Technological Forecasting & Social Change xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach

Qunwei Wang [a,b], Ye Hang [b], Licheng Sun [a], Zengyao Zhao [b,*]

[a] College of Economics and Management & Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[b] Research Center for Smarter Supply Chain, Dongwu Business School, Soochow University, No. 50 Donghuan Road, Suzhou 215021, China

ARTICLE INFO

Article history:
Received 23 October 2015
Received in revised form 14 March 2016
Accepted 18 April 2016
Available online xxxx

Keywords:
New energy enterprises
Innovation efficiency
Two-stage efficiency
Non-radial DEA

ABSTRACT

Enterprises driven by the ability to effectively innovate and market products and services (called "innovation enterprises") experience a complex progression from initial research to profitability. The paper considers activities related to innovation during two stages of growth experienced by new energy enterprises: the research and development (R&D) process and the marketing process. A non-radial data envelopment analysis method was used to construct indices to measure R&D efficiency, market efficiency, and integrated innovation efficiency. Empirical research using these indices and data about 38 Chinese new energy enterprises from 2009 to 2013 revealed three key findings. First, new energy enterprises are generally inefficient when it comes to innovating. This is particularly true during the R&D stage of innovation, and there is periodically a phenomenon where enterprises focusing less on R&D, and instead emphasizing marketing. Second, different types of new energy enterprises differ with respect to their efficiency in innovation. Of these, nuclear power enterprises are the most efficient in integrated innovation and marketing; wind energy enterprises are the most efficient in R&D innovations; and solar energy enterprises lag behind the others in R&D efficiency. Third, innovation activities are considered "effective and intensive" in only a small number of enterprises; innovation in most enterprises can be generally considered "extensive and inefficient". Enterprises with different innovation and marketing efficiency modes should implement targeted improvement strategies, based on efficiency characteristics.

1. Introduction

China's total energy consumption is rising as a result of rapid economic growth. In 2013, China's energy consumption was 3.75 billion tons of standard coal, accounting for 22.4% of global consumption (BP, 2013). According to International Energy Agency forecasts, China's energy consumption is expected to grow in the coming decades. Coal is the most important energy source in China, and environmental pollution caused by coal consumption creates challenges for sustainable development. Improving energy efficiency helps address this problem, and many studies have focused on estimating energy efficiency (Zhou et al., 2012; Wang et al., 2013a, 2013b; Zhang and Xie, 2015). However, optimizing the energy consumption structure is also needed to save energy and reduce emissions to target levels. China must implement new energy alternatives to reduce its dependency on coal and other fossil fuels and meet growing energy demands.

China's central government acknowledges the importance of developing new energy sources, and has launched supportive policies in response. The 12th Five-Year Plan proposed that renewable energy, such as wind energy, solar energy, nuclear energy account for 11.4% of total primary energy consumption by 2015. By 2020, the goal is to have 15% of total energy consumption come from non-fossil energy sources. The new energy industry is an emerging industry of great strategic importance in China; it is greatly supported by the government and there has been an increase in the installed capacity of new energy sources, such as solar, wind, hydroelectric, and other new energies.

Unfortunately, however, China's new energy enterprises have weak research and development (R&D) capabilities; and R&D investment is less than 20% of the international average (The Economic Observer, 2015). This leads to insufficient new core technology, and an inability for new energy enterprises to generate sufficient revenue from innovative products. In recent years, China's excess production capacity has become particularly obvious. Exporting new energy equipment and components has also been very difficult, in part due to global economic downturns and protectionist policies in developed countries.

New energy enterprises must enhance their competiveness in the market and achieve sustainable development, by having core technologies and successfully commercializing new technologies and products. Developing core technology and commercializing products depends on the enterprise's ability to independently innovate. Therefore, it is important for new energy enterprises to increase the efficiency of their innovation activities (called "innovation efficiency"). Previous researchers have discussed renewable energy technologies and innovation systems

* Corresponding author.
E-mail addresses: wqw0305@126.com (Q. Wang), zzy63@sina.com (Z. Zhao).

http://dx.doi.org/10.1016/j.techfore.2016.04.019
0040-1625/© 2016 Elsevier Inc. All rights reserved.

(Blum et al., 2015; Tigabu et al., 2015) and the efficiency of high-tech industries (Guan and Chen, 2010a; Chiu et al., 2012). However, few have focused on analyzing the efficiency of innovation in new energy enterprises, and the efficiency of different stages during the innovation process.

This paper evaluates two stages of innovation efficiency in new energy enterprises, using a non-radial data envelopment analysis (DEA) approach. Both integrated innovation efficiency and efficiency during different development phases are considered. These analyses may help reveal sources of lost efficiency and specific improvement measures.

2. Literature review

To measure innovation efficiency, researchers previously often used a ratio of single input to single output as an efficiency value. This method is intuitive and simple, but cannot address multiple inputs or outputs, and fails to detect sources of inefficiency. As efficiency calculation methods have improved, researchers have started to use tools that apply a frontier analysis approach, such as stochastic frontier analysis (SFA) and DEA. These tools have become mainstream methods to calculate innovation efficiency (Guan and Chen, 2010a, 2010b).

SFA is a parametric analysis method proposed by Aigner et al. (1977). It assumes a specific form in the relationship between the input and output functions, and applies econometric techniques to estimate unknown parameters to identify the frontier. The SFA method has been used to conduct efficiency assessments in manufacturing, banking, and other domains (Liadaki and Gaganis, 2010; Charoenrat and Harvie, 2014). Using SFA, Wang and Huang (2007) calculated innovation efficiencies in 30 countries, accounting for environmental factors, and exploring the relationship between R&D efficiency and income levels. Li (2009) used an SFA method proposed by Battese and Coelli (1995) to measure regional innovation performance and capabilities in China's 30 provinces between 1998 and 2005. SFA methods account for the influence of random factors on output (Aigner et al., 1977); however, they are not best for addressing scenarios with multiple outputs (Guan and Chen, 2010a).

In contrast, the DEA method accommodates data from multiple inputs and multiple outputs, without setting a particular functional form in advance (Guan and Chen, 2012). As such, the DEA method is more widely used to measure efficiency, and many innovation efficiency studies using DEA are found in the literature. Chen et al. (2006) used DEA to measure the performance of six high-tech industries in Taiwan from 1991 to 1999. Hashimoto and Haneda (2008) analyzed the research and innovation efficiency of the Japanese pharmaceutical industry between 1983 and 1992, using the DEA-Malmquist method. Building on the super-efficiency DEA method, Schmidt-Ehmcke and Zloczysti (2011) calculated and compared the innovation efficiency of 13 industries from 17 countries, including Germany, U.S., and Denmark, identifying a number of cutting-edge, technically efficient industries.

The studies described above measure innovation efficiency using different DEA methods, but all view the enterprise's innovation process as a black box, where the innovation process is a "single stage" process of converting input to output. These kinds of study do not assess the innovation system's internal mechanics, and do not address how internal operational systems and processes associated with innovation impact integrated innovation efficiency (Wang et al., 2013a, 2013b).

"Single stage" innovation processes do not reflect production practice. In fact, innovation processes in typical high-tech industries or businesses include two phases: upstream technology development and downstream economic transformation (Moon and Lee, 2005; Sharma and Thomas, 2008). For this reason, some scholars have applied a two-stage DEA model to evaluate innovation efficiency. Guan and Chen (2010a) used the relational network DEA model to compare the innovation efficiencies of high-tech industries in China's 26 provinces between 2002 and 2003. They found that the commercial efficiency is better than the R&D efficiency; and the overall innovation efficiency is more closely related to commercial efficiency.

A later study measured innovation efficiency of a national level, examining upstream knowledge production processes and downstream knowledge commercialization processes in 30 countries (Guan and Chen, 2012). Cullmann et al. (2012) empirically studies industrial innovation efficiency in Organization for Economic Co-operation and Development (OECD) countries, using a two-stage semi-parameter DEA method; this study improved measures for optimizing resource allocation. Wang et al. (2013a, 2013b) divided the first phase of the innovation process into "Basic production" and "R&D efforts," and then estimated the profitability and marketability efficiencies of Taiwan's 65 high-tech enterprises between 2006 and 2007. This study generated an R&D decision matrix to identify sources of operational and R&D efficiency for high-technology firms. The two-stage DEA method has been applied to study commercial banks (Seiford and Zhu, 1999; Chiu et al., 2016), insurance (Wanke and Barros, 2016), and industrial systems (Bian et al., 2015).

Most innovation efficiency studies have focused at a macro-level, such as an industry or geographic zone. Fewer studies have examined micro-level enterprises, such as new energy enterprises. Further, many studies use a radial DEA method when calculating two-stage innovation efficiency. This method, however, cannot account for the inefficiencies associated with the non-radial slacks of each input and output. As such, this study used a non-radial DEA method, and a two-stage innovation process to calculate integrated innovation efficiency and efficiency during different development phases, with a focus on new energy enterprises. The study also offers corresponding optimization strategies, based on different efficiency modes.

3. Two-stage innovation efficiency non-radial DEA model

3.1. Stages of innovation activities

Schumpeter, the founder of innovation theory, defined innovation as a "new combination" of production factors, from the perspective of the production process (Schumpeter, 1934). A combination of production factors directly impacts innovation efficiency; an enterprise's innovation process includes a series of complex innovation activities, including research, development, demonstration, and deployment (Su and Zhang, 2012).

Innovation activity inputs include human, finance, and material resources. Outputs include intermediate outputs from the R&D stage (i.e., scientific and technological achievements, new products) and the final outputs from technological commercialization (i.e., profits and market value). Intermediate outputs (i.e., scientific and technological achievements, new products) are the results of the R&D stage, but also serve as the foundation for technological marketing (commercialization). This results in two stages of innovation activity in new enterprises, including in new energy enterprises (Fig. 1).

The first stage is the R&D process, which encompasses R&D inputs and the new technology and products. This process measures R&D efficiency by assessing innovation resource inputs and outputs. The second stage uses the R&D outputs to obtain profits and create market value. This process reflects market efficiency, and represents the conversion of R&D achievements into economic benefits. The two stages are not independent; they are connected by the first stage's R&D outputs. Together, both stages promote integrated innovation efficiency.

3.2. Two-stage innovation efficiency model

This study assumes there are N new energy enterprises, denoted by $DMU_j (j=1,2,\ldots,N)$. Each DMU has $I(x_i, i=1,\ldots,I)$ inputs and $R(y_r, r=1,\ldots,R)$ intermediate outputs from the first innovation stage (R&D). Then, R intermediate outputs feed into the second stage (marketing,

Please cite this article as: Wang, Q., et al., Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.04.019

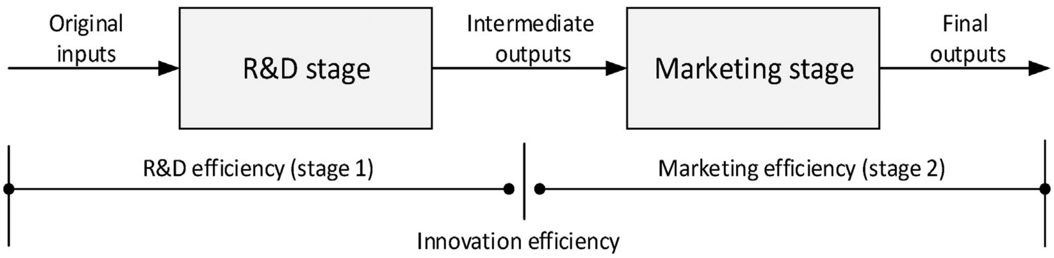

Fig. 1. Staged division of innovation activities.

commercialization) as that stage's inputs. The second stage has another $K(y_k, k=1,\ldots,K)$ final output. Therefore, the production technology (T) is defined as Eq. (1).

$$T = \left\{ \begin{array}{l} (x_i, y_r, y_k) : x_i \text{ can produce } y_r \text{ during R\&D stage,} \\ \text{and } y_r \text{ can produce } y_k \text{ during marketing stage} \end{array} \right\} \quad (1)$$

The production technology corresponding to T is assumed to be a closed set, with bounded convexity. In addition, inputs and outputs are assumed to be strongly or freely disposable. Using the DEA method, Eq. (2) defines the production technology under the assumption of constant returns to scale (CRS) for the R&D stage (T^D). Eq. (3) defines the production technology under the condition of CRS for the marketing stage (T^M).

$$T^D = \left\{ \begin{array}{ll} (x,y) : \sum_{j=1}^{N} \lambda_j^D x_{ij}^D \le x_{ij'}^D & i = 1,\ldots,I, \\ \qquad \sum_{j=1}^{N} \lambda_j^D y_{rj}^D \ge y_{rj'}^D & r = 1,\ldots,R, \\ \qquad \lambda_j^D \ge 0 & j = 1,\ldots,N \end{array} \right\} \quad (2)$$

$$T^M = \left\{ \begin{array}{ll} (x,y) : \sum_{j=1}^{N} \mu_j^M y_{rj}^D \le x_{ij'}^D & r = 1,\ldots,R, \\ \qquad \sum_{j=1}^{N} \mu_j^M y_{kj}^M \ge y_{kj'}^M & k = 1,\ldots,R, \\ \qquad \mu_j^M \ge 0 & j = 1,\ldots,N \end{array} \right\} \quad (3)$$

In Eqs. (2) and (3), the superscript D represents the R&D stage, and the superscript M represents the marketing stage. The variables λ_j^D and μ_j^M represent the weights of enterprise j associated with the R&D and marketing stages, respectively. To identify the slacks in inputs and outputs, the radial DEA methods represented by CRS (Charnes et al., 1978) and variable returns to scale (VRS) (Banker et al., 1984) proportionally decrease inputs or increase outputs.

These methods, however, do not account for different slacks of each input or output (Fukuyama and Weber, 2009). Instead, following Chen et al. (2012), this paper adopts a non-radial method by combining the directional distance function with a directional Russell measure of inefficiency. This allows for the simultaneously scaling of inputs and outputs, and accounts for all input and output slacks (Luenberger, 1992; Fukuyama and Weber, 2009; Chiu et al., 2013; Zhang and Choi, 2013a, 2013b, 2014).

Using the CRS model, the input-oriented and output-oriented models would generate the same result. For the non-radial DEA model, a different orientation generates different results, because each input and output is scaled non-proportionally. Therefore, it is important to orient the model as either input-oriented or output-oriented before using the non-radial DEA method to evaluate efficiency.

For the first innovation stage, maximizing R&D efficiency involves contracting inputs as much as possible, without adjusting R&D outputs. As such, it is input-oriented. Given a certain quantity of R&D output, we then want to maximize final outputs. Therefore, the output-oriented model is used to evaluate the efficiency of the second stage (marketing). This mixed orientation accommodates the reality that intermediate outputs cannot be treated in the same way as other stages. For example, suppose an output-oriented model were used for each stage. If R&D stage performance improves by increasing intermediate output using an output-oriented DEA model, the increased intermediate outputs may place marketing stage efficiency in an output orientation.

This study acknowledged the potential of reducing inputs, while also increasing innovation activity outputs. This was done using an integrated innovation efficiency index and sub-stage efficiency indices. Accordingly, we define the non-radial DEA model under a CRS assumption to maximize the beneficial combination of all input and output slacks, as shown in Eq. (4)[1].

$$\begin{aligned} IP &= \vec{D}\left(x_i^{j'}, y_i^{j'}, y_k^{j'}; g_x, g_y\right) = \max \frac{1}{2}\left(IP^D + IP^M\right) \\ &= \max \frac{1}{2}\left(\frac{1}{I}\sum_{i=1}^{I} \alpha_i^D + \frac{1}{K}\sum_{k=1}^{K} \beta_k^M\right) \end{aligned} \quad (4)$$

This expression is subject to the following equations:

a. R&D stage:

$$\begin{array}{ll} \sum_{j=1}^{N} \lambda_j^D x_{ij}^D \le (1-\alpha_i^D) x_{ij'}^D & i = 1,\ldots,I \\ \sum_{j=1}^{N} \lambda_j^D y_{rj}^D \ge y_{rj'}^D & r = 1,\ldots,R \\ \lambda_j^D \ge 0 & j = 1,\ldots,N \end{array} \quad (4-1)$$

[1] Halkos et al. (2014) classified the works on two-stage DEA models into four categories. (1) The independent two-stage DEA approach (Wang et al., 1997; Seiford and Zhu, 1999). (2) The connected two-stage DEA approach including value-chain model and network DEA (Chen and Zhu, 2004; Färe and Grosskopf, 1996). (3) The relational two-stage DEA approach, taking into account any mathematical relationship that exists between them (Kao and Hwang, 2008; Chen et al., 2009). (4) The game-theory approach (Liang, 2008). There are some differences between the model used here and typical network DEA models. First, the two-stage network DEA proposed by Färe and Grosskopf (1996) do not yield individual efficiencies; this paper's model simultaneously yields the integrated efficiency and the individual efficiencies. Second, typical network DEA models measure efficiency based on conventional CRS, VRS, and slack-based measures (Tone and Tsutsui, 2009). In contrast, our model combines the directional distance function with the directional Russell measure of inefficiency.

Please cite this article as: Wang, Q., et al., Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.04.019

b. Marketing stage:

$$\begin{aligned} &\sum_{j=1}^{N} \mu_j^M y_{rj}^D \leq y_{rj'}^D && r = 1, \ldots, R \\ &\sum_{j=1}^{N} \mu_j^M y_{kj}^M \geq \left(1+\beta_k^M\right) y_{kj'}^M && k = 1, \ldots, K \\ &\mu_j^M \geq 0 && j = 1, \ldots, N \end{aligned} \tag{4 – 2}$$

In Eq. (4), α_i^D represents the reduction of input i during the R&D stage, while β_k^M represents the increased potential of output k during the marketing stage. The intensity variables corresponding to the R&D and marketing stages are λ_j^D and μ_j^M, respectively. In the objective function, $IP^D = \frac{1}{I}\sum_{i=1}^{I} \alpha_i^D$ is the mean value of the reduction potential of all the inputs during the R&D stage, and $IP^M = \frac{1}{K}\sum_{k=1}^{K} \beta_k^M$ measures the mean value of the increase of all the outputs during the marketing stage. The variable IP shows the overall improvement potential of reducing inputs and increasing outputs during innovation activities. A larger IP indicates a stronger ability to reduce inputs while increasing outputs. If $IP = 0$, the enterprise cannot improve inputs or outputs, and has optimized its resource utilization level.

Chen et al. (2012) studied the inefficiencies of incineration plants in Taiwan, and decomposed these inefficiencies. Taking an opposite approach, we focused on analyzing enterprise efficiency. After computing proportional improvements in inputs and outputs, we further defined R&D efficiency, market efficiency, and integrated innovation efficiency indexes. In Eq. (4), given the same output level, redundant input i during the R&D stage is represented as $\alpha_i^D x_i$. This is the measure of inefficiency; efficiency is represented by $(1-\alpha_i)x_i$. Eq. (5) thereby defines the gap between the optimal input on the production frontier and the actual input.

Similarly, during the marketing stage, given a certain quantity of inputs, the maximum outputs on the best production frontier boundary is represented as $(1+\beta_k)y_k$. Eq. (6) shows that the efficiency of output k is the ratio of actual output to the maximum output on the production frontier. Eqs. (7)–(8)[2] express the R&D efficiency and market efficiency indexes, respectively. The integrated innovation efficiency is the comprehensive performance of all inputs and outputs during the R&D and marketing stages. Eq. (9) shows the integrated innovation efficiency index, incorporating all the input and output efficiency levels.

$$E_i^D = \frac{(1-\alpha_i)x_i}{x_i} = 1-\alpha_i \tag{5}$$

$$E_k^M = \frac{y_k}{(1+\beta_k)y_k} = \frac{1}{1+\beta_k} \tag{6}$$

$$E^D = \sum_{i=1}^{I} \theta_i (1-\alpha_i) \tag{7}$$

$$E^M = \sum_{k=1}^{K} \varphi_k \left(\frac{1}{1+\beta_k}\right) \tag{8}$$

$$E^{IP} = \omega_1 \left(\sum_{i=1}^{I} \theta_i (1-\alpha_i)\right) + \omega_2 \left(\sum_{k=1}^{K} \varphi_k \left(\frac{1}{1+\beta_k}\right)\right) \tag{9}$$

[2] Considering R&D and marketing stages are both focus areas for the enterprises; different factors in the same stage share the same importance. Therefore, this paper gives each factor the same weight in the same stage ($\theta_i = {}^1/_I, \varphi_k = {}^1/_K$) and the two stages are given the same weight ($\omega_1 = \omega_2 {}^1/_2$) in Eq. (9).

In Eqs. (7) and (9), θ_i represents the weight of input i during the R&D stage, reflecting the importance of input i in evaluating R&D efficiency. The variable φ_k represents the weight of and shows the importance of output k. The variables ω_1 and ω_2 are weights assigned to each of the two stages. When $\alpha_i = \beta_k = 0$, the new energy enterprise has optimized inputs and outputs during the innovation process, with no further improvement potential. In this case, both R&D efficiency and market efficiency are equal to the unit; and the integrated innovation efficiency is equal to the unit as well.

4. Empirical analysis and discussion

4.1. Data and sample

Using the IFinD database developed by Hithink Flush Information Network Company Limited in China, we extracted data from the years 2007–2013 about 68 new energy enterprises. Enterprises with negative total profits and those marked with a "delisting" risk during this period were removed from the sample. Based on the remaining data available, 38 energy enterprises were served as the sample. All 38 were listed on China's Shanghai and Shenzhen Stock Exchange during 2009–2013, and were engaged in new energy development, such as solar, wind, and nuclear power (Table 1).

As noted above, R&D is the first stage of new energy innovation, and input resources are mainly human, material, and financial. Consistent with Zhong et al. (2011), this study used R&D costs as the financial input, staff wages as the human resource input (Becheikh et al., 2006), and annual fixed assets as material inputs.

R&D outputs take the form of new technologies, new products, and patents (Hall and Ziedonis, 2001). Not all inventions are patented, and patents differ in quality (Griliches, 1990); as such, this study used software assets as a proxy for R&D outputs. Increases in new products and production process improvements also effectively promote operating results and increase revenues. Therefore, revenues served as another R&D output indicator (Wang et al., 2013a, 2013b).

R&D outputs are also marketing stage inputs (i.e., revenues and software assets). Total profits and the market value of the new energy enterprise serve as marketing outputs. Total profits reflect the comprehensive profitability of new energy enterprises, which is the earning output during the marketing stage. Market value represents future investor expectations and the enterprise's competitive capacity (Wang et al., 2013a, 2013b). In addition to input and output data extracted from the IFinD database, data were also derived from annual reports for new energy enterprises listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange. Table 2 provides descriptive statistics of the input and output variables.

4.2. Results and discussion

4.2.1. Overall analysis on innovation efficiency

Fig. 2 shows the integrated innovation efficiency, and efficiency at the two different stages across enterprises between 2009 and 2013

Table 1
Sample enterprises.

No.	Stock code	No.	Stock code	No.	Stock code	No.	Stock code
1	000012.SZ	11	600290.SH	21	002130.SZ	31	002224.SZ
2	600089.SH	12	600192.SH	22	002227.SZ	32	002249.SZ
3	002132.SZ	13	601727.SH	23	002266.SZ	33	000601.SZ
4	600522.SH	14	600875.SH	24	600066.SH	34	000652.SZ
5	002090.SZ	15	000539.SZ	25	600525.SH	35	000930.SZ
6	600884.SH	16	002060.SZ	26	600686.SH	36	600406.SH
7	000969.SZ	17	600456.SH	27	000559.SZ	37	600067.SH
8	002080.SZ	18	600558.SH	28	002085.SZ	38	002224.SZ
9	002009.SZ	19	002011.SZ	29	002126.SZ		
10	002202.SZ	20	002058.SZ	30	002196.SZ		

Table 2
Descriptive statistics for the 38 sampled energy enterprises.

Stage	Variable	Unit	Mean	Median	Max	Min	Std. Dev.
Inputs in R&D stage	Fixed assets	Million CNY	2611.635	153.411	41524.036	5.316	5103.118
	Staff wages	Million CNY	546.266	78.315	6876.122	17.643	990.987
	R&D costs	Million CNY	180.390	15.124	2128.885	0.276	339.135
Outputs in R&D stage	Software assets	Million CNY	32.391	4.888	384.220	0.000	66.807
	Revenues	Million CNY	7475.554	390.337	79214.931	113.589	12958.000
Outputs in marketing stage	Total profits	Million CNY	595.052	54.800	5803.558	5.334	1037.568
	Market value	Million CNY	11959.120	3533.467	115866.200	757.401	17468.110

when data are analyzed using Eqs. (4)-(9). The integrated innovation efficiency of the 38 new energy companies between 2009 and 2013 was 0.435. This shows that these 38 enterprises innovate less efficiently than they could, and have significant improvement potential. The new energy enterprises' average R&D efficiency and market efficiency were 0.368 and 0.502, respectively, and the standard deviations were 0.306 and 0.277, respectively. Low R&D and market efficiencies are common factors restricting innovation efficiency improvements, with the most significant efficiency loss occurring in the R&D stage.

Two paired-sample nonparametric Wilcoxon signed rank test of methods were used to assess whether efficiencies statistically significantly differed between the two stages. Table 3 indicates that market efficiency was statistically higher than R&D efficiency, further illustrating that lower R&D efficiency is driving overall low efficiencies. R&D management needs to be strengthened, and R&D investments must be rationally invested to avoid resource waste.

Our finding that market efficiency is better than R&D efficiency is consistent with Guan and Chen (2010a), who found that R&D efficiency has more under-exploited potential than commercial efficiency does. However, when assessing the two-stage efficiency of Taiwan's high-tech firms, Wang et al. (2013a, 2013b) found that average R&D efficiency was higher than marketability efficiency. This difference may be due to different research subjects or periods.

When plotted, the integrated innovation efficiency shows an inverted u-trend: there is an initial upward trend, an innovation efficiency peak in 2011 (0.468), and then a drop in efficiency. In September 2010, the Chinese government launched the "Decision of the State Council on accelerating the cultivation and development of strategic emerging industries." New energy industries were listed as a key emerging strategic area. This decision led to a significant acceleration in technology updates and research, as well as industry commercialization, which improved efficiencies. The R&D efficiency and market efficiency trends move in opposite directions. It is hard for enterprises to engage in both technology R&D and research transformation. When striving to improve the efficiency of a certain stage, efficiencies in other areas may suffer.

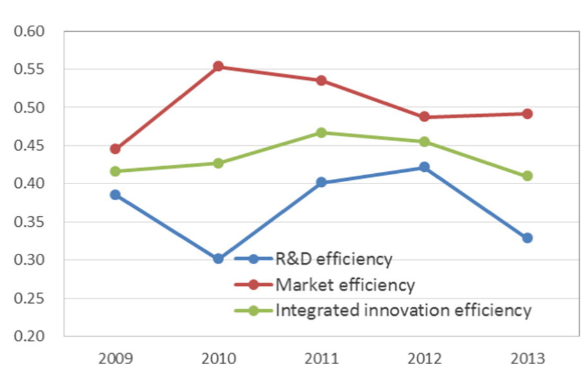

Fig. 2. Integrated and two-stage innovation efficiency across the study period.

4.2.2. Innovation efficiency of different types

Industry type is a factor in innovation efficiency for both R&D and marketing stages; as such, we assessed efficiency differences based on the type of new energy being explored. Solar energy, wind energy, and nuclear energy are the main sources of new energy in China, and for now, draw the most attention. As such, Table 4 and Fig. 3 focus on the innovation efficiency of these three types of energy enterprises.

The integrated innovation efficiency index of nuclear power enterprises was the highest of the three at 0.500. Solar and wind energy enterprises had similar innovation efficiencies, at 0.399 and 0.398, respectively. Both are below the average. The efficiency of nuclear power and wind energy enterprises first decreased and then increased during the study period. The two were similar between 2009 and 2011; starting in 2011, however, the innovation efficiency of wind enterprises significantly decreased, with its lowest level in 2013.

For R&D efficiency, wind efficiency was the highest at 0.447; solar energy efficiency is lowest, at only 0.248. This may be driven by the high market concentration rate of wind power equipment manufacturing in the new energy field. This allows wind enterprises to concentrate superior resources and abilities on improving R&D efficiency. R&D efficiency fluctuations of all three new energy enterprises are consistent with the integrated innovation efficiency. The R&D efficiency of solar and nuclear power enterprises fell to the lowest values in 2010, and then continuously improved. Efficiencies peaked in 2012, and then declined significantly. Fluctuations were seen in the R&D efficiency of wind energy enterprises; the peak of 0.594 was in 2011, followed by an abrupt decline of 50.8% to 0.292 in 2013. This was caused by the decreasing efficiency of fixed assets in the R&D stage.

The average market efficiency of solar energy, wind energy, and nuclear power enterprises were 0.550, 0.349, and 0.604 respectively. Among these, the market efficiency of wind energy enterprises was below average; the market efficiency of solar and nuclear energy enterprises was above average.

Fig. 3 shows the average innovation efficiency values during the R&D and marketing innovation stages for these three types of energy enterprises. Solar and nuclear power enterprises have higher market efficiencies than R&D efficiency; this lower R&D efficiency is a major cause of these enterprises' poor innovation efficiency. For example, for solar energy enterprises, the R&D efficiency is less than half the market efficiency. To balance innovation across the R&D and marketing stages, solar energy enterprises should focus on upgrading R&D efficiency.

For wind energy enterprises, the R&D efficiency is higher than market efficiency; improvements in management during the marketing stage would strengthen the transition of R&D achievements into commercial applications. In addition, the gap between the enterprise's R&D efficiency and market efficiency is small compared to solar energy enterprises. This indicates that, despite similar integrated innovation efficiency, wind power enterprises coordinate and balance the relationship between R&D and marketing.

4.2.3. Innovation efficiency improvement strategy

For the next stage of analysis, we set the development efficiency value as the abscissa, and market efficiency value as the ordinate.

Table 3
Results of Wilcoxon signed rank test.

	Null hypothesis	Z statistic	Asymptotic significance
Market efficiency- R&D efficiency	The Median of the difference between R&D efficiency and market efficiency is 0	−2.433	0.015

Note: The significance level is 0.05.

These establish boundaries for the combination matrix shown in Fig. 4. New energy enterprises were classified into four types based on innovation efficiency: Type A — efficient and intensive; Type B — emphasizing R&D, focusing less on market; Type C — extensive and inefficient; Type D — emphasizing market, focusing less on R&D.

Overall the innovation efficiency of most new energy enterprises is relatively low: 15 enterprises belong to the “extensive and inefficient” type (C), five enterprises belong to “effective and intensive” type (A). Next, we describe possible optimization strategies, based on each type's efficiency characteristics.

A total of five enterprises are in the Type A category: “efficient and intensive”. These enterprises have relatively high efficiency levels during the innovation process, and may be benchmarks of efficiency improvement for other enterprises. For these enterprises, it may be difficult to improve their innovation if they do not increase innovation inputs and outputs levels. Therefore, these enterprises should focus on raising innovation quality to build on high-level research, enhance high market efficiency, and maintain competitive advantage by adjusting the innovation strategy.

A total of nine enterprises are in the Type B category: “emphasizing R&D, focusing less on market”. These enterprises have high R&D efficiency, but low market efficiency. Type B enterprises should maintain their advantage of high R&D efficiency, while improving business performance. This may include a focus on increasing profits, controlling innovation costs, and building market value.

A total of 15 enterprises are in the Type C category, which is the “extensive and inefficient” type. Type C enterprises have invested significant human, financial, and material resources in the R&D stage. Unfortunately, the benefits have not been fully realized, because they did not focus on factors such as investment quality and business performance at the marketing stage. This led to a lower market efficiency. These enterprises must acknowledge the difficulty in improving innovation efficiency, and increase innovation from both R&D and marketing perspectives.

A total of nine enterprises are in the Type D category. This category emphasizes the market, with relatively low efficiencies in the R&D stage, and relatively high efficiencies in the marketing stage. These patterns point to the need for increased R&D awareness, including mastering core technologies, and promoting both R&D and integrated innovation efficiency.

For Type B, C, and D enterprises, three possible paths are possible to improve efficiencies in a way that will result in high R&D efficiency and high market efficiency (Fig. 5). Path 1 is a unilateral optimization path (B → A; D → A). Type B and C enterprises can improve their integrated innovation efficiency by improving management during the lower efficiency stage. Path 2 is a gradual improvement path (C → D → A; C → B → A), where Type C enterprises use their advantages to first evolve into Type B or D enterprises, and then ultimately Type A enterprises. Path 3 is the jumping optimization path (C → A), requiring enterprises to quickly respond to market demand, invest substantial financial resources, and facilitate rapid enterprise transformation.

5. Conclusions

New energy enterprises in China generally have two problems related to innovation: a weak R&D capacity, and a lack of core technology. Increasing the capability to innovate is key to the sustainable growth of new energy enterprises. This paper divided innovation activities into two stages, and then applied non-radial DEA methods to develop integrated innovation efficiency and all-phase efficiency indicators. An empirical analysis then examined 38 new energy enterprises in Shanghai and Shenzhen, China between 2009 and 2013. Key conclusions are as follows.

In general, the average innovation efficiency across all samples was 0.435. The R&D efficiency and market efficiency indices differed significantly, at 0.368 and 0.502. Low efficiency during the R&D stage was a driver for an enterprise's overall low innovation efficiency. To improve the innovation efficiency of new energy enterprises, efficiency levels during R&D must be improved.

In terms of efficiency over the studied timeframe, integrated innovation efficiency between 2009 and 2013 fit an inverted u-shape trend. R&D efficiency and market efficiency shows opposite characteristics. This suggests that should consider both technology R&D, and improving research achievement transformation during the innovation efficiency optimization process. This would improve integrated innovation efficiency.

Different types of new energy enterprises performed differently in terms of innovation efficiency, R&D efficiency, and market efficiency. Nuclear energy enterprises have the highest innovation efficiency; wind energy enterprises and nuclear power enterprises have lower innovation efficiencies. Wind energy enterprises have the highest R&D innovation efficiency; nuclear power enterprises have the highest market efficiency. The R&D efficiency is lower than the market efficiency for solar energy enterprises and nuclear power plants. These enterprises need to strengthen R&D capability and improve management to narrow the efficiency gap and balance between R&D and marketing. Wind energy enterprises have higher R&D efficiency than market efficiency, and

Table 4
Integrated and two-stage innovation efficiency for different types of new energy enterprises.

	Solar energy			Wind energy			Nuclear power		
	IP	IP^D	IP^M	IP	IP^D	IP^M	IP	IP^D	IP^M
2009	0.397	0.287	0.506	0.425	0.503	0.348	0.447	0.313	0.580
2010	0.413	0.161	0.665	0.406	0.433	0.379	0.437	0.293	0.582
2011	0.400	0.216	0.584	0.455	0.594	0.317	0.503	0.385	0.622
2012	0.414	0.338	0.489	0.392	0.414	0.370	0.584	0.528	0.640
2013	0.371	0.237	0.505	0.310	0.292	0.329	0.527	0.456	0.597
Mean	0.399	0.248	0.550	0.398	0.447	0.349	0.500	0.395	0.604

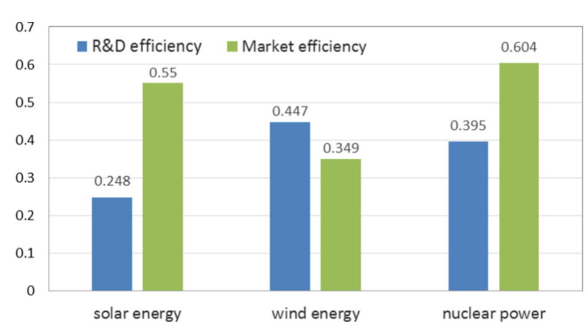

Fig. 3. Two-stage innovation efficiencies for different types of new energy enterprises.

Please cite this article as: Wang, Q., et al., Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.04.019

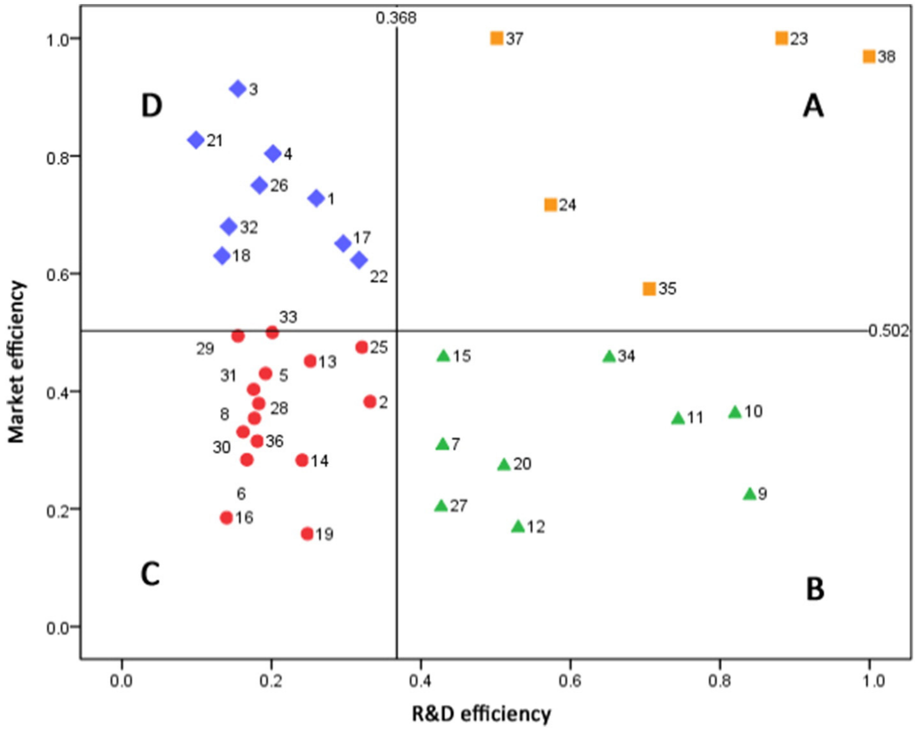

Fig. 4. Two-stage innovation efficiency matrix.

should focus on improving management during marketization, strengthening the transition velocity of R&D achievements.

Most new energy enterprises have a relatively low innovation efficiency level, and can be described as "extensive and inefficient." Only a few enterprises can be called "efficient and intensive." Enterprises with different efficiency modes should adjust their strategies, based on their efficiency characteristics. For enterprises without high R&D efficiency, but with high market efficiency, there are three possible paths: the unilateral improvement path, the gradual improvement path, and the jumping improvement path. The best path depends on the enterprise's abilities and current efficiencies.

Acknowledgements

One of the author, Qunwei Wang, is grateful to the financial support from the National Natural Science Foundation of China (nos. 71203151, 71573186), the Social Science Foundation of Jiangsu Province (no. 12GLC008) and Jiangsu Qing Lan project.

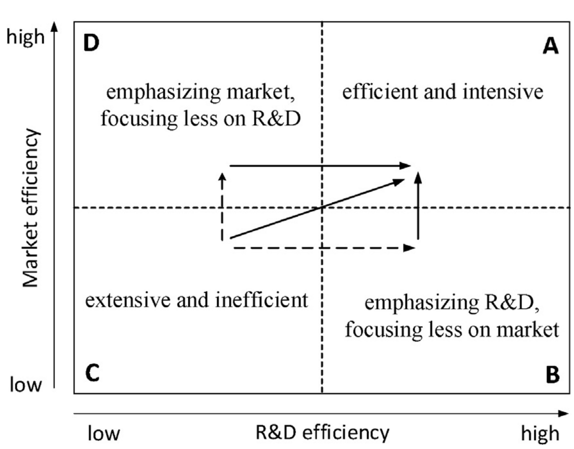

Fig. 5. Innovation efficiency optimization strategy.

References

Aigner, D., Lovell, C.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6 (1), 21–37.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag. Sci. 30 (9), 1078–1092.

Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20 (2), 325–332.

Becheikh, N., Landry, R., Amara, N., 2006. Lessons from innovation empirical studies in the manufacturing sector: a systematic review of the literature from 1993–2003. Technovation 26 (5), 644–664.

Bian, Y., Liang, N., Xu, H., 2015. Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. J. Clean. Prod. 87, 348–356.

Blum, N.U., Bening, C.R., Schmidt, T.S., 2015. An analysis of remote electric mini-grids in Laos using the Technological Innovation Systems approach. Technol. Forecast. Soc. Chang. 95, 218–233.

BP, 2013. Statistical review of World energy. (Available at <http://www.bp.com/zh_cn/china/reports-and-publications/bp_2013.html>).

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.

Charoenrat, T., Harvie, C., 2014. The efficiency of SMEs in Thai manufacturing: a stochastic frontier analysis. Econ. Model. 43, 372–393.

Chen, C.J., Wu, H.L., Lin, B.W., 2006. Evaluating the development of high-tech industries: Taiwan's science park. Technol. Forecast. Soc. Chang. 73 (4), 452–465.

Chen, P.C., Chang, C.C., Yu, M.M., Hsu, S.H., 2012. Performance measurement for incineration plants using multi-activity network data envelopment analysis: the case of Taiwan. J. Environ. Manag. 93 (1), 95–103.

Chen, Y., Cook, W.D., Li, N., Zhu, J., 2009. Additive efficiency decomposition in two-stage DEA. Eur. J. Oper. Res. 196 (3), 1170–1176.

Chiu, C.R., Chiu, Y.H., Chen, Y.C., Fang, C.L., 2016. Exploring the source of metafrontier inefficiency for various bank types in the two-stage network system with undesirable output. Pac. Basin Financ. J. 36, 1–13.

Chiu, C.R., Lu, K.H., Tsang, S.S., Chen, Y.F., 2013. Decomposition of meta-frontier inefficiency in the two-stage network directional distance function with quasi-fixed inputs. Int. Trans. Oper. Res. 20 (4), 595–611.

Chiu, Y.H., Huang, C.W., Chen, Y.C., 2012. The R&D value-chain efficiency measurement for high-tech industries in China. Asia Pac. J. Manag. 29 (4), 989–1006.

Cullmann, A., Schmidt-Ehmcke, J., Zloczysti, P., 2012. R&D efficiency and barriers to entry: a two stage semi-parametric DEA approach. Oxf. Econ. Pap. 64 (1), 176–196.

Färe, R., Grosskopf, S., 1996. Productivity and intermediate products: a frontier approach. Econ. Lett. 50 (1), 65–70.

Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical inefficiency. Socio Econ. Plan. Sci. 43 (4), 274–287.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey (No. w3301). Natl. Bur. Econ. Res.
Guan, J., Chen, K., 2010a. Measuring the innovation production process: a cross-region empirical study of China's high-tech innovations. Technovation 30 (5), 348–358.
Guan, J., Chen, K., 2010b. Modeling macro-R&D production frontier performance: an application to Chinese province-level R&D. Scientometrics 82 (1), 165–173.
Guan, J., Chen, K., 2012. Modeling the relative efficiency of national innovation systems. Res. Policy 41 (1), 102–115.
Halkos, G.E., Tzeremes, N.G., Kourtzidis, S.A., 2014. A unified classification of two-stage DEA models. Surv. Oper. Res. Manag. Sci. 19 (1), 1–16.
Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979–1995. RAND J. Econ. 101–128.
Hashimoto, A., Haneda, S., 2008. Measuring the change in R&D efficiency of the Japanese pharmaceutical industry. Res. Policy 37 (10), 1829–1836.
Kao, C., Hwang, S.N., 2008. Efficiency decomposition in two-stage data envelopment analysis: an application to non-life insurance companies in Taiwan. Eur. J. Oper. Res. 185 (1), 418–429.
Li, X., 2009. China's regional innovation capacity in transition: an empirical approach. Res. Policy 38 (2), 338–357.
Liadaki, A., Gaganis, C., 2010. Efficiency and stock performance of EU banks: is there a relationship? Omega 38 (5), 254–259.
Luenberger, D.G., 1992. Benefit functions and duality. J. Math. Econ. 21 (5), 461–481.
Moon, H.S., Lee, J.D., 2005. A fuzzy set theory approach to national composite S&T indices. Scientometrics 64 (1), 67–83.
Schmidt-Ehmcke, J., Zloczysti, P., 2011. Industries at the world technology frontier: measuring R&D efficiency in a non-parametric DEA framework (no. 8579). CEPR Discussion Papers.
Schumpeter, J.A., 1934. The Theory of Economic Development: an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. 55. Transaction Publishers.
Seiford, L.M., Zhu, J., 1999. Profitability and marketability of the top 55 US commercial banks. Manag. Sci. 45 (9), 1270–1288.
Sharma, S., Thomas, V., 2008. Inter-country R&D efficiency analysis: an application of data envelopment analysis. Scientometrics 76 (3), 483–501.
Su, J., Zhang, H.W., 2012. From R&D to R&3D: a framework for new energy technology innovation and its policy implications. China Soft Sci. 3, 93–99 (In Chinese).
The Economic Observer, 2015. The hollowing out of core components leading to the marketization of new energy vehicle worried. (Available at<http://www.eeo.com.cn/2015/0130/271908.shtml>, January 30).
Tigabu, A.D., Berkhout, F., van Beukering, P., 2015. The diffusion of a renewable energy technology and innovation system functioning: comparing bio-digestion in Kenya and Rwanda. Technol. Forecast. Soc. Chang. 90, 331–345.
Tone, K., Tsutsui, M., 2009. Network DEA: a slacks-based measure approach. Eur. J. Oper. Res. 197 (1), 243–252.
Wang, C.H., Gopal, R.D., Zionts, S., 1997. Use of data envelopment analysis in assessing information technology impact on firm performance. Ann. Oper. Res. 73, 191–213.
Wang, C.H., Lu, Y.H., Huang, C.W., Lee, J.Y., 2013a. R&D, productivity, and market value: an empirical study from high-technology firms. Omega 41 (1), 143–155.
Wang, E.C., Huang, W., 2007. Relative efficiency of R&D activities: a cross-country study accounting for environmental factors in the DEA approach. Res. Policy 36 (2), 260–273.
Wang, Q., Zhao, Z., Zhou, P., Zhou, D., 2013b. Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. Econ. Model. 35, 283–289.
Wanke, P., Barros, C.P., 2016. Efficiency drivers in Brazilian insurance: a two-stage DEA meta frontier-data mining approach. Econ. Model. 53, 8–22.
Zhang, N., Choi, Y., 2013a. Total-factor carbon emission performance of fossil fuel power plants in China: a metafrontier non-radial Malmquist index analysis. Energy Econ. 40, 549–559.
Zhang, N., Choi, Y., 2013b. Environmental energy efficiency of China's regional economies: a non-oriented slacks-based measure analysis. Soc. Sci. J. 50 (2), 225–234.
Zhang, N., Choi, Y., 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. Renew. Sust. Energ. Rev. 33, 50–59.
Zhang, N., Xie, H., 2015. Toward green IT: modeling sustainable production characteristics for Chinese electronic information industry, 1980–2012. Technol. Forecast. Soc. Chang. 96, 62–70.
Zhong, W., Yuan, W., Li, S.X., Huang, Z., 2011. The performance evaluation of regional R&D investments in China: an application of DEA based on the first official China economic census data. Omega 39 (4), 447–455.
Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO 2 emission performance in electricity generation: a non-radial directional distance function approach. Eur. J. Oper. Res. 221 (3), 625–635.

Dr. Qunwei Wang is a Professor with College of Economics and Management & Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics (NUAA), China. He got his PhD degree in Management Science and Engineering from NUAA in 2011, and his research focuses on sustainable development and energy economics. Up to now, he has published more than 20 papers in internationally peer-reviewed journals, including Energy Economics, Economic Modeling, Applied Energy etc.

Ms. Ye Hang is a graduate student with School of Business, Soochow University, China, supervised by Dr. Wang. Her research interests focus on innovation efficiency.

Dr. Licheng Sun is an Associate Professor with School of Management, Jiangsu University, China, as well as the research fellow of Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, China. His research interests are mainly related with regional innovation and economic growth.

Dr. Zengyao Zhao is a Professor with School of Business, Soochow University, China. His research directions include industrial organization and foreign direct investment.

Please cite this article as: Wang, Q., et al., Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.04.019