_{-10\%} = 0.1$	$p_{-5\%} = 0.2$	$p_0 = 0.4$	$p_{+5\%} = 0.2$	$p_{+10\%} = 0.1$

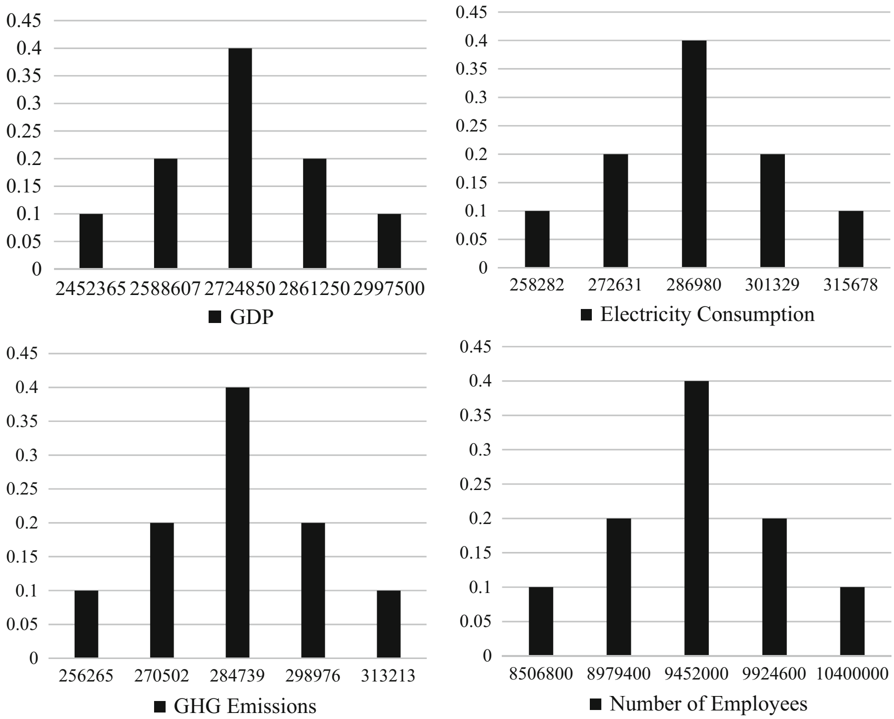

Fig. 1 Distribution of model criteria

Table 5 Results for different scenarios

Variables	Scenarios				
	$\omega_{-10\%}$	$\omega_{-5\%}$	ω_0	$\omega_{+5\%}$	$\omega_{+10\%}$
δ_1^+	4.020775	1.301352	0	2.375469	1.826949
δ_1^-	0.000000	0.000000	0.4921978	0.000000	0
δ_2^+	223,197.1	220,300.4	217,404.1	214,532.8	211,609.8
δ_2^-	0.000000	0.000000	0	0	0.000000
δ_3^+	1.663088	0.7192154	0.000000	0	0.4431071
δ_3^-	0.000000	0.000000	0.1633046	0.9695348	0
δ_4^+	1.000000	0.000000	0.000000	1.000000	0
δ_4^-	0.000000	0.1018634E−08	0	0	1.000000
X_1	230,000	230,000	230,000	230,000	230,000
X_2	87,695	94,009	100,323	106,635	112,949
X_3	611,000	611,000	611,000	611,000	611,000
X_4	1,338,000	1,338,000	1,338,000	1,338,000	1,338,000
X_5	4,413,479	4,852,211	5,290,942	5,729,481	6,171,569
X_6	210,000	210,000	210,000	210,000	210,000
X_7	896,627	924,180	951,735	979,485	1,006,483
X_8	720,000	720,000	720,000	720,000	720,000
Objective value	7.776,796	7.779,698	7.782,595	7.785,463	7.788,387

5.2 Model validation

To determine an optimal allocation of employees across the eight economic sectors to attain the year 2030 goals, constrained by GDP growth, the electricity consumption, the level of GHG emission, and the total number of available employees. For each criterion, the corresponding goal can take five possible values, according to the distribution of probabilities described in Table 4. Table 4 has been obtained by using historical data and forecasting the long-run solution of the phenomena under the assumption of normality.

Figure 1 shows the probability distribution for G_1, G_2, G_3 and G_4, which has a symmetrical probability distribution around the most likely value, GDP (ω_0). The methodology does not change if the probability distribution is supposed to be asymmetric instead.

For each scenario $\omega_j, j = 1, \ldots, 5$ the following integer linear programming (ILP) model has been implemented:

$$\begin{aligned}\text{MaxZ} = 8 - 10^{-6}\delta_1^+ - 10^{-6}\delta_1^- - 10^{-6}\delta_2^+ - 10^{-6}\delta_2^- - 10^{-6}\delta_3^+ - 10^{-6}\delta_3^- \\ -10^{-6}\delta_4^+ - 10^{-6}\delta_4^-\end{aligned}$$

Subject to:

$$\begin{cases} 0.03521739x_1 + 4.69696970x_2 + 0.18134206x_3 + 0.08385650x_4 \\ +0.17690457x_5 + 0.08095238x_6 + 1.05138889x_7 + 0.09569444x_8 \\ +\delta_1^- - \delta_1^+ = g_1(\omega_k) \\ 0.00479x_1 + 0.05912x_2 + 0.02502x_3 + 0.1874x_4 + \\ 0.01614x_5 + 0.00739x_6 + 0.14510x_7 + 0.00872x_8 + \delta_2^- - \delta_2^+ = g_2(\omega_k) \\ 0.01728696x_1 + 1.71707576x_2 + 0.06629133x_3 + 0.00267227x_4 \\ +0.00563352x_5 + 0.00258095x_6 + 0.03349306x_7 + 0.00305000x_8 \\ +\delta_3^- - \delta_3^+ = g_3(\omega_k) \\ x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + \delta_4^- - \delta_4^+ = g_4(\omega_k) \\ x_1 \geq 230000 \\ x_2 \geq 66000 \\ x_3 \geq 611000 \\ x_4 \geq 1338000 \\ x_5 \geq 1247000 \\ x_6 \geq 210000 \\ x_7 \geq 72000 \\ x_8 \geq 720000 \\ 0 \leq \delta_i^{\pm} \leq 10^6 \qquad i = 1, \ldots, 4 \\ x_j \text{ are integer} \qquad j = 1, \ldots, 8 \end{cases}$$

The model is solved using LINGO 14 and the output for each scenario is provided in Table 5.

Table 6 describes the interpretation of result for various scenarios, for each criterion and depending on the scenario ω_k, if the random goal has been achieved or not.

As discussed in Sect. 5.1, the scenario-based approach allows to draw precise conclusions based on particular scenario or on average. Table 7 provides, on

Table 6 Achievement levels

Criteria	Scenarios				
	$\omega_{-10\%}$	$\omega_{-5\%}$	ω_0	$\omega_{+5\%}$	$\omega_{+10\%}$
F_1	Achieved	Achieved	Achieved	Achieved	Achieved
F_2	Not achieved	Not achieved	Not achieved	Not achieved	Not achieved
F_3	Achieved	Achieved	Achieved	Achieved	Achieved
F_4	Achieved	Achieved	Achieved	Achieved	Achieved

Table 7 Expected values

Variable	Expected value
X_1	230,000
X_2	100,322
X_3	611,000
X_4	1,338,000
X_5	5,291,220
X_6	210,000
X_7	951,738
X_8	720,000

average, the optimal value of all input variables X_i. For instance, the expected value of X_2 is calculated as follows:

$$\begin{aligned} E(X_2) &= 87695 * 0.1 + 94009 * 0.2 + 100323 * 0.4 + 106635 * 0.2 + 112949 * 0.1 \\ &= 100322 \end{aligned}$$

The expected value provides the DM the optimal value for each input variable X_i that is the averaged across all possible scenarios. Similar calculations can be repeated for each decision variable. The significance of the expected value can be verified by calculating the variance of each random variable X_i and determine the dispersion around the expected value.

Finally, in the discrete context an optimal decision can be taken by using the highest probability criterion. In this case the optimal allocation of number of employees that can ideally contribute to the sustainability of long-run economic growth across different possible scenarios is presented below in Table 8.

6 Conclusions

In this paper we present a scenario-based stochastic goal programming model with satisfaction function for optimal employee allocation across various economic sectors. The model allows to draw macroeconomic conclusions regarding the long-run sustainability considering economic growth, electricity consumption, GHG

Table 8 Optimal values according to the highest probability criterion

Variable	Optimal value	Probability
X_1	230,000	1
X_2	100,323	0.4
X_3	611,000	1
X_4	1,338,000	1
X_5	5,290,942	0.4
X_6	210,000	1
X_7	951,735	0.4
X_8	720,000	1

emissions, and number of employees. This work emphasizes the importance of multi-criteria techniques as critical tools for policy planning and economic analysis relating to sustainable development.

The results of the model strongly justify the ongoing and planned investments in renewable and low emitting sources of energy to augment the growing demand of electricity ensuring the long-run stability of the UAE's sustainability targets. The prospective goals used to validate the model are obtained by using the current trends and projecting them over the next 15 years. This work extends the fuzzy GP model developed in Jayaraman et al. (2015b). The fuzzy variant of the model provides a general framework for studying the multi-criteria problem, however the stochastic model offers the advantage of obtaining more precise conclusions: in fact, the presence of an underlying probability distribution allows to consider different scenarios simultaneously and to determine the expected optimal solution that represents the weighted average (in probability) of all optimal solutions. In particular the model conclusions suggest that the electricity demand target is underestimated, observed by the expected positive deviation δ_2^+ that is significantly different than zero.

The above results offer significant insights to decision maker, in order to ideally compensate the discrepancies between the achievement level and corresponding goal for electricity demand, the decision maker should strongly rely on investments in renewable and green energy sources. The model results reveal the strong relationship and interdependencies between the variables and the need for a comprehensive energy policy integrating renewable energy sources in the energy portfolio for electricity generation. In fact such a policy ideally facilitates the targeted growth of GDP, required work force, and simultaneously controls GHG emissions.

Future research plans include cost analysis of investments in green and renewable energies as an additional criterion, which measures the cost/benefit analysis in a green energy-based economy. It is worth to note that this additional criterion will have very limited data which suggests that a fuzzy approach will be favored. An extension of the model for future work should also consider the effects of green taxation, assess trade-offs between various renewable alternatives factoring cost and penalties for increased energy use and pollution abatement efforts.

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