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An Investment Analysis for China's Sustainable Development Based on Inverse Data Envelopment Analysis

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Abstract: In the face of environmental degradation, sustainable development has become a common goal across the globe. Making a scientifically based investment scheme is of great significance to promote the sustainable development of China's economy. However, there is scarce research related to such an investment scheme of sustainable development. This paper proposes a new inverse data envelopment analysis method with undesirable outputs to make several scientifically based investment schemes from different perspectives, namely, the natural, regulation, and optimal perspectives. By this method, decision makers can scientifically forecast the specific amount of investment based on their actual sustainable development objectives, which is conducive for reducing the blindness of investment in the future. In addition, a new ideal perspective is defined to guide a definite direction for improving the level of sustainable development. Combined with the gray forecasting model GM(1,1), the methods proposed by this paper were then applied to analyze the investment problem for China's sustainable development during the 2015-2024 period. The results show that: the unbalanced distribution of labor investment and the excessive investment in capital and energy are serious barriers to China's sustainable development in the short term; and

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in the long term, the demand for investment in labor and capital will continue to increase along with a lower demand for energy investment, and that appropriately strengthening environmental regulations will not affect the overall demand for investment. Meanwhile, improvement directions for improving China's sustainable development are discussed, and the results show that most of developing and undeveloped regions in China have great potential for improvement. Finally, some suggestions are proposed in order to create better conditions for China's sustainable development.

Keywords: Inverse DEA; Undesirable output; Investment scheme; Sustainable development; China

1 Introduction

China's economy has achieved significant development since the implementation of 1978's reform and open policy and has become the second leading economic entity in the world following the United States (Zhang & Yang, 2013). However, large amounts of environmental pollution usually accompany an economic growth in production, and pose a threat to the process of sustainable development (Wang & Song, 2014). Thus, the Chinese government has to pay more attention to address the increasing pressure on resources and the environment without damaging economic growth. Since China incorporated sustainable development into national strategies in 1995, many studies have focused on it (Liu et al., 2014; Song et al., 2014). Sustainable development involves the design of integrated approaches that are capable of addressing environmental sustainability and waste while ensuring social and economic prosperity at the national or even global level, implying a macroeconomic scope (Khalili et al., 2015). Sueyoshi & Goto (2014) pointed out that effective investment for preventing industrial pollution is conducive to sustainable development. An effective investment scheme not only increases the utilization rate of resources and reduces waste and pollution by promoting an optimal distribution of resources but also benefits the social sustainability of China by maintaining a balanced distribution of resources (Sueyoshi & Yuan, 2015). Thus, making a scientifically based investment scheme is of great significance to promote the sustainable development of China's economy. However, there is scarce research related to such an investment scheme of sustainable development. Kardos (2014) discussed the relevance of foreign direct investment for sustainable development, and Sueyoshi & Goto (2014) evaluated the environmental efficiency of regional economies. Although these papers propose ways in which to make an investment scheme, specific amounts of investment cannot be obtained from them. In addition, even though existing prediction methods can be used to forecast the specific amount of investment in the future, such as the auto regressive moving average method (Valipour et al., 2013) and the gray forecasting method (Chang et al., 2015), their forecast results react to trend changes in time series rather than the demands of sustainable development. Thus, in this paper, a new method based on inverse data envelopment analysis (DEA) to make an effective investment scheme for sustainable development is provided.

DEA, first proposed by Charnes et al. in 1978, is a nonparametric approach to evaluate the relative efficiency of decision making units (DMUs) with multiple inputs and outputs. Since then, many scholars have been working in this area with numerous significant results, such as the BCC model (Banker et al., 1984), the eco-efficiency model (Egilmez, et al., 2016), and the cross efficiency model (Oral, et al., 2015). Among them, inverse DEA, first proposed by Wei et al. (2000), is an important research direction. Contrary to the traditional DEA method which is used to measure efficiency, inverse DEA is used to deal with two types of problems. The first type is related to the number of additional outputs that a particular DMU from a group of DMUs could produce for the given inputs, assuming that this DMU maintains its current efficiency value with respect to the rest. The second type is related to how much more input should that DMU be provided for the given outputs under the previous assumption. Yan et al. (2002) proposed an extended inverse DEA model with preference cone constraints to incorporate the preferences of the decision maker into resource reallocation decisions. Lertworasirikul et al. (2011) studied an inverse DEA model for the case of variable return to scale, i.e., inverse BCC model, and developed a linear programming model to solve this model for a Pareto-efficient solution. Ghobadi et al. (2014) introduced the inverse DEA model from both the theoretical and applied viewpoints, and then proposed some possible extensions and applications of this model in the presence of fuzzy data. Jahanshahloo et al. (2015) developed an inverse DEA model under an inter-temporal dependence assumption and introduced the concept of periodic weak Pareto optimality to solve this model.

However, the methods mentioned above only consider the traditional scenario, where decision makers expect fewer inputs to produce more desirable outputs.

Actually, it is necessary to consider undesirable outputs, such as waste and pollution, for evaluating the model’s efficiency regarding sustainable development (Rashidi & Saen, 2015). Undesirable outputs are not what decision makers expect but they usually appear along with desirable outputs during the production process. Therefore, we should form a new framework for analyzing the inverse DEA problem in the scenario where desirable and undesirable outputs both exist. To the best of our knowledge, there are no relevant studies of an inverse DEA model with undesirable outputs. Fortunately, technology has matured enough to address undesirable outputs within a DEA framework.

Ever since Färe et al. (1989) proposed a DEA model to deal with the problem of undesirable outputs, the DEA approach has been widely employed throughout the world to address the evaluation problem with undesirable outputs. This approach can be generally classified into several categories. The first category treats undesirable outputs as inputs for processing in a traditional DEA model (Hu & Wang, 2006). The second category translates undesirable outputs into desirable outputs by using a data transformation function (Seiford & Zhu, 2002). The third category deals with undesirable outputs by using different efficiency measurements in the DEA approach, such as the slack-based measure DEA model (Tao, et al. 2016) and the directional distance function DEA model (Huang, et al. 2015). The fourth category mainly focuses on the disposability of undesirable outputs (Liu, et al., 2013). In this paper, we chose the approach proposed by Seiford and Zhu (2002) to address undesirable outputs. This approach is not only simple to use, but also reflects the real production process. Actually, this approach is one of the most frequently used approaches to address undesirable outputs in DEA (Chen et al. 2015).

In addition, a relatively stable forecasting background is necessary for making the investment scheme based on inverse DEA method. Gray system theory, first proposed by Deng in 1982, has shown to be a concise and effective model to address uncertain systems with insufficient data. In this theory, GM(1,1) is the most frequently applied gray forecasting model because of its simplicity (Zhao et al., 2012). This model deals with data through an accumulating generation operator, and tries to find the inherent structure in a system without assuming a statistical distribution of the data. This model can also accurately predict the trends of times series based on small-sample observations. Because of these advantages, GM(1,1) has been widely applied in various fields and has produced many satisfactory results (Chang et al., 2015). In this paper, we chose the GM(1,1) model to predict the inputs/outputs data of DMUs for constructing a scientific and stable forecast background.

Unlike traditional research on investment schemes for sustainable development that do not yield the specific amount of investment required, and unlike the existing forecasting methods that only consider trend changes of time series, inverse DEA is an effective approach that can be used to obtain the optimal value of investment required for given development targets (Wei et al. 2000). However, traditional inverse DEA models cannot be used to analyze the issue of sustainable development because both desirable and undesirable outputs exist. Therefore, this paper makes the following theoretical contributions: first, through introducing a data transformation function proposed by Seiford and Zhu (2002), a new inverse DEA model was developed to analyze the investment problem in the situation where both desirable and undesirable outputs exist; second, three perspectives are defined to make several scientifically based investment schemes for different sustainable development objectives, namely, the natural, regulation, and optimal perspectives; third, a new ideal perspective is defined to guide a definite direction for improving the level of sustainable development. By these theoretical contributions, decision makers can scientifically forecast the specific amount of investment based on their basic and improvement demands for sustainable development, respectively, which is conducive for reducing the blindness of investment and promoting sustainable development. Combined with the gray forecasting model GM(1,1), these methods were applied to analyze the investment problem of sustainable development in 29 Chinese regions, and the results show that: the unbalanced distribution of labor investment and the excessive investment in capital and energy are serious barriers to China's sustainable development in the short term; and in the long term, the demand for investment in labor and capital will continue to increase along with a low demand for energy investment, and that appropriately strengthening environmental regulations will not affect the overall demand for investment. Finally, some suggestions are proposed to create better conditions for China's sustainable development.

These methods also provide a new analytical framework for solving other similar decision problems, such as the investment problem of medical resources among different hospitals, the optimal allocation problem of educational resources among different regions, and so on.

2 Preliminaries

2.1 Inverse DEA Model

Assume that there are n DMUs, and each DMU has m inputs and s outputs. The inputs and outputs values of $\mathrm{DMU}_j\,(j=1,\ldots,n)$ are represented by $x_{ij}\,(i=1,\ldots,m)$ and $y_{rj}\,(r=1,\ldots,s)$, respectively. Lertworasirikul et al. (2011) assumed that the a specific DMU, noted by DMU_0, with the efficiency θ_0^*, increased its outputs by Δy_{r0} (*r=1,2,...,s*). Then, the input's minimum increment Δx_{i0} (*i=1,2,...,m*) of this DMU could be obtained by model (1) as follows for remaining its efficiency unchanged.

$$\begin{aligned}
&\min\,(\Delta x_{10},\Delta x_{20},\ldots,\Delta x_{m0})\\
&\text{s.t. } \sum_{i=1}^{n}\lambda_j x_{ij}+\lambda_{0'}(x_{i0}+\Delta x_{i0})\le\theta_0^*(x_{i0}+\Delta x_{i0}),\quad i=1,2,\ldots,m\\
&\qquad \sum_{i=1}^{n}\lambda_j y_{ij}+\lambda_{0'}(y_{r0}+\Delta y_{r0})\ge y_{r0}+\Delta y_{r0},\quad r=1,2,\ldots,s\\
&\qquad \sum_{i=1}^{n}\lambda_j+\lambda_{0'}=1\\
&\qquad x_{i0}+\Delta x_{i0}>0,\quad i=1,2,\ldots,m\\
&\qquad \lambda_{0'},\lambda_j\ge 0,\quad j=1,2,\ldots,n
\end{aligned}\tag{1}$$

where θ_0^* is the optimal efficiency value of DMU_0 before the changes in its output values and λ_j is the multiple of DMU_j when evaluating DMU_0. Then, they proposed Theorem 1 to solve model (1), and proved it successfully.

Theorem 1. Assume that the relative efficiency value of DMU_0 with respect to other DMUs in a group of comparable DMUs is θ_0^*. For given changes $\Delta y_{r0}\ne 0$ in the output values of DMU_0, the minimum Δx_{i0} of DMU_0 can be obtained by solving model (2) as follows, which does not make any changes to its relative efficiency value.

$$
\begin{aligned}
&\min \mathrm{W}^T (\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t. } \sum_{i=1}^{n} \lambda_j x_{ij} \le \theta_0^* (x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\qquad \sum_{i=1}^{n} \lambda_j y_{ij} \ge y_{r0} + \Delta y_{r0}, \quad r = 1, 2, \ldots, s \\
&\qquad \sum_{i=1}^{n} \lambda_j = 1 \\
&\qquad \lambda_j \ge 0, \quad j = 1, 2, \ldots, n
\end{aligned}
\tag{2}
$$

where $\mathrm{W}^T = (w_1, w_2, \ldots, w_m)$ is the weight vector of Δx_{i0} ($i=1,2,\ldots,m$).

2.2 Gray Forecasting Model

Since gray forecasting model GM(1,1) is a well-known method, we will not discuss it in detail in this paper. Interested readers may refer to Wang et al. (2008) and Zhao et al. (2012) to gain an understanding of the general procedure of GM(1,1).

3 Methods for Analyzing the Investment Problem

3.1 Inverse DEA with Undesirable Outputs

Inverse DEA with undesirable outputs is different from the traditional inverse DEA approach because not all outputs are expected to increase. Actually, when we evaluate the process of sustainable development, both the desirable and undesirable outputs produced should be considered (Rashidi & Saen, 2015). Decision makers usually attempt to increase the vectors of desirable outputs as much as possible, with the given decreased vector of inputs and undesirable outputs (Bi et al., 2015). In this scenario, the traditional inverse DEA model cannot be applied to forecast the increment of the inputs, thus a new model needs to be constructed for addressing this problem.

In this paper, we chose the approach proposed by Seiford and Zhu (2002) to deal with undesirable outputs. Assume that there are *n* DMUs. Each DMU_j has *m* inputs x_{ij} ($i=1,2,\ldots,m$), *s* desirable outputs y_{rj} ($r=1,2,\ldots,s$), and *h* undesirable outputs z_{fj} ($f=1,2,\ldots,h$). Their relative efficiency values θ_j^* ($j=1,2,\ldots,n$) can be obtained by model (3), which was proposed by Seiford and Zhu (2002), as follows.

$$\begin{aligned} &\theta_0^* = \min \theta_0 \\ &s.t. \ \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_0 x_{i0}, \quad i = 1,2,\ldots,m \\ &\quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \quad r = 1,2,\ldots,s \\ &\quad \sum_{j=1}^{n} \lambda_j b_{fj} \ge b_{f0}, \quad f = 1,2,\ldots,h \\ &\quad b_{fj} = -z_{fj} + \beta_f, \\ &\quad \sum_{j=1}^{n} \lambda_j = 1, \\ &\quad \lambda_j \ge 0, \ j = 1,2,\ldots,n \end{aligned} \tag{3}$$

where β_f is a positive number, large enough so that every b_{fj} is positive. The fourth constraint is used to transform the undesirable outputs to the new variables, whose values are better the larger they are, by using a linear monotone decreasing transformation.

Suppose that the values of desirable outputs of DMU_0 are changed from y_{r0} to $y_{r0}+\Delta y_{r0}$, $\Delta y_{r0} \ne 0$, and the values of undesirable outputs are changed from z_{f0} to $z_{f0}+\Delta z_{f0}$, $\Delta z_{r0} \ne 0$. Then, the minimum increment Δx_{i0} ($i=1,2,\ldots,m$) of inputs for DMU_0 can be obtained by model (4) as follows.

$$
\begin{aligned}
&\min\ (\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t.}\ \sum_{j=1}^{n} \lambda_j x_{ij} + \lambda_{0'}(x_{i0} + \Delta x_{i0}) \le \theta_0^*(x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} + \lambda_{0'}(y_{r0} + \Delta y_{r0}) \ge y_{r0} + \Delta y_{r0}, \quad r = 1, 2, \ldots, s \\
&\qquad \sum_{j=1}^{n} \lambda_j b_{fj} + \lambda_{0'} b_{f0'} \ge b_{f0'}, \quad f = 1, 2, \ldots, h \\
&\qquad b_{fj} = -z_{fj} + \beta_f, \\
&\qquad b_{f0'} = -(z_{f0} + \Delta z_{f0}) + \beta_f, \\
&\qquad \sum_{j=1}^{n} \lambda_j + \lambda_{0'} = 1 \\
&\qquad x_{i0} + \Delta x_{i0} > 0, \\
&\qquad \lambda_{0'}, \lambda_j \ge 0, \quad j = 1, 2, \ldots, n
\end{aligned} \tag{4}
$$

where $\mathrm{DMU}_{0'}$ is regarded as a perturbed DMU, which has *m* inputs $x_{i0} + \Delta x_{i0}$, *s* desirable outputs $y_{r0} + \Delta y_{r0}$, and *h* undesirable outputs $z_{f0} + \Delta z_{f0}$.

Theorem 2. Assume that the relative efficiency value of DMU_0 with respect to other DMUs in a group of comparable DMUs is θ_0^*. For the given changes $\Delta y_{r0} \ne 0$ and $\Delta z_{f0} \ne 0$ in the desirable and undesirable outputs values of DMU_0, respectively, the minimum Δx_{i0} of DMU_0 can be obtained by solving model (5) as follows, which does not make any changes to the its relative efficiency value.

$$
\begin{aligned}
&\min\ W^T(\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t.}\ \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_0^*(x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} + \Delta y_{r0}, \quad r = 1, 2, \ldots, s \\
&\qquad \sum_{j=1}^{n} \lambda_j b_{fj} \ge b_{f0'}, \quad f = 1, 2, \ldots, h \\
&\qquad b_{fj} = -z_{fj} + \beta_f, \\
&\qquad b_{f0'} = -(z_{f0} + \Delta z_{f0}) + \beta_f, \\
&\qquad \sum_{j=1}^{n} \lambda_j = 1 \\
&\qquad \lambda_j \ge 0, \quad j = 1, 2, \ldots, n.
\end{aligned} \tag{5}
$$

Proof. See **Appendix**. □

3.2 Different Perspectives of Investment Analysis

Based on the inverse DEA model with undesirable outputs proposed in this paper, we can solve the problem of determining the minimum increment of inputs required for given desirable and undesirable outputs so that the current efficiency value of a considered DMU_0 with respect to other DMUs remains unchanged. According to the studies of Khasraghi et al. (2015) and Valipour (2012), taking different perspectives into account is crucial for decision makers to make scientifically based decisions. Thus, we tried to develop some reasonable perspectives to forecast an investment scheme for sustainable development.

Considering that the Gray forecasting GM(1,1) model has good ability to forecast time series with a small sample size (Chen & Huang, 2013), we chose it to predict the data of inputs and outputs. Assume that $\hat{x}_{ij}^{(t)}$ ($i=1,2,\ldots,m$), $\hat{y}_{rj}^{(t)}$ ($r=1,2,\ldots,s$), and $\hat{z}_{fj}^{(t)}$ ($f=1,2,\ldots,h$) represent the predicted values of inputs, desirable outputs, and undesirable outputs, respectively, of DMU_j in year t, obtained by the GM(1,1) model according to the time series of the last 10 years. $\tilde{x}_{ij}^{(t)}$ ($i=1,2,\ldots,m$), $\tilde{y}_{rj}^{(t)}$ ($r=1,2,\ldots,s$), and $\tilde{z}_{fj}^{(t)}$ ($f=1,2,\ldots,h$) represent the target values of inputs, desirable outputs, and undesirable outputs of DMU_j in year t, respectively, and were proposed by the government for sustainable development. Moreover, the predicted values can be regarded as the most probable value in the future without any regulation (Chen & Chen, 2011), while the target value is the goal that the government enforces. Therefore, we define the optimal desirable outputs $\bar{y}_{rj}^{(t)}$ ($r=1,2,\ldots,s$) in year t as the maximum of the predicted values $\hat{y}_{rj}^{(t)}$ and the target values $\tilde{y}_{rj}^{(t)}$. This is done because if $\hat{y}_{rj}^{(t)} > \tilde{y}_{rj}^{(t)}$, decision makers would ignore the target values and go for their maximum optimal outputs; otherwise, they would be forced to realize $\tilde{y}_{rj}^{(t)}$ by the government. In contrast, the optimal undesirable outputs $\overline{z}_{fj}^{(t)}$ (f=$1,2,\ldots,h$) are defined as the minimum of the predicted values $\hat{z}_{fj}^{(t)}$ and the target values $\tilde{z}_{fj}^{(t)}$, because it is best to reduce the values of undesirable outputs.

Ramanathan (2006) noted that efficiency can be used by decision makers to forecast the future relationship between inputs and outputs. Vaninsky (2006) stated that prospective data can be used to forecast future efficiency. Therefore, the prospective data of the inputs, determined by the prospective data of the outputs and efficiency, can also reflect future requirements on investment. According to the present situation, three perspectives are proposed for forecasting future requirements on investment, namely, the natural perspective, the regulation perspective, and the optimal perspective. They are defined as follows.

Definition 1. The investment problem from the **natural perspective** is a problem of determining the best possible inputs $x_{i0}^{N(t)}$ of DMU_0 for the predicted desirable output $\hat{y}_{r0}^{(t)}$ and undesirable outputs $\hat{z}_{j0}^{(t)}$ in year t, such that the efficiency value of DMU_0 remains unchanged with respect to other DMUs, which have predicted inputs $\hat{x}_{ij}^{(t)}$ and predicted outputs $\hat{y}_{rj}^{(t)}$ and $\hat{z}_{fj}^{(t)}$, i.e., $\theta_0^{(t)*} = \theta_0^{(t-1)*}$.

Definition 2. The investment problem from the **regulation perspective** is a problem of determining the best possible inputs $x_{i0}^{R(t)}$ of DMU_0 for the target desirable output $\tilde{y}_{r0}^{(t)}$ and undesirable outputs $\tilde{z}_{j0}^{(t)}$ in year *t*, such that the efficiency value of DMU_0 remains unchanged with respect to other DMUs, which have predicted inputs $\hat{x}_{ij}^{(t)}$ and predicted outputs $\hat{y}_{rj}^{(t)}$ and $\hat{z}_{fj}^{(t)}$.

Definition 3. The investment problem from the **optimal perspective** is a problem of determining the best possible inputs $x_{i0}^{O(t)}$ of DMU_0 for the optimal desirable output $\overline{y}_{r0}^{(t)}$ and undesirable outputs $\overline{z}_{j0}^{(t)}$ in year *t*, such that the efficiency value of DMU_0 remains unchanged with respect to other DMUs, which have predicted inputs $\hat{x}_{ij}^{(t)}$ and predicted outputs $\hat{y}_{rj}^{(t)}$ and $\hat{z}_{fj}^{(t)}$.

It is worth noting that no DMU wants to reduce its efficiency (Wu et al., 2016). Thus, the fact that the efficiency value of DMU_0 remains unchanged can reflect the basic requirement of decision makers in the investment scheme. In addition, DMU_0 cannot predict the investment scheme of others DMUs, so we regard the predicted data of these DMUs as the forecasting background (Chen & Chen, 2011).

The natural perspective is used to determine the minimum amount of inputs invested by decision makers according to the natural growth trends of desirable and undesirable outputs. This perspective is applicable in situations where decision makers can make investment schemes without external control and constraints. The regulation perspective is used to determine the minimum amount of inputs invested by decision makers on the premise that the target for outputs has been reached. Actually, the regulation on production processes for reaching the target outputs has always existed (Ramanathan et al., 2016). The optimal perspective is used to determine the minimum amount of inputs required for achieving the best possible outputs under the regulations for target outputs.

According to Theorem 2 and Definition 1, the minimum increment $\Delta x_{i0}^{N(t)}$ from the natural perspective can be obtained by the following model:

$$
\begin{aligned}
\min\ & \sum_{i=1}^{m} w_i * \Delta x_{i0}^{N(t)} \\
\text{s.t.}\ & \sum_{j=1;\, j\neq 0}^{n} \lambda_j \hat{x}_{ij}^{(t)} + \lambda_0 x_{i0}^{N(t-1)} \le \theta_0^{*} (x_{ij}^{N(t-1)} + \Delta x_{i0}^{N(t)}), \quad i = 1, 2, \ldots, m \\
& \sum_{j=1;\, j\neq 0}^{n} \lambda_j \hat{y}_{rj}^{(t)} + \lambda_0 \hat{y}_{r0}^{(t-1)} \ge \hat{y}_{r0}^{(t)}, \quad r = 1, 2, \ldots, s \\
& \sum_{j=1;\, j\neq 0}^{n} \lambda_j \hat{b}_{fj}^{(t)} + \lambda_0 \hat{b}_{f0}^{(t-1)} \ge \hat{b}_{f0'}^{(t)}, \quad f = 1, 2, \ldots, h \\
& \hat{b}_{fj}^{(t)} = -\hat{z}_{fj}^{(t)} + \beta_f, \qquad j = 1, 2, \ldots, n, \quad j \neq 0 \\
& \hat{b}_{f0'}^{(t)} = -\hat{z}_{f0}^{(t)} + \beta_f, \\
& \hat{b}_{f0}^{(t-1)} = -\hat{z}_{f0}^{(t-1)} + \beta_f, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \ge 0, \qquad j = 1, 2, \ldots, n.
\end{aligned}
\tag{6}
$$

Then the specific investment schemes $x_{i0}^{N(t)} = x_{i0}^{N(t-1)} + \Delta x_{i0}^{N(t)}$ in year t from the natural perspective can be obtained.

Similarly, the specific investment schemes $x_{i0}^{R(t)} = x_{i0}^{R(t-1)} + \Delta x_{i0}^{R(t)}$ and $x_{i0}^{O(t)} = x_{i0}^{O(t-1)} + \Delta x_{i0}^{O(t)}$ from the regulation and optimal perspectives, respectively, can also be obtained by this way.

4 Investment Analysis for Sustainable Development in China

As the largest manufacturing country, China has expressed great concern over sustainable development. However, low efficiency of resource utilization and heavy environmental pollution are entrenched in China. Making a scientifically based investment scheme from different perspectives will help the Chinese government to allocate resources more reasonably for different sustainable development objectives.

4.1 Data and Variables

Twenty-nine provinces, autonomous regions and municipalities in mainland China were selected for this paper (due to lack of data, Tibet province was not included in this paper, and Chongqing municipality was incorporated into Sichuan province in this analysis). In researches on the efficiency for sustainable development, input indicators generally include labor, capital, and energy consumption (Chen & Jia, 2016; Li & Shi, 2014; Valipour, 2015). The number of employed people x_{1j} is the most commonly used indicator to reflect the labor investment, capital stock x_{2j} is the best proxy indicator for capital input, and total energy consumption x_{3j} can directly reflect investments in energy. Hence, they are selected as inputs. Gross regional product (GRP) y_{1j} is taken as one final desirable output in the production stage. The total volume of sulphur dioxide (SO_2) emissions z_{1j}, the total volume of chemical oxygen demand (COD) discharged z_{2j}, and the total volume of carbon dioxide (CO_2) emissions z_{3j} are taken as the undesirable outputs. z_{1j} and z_{2j} are the main pollutants monitored by the government in the air and the water, respectively, and they can reflect the degree of environmental pollution to a great extent. z_{3j} is also a key factor to evaluate the level of China's sustainable development.

The data comes from China Statistical Yearbook 2006~2015 and China Energy

Statistical Yearbook 2006~2015. Descriptive statistics of the data are summarized in Table 1.

Table 1 Descriptive statistics for the data set (2005-2014)

Indicator	x_{1j} (10000 persons)	x_{2j} (100 million yuan)	x_{3j} (10000 tce)	y_{1j} (100 million yuan)	z_{1j} (10000 tons)	z_{2j} (10000 tons)	z_{3j} (10000 tons)
Max	1973.28	46973.40	38899.25	16527.31	214.10	198.25	36387.84
Min	42.64	415.60	822.20	127.20	2.17	7.16	1311.94
Mean	478.49	8105.48	12725.47	3411.99	78.19	60.72	11242.05
Std.dev	317.25	7627.49	8191.31	3006.87	48.46	42.97	7274.11

Note: Since the data of capital stock is not available in China, we used the method proposed by Zhang et al. (2004) to estimate the capital stock. GRP data was adjusted by the gross domestic production (GDP) deflator in order to eliminate the price factor in the time series. The data of both capital stock and GRP take 1978 as the base year. The total volume of CO_2, z_{3j}, was obtained by using the IPCC's method (2006), which is one of the most commonly used methods to calculate the value of z_{3j}.

According to the data in Table 1, we define β_f in model (5) as the following function.

$$\beta_f = \max_{j=1,\dots,n} z_{fj} + \min_{j=1,\dots,n} z_{fj}, \quad f = 1, 2, \dots, h \tag{6}$$

This model is used to ensure that the numerical oscillations of these data are not too wild when the linear monotone decreasing transformation is used in model (5).

According to the 13th five-year plan proposed by the Chinese government in 2016, the government formulated targets that indicated that the annual growth rate of GDP should be no less than 6.5%, the total emission of SO_2 should be reduced by 15%, the total emission of COD should be reduced by 10%, and the emission of CO_2

per unit of GDP should be reduced by 18% during the 2016-2020 period. Assuming that the annual reduction rate of undesirable outputs is the same, the total emission of SO_2 should be reduced by almost 3.198% per year, the total emission of COD should be reduced by almost 2.085% per year, and the emission of CO_2 per unit of GDP should be reduced by almost 3.891% per year. It is worth noting that the total emission of CO_2 would continue to increase because GDP would be increasing by 6.5% per year. Thus, the target values of desirable outputs $\tilde{y}_{1j}^{(t)}$ and undesirable outputs $\tilde{z}_{fj}^{(t)}$ can be obtained by $\tilde{y}_{1j}^{(t)} = (1+6.5\%)y_{1j}^{(t-1)}$, $\tilde{z}_{1j}^{(t)} = (1-3.198\%)z_{1j}^{(t-1)}$, $\tilde{z}_{2j}^{(t)} = (1-2.085\%)z_{2j}^{(t-1)}$, and $\tilde{z}_{3j}^{(t)} = (1-3.891\%)\tilde{y}_{1j}^{(t)} z_{3j}^{(t-1)} / y_{1j}^{t-1}$. As for the predicted values, we predicted them by using the GM(1,1) model according to the time series during the 2005-2014 period. According to the results, we found that the deviations of the original time series and the forecast time series of all data were no more than 5%. This means that the forecast time series can successfully predict future trends (Valipour & Eslamian, 2014). It is worth noting that the statistical caliber of z_{2j} suffered dramatic changes during the 2010-2011 period. However, the trend of the time series can be represented as two approximate parallel lines. Thus, we took the difference of z_{2j} between 2010 and 2011 as the missing value during the 2005-2010 period, and used it to deal with the time series by adding this difference to the value of z_{2j} during the 2005-2010 period. Then, a new time series was formed. We found that the deviations of the original time series and the new time series of z_{2j} during the 2011-2014 period were no more than 3%. Thus, we think that the new time series of z_{2j} can be used to predict the value of z_{2j} during the 2015-2024 period.

Because of the large amount of data, we will not provide a detailed description here. The descriptive statistics of the predicted values are summarized in Table 2, while the descriptive statistics of the target values and optimal values are summarized in Table 3. It is worth noting that $\tilde{x}_{ij}$ and $\bar{x}_{ij}$ are not included in Table 3. This is because of two reasons. First, there is no clearly objective regulation for investment. Second, these data are not required in the process of prediction.

Table 2 Descriptive statistics for the predicted values during 2015-2024

Indicator	$\hat{x}_{1j}$ (10000 persons)	$\hat{x}_{2j}$ (100 million yuan)	$\hat{x}_{3j}$ (10000 tce)	$\hat{y}_{1j}$ (100 million yuan)	$\hat{z}_{1j}$ (10000 tons)	$\hat{z}_{2j}$ (10000 tons)	$\hat{z}_{3j}$ (10000 tons)
Max	5501.92	157031.62	50847.53	43589.54	165.88	178.75	69148.35
Min	70.23	1797.16	2075.94	415.12	3.09	10.75	4605.44
Mean	937.94	32802.43	20680.47	9335.46	61.74	71.15	21927.78
Std.dev	857.49	27935.46	11635.84	7661.49	39.69	42.87	13279.76

Note: The data of both $\hat{x}_{2j}$ and $\hat{y}_{1j}$ take 1978 as the base year for eliminating the price factor in the time series. Meanwhile, there was 100 yuan$\approx$63.41 dollars in 1978. The exchange between yuan and dollars has a floating rate, which may constantly change.

Table 3 Descriptive statistics for the target and optimal values during 2015-2024

Target	$\tilde{y}_{1j}$ (100 million yuan)	$\tilde{z}_{1j}$ (10000 tons)	$\tilde{z}_{2j}$ (10000 tons)	$\tilde{z}_{3j}$ (100 million tons)
Max	31024.03	153.94	174.33	45934.41
Min	386.92	2.35	8.51	3750.49
Mean	7376.64	57.17	70.51	16415.29
Std.dev	5975.67	34.42	43.45	9690.20
Optimal	$\bar{y}_{1j}$ (100 million yuan)	$\bar{z}_{1j}$ (10000 tons)	$\bar{z}_{2j}$ (10000 tons)	$\bar{z}_{3j}$ (100 million tons)
Max	43589.54	153.94	174.33	45934.41
Min	415.12	2.35	8.51	3750.49
Mean	9335.46	54.26	69.49	16415.03
Std.dev	7661.49	34.45	42.64	9690.04

Note: The data of $\tilde{y}_{1j}$ and $\bar{y}_{1j}$ take 1978 as the base year.

4.2 Investment Analysis from Different Perspectives

In this section, we analyze the investment problem for China's sustainable development in 2015. Actually, there is no obvious evidence for which kind of investment is more important, thus we let $W^T = (w_1, w_2, w_3) = (1,1,1)$ be the weights of input increment Δx_{i0} ($i=1,2,3$). By applying model (3) and (5) from the natural, regulation, and optimal perspectives, the minimum increment of inputs in 2015 can be obtained for each perspective. The results are shown in Table 4.

Table 4 Results of investment analysis from different perspectives in 2015

Region	$\theta_j^{(2014)*}$	Natural perspective			Regulation perspective			Optimal perspective		
		$\Delta x_{1j}^{N(2015)}$	$\Delta x_{2j}^{N(2015)}$	$\Delta x_{3j}^{N(2015)}$	$\Delta x_{1j}^{R(2015)}$	$\Delta x_{2j}^{R(2015)}$	$\Delta x_{3j}^{R(2015)}$	$\Delta x_{1j}^{O(2015)}$	$\Delta x_{2j}^{O(2015)}$	$\Delta x_{3j}^{O(2015)}$
Anhui	1.00	-122.15	193.79	-4985.56	-98.84	607.51	-4596.29	-68.11	1152.82	-4083.20
Beijing	1.00	-101.75	-2643.89	-151.04	-2.06	134.32	307.12	19.60	604.00	373.41
Fujian	0.87	**-186.36**	162.16	-3884.86	**-158.98**	648.13	-3427.61	**-127.78**	1201.77	-2906.69
Gansu	0.65	2.37	**-1342.80**	-2517.38	15.64	**-1107.30**	-2295.79	26.18	**-920.25**	-2119.80
Guangdong	1.00	-453.78	**1585.72**	-3129.10	-788.92	**11732.18**	-3538.40	-735.97	**11884.77**	-3878.52
Guangxi	0.57	167.70	2929.40	1600.75	198.35	3445.01	1606.28	257.49	5685.24	3669.43
Guizhou	0.66	-77.19	91.21	-5370.78	-66.45	281.81	-5191.45	-56.43	459.60	-5024.16
Hainan	1.00	**262.47**	2910.67	3335.44	**203.70**	255.22	19.10	**25.11**	163.06	-224.84
Hebei	0.80	6.54	**-11086.87**	-17813.36	46.30	**-10381.34**	-17149.52	86.06	**-9675.80**	-16485.67
Heilongjiang	0.79	-72.57	143.20	-5190.15	-51.35	519.76	-4835.85	-23.55	1013.20	-4371.57
Henan	0.49	4.37	-6494.84	-3587.13	71.36	-5306.09	-2468.62	139.73	-4092.83	-1327.05
Hubei	0.71	-2.53	-1115.39	-4059.82	39.47	-369.95	-3358.43	97.42	658.43	-2390.81
Hunan	0.82	-136.57	141.38	-7180.39	-109.85	615.64	-6734.16	-72.71	1274.67	-6114.07
Inner Mongolia	0.87	36.17	-12385.32	**-12265.57**	55.06	-12050.09	**-11950.15**	96.99	-11306.03	**-11250.06**
Jiangsu	1.00	-203.53	-3935.14	**-898.20**	-242.33	1064.36	**-668.58**	-183.70	2324.01	**-703.37**
Jiangxi	1.00	-8.21	657.57	-130.93	-1.60	1249.90	124.58	38.88	1650.18	233.50
Jilin	0.71	29.42	-4475.02	-1987.95	49.34	-4121.65	-1655.46	86.45	-3463.12	-1035.84
Liaoning	0.78	7.75	-7464.54	**-10114.91**	48.09	-6748.75	**-9441.42**	113.40	-5589.71	**-8350.87**
Ningxia	1.00	29.91	-353.17	-2870.16	29.91	-353.17	-2870.16	29.91	-353.17	-2870.16
Qinghai	1.00	34.51	-167.23	-255.68	5.30	400.85	515.68	201.25	2674.05	2807.58
Shaanxi	0.63	-51.81	138.42	-2902.19	-25.83	599.55	-2468.30	14.89	1322.14	-1788.42
Shandong	0.89	**172.24**	-12378.13	-12751.30	**331.87**	-9772.64	-10248.53	**494.72**	-7114.58	-7695.28
Shanghai	1.00	2.41	**790.76**	359.43	57.75	**640.71**	-131.35	50.70	**419.79**	-261.14

Shanxi	0.47	43.92	-6433.52	-10829.12	70.50	-5961.72	-10385.20	97.94	-5474.80	-9927.05
Sichuan	0.84	-385.25	-1419.66	-14056.32	-262.57	584.43	-12131.69	-67.86	3762.51	-9078.91
Tianjin	1.00	53.66	-3263.01	-378.32	71.27	-3018.31	-158.07	132.53	-2632.59	-268.37
Xinjiang	0.47	**-19.53**	86.23	**-9217.10**	**-5.85**	329.09	**-8988.59**	**1.17**	453.56	**-8871.48**
Yunnan	0.49	109.60	5929.83	536.86	137.61	6216.69	145.61	177.11	7743.10	1624.05
Zhejiang	0.60	-31.86	-2748.71	-361.69	33.34	-1591.66	726.99	117.13	-190.03	2065.01
Total		-890.07	-61946.90	-131056.56	-349.77	-31457.50	-121248.25	968.55	-6365.99	-100254.36

Note: the bold typeface in Table 4 is used to draw attention to values pertaining to the following analysis of results.

The optimal efficiency $\theta_j^{(2014)*}$ in 2014 is shown in Table 4, where we can see that there are 10 regions that performed well (i.e., regions with their $\theta_j^{(2014)*}=1$), such as Guangdong, Hainan provinces, and Beijing municipality. The other DMUs were inefficient. In order to maintain efficiency under the different perspectives in 2015, DMUs need to adjust their investment scheme in the way shown in Table 4. The general characteristics of these adjustments can be summarized into the following aspects for every perspective.

First, the unbalanced distribution of labor resources affects sustainable development in China. In rapidly developing regions, such as Hainan province, the shortage problem of labor investment is obvious; thus, labor investment needs to continue to increase in 2015. This may be because the demand for high quality talents keeps rising along with a larger industry scale. In some developed regions in China, the phenomenon of excessive investment in labor has occurred. For example, the model yielded a value of $\Delta x_{1j}^{N(2015)}=-186.36$ in Fujian province. This may be because large floating populations cause an overflow in labor investment (Chen et al., 2016). In undeveloped regions, such as Xinjiang province, the problem of insufficient labor investment was not serious. This may be because Chinese policies in undeveloped regions are conducive to attracting talent, while their economy has not reached a certain scale.

Second, excessive investment in capital is an important obstacle for China's sustainable development, and the amount of this type of investment should be reduced in 2015. This problem is especially serious in heavy-industry based regions such as Hebei province. This reflects that economic growth in China remains heavily dependent on capital investment. In some developed regions in China, such as Guangdong province and Shanghai municipality, capital investment has been put to good use, and further investments should be made in 2015. This means that these developed regions are at the front position of economic transition, and they are accelerating the transformation toward intensive development with some success. It is interesting to note that in some undeveloped regions in western China, such as Gansu province, there exists excessive investment in capital and less investment in labor. This reflects that a large amount of capital is being transferred to a part of the western area that does not have the corresponding talent and technology in the implementation process of the western development strategy; this will cause many resources to be wasted.

Third, excessive investment in energy is a common problem, which has seriously affected sustainable development in China. Most regions in China could utilize less energy to produce what they want, such as Jiangsu, Liaoning, and Xinjiang provinces. This reflects that economic growth in these regions, which shows marked characteristics of extensive growth patterns, is mainly driven by energy consumption.

Especially in the regions with abundant mineral resources, such as Inner Mongolia province, excessive investment in energy is usually more serious. This may be caused by low energy costs and weak environmental awareness.

In addition, we need to emphasize that there are different investment schemes based on different perspectives. If decision makers develop the regional economies without any environmental regulations, the best way to adjust the investment scheme in order to maintain efficiency comes from the natural perspective. Considering the task of sustainable development proposed by the Chinese government, the basic investment scheme obtained from the regulation perspective needs to be guaranteed, while the optimal investment scheme can be followed in order to pursue the maximization of profits from the optimal perspective.

To summarize, by combining different perspectives, the new inverse DEA model can be applied to obtain the specific amount of investment required for a given efficiency and outputs. Various scientifically based investment schemes were obtained for different objectives regarding China's sustainable development. These results provide a good reference for decision makers, so that they can allocate limited resources reasonably in order to meet their own requirements for sustainable development.

4.3 Investment Analysis for the Next Several Years

In this section, we analyze the investment problem for China's sustainable development in the next several years. Considering the length of this paper, we analyze the changing trends of total investment in China during the 2012-2024 period from different perspectives, and then take them as an example for illustrating the long-term investment problem. The results are shown in Figs. 1-3.

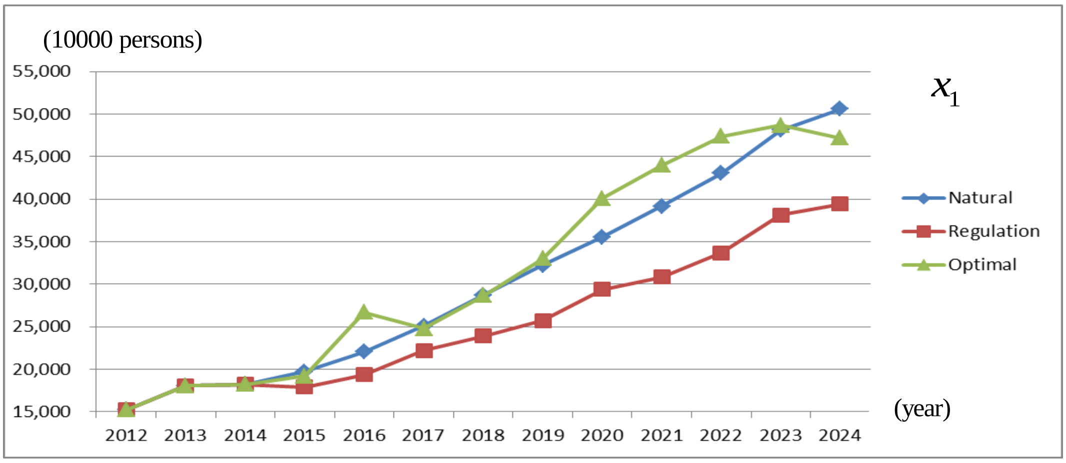

Fig. 1 Changing trend of x_1 from different perspectives

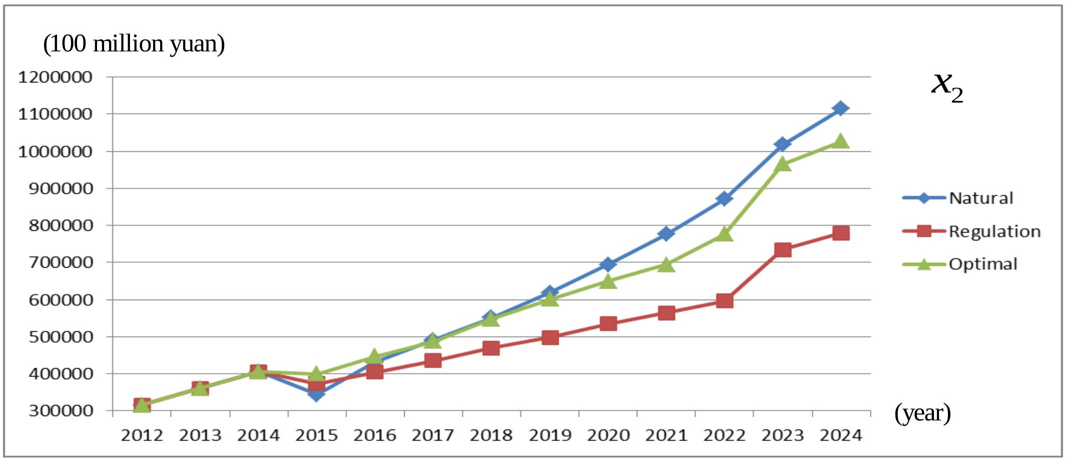

Fig. 2 Changing trend of x_2 from different perspectives

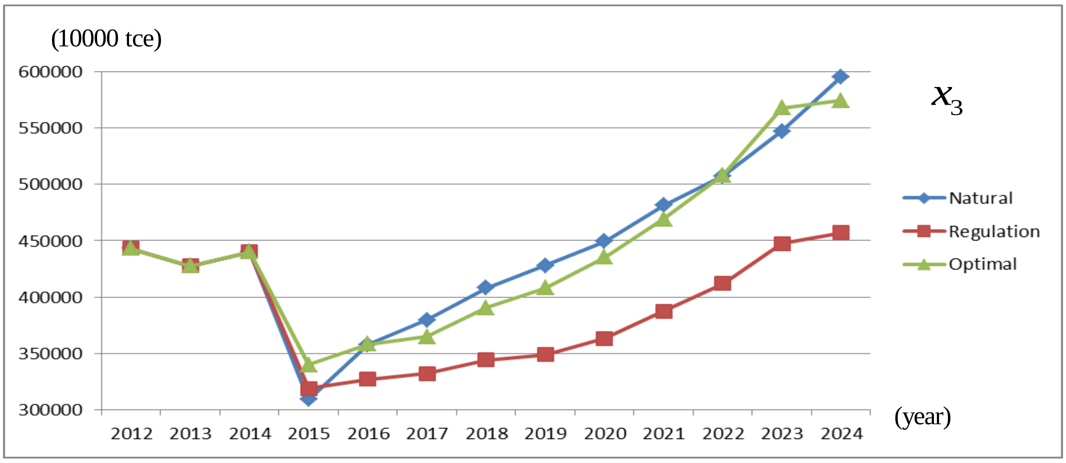

Fig. 3 Changing trend of x_3 from different perspectives

Through Figs. 1-3, we can see that the total investment of China from different perspectives shows similar trends during the 2012-2024 period. There are some common features between predictions obtained from different perspectives. First, the demand for labor rapidly grows during the 2012-2024 period. This reflects that talent is the key factor for sustainable development. Second, the demand for investment in capital grows steadily every year after an adjustment in 2015. This reflects that China's sustainable development will continue to rely on investment in capital in the upcoming years. Third, the problem of excessive investment in energy is outstanding, especially from the regulation perspective, since the total energy consumption for the target of sustainable development in 2024 is similar to what was invested in 2014.

In addition, the three different perspectives show similar trends of investment in the short term, especially the natural and optimal perspectives. However, in the long term, the gap between trends from different perspectives will become increasingly larger. Out of all three perspectives, minimum investment is required from the regulation perspective; this provides a reference for the Chinese government to make a long-term minimal-standard investment scheme to ensure sustainable development. The investment from the optimal perspective is not higher than from the natural perspective. This is because the long-term existence of regulations is conducive to improving environmental protection technology, and this will lead to a reduction of the demand for investment under the given efficiency and outputs. In comparison with the investment scheme from the optimal perspective, the investment scheme from the natural perspective needs more input to produce less desirable output and more undesirable output. Thus, it is clearly not conducive to Chinese sustainable development in the long term.

4.4 Comparison of Methods

To the best of our knowledge, analyzing the investment problem of sustainable development based on an inverse DEA model with undesirable outputs from different perspectives is a new research field. In order to demonstrate the effect of our proposed method, we compared the results of the gray forecasting model GM(1,1) and the inverse DEA model considering only desirable outputs (i.e., model (2) proposed by Lertworasirikul (2011)) with the results of our method from the optimal perspective in 2015. The comparative results are shown in Figs. 4-6.

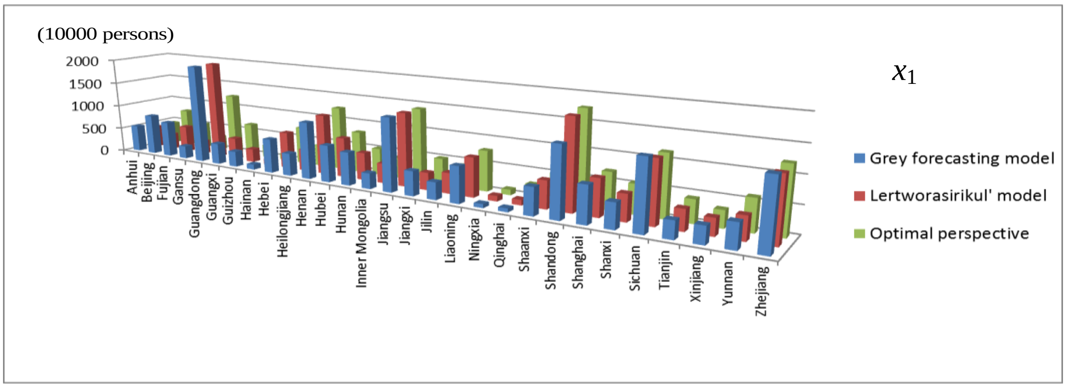

Fig. 4 Comparison results for x_1 in 2015

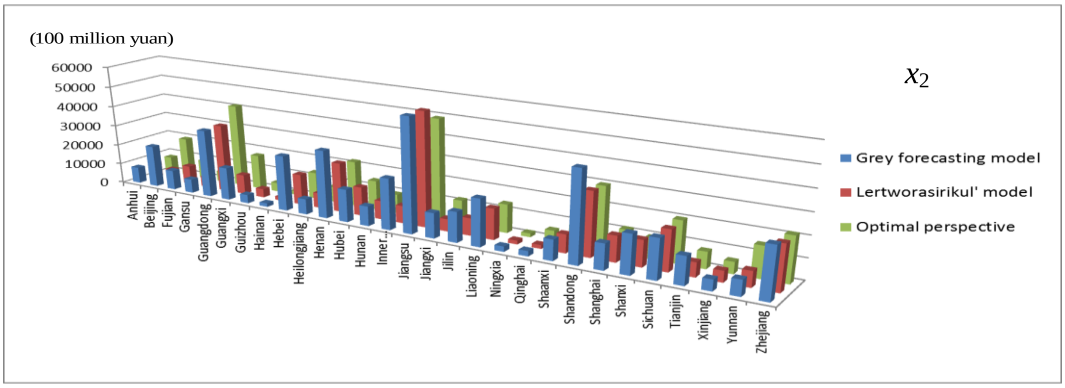

Fig. 5 Comparison results for x_2 in 2015

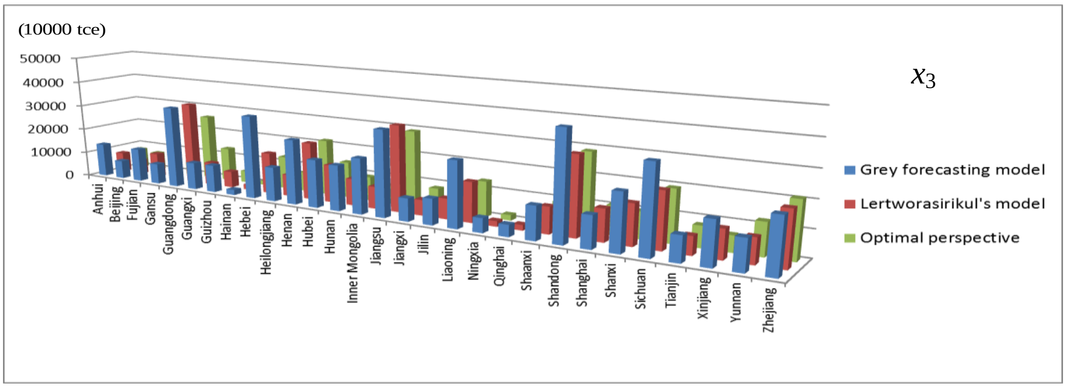

Fig. 6 Comparison results for x_3 in 2015

As shown in Figs. 4-6, and compared with the results of the gray forecasting model, the results of our method emphasize on the reasonable reduction of investment in capital and energy in 2015, with a continued increase in labor investment. It is clear that the results of our method are more scientific than the results obtained by the gray forecasting model; this is because the gray forecasting model predicts the values of inputs simply by analyzing the trends of the time series, and finds it hard to reflect the actual investment demand of the DMUs for sustainable development. For example, due to the characteristics of labor, the growth of labor investment was slow in the past. When using the gray forecasting model, this phenomenon would lead to an underestimation of labor investment because of the long-term shortage in labor investment. Our method forecasts the values of inputs based on different objectives of sustainable development, which can greatly reduce the blindness of prediction process.

In contrast with the results of Lertworasirikul's model, our method creates the investment scheme in a scenario where desirable and undesirable outputs both exist, which is a more reasonable and comprehensive approach for sustainable development (Chang et al., 2016). Considering undesirable outputs, we found that more investment in capital and labor is required in China, as well as a lower energy consumption. This phenomenon shows that the transformation from an energy-intensive industry to a technology-intensive industry is conducive to better environmental protection. In addition, it also shows that China is still enduring throe brought by economic transitions, and it may help to explain why minority regions are not cooperating with the implementation of sustainable development strategies.

4.5 Discussion of Improvement Direction

In this section, we discuss the improvement direction of the investment scheme for a given efficiency. The natural, regulation, and optimal perspectives are used to make an investment scheme on the premise of unchanging efficiency, i.e., $\theta_0^{(t)*} = \theta_0^{(t-1)*}$. However, even if the investment scheme from these perspectives is fully implemented, the level of sustainable development achieved would just meet the basic requirements imposed on decision makers. If DMU_j wants to be an efficient DMU for sustainable development, it must make its efficiency be 1 (Mirdehghan, 2016), which is defined as the ideal efficiency $\theta_j'^{(t)*}$. Actually, for most inefficient DMUs, the ideal efficiency $\theta_j'^{(t)*}$ is usually an unrealistic goal when considering their regional technological level. However, this does not mean $\theta_j'^{(t)*}$ is an unsuitable guide for DMU_j to achieve higher levels of sustainable development. Therefore, we propose the ideal perspective, which is defined as follows.

Definition 4. The investment problem from the **ideal perspective** is a problem of determining the best possible inputs $x_{i0}^{I(t)}$ of DMU_0 for the optimal desirable outputs $\bar{y}_{r0}^{(t)}$ and undesirable outputs $\bar{z}_{j0}^{(t)}$ in year *t*, such that the efficiency value of DMU_0 equals one with respect to other DMUs, which have the predicted inputs $\hat{x}_{ij}^{(t)}$, predicted outputs $\hat{y}_{rj}^{(t)}$ and $\hat{z}_{fj}^{(t)}$, i.e., $\theta_0'^{(t)*}=1$.

According to Definition 4, the amount of investment $x_{i0}^{I(2015)}$ in 2015 from the ideal perspective can be obtained based on model (5). The results are shown in Table 5 together with the results obtained from the optimal perspective.

Table 5 Results from the perspectives of ideal and optimal in 2015

Region	$\theta_j^{(2014)*}$	Optimal perspective			Ideal perspective		
		$x_{1j}^{O(2015)}$	$x_{2j}^{O(2015)}$	$x_{3j}^{O(2015)}$	$x_{1j}^{I(2015)}$	$x_{2j}^{I(2015)}$	$x_{3j}^{I(2015)}$
Anhui	1.00	453.63	8016.56	7927.82	453.63	8016.56	7927.82
Beijing	**1.00**	**775.46**	**19463.74**	**7204.64**	**775.46**	**19463.74**	**7204.64**
Fujian	**0.87**	**526.86**	**9311.24**	**9203.03**	**458.88**	**8109.78**	**8015.53**
Gansu	0.65	290.93	5111.31	5401.64	189.07	3321.79	3510.48
Guangdong	1.00	1237.31	41139.94	25714.74	1237.31	41139.94	25714.74
Guangxi	0.57	658.95	17005.29	13184.76	374.65	9668.47	7496.28
Guizhou	0.66	248.31	4355.62	4684.62	163.02	2859.56	3075.56
Hainan	1.00	126.63	1790.39	1595.09	126.63	1790.39	1595.09
Hebei	0.80	742.24	13129.87	12834.54	594.63	10518.73	10282.14
Heilongjiang	0.79	427.33	7541.02	7583.33	337.17	5949.91	5983.29
Henan	**0.49**	**1248.62**	**22090.21**	**21562.87**	**617.84**	**10930.64**	**10669.70**
Hubei	0.71	804.22	14224.12	13929.44	567.20	10031.96	9824.13
Hunan	0.82	525.19	9278.94	9202.76	428.24	7566.11	7503.99
Inner Mongolia	0.87	398.44	7032.30	7059.00	346.84	6121.50	6144.75
Jiangsu	1.00	1418.71	49297.41	29159.67	1418.71	49297.41	29159.67
Jiangxi	1.00	504.14	11903.58	8288.86	504.14	11903.58	8288.86
Jilin	0.71	420.86	7421.57	7523.95	299.52	5281.86	5354.72
Liaoning	0.78	778.57	13773.60	13452.51	608.20	10759.50	10508.68
Ningxia	1.00	103.16	1797.16	2075.94	103.16	1797.16	2075.94

Qinghai	1.00	264.44	5129.67	6799.28	264.44	5129.67	6799.28
Shaanxi	0.63	531.41	9377.22	9434.04	334.86	5909.00	5944.80
Shandong	0.89	1761.06	29832.61	28815.71	1559.70	26421.49	25520.86
Shanghai	1.00	699.57	11584.69	10823.49	699.57	11584.69	10823.49
Shanxi	0.47	550.04	9689.77	9935.70	258.70	4557.41	4673.08
Sichuan	0.84	1155.36	20012.56	19392.48	964.77	16711.21	16193.42
Tianjin	1.00	428.04	7958.49	7876.68	428.04	7958.49	7876.68
Xinjiang	**0.47**	**317.81**	**5569.10**	**6054.61**	**150.20**	**2631.96**	**2861.41**
Yunnan	0.49	596.68	14914.32	12078.88	289.73	7242.12	5865.28
Zhejiang	0.60	1219.81	21505.83	20891.43	736.97	12993.10	12621.91
Total		19213.78	399258.14	339691.54	15291.28	325667.74	269516.23

Note: the bold typeface in Table 5 is used to draw attention to values pertaining to the following analysis of results.

As shown in Table 5, if $\theta_0^{(2014)*}=1$, then the amount of investment $x_{i0}^{I(2015)}$ is equal to $x_{i0}^{O(2015)}$ because these regions cannot further improve their efficiency, such as Beijing municipality. If $\theta_0^{(2014)*}\neq 1$, the amount of investment $x_{i0}^{I(2015)}$ is less than $x_{i0}^{O(2015)}$ because the efficiency requirement is higher from the ideal perspective. This implies that if DMU_0 achieves optimal efficiency $\theta_0^{(2014)*}$, it can continue to reduce its investment while maintaining fixed outputs in the case that $x_{i0}^{O(2015)} > x_{i0}^{I(2015)}$ ($i=1,2,3$), so that DMU_0 will be as close to the production frontier as possible. It is clear that inefficient DMUs are basically concentrated in the developing and undeveloped regions, such as Henan and Xinjiang provinces. This means that these regions are facing greater pressure for sustainable development, and that they have more potential to improve from the ideal perspective.

The amount of investment $x_{i0}^{I(2015)}$ from the ideal perspective provides a definite direction to adjust the investment scheme of DMU_0 after DMU_0 has achieved optimal efficiency from the optimal perspective. For example, for Fujian province, if the investments in x_1, x_2, and x_3 are reduced to 526.86, 9311.24, and 9203.03, respectively, its efficiency would be 0.87 in 2015. In addition, if these investments are further reduced to 458.88, 8109.78, and 8015.53 in 2015, respectively, then it would be an efficient DMU with $\theta_0^{(2015)*} = 1$.

Similarly, this method can also be extended to the other perspectives and for other given efficiency values for sustainable development in China. Then decision makers can make the specific investment scheme based on their actual improvement demands for sustainable development. It is worth noting that the investment scheme for improving the efficiency of sustainable development may be impractical, which is just used to provide an improvement direction for decision makers. This is because the given efficiency target may be too high for DMU.

5 Conclusions and Suggestions

In the last several decades, the contradiction between economic development and environmental protection has become increasingly conspicuous in the world. Sustainable development must be given top priority, especially in China, which has become one of the most polluted countries in the world. Thus, making a scientifically based investment scheme is significant because it can enable the government to utilize its resources properly in order to achieve sustainable development. In this paper, we proposed a new inverse DEA method with undesirable outputs to analyze the investment problem of sustainable development. Then, we defined four perspectives to make an investment scheme for different sustainable development objectives, namely, the natural, regulation, optimal, and ideal perspectives. In comparison with existing prediction methods, the main advantages of our methods are that they can forecast the specific amount of investment based on the actual demands of decision makers, and that they can define a clear direction to improve the investment scheme for promoting the process of sustainable development.

These methods were applied to analyze the investment problem of sustainable development in China. The results show that the unbalanced distribution of labor resources and excessive investment in capital and energy are serious barriers to China's sustainable development in the short term. The results also show that the demand for investment in labor and capital will continue to increase in the long term, along with a lower demand for energy investment. According to these results, some suggestions on investment schemes are proposed for the Chinese government in order to promote the process of sustainable development.

- First, the Chinese government should allocate labor resources reasonably and improve the quality of individual labor. As shown in Fig. 1, the demand for investment in labor will continue to increase in the future. However, due to the limitedness of labor resources, it is very difficult to greatly increase investment in labor. The best way of solving this problem is to increase investment in education and introduce talents from other countries or regions to improve the quality of individual labor.
- Second, the Chinese government should steadily increase investment in capital after a proper adjustment. This is so because, even though there is a problem of excessive investment in capital in the present, China's sustainable development

will continue to rely on the investment in capital in the upcoming years. It is worth noting that investments in capital should be made along with the corresponding talent and technology, to ensure a rational utilization of capital. Meanwhile, developed regions, such as Shanghai province, can be regarded as a benchmark to accelerate the transformation of economic growth from the extensive mode into the intensive one because their investment in capital has been put to good use in recent years.

- Third, the Chinese government should reduce the dependence of economic development on energy investment with innovations in management and technology. This is because the investment in energy is much higher than its actual demand in most regions of China. In addition, considering resource scarcity and environmental degradation, it is necessary to develop new technologies for improving energy utilization efficiency and increase investments directed at opening up new energy resources.
- Fourth, the Chinese government should strengthen environmental regulations appropriately. This may cause some problems in the short term, such as more investment in labor and capital. However, in the long term, an appropriate strengthening of environmental regulations would not affect the overall demand for investment because it is conducive to technological innovation and sustainable development.
- Fifth, the Chinese government should focus more on the economic transition of inefficient regions and appropriately increase investment in efficient regions after

most regions have achieved the optimal level. This is not only conductive to an optimal allocation of resources, but also promotes China's sustainable development towards reaching an ideal level.

By following these suggestions, better development conditions will be created for sustainable development in China.

Although the method proposed in this paper can be used to analyze the investment problem with crisp data, uncertainty data often needs to be considered during the process of decision-making. Therefore, in future research efforts, some extensive work might be done for analyzing the investment problem of sustainable development under uncertain circumstances.

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Appendix

Proof. Actually, through the approach proposed by Seiford and Zhu (2002), undesirable outputs can be regarded as the new desirable outputs according to the third, fourth and fifth constraints in model (4). Then, we can use $y_{b(fj)}$ instead of b_{fj}. $b_{f0'}$ can be expressed as $b_{f0} + \Delta b_{f0}$ (*f*=*1,2,…,h*), and can be replaced by $y_{b(f0')}$. By this way, the fourth and fifth constraints in model (4), which is used to determine the values of b_{fj} (f=$1,2,\ldots,h$), can be ignored here. Thus, model (4) can be rewritten as follows.

$$\begin{aligned}
&\min\ (\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t.}\ \sum_{j=1}^{n} \lambda_j x_{ij} + \lambda_{0'}(x_{i0} + \Delta x_{i0}) \le \theta_0^*(x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} + \lambda_{0'}(y_{r0} + \Delta y_{r0}) \ge y_{r0} + \Delta y_{r0}, \quad r = 1, 2, \ldots, s \\
&\quad \sum_{j=1}^{n} \lambda_j y_{b(fj)} + \lambda_{0'} y_{b(f0')} \ge y_{b(f0')}, \quad f = 1, 2, \ldots, h \\
&\quad \sum_{j=1}^{n} \lambda_j + \lambda_{0'} = 1 \\
&\quad x_{i0} + \Delta x_{i0} > 0, \\
&\quad \lambda_{0'}, \lambda_j \ge 0, \quad j = 1, 2, \ldots, n
\end{aligned}$$

where $y_{b(f0')} = y_{b0} + \Delta y_{b0}$. We combine $y_{b(fj)}$ with y_{rj} to obtain the following model.

$$\begin{aligned}
&\min\ (\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t.}\ \sum_{j=1}^{n} \lambda_j x_{ij} + \lambda_{0'}(x_{i0} + \Delta x_{i0}) \le \theta_0^*(x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\quad \sum_{j=1}^{n} \lambda_j y_{r'j} + \lambda_{0'}(y_{r'0} + \Delta y_{r'0}) \ge y_{r'0} + \Delta y_{r'0}, \quad r' = 1, 2, \ldots, s, s+1, \ldots, s+h \\
&\quad \sum_{j=1}^{n} \lambda_j + \lambda_{0'} = 1 \\
&\quad x_{i0} + \Delta x_{i0} > 0, \\
&\quad \lambda_{0'}, \lambda_j \ge 0, \quad j = 1, 2, \ldots, n
\end{aligned}$$

According to Theorem 1 proposed by Lertworasirikul et al. (2011), the optimal solution of model (4) can be obtained by the model as follows.

$$
\begin{aligned}
&\min\ W^T(\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})^T \\
&\text{s.t.}\ \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_0^*(x_{i0} + \Delta x_{i0}), \quad i = 1, 2, \ldots, m \\
&\quad \sum_{j=1}^{n} \lambda_j y_{r'j} \ge y_{r'0} + \Delta y_{r'0}, \quad r' = 1, 2, \ldots, s, s+1, \ldots, s+h \\
&\quad \sum_{j=1}^{n} \lambda_j = 1 \\
&\quad \lambda_j \ge 0, \qquad j = 1, 2, \ldots, n
\end{aligned}
$$

Finally, we return the above model to the original form, and model (5) can be obtained. □

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