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# Distributionally robust goal programming approach for planning a sustainable development problem

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ABSTRACT

Sustainable development requires the implementation of appropriate policies to conduct resource allocation, and it often involves two main challenges related to the multiple conflicting objectives and imprecise distributions. This paper proposes a new distributionally robust goal programming model to balance three goals based on the priority structure and capture the distribution uncertainty of per capita contributions and unemployment rates using ambiguity sets. In our model, the three goals represent the minimizing the risks regarding the environment, economy and energy. Risk measures are characterized by mean semi-deviations. The proposed model is practical and effective because satisfactory policies can be obtained by solving its tractable robust counterpart model under ambiguous sets. The application of our model is demonstrated by a case study of the sustainable development of Gulf Cooperation Council (GCC) countries by the year 2030. The results indicate the appropriate development trends related to the environment, economy and energy and the sectors that the member countries should focus on to achieve sustainability. A sensitivity analysis reveals that the optimal decisions for different perturbation data are active. Comparison studies of our model with the nominal stochastic and deterministic models confirm that the proposed model with distribution uncertainty can provide more substantive decisions.


## 1. Introduction

This paper studies the sustainable development problem, which involves multiple conflicting aspects: environmental, economic, energy and social factors. The sustainable development problem was initially identified in the 1980s and refers to meeting current needs without compromising future development (WCED, 1987). With the rapid development of the economy and increasing energy consumption, environmental pollution has increased sharply, which has had an extremely adverse effect on global development (Omri, 2013). Since the winter of 2012, haze has affected a wide area, and serious environmental issues have attracted worldwide attention (Liu and Lin, 2019). Consequently, a large number of countries no longer blindly pursue fast-tracked economic development but are paying more attention to national sustainable development. The United Nations 2030 Agenda on Sustainable Development proposed 17 sustainable development goals (Jayaraman et al., 2017a). As a theme of global concern, the sustainable development problem is fundamentally understood as a combination of environmental, economic, energy and social aspects (Mohammed et al., 2018). The problem aims to allocate resources to balance the trade-offs within the economy-energy-environment-social system (Jayaraman et al., 2017a). Accordingly, to achieve sustainable development, countries need to adopt appropriate policies for resource allocation to balance the economic, environmental, energy and social systems.

In planning for sustainable development, policy-makers often face a limited amount of available data and a challenges associated with balancing multiple conflicting goals. This paper considers that the true distributions of the per capita greenhouse gases (GHG) emissions, GDP, electricity consumption and the unemployment rate are imprecise. In particular, this paper characterizes the imprecise distributions by ambiguity sets and suggests that the true distributions lie within ambiguity sets. The decisions to be optimized by policy-makers involve four conflicting criteria related to the environment, economy, energy and society. Towards this end, we build a new distributionally robust goal programming model including three goals with a priority structure. The three goals

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represent the minimum risks related to the environment, GDP and energy. Moreover, we also incorporate the risk measure for society and set it as a constraint. This proposed method ensures that the optimal policies obtained under distribution uncertainty are consistent with the expected level and thus prevent high risks to policy makers. Our approach is novel and especially effective for applications in planning sustainable development under distribution uncertainty and multiple conflicting goals. We summarize our contributions in detail after reviewing the related literature.

### 1.1. Literature review

In this work, the literature review is presented from four aspects. First, the certain sustainable development problems are discussed. Second, the studies that consider uncertainty are highlighted. Third, robust sustainable development references are reviewed. Finally, the current reference bottlenecks are enumerated to mirror our study contribution.

(1) *Certain sustainable development problem.* With the increasing interest in sustainable development and urgent need for solutions, many researchers initially embarked on studies of certain sustainable development problems. Since the acclaimed definition related to sustainable development was first presented by World Commission on Environment and Development (WCED, 1987), the sustainable development concept evolved, and its meaning and conceptual perspectives have been given by Simon (1989); Veeman (1989) and Curtin and Busby (1999). After that, de Carvalho Simas et al. (2013) proposed and analysed how the sustainable development can be integrated into the implementation of organizational strategies. They also proposed a conceptual model to address the relationship between sustainable development and organizational strategy implementation. Subsequently, several related studies involving aspects of economic, energy, environmental and social sustainability were documented based on goal programming methods (Charnes and Cooper, 1957). Jayaraman et al. (2015) analysed the sustainable development problem to take into account economic, environmental, energy and social goals. They also proposed a multi-criteria goal programming (MCGP) model to probe the sustainability of the United Arab Emirates (UAE). Further, Jayaraman et al. (2017a) employed a weighted goal programming (WGP) model to the sustainable development of GCC countries. These studies investigated related problem using certain optimization methods, which are summarized in Table 1 in rows 3 to 4. With in-depth studies of the related topics, uncertain sustainable development problems should become a focus due to the limited available data.

(2) *Uncertain sustainable development problem.* In real-world sustainable development problems, uncertainty always exists and cannot be completely avoided. Many researchers have identified uncertain information and characterized uncertain parameters by assuming known distributions. The most related studies to our work are those that explored the sustainable development of the economy-environment-energy-society system; however, only a few studies have been conducted. Jayaraman et al. (2017b, c) considered the right-hand aspiration levels related to GDP, GHG emissions, electricity consumption and number of labourers as uncertain parameters. And they assumed that these uncertain parameters obey scenario-based stochastic uncertainty and fuzzy uncertainty. As result, they developed stochastic goal programming (SGP) and fuzzy goal programming (FGP) models to analyse the sustainable development of the UAE. Based on the works by Jayaraman et al. (2015, 2017c), Nomani et al. (2017) also highlighted that the right-hand aspiration levels were provided with potential fuzzy uncertainty and thus characterized uncertain parameters by fuzzy sets, and then they proposed a fuzzy goal programming model to study sustainable development in India. Drawn the idea of above studies, Gupta et al. (2018) analysed the sustainable goals associated with GDP, electricity consumption and GHG emissions of India. They provided a resource allocation policy by building a fuzzy goal programming model incorporating fuzzy aspiration levels. In Table 1, the above works have been arranged in rows 2 and 5 to 7.

Some other papers also studied the uncertain sustainable development but were more focused on the sustainability of the environmental, energy or other systems. For example, Yu et al. (2018) developed a scenario-based interval-stochastic basic-possibilistic programming method for planning a sustainable energy system of Beijing. The uncertainty related to fuel/electricity price, capacity-expansion options, electricity demand, and vehicle ownership were considered and expressed by interval-possibilistic variables and interval-stochastic-possibilistic variables. Rodriguez-Gonzalez et al. (2018) studied a real-world humane ecosystem and considered mortality and birth rates as uncertain parameters in their problem, and these parameters were captured in an integrated stochastic economic-ecological-social model. Singh and Sarkar (2020) analysed the sustainable product development and proposed a hybrid framework based on the fuzzy Delphi and DEMATEL approach to study the Indian automotive industry. Samaie et al. (2020) studied the sustainability of electric vehicle development in Tehran and utilized a fuzzy TOPSIS method to calculate the closeness coefficient of each policy scenario.

**Table 1**
Knowledge gap with the most related researches.

| Researches | Problem type | Uncertain parameters | | Distribution information | | | Priority | Unemployment | Risk | Optimization |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Aspiration levels | Coefficients | Known | Imprecise | Free | structure | rate | measure | technique |
| Bai et al. (2019) | DRO | | ▲ | | ▲ | | | | | CSOP |
| Gupta et al. (2018) | Fuzzy | ▲ | | ▲ | | | | | | FGP |
| Jayaraman et al. (2015) | Certain | | | | | | | | | MCGP |
| Jayaraman et al. (2017a) | Certain | | | | | | | | | WGP |
| Jayaraman et al. (2017b) | Stochastic | ▲ | | ▲ | | | | | | SGP |
| Jayaraman et al. (2017c) | Fuzzy | ▲ | | ▲ | | | | | | FGP |
| Nomani et al. (2017) | Fuzzy | ▲ | | ▲ | | | | | | FGP |
| Jia et al. (2019) | Robust | | ▲ | | | ▲ | | ▲ | | RMO |
| This paper | DRO | | ▲ | | ▲ | | ▲ | ▲ | MSD | DRGP |

(3) *Robust sustainable development problem*. Due to the complexity for evaluating distributions of uncertain parameters, a few works have employed the robust optimization method (Ben-Tal et al., 2009), which does not require distribution information to study the related topic. For sustainable energy systems, Dong et al. (2016) proposed a robust energy system optimization (RESO) approach to optimize the sustainable energy system of Qiqihar and took into account uncertain demand, which was characterized by the Bayesian interval. The most related study is by Jia et al. (2019), who presented a robust multi-objective optimization (RMO) formulation for allocating labour across sectors to simultaneously satisfy GDP, GHG emissions, electricity and labour. In their work, the left-hand per capita GDP, per capita electricity consumption, per capita GHG and per capita rate of unemployment were robust uncertainties. They then transformed the multi-objective model into a single-objective model related to the maximum GDP and reduced the tractable robust counterpart model to further tackle the sustainability for the UAE. Their work is presented in row 8 of Table 1. Although robust optimization method can completely avoid parameter distribution information, policies obtained by robust optimization are often too conservative.

Policy-makers are usually able to acquire partial distribution information for uncertain parameters according to the collected data. The distributionally robust optimization (DRO) method, pioneered by Scarf (1958), is a powerful approach that can resist the distribution uncertainty of the parameters. This approach can provide a tractable form of a distributionally robust model when the true distributions of uncertain parameters lie within an appropriate ambiguity set. The tractable approximations of distributionally robust model under different ambiguity sets were further discussed by Goh and Sim (2010); Wiesemann et al. (2014); Postek et al. (2018). In addition, Bai et al. (2019) applied DRO to deal with imprecise possibility distributions of per capita GDP, electricity consumption and GHG emissions in the sustainable development problem. However, (i) they considered only GDP as an objective and thus developed a credibilistic single-objective programming (CSOP) model to optimize this topic, rather than balance the multiple conflicting goals; and (ii) they did not consider the unemployment rate and risk measures associated with imprecise distributions. However, they recognized that imprecise possibility distributions of left-hand coefficients are important considerations for the sustainable development problem. Their work is presented in row 1 of Table 1. Moreover, this method has been applied in other research fields, such as two-stage problems (Hanasusanto and Kuhn, 2018; Jiang and Guan, 2018), portfolio problems (Jia and Bai, 2018), crop area planning (Zhang et al., 2018), transportation problems (Zhang and Yang, 2018), and p-hub median problems (Yin et al., 2019).

(4) *Reference bottlenecks*. Based on the above literature review, the most related researches are present in Table 1, and four reference bottlenecks are identified in these studies. (i) Few of the most relevant references realized that the right-hand uncertain aspiration levels essentially result from the uncertainty of the left-hand coefficients. To some extent, the location of uncertain parameters will affect the complexity of optimization. The left-hand uncertain coefficients usually result in a more complex decision process. In Table 1, the uncertain parameters are summarized in columns 3–4. (ii) Although some studies have taken uncertainty into consideration, the risk triggered by potential uncertainty has not been avoided in their works. In Table 1, the risk measure is shown in column 11. (iii) Despite the inherent occurrence of potential uncertain information, distribution uncertainty has been underdeveloped in most relevant quantitative works, which may be because of the intractability of programming in the case of distribution uncertainty. How to deal with the intractable issue becomes a major bottleneck for current related studies from the fixed distribution to a more practical consideration. In Table 1, the types of distribution information are summarized in columns 5–7. (iv) The above studies using goal programming treated all goals equally without incorporating the policy-maker's preference for goal realization and the priority of current development. In Table 1, the priority structure is presented in column 8.

The above reference bottlenecks motivate us to further study this problem from a new perspective. The method developed in this paper enables policy-makers to settle these bottlenecks. Most importantly, our new model is practical and effective because satisfactory policies can be obtained by solving its computable robust counterpart model under ambiguous distribution sets. The contributions of our work are summarized below.

### 1.2. Summary of our contributions

In this paper, we develop a new approach for the sustainable development problem. Specifically, we highlight the following main contributions of this work.

- From a practical standpoint, we highlight how imprecise distributions of uncertain per capita GHG emissions, per capita GDP, per capita electricity consumption and unemployment rate are embodied in the sustainable development problem. Specifically, the true distributions of uncertain parameters lie within moment-based ambiguity sets.
- In the modelling process, we incorporate risk measures into the problem to prevent significant deviations from the expected level and avoid high risks for policy-makers. More concretely, the risk measures are characterized by mean semi-deviations. The type of risk measure is the first considered in the sustainable development problem.
- To help ambiguity-averse policy-makers determine the labour allocation to achieve sustainable development, this paper develops a new distributionally robust goal programming model with priority structure among multiple goals. To the best of our knowledge, this is the first attempt to apply the model for the sustainable development problem.
- We derive a new computationally tractable robust counterpart model for a distributionally robust goal programming model under ambiguous distribution sets. The ambiguity sets are characterized by random variables' descriptive statistics of support, mean values and mean upper semi-deviations.
- We show that our tractable model enables us to analyse the sustainable development of GCC countries in the year 2030. The numerical results demonstrate the credibility and superiority of our new model and provide an in-depth analysis for optimizing the sustainable development of GCC countries.

### 1.3. Outline

The remainder of this paper is organized as follows. Section 2 describes the problem in detail and develops a distributionally robust goal optimization model. Section 3 proposes a moment-based ambiguity set and transforms the proposed model into its tractable form. Section 4 carries out a case study based on the GCC countries to verify the effectiveness of our new model. Section 5 draws some conclusions and future research directions.

## 2. Distributionally robust sustainable development model

### 2.1. Problem description

The problem in this paper is to perform sustainable development problem under distribution uncertainty, which stems from the increased concern for the sustainability of the economy, environment, energy and society. The purpose of this problem is to determine the optimal labour allocation across various key economic sectors to plan for sustainable development under uncertainty and multiple criteria. In this problem, multiple conflicting aspects related to GHG emissions, GDP, electricity consumption and the total number of employees are involved. From a practical standpoint, the distributions of the per capita GHG emissions, GDP, electricity consumption and unemployment rate are only partially available and belong to ambiguous distribution sets. Moreover, we consider $n$ economic sectors and take the economic sector as a unit to allocate labourers. We assume that each objective function is linearly dependent on each of the decision variables and set a specific time period for one year. A brief illustration of this problem is shown in Fig. 1.

### 2.2. Distributionally robust goal programming model

In this subsection, we formally formulate a new distributionally robust goal programming model for the sustainable development problem. The proposed model involves four conflicting aspects related to environment, economy, energy and society and considers three goals. The three goals represent the minimum risks related to the environment, economy and energy. Among the three goals, this model considers the priority of the environment, economy and energy and thus tackles them by goal programming. In the following discussion, we explicitly elaborate on each part of our model.

Constraint conditions.

**GHG emissions:** The formula of the total sectoral GHG emissions (in gigagram equivalent of $CO_2$) based on the resulting optimal labour allocation among $n$ sectors in a year is as follows:

$$Z_1(x, \mathbf{a}(\zeta_a)) = \mathbf{a}_1(\zeta_a)x_1 + \mathbf{a}_2(\zeta_a)x_2 + \ldots + \mathbf{a_n}(\zeta_a)x_n,$$

where decision variable $x_j$ denotes the number of employees in the $j$th economic sector, and parameter $\mathbf{a}_j(\zeta_a)$ denotes the per capita GHG emission of the $j$th economic sector, $j \in [J] = \{j = 1, \ldots, n\}$. $x = (x_1; x_2; \ldots; x_n)$ and $\mathbf{a}(\zeta_a) = (\mathbf{a}_1(\zeta_a); \mathbf{a}_2(\zeta_a); \ldots; \mathbf{a_n}(\zeta_a))$. Uncertain per capita GHG emission $\mathbf{a}(\zeta_a)$ represents a linear mapping of random vector $\zeta_a = (\zeta_a^1; \ldots; \zeta_a^L)$, i.e., $\mathbf{a}(\zeta_a) = a^0 + \sum_{l=1}^{L} \zeta_a^l a^l$. Parameters $a^0$ and $a^l$ are the nominal vector and the perturbation data, respectively.

We have access to only limited distribution information (e.g., the mean and semi-deviation) of $\mathbf{a}(\zeta_a)$, which is insufficient to precisely define the true distribution and leads to the imprecise distribution of the total sectoral GHG emissions $Z_1(x, \mathbf{a}(\zeta_a))$. Under these circumstances, policy-makers may be tempted to impede goals from a desired direction of development. Based on the above consideration, we explore the following hard and soft constraints on GHG emissions.

Hard constraint

$$\mathbb{E}_{\zeta_a \sim \mathbb{P}_a}[Z_1(x, \mathbf{a}(\zeta_a))] \leq Z_1^0, \quad \forall \mathbb{P}_a \in \mathscr{P}_a \tag{1}$$

Stipulates that the expected GHG emissions do not exceed a given GHG emissions level $Z_1^0$. $\mathbb{P}_a \in \mathscr{P}_a$ represents that distribution $\mathbb{P}_a$ of $\zeta_a$ resides in ambiguity set $\mathscr{P}_a$.

We model the risk related to GHG emissions as a soft constraint. The risk of GHG emissions exceeding the expected level should be as small as possible. Specifically, we characterize the risk measure by the mean upper semi-deviation, which is mathematically performed by imposing the following soft constraint:

$$\mathbb{E}_{\zeta_a \sim \mathbb{P}_a}\left[Z_1(x, \mathbf{a}(\zeta_a)) - \mathbb{E}_{\zeta_a \sim \mathbb{P}_a}(Z_1(x, \mathbf{a}(\zeta_a)))\right]^+ - d_1^+ \leq g_1, \quad \forall \mathbb{P}_a \in \mathscr{P}_a, \tag{2}$$

which limits the mean upper semi-deviation of the total sectorial

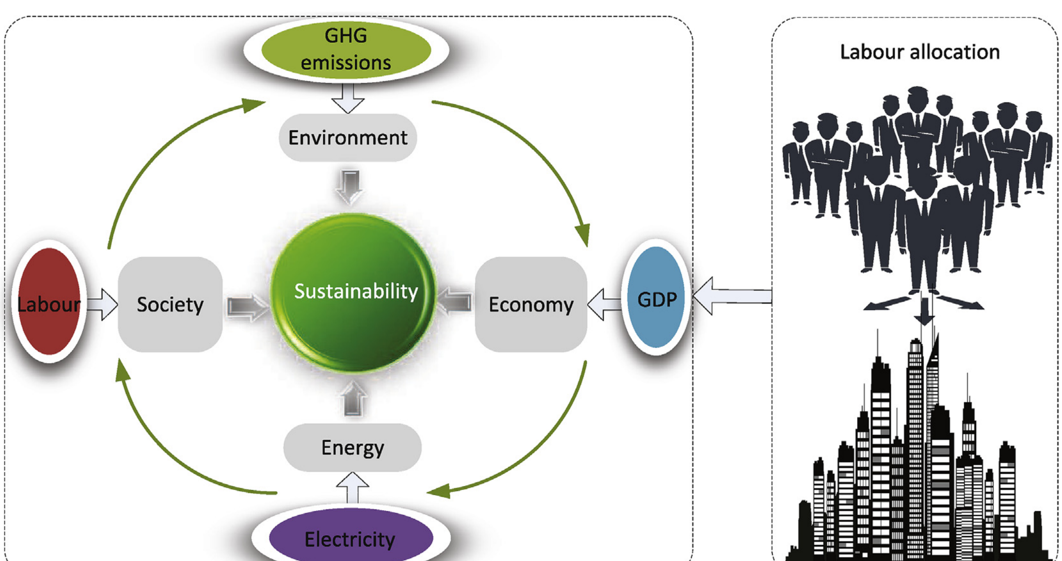


**Fig. 1.** Graphical representation.

GHG emissions. That is, the risk that GHG emissions are higher than the expected level can not exceed a goal value $g_1$ as possible. Positive deviation $d_1^+$ denotes the segment of the risk level related to GHG emissions exceeding its goal value.

**GDP:** The cumulative amount $Z_2(x,\mathbf{b}(\zeta_b))$ of the per capita GDP in $n$ economic sectors is as follows:

$$Z_2(x,\mathbf{b}(\zeta_b))=\mathbf{b}_1(\zeta_b)x_1+\mathbf{b}_2(\zeta_b)x_2+\ldots+\mathbf{b_n}(\zeta_b)x_n,$$

where the per capita GDP $\mathbf{b}_j(\zeta_b)$ is also provided with an imprecise distribution. Uncertain per capita GDP $\mathbf{b}_j(\zeta_b)=b^0+\sum_{l=1}^{L}\zeta_b^l b^l$, in which $\zeta_b=(\zeta_b^1;\ldots;\zeta_b^L)$ is also random vector; $b^0$ is the nominal vector; $b^l$ is the perturbation data. Therefore, the distribution information of the total sectoral GDP $Z_2(x,\mathbf{b}(\zeta_b))$ is also ambiguous.

Based on the aforementioned analysis, we consider the following hard and soft constraints simultaneously.

Hard constraint

$$\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}[Z_2(x,\mathbf{b}(\zeta_b))]\geq Z_2^0,\quad\forall\,\mathbb{P}_b\in\mathscr{P}_b \tag{3}$$

Ensures that the GDP must satisfy a given level $Z_2^0$. $\mathbb{P}_b\in\mathscr{P}_b$ means that distribution $\mathbb{P}_b$ of $\zeta_b$ lies in ambiguity set $\mathscr{P}_b$.

A soft constraint on the GDP is considered from a risk perspective. We want the risk that GDP is below the expected GDP level to be smaller than a given value. Accordingly, we impose the soft constraint in the following mathematical form as follows:

$$\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}(Z_2(x,\mathbf{b}(\zeta_b)))\right]^- -d_2^+\leq g_2,\quad\forall\,\mathbb{P}_b\in\mathscr{P}_b, \tag{4}$$

which restricts the mean lower semi-deviation of the total sectoral GDP $Z_2(x,\mathbf{b}(\mathbf{z}_b))$. Namely, the risk that GDP is lower than expected level does not exceed a goal value $g_2$ as possible. Positive deviation $d_2^+$ denotes the segment of the risk level related to GDP exceeding its goal value.

**Electricity consumption:** The total level of sectoral electricity consumption (in gigawatt hours (GWh)), $Z_3(x,\mathbf{c}(\zeta_c))$, is as follows:

$$Z_3(x,\mathbf{c}(\zeta_c))=\mathbf{c}_1(\zeta_c)x_1+\mathbf{c}_2(\zeta_c)x_2+\ldots+\mathbf{c_n}(\zeta_c)x_n,$$

where the per capita electricity consumption $\mathbf{c}_2(\zeta_c)$ can be mapped by a random vector $\zeta_c=(\zeta_c^1;\ldots;\zeta_c^L)$, i.e., $\mathbf{c}_2(\zeta_c)=c^0+\sum_{l=1}^{L}\zeta_c^l c^l$. Parameters $c^0$ and $c^l$ are the nominal vector and the perturbation data, respectively.

Similarly, the imprecise distribution of $\mathbf{c}_j(\zeta_c)$ leads to distribution uncertainty of the total sectoral electricity consumption $Z_3(x,\mathbf{c}(\zeta_c))$. Under this consideration, we give the following hard constraint and soft constraint.

Hard constraint

$$\mathbb{E}_{\zeta_c\sim\mathbb{P}_c}[Z_3(x,\mathbf{c}(\zeta_c))]\leq Z_3^0,\quad\forall\,\mathbb{P}_c\in\mathscr{P}_c \tag{5}$$

represents that the expected electricity consumption must be under $Z_3^0$, thus inducing an upper bound on the electricity consumption. $\mathbb{P}_c\in\mathscr{P}_c$ expresses that distribution $\mathbb{P}_c$ of $\zeta_c$ locates in ambiguity set $\mathscr{P}_c$.

Similarly, we characterize the risk on electricity consumption as a soft constraint.

$$\mathbb{E}_{\zeta_c\sim\mathbb{P}_c}\left[Z_3(x,\mathbf{c}(\zeta_c))-\mathbb{E}_{\zeta_c\sim\mathbb{P}_c}(Z_3(x,\mathbf{c}(\zeta_c)))\right]^+ -d_3^+\leq g_3,\quad\forall\,\mathbb{P}_c\in\mathscr{P}_c \tag{6}$$

limits the mean upper deviation of the total sectoral electricity consumption $Z_3(x,\mathbf{c}(\zeta_c))$, which implies that the risk of electricity consumption exceeding expected level does not exceed a given goal value $g_3$ as possible. Positive deviation $d_3^+$ denotes the segment of the risk level on electricity consumption exceeding its goal value.

**Population:** For the population, we impose the following constraint:

$$\mathbb{E}_{\zeta_d\sim\mathbb{P}_d}\left[\mathbf{d}(\zeta_d)^T x\right]\geq m,\quad\forall\,\mathbb{P}_d\in\mathscr{P}_d. \tag{7}$$

The inequality ensures that the expected total labour across all economic sectors satisfies $m$, thereby inducing a lower bound on expected number of the required employees. Vector $\mathbf{d}(\zeta_d)=(\mathbf{d}_1(\zeta_d);\mathbf{d}_2(\zeta_d);\ldots;\ \mathbf{d_n}(\zeta_d))$ represents uncertain per capita employee contribution, where random vector $\zeta_d=(\zeta_d^1;\ldots;\zeta_d^L)$. Uncertain per capita employee contribution $\mathbf{d}(\zeta_d)=d^0+\sum_{l=1}^{L}\zeta_d^l d^l$, in which $d^0$ and $d^l$ represent the nominal vector and perturbation data, respectively. $\mathbb{P}_d\in\mathscr{P}_d$ indicates distribution $\mathbb{P}_d$ of $\zeta_d$ situated in ambiguity set $\mathscr{P}_d$. Furthermore, constraint

$$\mathbb{E}_{\zeta_d\sim\mathbb{P}_d}\left[\mathbf{d}(\zeta_d)^T x-\mathbb{E}_{\zeta_d\sim\mathbb{P}_d}\left(\mathbf{d}(\zeta_d)^T x\right)\right]^-\leq t,\quad\forall\,\mathbb{P}_d\in\mathscr{P}_d \tag{8}$$

guarantees that the mean lower semi-deviation of total employed labour does not exceed $t$, thereby inducing an upper bound on the mean lower semi-deviation, which means the risk that the assigned labour are less than the expected labor does not exceed $t$.

**Nonnegative constraints:** Constraints

$$x_j\geq e_j, x_j \text{ is integer},\quad j=1,2,\ldots,n \tag{9}$$

ensure that the number of employees $x_j$ of each economic sector $j\in[J]$ are integers. Moreover, the constraint stipulates that the number of employed labourers satisfies the current number of employees for each economic sector $j\in[J]$, which guarantees sustainability.

The positive deviations mentioned above satisfy the nonnegativity.

$$d_1^+\geq 0,\ d_2^+\geq 0,\ d_3^+\geq 0. \tag{10}$$

Since we consider minimizing risks in which the total levels deviate from the expected levels in this problem, this paper needs to introduce only positive deviations.

**Objective function:** There are multiple conflicting goals in the sustainable development problem that may not be achieved simultaneously, as indicated by Jayaraman et al. (2017a). In this case, a priority structure between multiple goals should be considered based on the preferences of policy-makers and the development requirements in the current era. As a result of the importance currently attached to the environment, policy-makers first must take into account the environment. Then, because the economy is the foundation of a country's sustainable development, the fulfilment regarding the economy should take precedence over the realization related to energy. Accordingly, under the constraints related to expected levels and satisfying other limitations, this paper considers that the first priority is to realize the goal on risk limitation of GHG emissions, the second priority is to actualize the goal on risk limitation of the GDP, and the third priority is to fulfil the goal on risk limitation of electricity consumption. For the theory of goal programming with a priority structure, readers may refer to Ijiri (1965). Based on the above analysis, the objective function, which is to minimize the deviation, is modelled as follows:

$$\min \quad P_1 d_1^+ + P_2 d_2^+ + P_3 d_3^+, \tag{11}$$

where $P_1$, $P_2$ and $P_3$ comply with $P_1 \gg P_2 \gg P_3$, which are the priority levels that show the relative importance of the goals related to the risks of GHG emissions, GDP and electricity consumption, respectively.

**New Model:** Based on the above analysis, we establish the following distributionally robust goal programming model:

$$\begin{aligned} \min \quad & P_1 d_1^+ + P_2 d_2^+ + P_3 d_3^+ \\ \text{s. t.} \quad & \text{constraints } (1) - (10), \end{aligned} \tag{12}$$

where goal values $g_1$, $g_2$ and $g_3$ are given based on previous information or personal preference.

In this model, the distributions of uncertain parameters in constraints (1)–(7) are provided with generality and cannot be fixed accurately, which leads to an infinite number of constraints on the problem. Therefore, model (12) faces a computationally intractable issue. It is well known that the tractability of a distributionally robust programming problem is highly dependent on the choice of the ambiguity set. To build the tractable formulation of the problem, moment-based ambiguity sets $\mathscr{P}_i$ $(i \in [I] = \{a, b, c, d\})$ (see Sect. 3) is considered. This process of building the tractable formulation of the model is carried out in the following section.

## 3. Ambiguity set and tractable formulation

To solve the model (12), the key challenge is to address the imprecise distributions with respect to the per capita GHG emissions, GDP, electricity consumption and unemployment rate. For suitable ambiguity sets, a distributionally robust model is thus computationally tractable. Postek et al. (2018) proposed a mean-deviation ambiguity set including support, mean value and mean absolute deviation. As an extension, mean semi-deviation $(\mu, d^+)$ ambiguity sets $\mathscr{P}_i$ $(\forall i \in [I])$ are proposed in this section, which enable our formulation to be linear and computationally tractable. More specifically, let $\mu_i^l$ and $(d_i^l)^+$ $(i \in [I])$ represent the mean value and mean upper semi-deviation of the random variable $\zeta_i^l$, $\forall l \in [L]$, which are expressed as $\mathbb{E}_{\zeta_i \sim \mathbb{P}_i}(\zeta_i^l) = \mu_i^l$ and $\mathbb{E}_{\zeta_i \sim \mathbb{P}_i}[\zeta_i^l - \mu_i^l]^+ = (d_i^l)^+$. The support of random variable $\zeta_i^l$ is $\mathrm{supp}(\zeta_i^l) \subseteq [-1, 1]$. Then the probability distributions $\mathbb{P}_i$ of random vectors $\zeta_i = (\zeta_i^1; \ldots; \zeta_i^l; \ldots; \zeta_i^L)$ $(i \in [I])$ belong to the following ambiguity sets:

$$\mathscr{P}_i = \left\{ \mathbb{P}_i : \mathrm{supp}\left(\zeta_i^l\right) \subseteq [-1,\ 1],\ \mathbb{E}_{\zeta_i \sim \mathbb{P}_i}\left(\zeta_i^l\right) = \mu_i^l,\ \mathbb{E}_{\zeta_i \sim \mathbb{P}_i}\left[\zeta_i^l - \mu_i^l\right]^+ = \left(d_i^l\right)^+,\ \forall l \in [L] \right\},\ \forall i \in [I], \tag{13}$$

where $-1 \le \mu_i^l \le 1$, random variables $\zeta_i^l$ $\forall l \in [L]$, are mutually independent. By referring to Ben-Tal and Hochman (1972), the mean absolute deviation $d_i^l$ satisfies $0 \le d_i^l \le \frac{2(1-\mu_i^l)(\mu_i^l+1)}{1-(-1)}$. Thus the mean upper semi-deviation is known to satisfy the following bound: $0 \le (d_i^l)^+ \le \frac{(1-\mu_i^l)(\mu_i^l+1)}{2}$, which is because of $(d_i^l)^+ = \frac{1}{2} d_i^l$.

A distinguishing feature of ambiguity sets (13) is that they enables a computationally tractable structure of the model (12). For ease of understanding, a simple example is given as follows.

**Example 1.** Consider the following distributionally robust problem:

$$\begin{aligned} \min \quad & \mathbb{E}_{\zeta \sim \mathbb{P}}[\zeta x - \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta x)]^+ \\ \text{s. t.} \quad & x \ge 1, \end{aligned}$$

*where the distribution $\mathbb{P}$ of random vector $\zeta$ belongs to the following ambiguity set:*

$$\mathscr{P} = \{\mathbb{P} : \mathrm{supp}(\zeta) \in [-1, 1],\ \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta) = 0,\ \mathbb{E}_{\zeta \sim \mathbb{P}}[\zeta - 0]^+ = 0.03\}.$$

The objective in the above model is to minimize the worst-case value of the objective function:

$$\begin{aligned} \min \quad & \sup_{\mathbb{P} \in \mathscr{P}} \mathbb{E}_{\zeta \in \mathbb{P}}[\zeta x - \mathbb{E}_{\zeta \in \mathbb{P}}(\zeta x)]^+ \\ \text{s. t.} \quad & x \ge 1. \end{aligned}$$

Then, we have the following:

$$\sup_{\mathbb{P} \in \mathscr{P}} \mathbb{E}_{\zeta \sim \mathbb{P}}[\zeta x - \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta x)]^+ = \sup_{\mathbb{P} \in \mathscr{P}} \frac{1}{2} \mathbb{E}_{\zeta \sim \mathbb{P}} \left| \zeta x - \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta x) \right.$$

$$= x \sup_{\mathbb{P} \in \mathscr{P}} \frac{1}{2} \mathbb{E}_{\zeta \sim \mathbb{P}} \left| \zeta - \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta) \right| = x \sup_{\mathbb{P} \in \mathscr{P}} \mathbb{E}_{\zeta \sim \mathbb{P}}[\zeta - \mathbb{E}_{\zeta \sim \mathbb{P}}(\zeta)]^+ = 0.03x. \Big|$$

In this case, the optimal solution is given by $x^* = 1$, which shows the tractability of a simple distributionally robust model by using the $(\mu, d^+)$ ambiguity set. Before proceeding with treating problem (12), we first consider the following lemma:

**Lemma 1.** *For total GHG emissions $Z_1(x, \mathbf{a}(\zeta_a))$, GDP $Z_2(x, \mathbf{b}(\zeta_b))$, electricity consumption $Z_3(x, \mathbf{c}(\zeta_c))$ and number of employees $\mathbf{d}(\zeta_d)^T x$. If distributions $\mathbb{P}_i$ of random vectors $\zeta_i$ $(i \in [I])$ satisfy ambiguity sets (13), then the following bounds hold for the mean upper semi-deviations of total sectoral GHG emissions, GDP, electricity consumption and the number of employees:*

$$\sup_{\mathbb{P}_a \in \mathscr{P}_a} \mathbb{E}_{\zeta_a \sim \mathbb{P}_a}[Z_1(x, \mathbf{a}(\zeta_a)) - \mathbb{E}_{\zeta_a \sim \mathbb{P}_a}(Z_1(x, \mathbf{a}(\zeta_a)))]^+ = \left| \tilde{a}(x) \right|^T d_a^+ \tag{14}$$

$$\sup_{\mathbb{P}_b \in \mathscr{P}_b} \mathbb{E}_{\zeta_b \sim \mathbb{P}_b}[Z_2(x, \mathbf{b}(\zeta_b)) - \mathbb{E}_{\zeta_b \sim \mathbb{P}_b}(Z_2(x, \mathbf{b}(\zeta_b)))]^- = \left| \tilde{b}(x) \right|^T d_b^+ \tag{15}$$

$$\sup_{\mathbb{P}_c \in \mathscr{P}_c} \mathbb{E}_{\zeta_c \sim \mathbb{P}_c}[Z_3(x, \mathbf{c}(\zeta_c)) - \mathbb{E}_{\zeta_c \sim \mathbb{P}_c}(Z_3(x, \mathbf{c}(\zeta_c)))]^+ = \left| \tilde{c}(x) \right|^T d_c^+ \tag{16}$$

$$\sup_{\mathbb{P}_d \in \mathscr{P}_d} \mathbb{E}_{\zeta_d \sim \mathbb{P}_d}\left[\mathbf{d}(\zeta_d)^T x - \mathbb{E}_{\zeta_d \sim \mathbb{P}_d}\left(\mathbf{d}(\zeta_d)^T x\right)\right]^- = \left| \tilde{d}(x) \right|^T d_d^+ \tag{17}$$

*Proof.* *Let $y = {}^{T} Z_1(x, {}^{T}\mathbf{a}(\zeta_a))$, that is, $y = [a^0]^T x + \sum_{l=1}^{L} \zeta_a^l [a^l]^T x = [a^0]^T x + [\tilde{a}(x)]^T \zeta_a$, then*

$$\mathscr{P}_y = \left\{ \mathbb{P}_y : \mathrm{supp}\left(y\right) \subseteq \left[\left[a^0\right]^T x - \| \tilde{a}\left(x\right) \|_1,\ \left[a^0\right]^T x + \| \tilde{a}\left(x\right) \|_1\right], \mathbb{E}_{y \sim \mathbb{P}_y}\left(y\right) = \left[a^0\right]^T x + \left[\tilde{a}\left(x\right)\right]^T \mu_a, \mathbb{E}_{y \sim \mathbb{P}_y}\left[y - \mathbb{E}_{y \sim \mathbb{P}_y}\left(y\right)\right]^+ = \mathbb{E}_{\zeta_a \sim \mathbb{P}}\left[\left[\tilde{a}\left(x\right)\right]^T \zeta_a - \left[\tilde{a}\left(x\right)\right]^T \mu_a\right]^+ \right\} \tag{18}$$

*Based on ambiguity sets $\mathscr{P}_y$ (18) and $\mathscr{P}_i$ (13), we have the* *following bound hold for the mean upper semi-deviation of y*

That is,

$$\mathbb{E}_{y\sim\mathbb{P}_y}\left[\left[y-\mathbb{E}_{y\sim\mathbb{P}_y}(y)\right]\right]^+=\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left[\sum_{l=1}^{L}a^l(x)\zeta_a^l-\sum_{l=1}^{L}a^l(x)\mu_a^l\right]^+=\frac{1}{2}\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left|\sum_{l=1}^{L}a^l(x)\zeta_a^l-\sum_{l=1}^{L}a^l(x)\mu_a^l\right|\le\frac{1}{2}\sum_{l=1}^{L}\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left|a^l(x)\zeta_a^l-a^l(x)\mu_c^l\right|$$

$$=\sum_{l=1}^{L}\left|a^l(x)\right|\left\{\frac{1}{2}\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left|\zeta_a^l-\mu_c^l\right|\right\}=\sum_{l=1}^{L}\left|a^l\left(x\right)\right|\left(d_a^l\right)^+=\left|\tilde{a}\left(x\right)\right|^Td_a^+. \tag{19}$$

$$\sup_{\mathbb{P}\in\mathscr{P}}\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left[y-\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}(y)\right]^+=\left|\tilde{a}(x)\right|^Td_a^+$$

*Similarly, upper bound for mean upper semi-deviation on sectoral electricity consumptions $Z_3(x,\mathbf{c}(\zeta_c))$ can also be written as the kind of form.*

*For sectorial GDP $Z_2(x,\mathbf{b}(\zeta_b))$, according to above analysis, one has*

$$\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}(Z_2(x,\mathbf{b}(\zeta_b)))\right]\right]^+\le\sum_{l=1}^{L}\left|b^l(x)\right|\left(d_b^l\right)^+$$
$$=\left|\tilde{b}(x)\right|^Td_b^+.$$

*Since*

$$\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}(Z_2(x,\mathbf{b}(\zeta_b)))\right]\right]^-=\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}(Z_2(x,\mathbf{b}(\zeta_b)))\right]\right]^+$$

*, then*

$$\sup_{\mathbb{P}_b\in\mathscr{P}_b}\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}(Z_2(x,\mathbf{b}(\zeta_b)))\right]\right]^-$$
$$=\sum_{l=1}^{L}\left|b^l(x)\right|\left(d_b^l\right)^-=\left|\tilde{b}(x)\right|^Td_b^+.$$

*Therefore, upper bound for mean lower deviation on sectoral number of employees $\mathbf{d}(\zeta_d)^Tx$ can also be written as the above form. The Proof of lemma is complete.* ∎

*As a useful consequence of Lemma 1, this technique can be applied straightforwardly to deduce the computational tractable formulation of the proposed model (12) by the following theorem.*

**Theorem 1.** *For the distributionally robust sustainable development model (12), let uncertain* per capita *GHG emission $\mathbf{a}(\zeta_a)$, GDP $\mathbf{b}(\zeta_b)$, electricity consumption $\mathbf{c}(\zeta_c)$ and employee contribution $\mathbf{d}(\zeta_d)$ are parameterized by random vectors $\zeta_i$ ($i\in[I]$) depending on ambiguity sets $\mathscr{P}_i$ (13). Then model (12) has the following equivalent robust counterpart representation:*

$$\begin{aligned}
&\min P_1d_1^++P_2d_2^++P_3d_3^+\\
&\text{s. t.}\sum_{l=1}^{L}\left|\left[a^l\right]^Tx\right|\left(d_a^l\right)^+-d_1^+\le g_1\\
&\sum_{l=1}^{L}\left|\left[b^l\right]^Tx\right|\left(d_b^l\right)^+-d_2^+\le g_2\\
&\sum_{l=1}^{L}\left|\left[c^l\right]^Tx\right|\left(d_c^l\right)^+-d_3^+\le g_3\\
&\sum_{l=1}^{L}\left|\left[d^l\right]^Tx\right|\left(d_d^l\right)^+\le t\\
&\left[a^0\right]^Tx+\sum_{l=1}^{L}\left[a^l\right]^Tx\mu_a^l\le Z_1^0\\
&\left[b^0\right]^Tx+\sum_{l=1}^{L}\left[b^l\right]^Tx\mu_b^l\ge Z_2^0\\
&\left[c^0\right]^Tx+\sum_{l=1}^{L}\left[c^l\right]^Tx\mu_c^l\le Z_3^0\\
&\left[d^0\right]^Tx+\sum_{l=1}^{L}\left[d^l\right]^Tx\mu_d^l\ge m
\end{aligned}\tag{20}$$

constraints (9) – (10).

*Proof. In the mean semi-deviations $(\mu,d^+)$ ambiguity sets $\mathscr{P}_i$, optimizing the model (12) is equivalent to optimizing the following programming model:*

$$\begin{aligned}
&\min P_1d_1^++P_2d_2^++P_3d_3^+\\
&\text{s. t.}\sup_{\mathbb{P}_a\in\mathscr{P}_a}\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left[Z_1(x,\mathbf{a}(\zeta_a))-\mathbb{E}_{\zeta_a\sim\mathbb{P}_a}(Z_1(x,\mathbf{a}(\zeta_a)))\right]^+-d_1^+\le g_1\\
&\sup_{\mathbb{P}_b\in\mathscr{P}_b}\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}\left[Z_2(x,\mathbf{b}(\zeta_b))-\mathbb{E}_{\zeta_b\sim\mathbb{P}_b}(Z_2(x,\mathbf{b}(\zeta_b)))\right]^--d_2^+\le g_2\\
&\sup_{\mathbb{P}_c\in\mathscr{P}_c}\mathbb{E}_{\zeta_c\sim\mathbb{P}_c}\left[Z_3(x,\mathbf{c}(\zeta_c))-\mathbb{E}_{\zeta_c\sim\mathbb{P}_c}(Z_3(x,\mathbf{c}(\zeta_c)))\right]^+-d_3^+\le g_3\\
&\sup_{\mathbb{P}_d\in\mathscr{P}_d}\mathbb{E}_{\zeta_d\sim\mathbb{P}_d}\left[\mathbf{d}(\zeta_d)^Tx-\mathbb{E}_{\zeta_d\sim\mathbb{P}_d}\left(\mathbf{d}(\zeta_d)^Tx\right)\right]^-\le t
\end{aligned}\tag{21}$$

constraints (1), (3), (5), (7), (9), (10).

*According to Lemma 1 and ambiguity sets $\mathscr{P}_y$ (18), we can give the following equations on GHG emissions*

$$\sup_{\mathbb{P}_a\in\mathscr{P}_a} \mathbb{E}_{\zeta_a\sim\mathbb{P}_a}\left[Z_1(x,\mathbf{a}(\zeta_a)) - \mathbb{E}_{\zeta_a\sim\mathbb{P}_a}(Z_1(x,\mathbf{a}(\zeta_a)))\right]^+ = \left|\tilde{a}(x)\right|^T d_a^+$$

$$\mathbb{E}_{y\sim\mathbb{P}_y}(y) = \left[a^0\right]^T x + \left[\tilde{a}(x)\right]^T \mu_a,$$

*where* $\left|\tilde{a}(x)\right|^T d_a = \sum_l^L \left|\left[a^l\right]^T x\right| d_a^l$. *Similarly, the constraints on GDP, electricity consumption and the number of employees can also expressed as a type of formulation.*

*Substituting above equalities into model* (21), *we obtain the equivalent model* (20) *of problem* (12). *The Proof of theorem is complete.* ∎

*Theorem 1 shows that we can transform the distributionally robust sustainable development model* (12) *into a computationally tractable robust counterpart model* (20) *in the case of* $(\mu, d^+)$ *ambiguity sets* (13). *That is, any decision vector x satisfying the tractable model* (20) *coincides with that of model* (12).

## 4. Case study

In the section, we carry out a case study for the year 2030 sustainability goals of the GCC countries. All mathematical models are solved by CPLEX studio 12.6.3 on personal computer (Intel(R) Core(TM) i5-4200M 2.50 GHz CPU and RAM 4.00 GB) by using the Microsoft Windows 8 operating system.

### 4.1. Data source and analysis

The GCC countries (the UAE, Oman, Bahrain, Qatar, Kuwait and Saudi Arabia) are important regional organizations in the Middle East. Fig. 2 shows the locations of the GCC member countries. In recent years, the GCC countries have shown a keen interest in engaging in a more sustainable development path (Mondal et al., 2016). However, the GCC countries are facing significant challenges. The fast-tracked economic development of the GCC countries has placed incremental challenges on labour demand, development and infrastructure projects, electricity consumption, and GHG emissions (Jayaraman et al., 2017a). Moreover, Jayaraman et al. (2017a) also noted that the increase in electricity demand in the GCC countries far exceeds the global average due to the growing economic base and the associated development projects in the region. Three of the GCC countries are identified as having the highest per capita energy consumption worldwide (Jayaraman et al., 2017a) by the United Nations Environment Programme. The GCC country-wise contributions to the total GHG emissions in 2005 were 56% by Saudi Arabia, 18.75% by the UAE, 10.43% by Kuwait, 7.3% by Qatar, 4% by Oman and 3.4% by Bahrain (Luomi, 2014). Accordingly, one potential option for the GCC is to focus on the interplay and explore potential trade-offs among environmental responsibility, economic growth, energy consumption and labour development.

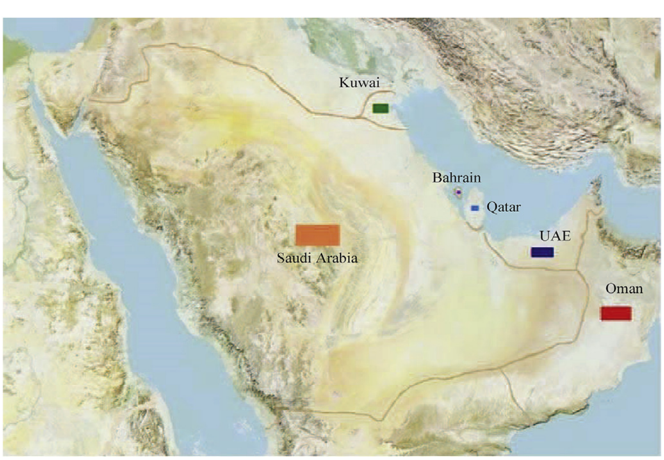


**Fig. 2.** Locations of six GCC member countries.

In this case study, we consider the six GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the UAE). There are 8 economic sectors and corresponding original data found in Jayaraman et al. (2017a). We set the original data as the nominal data $[a^0; b^0; c^0]$ and the uncertain parameter $\mathbf{d}_j$ based its value in segment $[0.98, 1.00]$ with the nominal data $d_j^0 = 0.99$. In Table 2, we provide the data of $Z_1^0$, $Z_2^0$, $Z_3^0$, $m$, $t$, $g_1$, $g_2$, and $g_3$ based on original data and practical considerations for the six countries of the GCC. Moreover, we assume the following: mean values of $\mu_i^l = 0$, mean upper semi-deviations of $(d_i^l)^+ = 0.025$ $(i \in [I])$ and pre-emptive priority levels of $P_1 = 10^6$, $P_2 = 10^4$, and $P_3 = 10^2$. Using the available data above, we can begin the case study.

### 4.2. Computational results

Before proceeding to this set of experiments, some perturbation data used in formulating the model and searching for solutions need to be determined. The perturbation data of uncertain per capita contributions $[\mathbf{a};\ \mathbf{b};\ \mathbf{c}]$ are set to 10% relative to their nominal values $[a^0;\ b^0;\ c^0]$, and the perturbation data $d_j^l = 0.01$. Table 3 summaries these perturbation values of uncertain per capita contributions $[\mathbf{a};\ \mathbf{b};\ \mathbf{c};\ \mathbf{d}]$ for Bahrain, whereas the perturbation values can also be given in a similar way for the other five countries. In Table 3, $a^l = a_j^l(0_{j-1,1}; 1; 0_{8-j,1})$, $b^l = b_j^l(0_{j-1,1}; 1; 0_{8-j,1})$, $c^l = c_j^l(0_{j-1,1}; 1; 0_{8-j,1})$ and $d^l = d_j^l(0_{j-1,1}; 1; 0_{8-j,1})$ $1 \le j, l \le 8$, and we assume $l = j$. Based on the above data, we can conduct a set of experiments, and the computational results are summarized in Table 4. Furthermore, the comparison between the optimal proportions of labour allocation and the current proportions of labour for the six GCC countries are depicted in Fig. 3.

Table 4 shows the optimal labour allocation and the fulfilment degree of each goal for the six GCC countries. The optimal distribution of labour in the 8 economic sectors can provide advice for policy-makers. Moreover, the resulting analysis on the fulfilment degree of each goal is interpreted as follows:

- Regarding the GHG emissions, we can observe that all risks related to GHG emissions are fulfilled for the six GCC countries, implying that the risk of GHG emissions beyond the expected GHG emissions does not exceed the given value $g_1$. That is, a suitable long-term environmental scenario can keep the risk under control.
- Regarding the GDP, Bahrain, Kuwait, Oman and Qatar show non-zero positive deviations for the risk related with GDP, with a minor positive deviation $(d_2^+ = 0.8675)$ for Bahrain and a relatively large deviation $(d_2^+ = 77.226)$ for Oman. This finding means that the risk of the GDP under the expected level exceeds the given risk value $g_2$. Namely, the required GDP growth trend in the four countries may cause the risk to become out of control. Thus, the four countries should appropriately adjust their GDP development strategies.
- Regarding electricity consumption, the six GCC countries all show a non-zero positive deviation $(d_3^+)$, which indicates that the risk of beyond-expected consumption exceeds the given risk value $g_3$. This finding illustrates the expected energy consumption strategy is not able to limit the risk to a manageable level. Therefore, the long-term energy consumption scenario will not permit electricity consumption growth in line with the current trends.

**Table 2**
Data table.

| Parameter values | Bahrain | Kuwait | Oman | Qatar | Saudi Arabia | UAE |
|---|---|---|---|---|---|---|
| $Z_1^0$ | 59,237 | 1,264,670 | 571,667 | 274,311 | 1,346,292 | 286,051 |
| $Z_2^0$ | 64,347 | 299,999 | 190,890 | 429927.5 | 1,925,490 | 3,110,323 |
| $Z_3^0$ | 90,552 | 135,470 | 80,767 | 285,717 | 584,589 | 392119.86 |
| $m$ | 1,337,222 | 2,966,679 | 2,620,394 | 2,687,870 | 20,416,224 | 9,115,735 |
| $t$ | 400 | 800 | 800 | 700 | 10,000 | 2500 |
| $g_1$ | 120 | 600 | 350 | 650 | 1700 | 700 |
| $g_2$ | 160 | 700 | 400 | 1000 | 10,000 | 8000 |
| $g_3$ | 120 | 200 | 80 | 400 | 800 | 800 |

**Table 3**
Perturbation data table.

| Sectors | Perturbation values | | | |
|---|---|---|---|---|
| | $a_j^l$ | $b_j^l$ | $c_j^l$ | $d_j^l$ |
| Agriculture | 0.002138 | 0.006285 | 0.003688 | 0.01 |
| Curde oil, Natural gas & Mining | 0.042291 | 0.023323 | 0.000505 | 0.01 |
| Manufacturing & Electricity | 0.009047 | 0.005118 | 0.005018 | 0.01 |
| Construction & Real Estate | 0.002858 | 0.001739 | 0.003949 | 0.01 |
| Trade & Transport | 0.001375 | 0.002089 | 0.002047 | 0.01 |
| Restaurant & Hotels | 0.002213 | 0.004577 | 0.004483 | 0.01 |
| Banking & Financial Services | 0.015673 | 0.030844 | 0.030233 | 0.01 |
| Government, Social & Personal Services | 0.001349 | 0.002656 | 0.002721 | 0.01 |

**Table 4**
Computational results.

| Variable | Bahrain | Kuwait | Oman | Qatar | Saudi Arabia | UAE |
|---|---|---|---|---|---|---|
| $d_1^+$ | 0 | 0 | 0 | 0 | 0 | 0 |
| $d_2^+$ | 0.8675 | 49.998 | 77.226 | 74.819 | 0 | 0 |
| $d_3^+$ | 0.23376 | 72.095 | 28.457 | 15.7 | 256.66 | 162.79 |
| $x_1$ | 484,364 | 75,250 | 82,068 | 19,433 | 461,957 | 258,867 |
| $x_2$ | 33,087 | 11,096 | 144,735 | 124,809 | 120,896 | 74,611 |
| $x_3$ | 89,156 | 1,603,545 | 167,446 | 118,204 | 776,809 | 687,686 |
| $x_4$ | 185,672 | 237,775 | 673,880 | 545,587 | 1,808,873 | 1,505,931 |
| $x_5$ | 310,721 | 600,856 | 191,608 | 234,428 | 2,118,919 | 5,026,721 |
| $x_6$ | 36,995 | 173,002 | 1,693,640 | 1,005,800 | 264,920 | 236,357 |
| $x_7$ | 16,371 | 219,596 | 60,935 | 369,963 | 122,752 | 1,399,458 |
| $x_8$ | 194,364 | 278,880 | 185,688 | 381,776 | 14,947,323 | 810,369 |

Fig. 3 depicts the optimal labour proportion obtained by the results in Table 4 and the current labour proportion calculated using original data for the six GCC countries. From Fig. 3, we can intuitively see that the optimal proportion and the current proportion for the six GCC countries are different. The gap is very obvious for Bahrain, Kuwait, Oman, Qatar and Saudi Arabia (SA). The analysis in Fig. 3 can be summarized as follows:

- For Bahrain, the optimal proportion of labour allocation far exceeds the current proportion for the sectoral labour for Agriculture. Therefore, the country should focus on the development of Agriculture to add sectoral labour. The sectoral optimal proportions over Construction & Real Estate and Government, Social & Personal Services are far less than the current proportions, and the resulting labour levels of these sectors as shown in Table 4 are almost equal to the current levels. The illustrates that the country should retain the sectoral current labour levels of the Construction & Real Estate and Government, Social & Personal Services sectors;
- For Kuwait, the optimal proportion of labour allocation far exceeds the current proportion of labour for the Manufacturing & Electricity sector. Moreover, the optimal proportion of Trade & Transport sector is far less than the current proportion because the total number of labour increases but the labour level in this sector does not increases. The above findings imply that the country should focus on the development of the Manufacturing & Electricity sector to increase sectoral labour and maintain the current labour level for the Trade & Transport sector;
- Regarding Oman and Qatar, the optimal proportion of labour allocation far exceeds the current proportion of sectoral labour for the Restaurant & Hotels sector. In addition, the optimal proportion of the Construction & Real Estate sector is far less than the current proportion, which is because the total number of labourers increases but the labour level of this sector reported in Table 4 remains unchanged. These results mean that the country should focus on the development of the Restaurant & Hotels sector to raise sectoral labour and maintain the current labour level for the Construction & Real Estate sector;
- Regarding the UAE, the optimal proportion of labour allocation far exceeds the current proportion of sectoral labour for the Trade & Transport sector, implying that the country should pay close attention to the development of that sector


**Fig. 3.** Proportion of labour over 8 economic sectors.

**Table 5**
Sensitivity analysis on objectives.

| Variable | Bahrain | | Kuwait | | SA | | UAE | | Qatar | | Oman | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (I) | (II) | (I) | (II) | (I) | (II) | (I) | (II) | (I) | (II) | (I) | (II) |
| $d_1^+$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $d_2^+$ | 0.8675 | 81.301 | 49.998 | 425 | 0 | 3735.8 | 0 | 3663.7 | 74.819 | 612.23 | 77.226 | 315.84 |
| $d_3^+$ | 49.153 | 60.351 | 97.006 | 208.14 | 511.145 | 785.85 | 634.69 | 644.18 | 205.61 | 223.55 | 46.872 | 82.685 |

to improve sectoral labour. Likewise, SA should focus on the development of the Government, Social & Personal Services sector to improve sectoral labour.

### 4.3. Sensitivity analysis

To investigate the impact of different perturbation data on the optimal results, we carry out a sensitivity analysis under two sets of

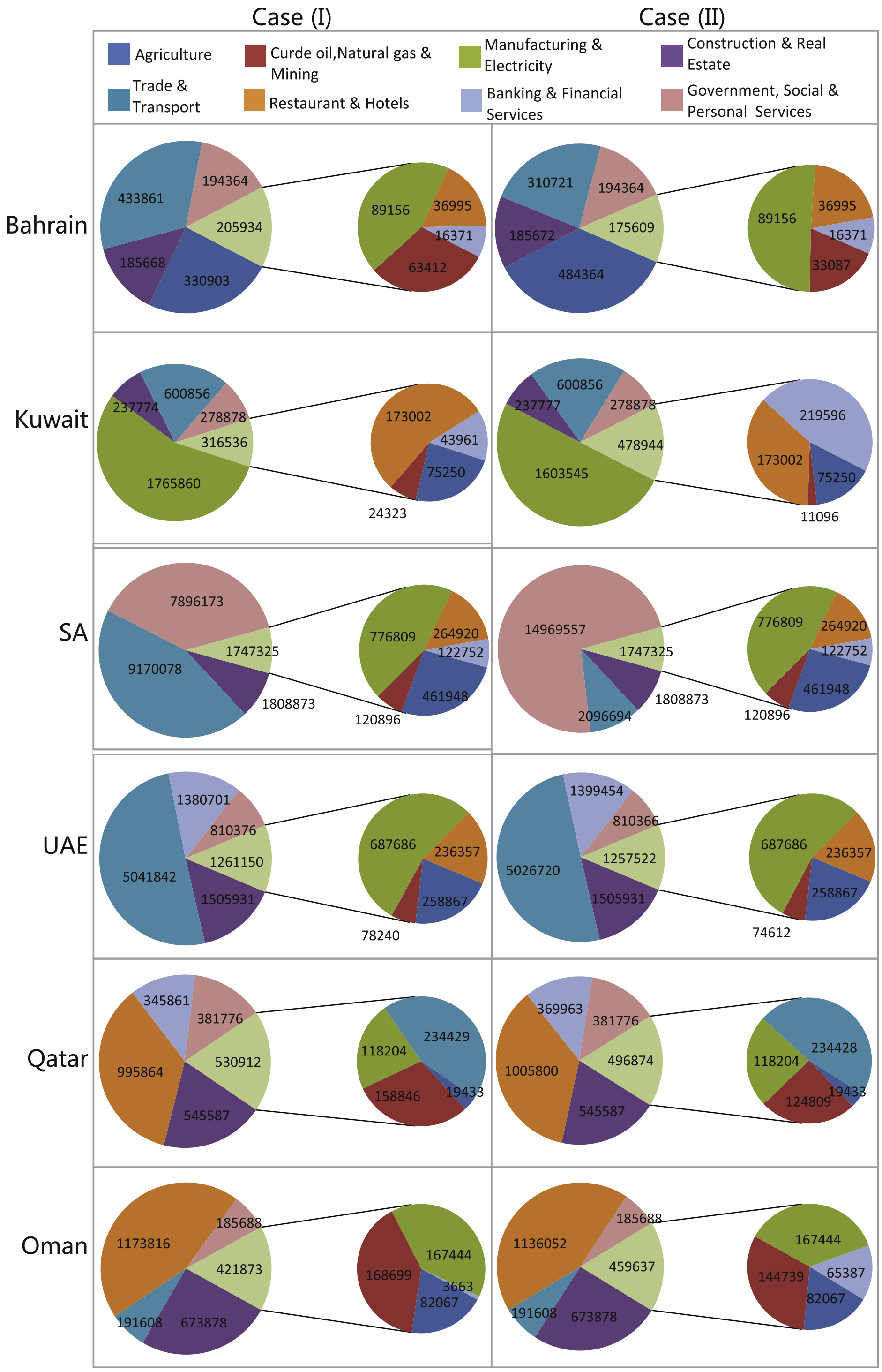


**Fig. 4.** Sensitivity analysis on labour allocation.

perturbation data $[a_j^l; b_j^l; c_j^l]$: (I) $[a_j^l; b_j^l; c_j^l] = [5\%a_j^0; 10\%b_j^0; 15\%c_j^0]$, and (II) $[a_j^l; b_j^l; c_j^l] = [10\%a_j^0; 15\%b_j^0; 15\%c_j^0]$. We report the analysis results in Table 5 and Fig. 4.

From Table 5, we find the sensitivity of the fulfilment degree of each goal by the alteration of the perturbation data. The fulfilment degree of each goal corresponding to the two sets of perturbation data is different. For example, for SA, the first two goals are achieved under perturbation data as in case (I) while only the first goal is fulfilled corresponding to case (II). Furthermore, we can observe that the unfulfilled degree of each goal is different even if the same number of goals is unrealized. For example, for Kuwait, the latter two goals are always unrealized in cases (I) and (II) while the unfulfilled degree corresponding to case (I) is different from the unfulfilled degree under case (II).

Fig. 4 indicates the sensitivity of optimal labour allocation across the 8 economic sectors under two sets of perturbation data. It is intuitively observed that the obtained labour allocation of the two sets of perturbation data are different. For instance, when perturbation data are set as in case (I), the number of labour allocated corresponding to the Agriculture sector, Crude oil, Natural gas & Mining sector and Trade & Transport sector for Bahrain are different from that corresponding to the perturbation data as in case (II).

From the sensitivity analysis, the optimal labour allocation and the fulfilment degree of each goal for the perturbation data are active. In this case, it is important for policy-makers to confirm the size of the perturbation data to formulate good strategic planning for sustainable development of the GCC countries by 2030.

### 4.4. Comparison study

To show our model performance, we conduct two sets of comparison experiments with a nominal stochastic model and deterministic model.

#### 4.4.1. Comparison with the nominal stochastic model

In this subsection, we compare our distributionally robust goal programming model under an imprecise distribution with the nominal stochastic model to evaluate the effectiveness and viability of the proposed model. Under the ambiguity set $\mathscr{P}$ (13), we consider that $\zeta_i^l$ $(i \in [I])$ are independent Gaussian random variables. According to the mean values $\mu_i^l = 0$ and mean upper semi-deviations $(d_i^l)^+ = 0.025$, we can obtain the random variable $\zeta_i^l \sim N(0, (0.025\sqrt{2\pi})^2)$. Due to the standard deviation $\sigma = 0.025\sqrt{2\pi}$, the $-3\sigma = -0.18799712 \gg -1$ and the $3\sigma = 0.18799712 \ll 1$, which means that the nominal Gaussian distribution resides in ambiguity set $\mathscr{P}$ (13) with a probability that is almost equal to 1. It follows that the probability that the support of the Gaussian random variable $\zeta_i^l$ exceeds $[-1, 1]$ is extremely small, even negligible. Based on the above analysis, the uncertain per capita contributions $\mathbf{a}_j = a_j^0 + a_j^l\zeta_a^l$, $\mathbf{b}_j = b_j^0 + b_j^l\zeta_b^l$, $\mathbf{c}_j = c_j^0 + c_j^l\zeta_c^l$ and $\mathbf{d}_j = d_j^0 + d_j^l\zeta_d^l$ obey the nominal Gaussian distribution, i.e., $\mathbf{a}_j \sim N(a_j^0, (0.025\sqrt{2\pi}a_j^l)^2)$, $\mathbf{b}_j \sim N(b_j^0, (0.025\sqrt{2\pi}b_j^l)^2)$, $\mathbf{c}_j \sim N(c_j^0, (0.025\sqrt{2\pi}c_j^l)^2)$ and $\mathbf{d}_j \sim N(d_j^0, (0.025\sqrt{2\pi}d_j^l)^2)$. Hence, $\mathbf{a}_j x_j$, $\mathbf{b}_j x_j$, $\mathbf{c}_j x_j$ and $\mathbf{d}_j x_j$ also obey Gaussian distributions. As a result, the nominal stochastic model can be written as follows:

$$
\begin{aligned}
&\min P_1 d_1^+ + P_2 d_2^+ + P_3 d_3^+ \\
&\text{s. t.} 0.025\sqrt{\sum_{l=1}^{8}\left(\left[a^l\right]^T x\right)^2} - d_1^+ \le g_1 \\
&0.025\sqrt{\sum_{l=1}^{8}\left(\left[b^l\right]^T x\right)^2} - d_2^+ \le g_2 \\
&0.025\sqrt{\sum_{l=1}^{8}\left(\left[c^l\right]^T x\right)^2} - d_3^+ \le g_3 \\
&0.025\sqrt{\sum_{l=1}^{8}\left(\left[d^l\right]^T x\right)^2} \le t \\
&\left[a^0\right]^T x \le Z_1^0 \\
&\left[b^0\right]^T x \ge Z_2^0 \\
&\left[c^0\right]^T x \le Z_3^0 \\
&\left[d^0\right]^T x \ge m
\end{aligned}
\tag{22}
$$

constraints (9) – (10).

To proceed with this set of experiments and obtain the robust solutions and nominal solutions, we assume the values of $Z_1^0$, $Z_2^0$, $m$ and $t$ shown in Table 2 and the values of $g_1$, $g_2$ and $g_3$ are half of the values shown in Table 2. In addition, we consider the perturbation data $a_j^l$, $b_j^l$ and $c_j^l$ as in case (I), $d_j^l = 0.01$ and $d_j^0 = 0.99$. Table 6 provides the comparison results for the six GCC countries.

From Table 6, it can be observed that the labour allocation decision across the 8 economic sectors under robustness is different from that without robustness. On the other hand, the positive deviations $d_1^+$, $d_2^+$ and $d_3^+$ under robustness are higher than that without robustness. Intuitively, this type of case may mean that the nominal optimal labour allocation decision can engender a smaller risk than the robust optimal decision, although it does not illustrate that the nominal stochastic model can provide a more substantive decision than the distributionally robust model. This is principally because the distributionally robust model works well against the ambiguous distribution. If the assumed distribution is different from the exact distribution, the optimal labour allocation decision obtained by a given nominal distribution may perform poorly and may even lead to wrong decision-making. Under these circumstances, the proposed model can provide an effective and substantive decision for policy-makers to better plan sustainability under uncertainty.

#### 4.4.2. Comparison with the deterministic model

To further illustrate our model performance, we also compare our distributionally robust goal programming model with a deterministic model that is reduced as follows.

$$
\begin{aligned}
&\min P_1(\bar{d}_1^+ + \bar{d}_1^-) + P_2(\bar{d}_2^+ + \bar{d}_2^-) + P_3(\bar{d}_3^+ + \bar{d}_3^-) \\
&\text{s. t.} \left[a^0\right]^T x + \bar{d}_1^- - \bar{d}_1^+ = Z_1^0 \\
&\left[b^0\right]^T x + \bar{d}_2^- - \bar{d}_2^+ = Z_2^0 \\
&\left[c^0\right]^T x + \bar{d}_3^- - \bar{d}_3^+ = Z_3^0 \\
&\left[d^0\right]^T x \ge m \\
&\bar{d}_i^- \ge 0,\ \bar{d}_i^+ \ge 0,\ i = 1,\ 2,\ 3
\end{aligned}
\tag{23}
$$

constraint (9),

where $\bar{d}_i^-$ and $\bar{d}_i^+$ represent the negative and positive deviations.

We still use the robust solutions shown in Table 6 to compare with the obtained deterministic solutions. The comparison results related to the proportions of labour allocation are depicted in Fig. 5.

Fig. 5 shows the sectoral proportions of robust and deterministic labour allocation schemes. The horizontal axis represents the eight sectors, and the vertical axis represents the sectoral proportions of labour allocation. In Fig. 5, the blue curve depicts the labour distribution proportion calculated by the solutions obtained by the deterministic method. while the red curve portrays the labour distribution proportion solved based on our new model. Fig. 5 shows considerable, the great differences between the robust decisions and deterministic decisions. Although a set of solutions can be obtained by the deterministic model, the allocation scheme formulated according to this solutions may be invalid or even erroneous because of the influence of potential uncertainty. Therefore, uncertainty as an important attribute of sustainable development problem cannot be ignored because the high associated costs.

**Table 6**
Comparison results under case (I).

| variables | Bahrain | | Kuwait | | Oman | | Qatar | | Saudi Arabia | | UAE | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | robust | nominal | robust | nominal | robust | nominal | robust | nominal | robust | nominal | robust | nominal |
| $d_1^+$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0011685 | 0 |
| $d_2^+$ | 80.868 | 0 | 400 | 0.00020746 | 277.23 | 49.188 | 574.82 | 0 | 4157.2 | 0 | 3775.8 | 0 |
| $d_3^+$ | 120.35 | 8.0302 | 308.14 | 26.623 | 122.69 | 99.469 | 423.55 | 66.444 | 1185.8 | 226.46 | 1044.2 | 163.18 |
| $x_1$ | 484,364 | 272,110 | 75,250 | 468,861 | 82,067 | 477,521 | 19,433 | 1,874,817 | 461,948 | 2,502,925 | 258,867 | 260,135 |
| $x_2$ | 33,087 | 62,598 | 11,096 | 14,161 | 144,739 | 74,477 | 124,809 | 151,749 | 120,896 | 120,896 | 74,612 | 77,864 |
| $x_3$ | 89,156 | 89,156 | 1,603,544 | 2,866,142 | 167,444 | 859,317 | 118,204 | 118,207 | 776,809 | 863,320 | 687,686 | 709,728 |
| $x_4$ | 185,672 | 185,668 | 237,777 | 348,566 | 673,878 | 673,878 | 545,587 | 734,127 | 1,808,873 | 1,808,873 | 1,505,931 | 1,575,114 |
| $x_5$ | 310,721 | 349,223 | 600,856 | 817,214 | 191,608 | 935,956 | 234,428 | 1,099,687 | 2,096,694 | 9,298,216 | 5,026,720 | 3,811,759 |
| $x_6$ | 36,995 | 131,838 | 173,003 | 949,325 | 1,136,052 | 768,034 | 1,005,800 | 1,237,426 | 264,920 | 656,849 | 236,357 | 6,990,241 |
| $x_7$ | 16,371 | 16,371 | 219,596 | 47,476 | 65,387 | 150,226 | 369,963 | 131,962 | 122,752 | 122,752 | 1,399,454 | 609,489 |
| $x_8$ | 194,364 | 243,766 | 278,878 | 328,896 | 185,688 | 453,493 | 381,776 | 995,568 | 14,969,557 | 5,247,497 | 810,366 | 5,759,958 |

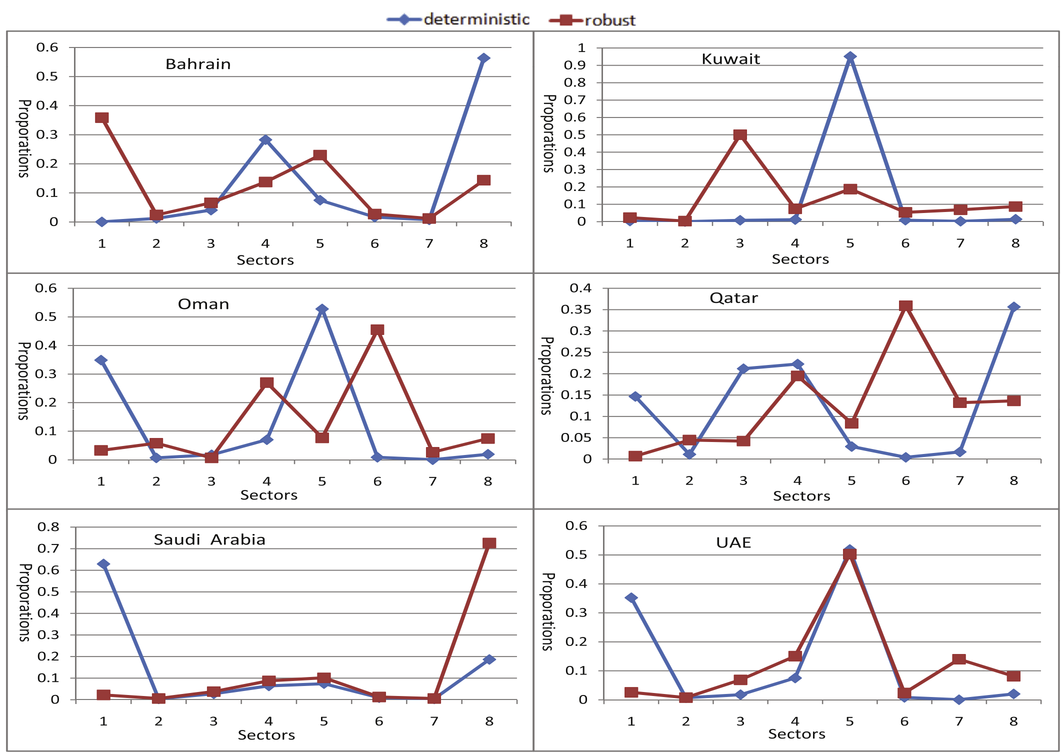


**Fig. 5.** The comparison result with deterministic solution.

### 4.5. Management implications

Through the case study and obtained results, we summarize some management implications below.

The results obtained by this case study provide advice for policy-makers to plan for the year 2030 sustainable development of the six GCC countries. (1) The allocation results of Table 4 serve as a guideline for policy-makers to allocate labour across the eight economic sectors. More deeply, the analysis of Table 4 reveals the appropriate development trend that should be adopted by each GCC state to achieve sustainable development within controllable risks. (2) The in-depth analysis of Fig. 3 indicates which sector that the six GCC countries should further develop to achieve sustainability. (3) The sensitivity analysis highlights that optimal decisions differ by adjusting the size of perturbation data. More importantly, the comparison results of Table 4 confirm that policy-makers cannot overlook uncertainty in planning real-life problems. Otherwise, policy-makers may not identify the optimal policy. In this case, our model may be a perfect method for policy-makers to formulate more comprehensive policies.

The developed method for the sustainable development problem is flexible and may adapt to the various policy requirements. That is, the model may be extended or modified in line with different policy needs. Specifically, (1) risk in this paper is characterized by the mean semi-deviation with direction. Policy-makers may also choose other methods of measuring risk based on specific policy requirements, e.g., the variance and absolute deviation without direction. (2) The priority structure in this paper is a) environment, b) economy and c) energy. According to the development needs of different eras and the willingness of policy-makers, different priority structures may be considered. (3) The proposed model may be adapted to different case studies over the related problem in an uncertain environment.

## 5. Conclusions

This paper developed a new model for the sustainable development problem and implemented a realistic case to demonstrate the applicability of the proposed model. The main conclusions are summarized as follows: Model and Application.

(i) Model: A novel distributionally robust goal programming model was proposed for the sustainable development problem. Our model not only resisted the distribution uncertainty of per capita GHG emissions, GDP, electricity consumption and unemployment rate, but also simultaneously balance three goals of minimizing risks related to the environment, economy and energy based on priority levels. Moreover, this model also incorporated the risk measure related to society and characterized these risk measures by the mean semi-deviations. Furthermore, this paper characterized imprecise distributions by moment-based ambiguity sets and thus deducted the tractable robust counterpart model, which was calculated directly using the software CPLEX.

(ii) Application: A case regarding the year 2030 sustainable development of the GCC countries was implemented with the proposed model. The computational results analysis may provide guidance for policy-makers to formulate sustainable policies for the GCC. The sensitivity analysis results showed that the optimal labour allocation and the fulfilment degree of each goal for the perturbation data were sensitive. The comparison results showed that the nominal solutions and the deterministic solutions are significantly different from the robust solutions. The obtained results illustrated that our new model can provide substantive policies under distribution uncertainty.

Future works may include the following directions. The first direction is to consider various measures to depict the energy and environment aspects in addition to electricity consumption and GHG emissions. The second direction is that some parameters are also influenced by subjective factors, such as human behaviour. In this case, we may take advantage of the fuzzy optimization method (Bai and Liu, 2015, 2018; Liu et al., 2002, 2017) to study related problem in the future. The third direction is to consider other ambiguity sets based on different distribution information, for example, mean-dispersion ambiguity sets (Postek et al., 2018), Wasserstein balls (Hanasusanto and Kuhn, 2018) and density-based ambiguity sets (Jiang and Guan, 2018). The last direction is to adopt globalized robust optimization (Ben-Tal et al., 2009) to study related problems when uncertain parameters are distribution-free.

## Declaration of competing interest

Our paper \Distributionally robust goal programming approach for planning a sustainable develop-ment problem" by R.R. Jia, Y.K. Liu, and X.J. Bai is submitted to **Journal of Cleaner Production** for possible publication. The authors declare that they have no conflicts of interest.

## CRediT authorship contribution statement

**Ruru Jia:** Methodology, Data curation, Writing - original draft, Software. **Yankui Liu:** Conceptualization, Methodology, Validation. **Xuejie Bai:** Visualization, Supervision, Validation, Writing - review & editing.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.120438.

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