Abstract

The main objective of the analysis of technology forecasting is to assess the technology development efficiency of countries and industries. In particular, developing countries need to realize their technology position compared to advanced countries to create a tailored strategy of technology growth. However, when only quantitative or qualitative factors are used, the ability to provide precise information and evaluations is limited. In this study, we provide a model that considers both quantitative and qualitative factors. To collect the qualitative data, we used the Delphi method to accommodate experts’ opinions through questionnaires. We then applied the analytic hierarchy process (AHP) method and the Martino model. Finally, we suggested a mixed model for technology level assessment and forecasting, considering patents, SCI papers, and the World Index data. The ranks of the top-tier countries changed in the obtained results, because each country has its own strengths or weaknesses. Therefore, we found that technology level assessment is sensitive by used information. As bias can appear when analyzing only with limited information, we conclude that both quantitative and qualitative data need to be applied simultaneously in order to avoid such bias in the estimation. Finally, the mixed model is expected to improve when the weight reflects depending on the technology readiness level.

Keywords: Technological Forecasting, Photovoltaic Technology, Mixed Model

1. Introduction

The analysis of technology forecasting are used in technology growth strategies at the national level and in R&D strategies at the firm level mainly to compare technology levels and assesses development progress. The methodology is commonly applied by developing countries in the quest for technology development. In South Korea, there is a Basic Science and Technology Law in order to forecast technology level for core technologies every two years.

Previous analyses of the technology forecasting have focused more on the competitiveness of technology rather than the level of technology. Qualitative analyses, including the Delphi method and expert interviews, have mostly been applied in this research; however, those analyses not only have a high probability of overestimation but also are unable to accommodate quantitative data such as patents, SCI papers, and World index data. Moreover, different results are possible depending on technology readiness levels or methodologies. To eliminate such weaknesses, quantitative indicator models (e.g., bibliographic analyses, scoring models, and analytic hierarchy process (AHP)) methods have been adopted. However the quantitative models also have weaknesses. As bibliographic analysis only considers research performance, it is limited in its ability to cover entire technology levels. Scoring model is difficult to integrate various information. In addition, the AHP method has a tendency to underestimate future technologies and overestimate current ones.

Previous studies applied only one of the qualitative or quantitative methodologies, so there are limitations. Therefore, this study seeks an improvement over the models used previously. In this study, we propose a technology forecasting analysis method considering both qualitative and quantitative data and focusing on the photovoltaic technology, mainly supported by the Government of South Korea as a future technology.

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2. Literature review

Various researchers have analyzed technology forecasting. The Delphi method has mostly been utilized when analyzing large targets, countries, or industries [8]. Moreover, the reliability and accuracy of the Delphi model is relatively higher [13]. However, the model has such weaknesses as the potentiality of low response rates, the consumption of large blocks of time, the possibility of molding opinions, and knowledge differences in experts [3]. The model is also unable to take quantitative data, and it is possible to have different results depending on technology maturity.

In order to overcome such limitations, patent and quantitative methods have also been exploited in the studies. Ernst opines that technology forecasting methodology using patent information is a low-cost and high-efficiency model [1]. Verspagen, conversely, argues the model has the limitation of focusing only on patent information [12]. AHP is developed by Saaty to solve complex decision-making problems that are appropriate to the analysis of technology forecasting [9]. Vaidya and Kumar are of the opinion that the use of AHP in the forecasting of technologies offers the possibility of including both tangible and non-tangible factors, and the ability to make some future developments of the environmental factors [11]. Kim and Whang used AHP method along with growth curve models for technological forecasting [4]. They classify the element technologies according to industries, and an expert questionnaire is circulated to obtain relevant time series data. Lee et al. adopted quantitative data such as research literature, R&D labor, R&D investment, and infrastructure to apply the AHP method to calculate technology competitiveness [6]. For scoring models, both the Gordon and Martino models are widely used. A scoring model has a variety of calculative functions based on technology development. These two models are used according to the technology-specific factors. Gordon and Munson contend that when the technology level increases exponentially, it is appropriate to use the Martino model, and when technology follows the growth curve (S-curve), it can be expressed by the Gordon model [2]. The Martino model, a representative scoring model, generally estimates technology level with complex factors [7].

Various countries have attempted to analyze technology level to improve their technology competitive power; for example, there is the OSTP (Office of Science and Technology Policy) in the U.S., NRCSTD (National Research Centre for Science and Technology for Development) in China, NISTEP (National Institute for Science and Technology Policy) in Japan, and KISTEP (Korea Institute of S&T Evaluation and Planning) in Korea. The OSTP uses Likert scales to evaluate the technology level of the U.S. compared to Europe and Japan; the NRCSTD utilizes the Delphi method to assess China’s technical position for IT, BT, and new materials; and the NISTEP employs expert interviews together with research literature and to compare core technologies globally. The KISTEP applies the technology growth model and the Delphi method to compare the technology levels and gaps among five countries including the U.S., Japan, the EU, China, and South Korea.

3. Mixed model for technological forecasting

As mentioned above, there are two lines of methods, quantitative and qualitative, in technology forecasting analysis. In this study, we suggest a hybrid model combining these two methods for analyzing photovoltaic technology. The structure of the developing model is shown below.

3.1. Photovoltaic technology map

Before structuring the model, we classify the photovoltaic field into 5 main-classification and 17 sub-classification as shown in Figure 1. The above classification of technology has been referred to by KETEP (Korea Institute of Energy Technology Evaluation and Planning), Korea’s responsible authority for developing strategies of technology development in the field of energy. The quantitative data such as patents, SCI papers, and the World Index are also reflected in this model.
**3.2. Scoring model**

Scoring model is an equation that assigns score based on related data to forecast an unknown result. Martino model is a representative model in the scoring model. Martino utilizes the scoring model to apply technological parameters for analyzing technology forecasting, which combines various characteristics and parameters [7]. Our study adopted the Martino model because the model can consider both interchangeability and importance between technologies. The Martino model is shown below [7]:

\[
\text{Technological Level} = \frac{d^2B^2(c+d+e)^2(f+f+g)2(1+h)^2}{(l+f)^2(1+k)^2}
\]

where A and B represent overriding factors, (C, D, E) (F, G) (I, J) are exchangeable or tradable factors within representative bracket, and H and K are unexchangeable and not significant factors [7]. Each capital letter is a factor that composes the technological state [5]. Also, lower case letters are the weighted values and are defined as c+d+e =1, f+g =1, a+b+z+y+x =1, w+v=1.

**3.3. Estimation of parametric weight**

To apply the above mentioned equation to the real case, the estimations of parameters and weighted values must be needed. This study utilizes AHP with ratings model [10], one of the AHP methodologies for calculating the importance of each parameter. Unlike general methods, which use paired comparison, AHP with ratings model is focused on ratings, which relieves the tendency of excessive differences in technology. The primary advantage of the ratings model is to decrease necessary comparisons [10]. Therefore, the use of ratings allows the representation of a complex selection or prioritization process. In this model, we apply AHP in the main-classification and weight allocation in the sub-classification to prevent excessive deviation when only applying paired comparison to photovoltaic technology, which is still being developed. The ratings have the advantage of simplifying the comparison of weights as well.

**3.4. The Delphi method**

To structure the mixed model, we survey and analyze according to two phases. The first survey, focusing on experts, asks questions on the exchange possibilities and importance of photovoltaic technologies. This information has been utilized to examine overriding factors, tradable factors, and
unexchangeable factors as shown in Figure 1. The second survey concerns the technology level compared to advanced countries, time of follow up, and relative importance for AHP with the ratings model.

3.5. Information on patents, Publication and World Index

We used the KETEP data to count the number of patents and SCI papers related to photovoltaic energy. There are 13,377 SCI papers from the U.S., Europe (England, Germany, and France), Japan, and South Korea. Out of the total number of SCI papers, 34.5% were published in the U.S., 31.2% in Europe, 17.5% in South Korea, and 16.8% in Japan. On the other hand, patents have different result. In a total of 6,631 patents, the U.S. has 58.7%, Japan has 17.1%, and Europe has 14.2%. South Korea has 665 patents, accounting for 10.0% of the total shares. Our model employs the World Index from “Energy Balance of OECD Countries in 2013” developed by the International Energy Agency (IEA). We used two data that are rate of photovoltaic energy supply among total renewable energy supply and rate of renewable energy supply among total energy supply. The rates of photovoltaic energy supply among total renewable energy supply are 3.7% in South Korea, 2.1% in Japan, and 2.0% in U.S. and Europe. The rates of renewable energy supply among total energy supply are 11.2% in Europe, 6.1% in U.S., 3.5% in Japan, and 0.7% in South Korea.

3.6. Process of Mixed model

Here is the process of our model. First, we applied the expert survey by using Delphi method. Depending on the technology classification system, the outcomes from the first step are adapted to the Martino. The AHP with the rating model draws the weighted value used in the scoring model. In other words, the weighted value in Martino model was drawn from the AHP with the ratings model. We figured out the result from Martino model in the first step. And then we combined the data from patents, SCI papers, and the World Index with the value from the Martino model to reach a conclusion.

4. Results

4.1. The results of technology forecasting in each model

In previous chapter, we suggested a mixed model considering both quantitative and qualitative characteristics. In this chapter, we test the fitness of mixed model through the application to photovoltaic energy technology. Comparing mixed model with other models, we observe the differences between a mixed model and other models, and find the advantage of the mixed model.

In Table 1, we describe the definition of four models including the mixed model (Model 4) this paper proposes. Models 1, 2, and 3 represent alternative specifications shown in the previous researches and are implemented for the purpose of comparison with the outcome of mixed model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Definition</th>
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<tbody>
<tr>
<td>Model 1</td>
<td>Analyzing the technology level qualitatively based on the Delphi survey</td>
</tr>
<tr>
<td>Model 2</td>
<td>Analyzing the technology level quantitatively based on patents and papers index (PP index)</td>
</tr>
<tr>
<td>Model 3</td>
<td>Analyzing the technology level quantitatively based on the World Index</td>
</tr>
<tr>
<td>Model 4</td>
<td>Mixed model considering both qualitative and quantitative characteristics</td>
</tr>
</tbody>
</table>

A Delphi survey was adopted for the first model with 20 professionals in the photovoltaic sector. We estimate the average scores from the answers drawn by professionals in model 1, setting the highest scored country as 100 for the standardization. This standardization also applies to other models. In the second model, we consider the number of papers and patents related to photovoltaic technology possessed by each country. In model 3, we utilized the 2011 data of “Energy balance of OECD countries” documented by the IEA. In this data, we could obtain the information related to both the
ratio of the renewable energy supply among the total energy supply of each country and the ratio of the photovoltaic energy supply among the renewable energy supply. In model 4, we suggest the mixed model as the new methodology, combining the Martino model with the PP (Paper-Patent) index and the World Index (WI). For the Martino model, we bring the weighted value from the AHP with ratings procedure. The mixed model equation is shown below:

\[
\text{Technological Level (Mixed Model)} = \alpha \cdot \text{MAR} + \beta \cdot \text{PPI} + \gamma \cdot \text{WI}
\] (2)

where MAR (Martino model Index) depicts technology level derived by Martino model based on Delphi survey (Model 1) which represents quantitative approach, PPI is technology level derived from SCI papers and patents (Model 2), and WI shows technology level derived from World Index (Model 3). Here, the sum of \(\alpha\), \(\beta\), and \(\gamma\) is unity.

Table 2 shows that the ranks of the countries changed according to the models, which means that the results differed based on the applied factors: the experts’ evaluation (Model 1), the competitiveness of knowledge production (Model 2), the World Index (Model 3), and the mixed model (Model 4).

Model 1 applied the Delphi method, the qualitative methodology of analyzing technology forecasting. The Delphi method is the most common way to analyze the technology level. The result of model 1 shows that there is no large difference in technology level among USA, EU and Japan.\(^1\) This means that among these three countries there is no gap in technology level. However, from another point of view, this result can be interpreted that when there is no large difference in technology level among the countries, the experts have its limitation to estimate the technology level accurately. In model 2 and model 3, we used patents and papers index (PP index) and the World Index, as the quantitative information. The results of these two models have significantly larger differences compared to model 1. This means that the result could be biased as it was affected dominantly by specific and very limited information. Model 4 is the mixed model suggested in our study. The values of \(\alpha\), \(\beta\), and \(\gamma\) are set to be 0.8, 0.1, and 0.1, respectively. The result of model 4 is similar to that of model 1, but the gap between EU and other countries is larger. Moreover, the gap between Korea and other countries is also larger. It means that the sensitivity of technology level estimated by the mixed model is improved compared to Delphi method. In addition, the result of model 4 shows that the differences decrease compared with model 2 and model 3. This means that the problem that a specific factor dominantly affects, occurring in model 2 and model 3, also was lessened. Consequently, by using model 4, we can utilize much more information and at the same time retain the sensitivity of technology forecasting estimation. Moreover, the problem which a specific factor affects dominantly can be also resolved.

<table>
<thead>
<tr>
<th>Country</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>KOR</td>
<td>89.13</td>
<td>32.66</td>
<td>34.99</td>
<td>84.38</td>
</tr>
<tr>
<td>USA</td>
<td>98.64</td>
<td>100</td>
<td>23.19</td>
<td>95.91</td>
</tr>
<tr>
<td>JPN</td>
<td>99.93</td>
<td>39.5</td>
<td>56.7</td>
<td>94.59</td>
</tr>
<tr>
<td>EU</td>
<td>100</td>
<td>52.91</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

4.2. The results of technology forecasting depend on weighted values in the mixed model

In the view of the technology readiness level, the method of technology forecasting has to be changed with the technology lifecycle, as emphasized by Martino [8]. During the initial phase of the research and development, knowledge competitiveness such as academic papers and patents is the critical elements; however, in the transitory phase, the opinions suggested by experts are more

\(^1\) China, which is one of the world-leading energy consumers, is not considered in this study because World Index data were provided only for OECD countries by the International Energy Agency (IEA).
percipient information. On the other hand, the degree of technology supply can be the important factor in the mature phase. Therefore, the values of $\alpha$, $\beta$, and $\gamma$ has to be set considering its own technology readiness level.

Table 3 shows the changes of estimated technology level depending on weighted values in the mixed model. In case of model 4A, the importance of PP index (the value of $\alpha$) is higher while the importance of experts’ opinion (the value of $\beta$) is lower. This has to be applied in case of low technology readiness level or research phase. As shown Table 3, there is large difference among the estimated result emphasizing PP index (Model 4A), the result based on World Index (Model 4B), and that of Model 4C, which is a combination of Model 4A and Model 4B. We considered the energy supply data as the World Index data in this paper. This model fits the case of higher technology readiness level or mature technology in the commercialization or production stage.

Table 3. Technology level values according to weight of mixed model

<table>
<thead>
<tr>
<th>Model</th>
<th>Score</th>
<th>Rank</th>
<th>Score</th>
<th>Rank</th>
<th>Score</th>
<th>Rank</th>
<th>Score</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 4</td>
<td></td>
<td></td>
<td>Model 4A</td>
<td></td>
<td></td>
<td>Model 4B</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha = 0.8 \beta = 0.1 \gamma = 0.1$</td>
<td></td>
<td></td>
<td>$\alpha = 0.6 \beta = 0.3 \gamma = 0.1$</td>
<td></td>
<td></td>
<td>$\alpha = 0.6 \beta = 0.1 \gamma = 0.3$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KOR</td>
<td>84.38</td>
<td>4</td>
<td>74.73</td>
<td>4</td>
<td>72.34</td>
<td>4</td>
<td>75.87</td>
<td>4</td>
</tr>
<tr>
<td>USA</td>
<td>95.91</td>
<td>2</td>
<td>100</td>
<td>1</td>
<td>79.96</td>
<td>3</td>
<td>92.65</td>
<td>2</td>
</tr>
<tr>
<td>JPN</td>
<td>94.59</td>
<td>3</td>
<td>84.96</td>
<td>3</td>
<td>85.32</td>
<td>2</td>
<td>87.87</td>
<td>3</td>
</tr>
<tr>
<td>EU</td>
<td>100</td>
<td>1</td>
<td>93.68</td>
<td>2</td>
<td>100</td>
<td>1</td>
<td>100</td>
<td>1</td>
</tr>
</tbody>
</table>

5. Conclusion

Technology forecasting is conducted by various countries and industries, and the results are used for technology development and R&D strategies. However, the information and evaluation results will be biased because the evaluation model uses only quantitative or qualitative method. In this study, we suggested a mixed model, considering both quantitative and qualitative characteristics, and compared it with existing models. The results of the comparison revealed that the ranking of countries changed significantly with the models of choice, because they had their own strengths and weaknesses. In addition, we found that the results differ according to the weighted values between quantitative and qualitative factors, and the weighted values had to be applied to differently according to technology readiness level. In this point of view, the mixed model has many advantages in technology forecasting. First, we can utilize a broader range of information, such as the experts’ evaluation, PP index, and World Index, in technology forecasting. Second, the mixed model allows a larger flexibility comparing with other exiting models. Lastly, we can also consider technology readiness level in estimation of technology forecasting.

6. References