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Comprehensive Evaluation of Smart Industrial Park Based on Hesitant Fuzzy Theory

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Abstract

With the development of communication technology, the era of interconnection of everything is beginning. Smart industrial parks have become a key part of smart cities. At present, there is little research on comprehensive evaluation of smart industrial parks. Through scientific and reasonable evaluation of smart industrial parks, it is beneficial to improve the comprehensive level of smart industrial parks and provide practical decision-making suggestions. In the research process, a comprehensive evaluation method of smart industrial park based on hesitant fuzzy theory is designed. By minimizing the decision maker's divergence degree model, the weights of experts and indicators are reasonably set, and more reliable evaluation results are obtained.

Keywords

Smart Industrial Park; Multi-criteria Decision Making; hesitant Fuzzy Theory; TOPSIS.

1. Introduction

In the process of continuous development of science and technology, the Internet of Things and intelligent technology are widely used, and the intelligent era of the Internet of Things is opening. In 2009, IBM first proposed the concept of smart city [1], pointing out that the new generation of information and communication technology will be applied to urban resource management, traffic management, public infrastructure and public services to improve the ecological efficiency of the city and transform the city into an environment-friendly low-carbon city.

Industrial park refers to the industrial company cluster and infrastructure sharing in a certain region. It not only strengthens the cooperation between companies, but also improves the economic output of unit land, and has a significant driving role for the economic development of the whole country. Due to intensive energy consumption and serious environmental pollution, it is essential to transform industrial parks into more eco-efficient parks. The report of the "Twentieth Chinese National Congress" stressed the need to "promote green development and promote harmonious coexistence between human and nature". The transformation of industrial parks is imperative.

Intelligent technologies and systems provide solutions for energy and material optimization and the construction of eco-efficient industrial parks. In the context of the continuous development of sensor and communication technologies, data collection and management are becoming easier and easier. Through cloud-based applications, green and intelligent logistics and new generation of Internet technologies (such as the concept of Industry 4.0), information processing capabilities and processing convenience are enhanced. Industrial parks can operate and manage in the mode of smart industrial parks [2]. In the practice of smart industrial park, energy management, resource management, economic efficiency and operation and maintenance efficiency are the key components.

At present, there are few evaluations on smart industrial parks, and scientific and reasonable evaluation will help promote the construction of smart industrial parks and provide decision-making suggestions for improving the comprehensive level of existing smart industrial parks. The multi-criteria evaluation method [3] is widely used, which can simultaneously take the indicator level and evaluator level into consideration. The evaluation information involves specific indicators and evaluation results. Based on this information, the accuracy of evaluation is further improved [4], so it is suitable for application to decision-making and other issues [5,6,7]. In this study, a comprehensive evaluation of smart industrial parks was carried out based on the above methods, providing guidance for improving the management level of smart industrial parks.

2. Comprehensive evaluation method of smart industrial park

2.1. The framework of comprehensive evaluation method of smart industrial park

The framework of the comprehensive evaluation method for the smart industrial park is as follows: the number of known evaluators and indicators is n and p, respectively, and are expressed as V_m (m=1,2,…,n) and C_k (k=1,2,…,p). In this study, the multi-criteria evaluation method is used, involving two different levels of evaluators and indicators, and the weights of the two are reasonably set. After obtaining all the index data, the final evaluation result is further obtained with TOPSIS.

2.1.1. Relevant indicators of energy management

One of the important manifestations of the smart industrial park is the intelligence and automation of energy management. Relevant indicators of energy management mainly include intelligent buildings, energy consumption monitoring and intelligent lighting.

Intelligent building (C_{11}): The buildings in the park should have a unified building management and control system, which can monitor or remotely control the status of electricity, water supply and drainage, elevators, air conditioners and other equipment in the building. If one function is achieved, 1 point can be obtained.

Energy consumption monitoring (C_{12}): The energy monitoring system in the park can collect and monitor the use of water, electricity, gas and other energy in the park in real time. If one function is realized, 1 point will be obtained.

Intelligent lighting (C_{13}): The lighting equipment in the park should have the timing function, and the lighting equipment should be real-time sensing through light, sound, infrared and other equipment. If one function is achieved, 1 point can be obtained.

2.1.2. Relevant indicators of resource management

Resource management emphasizes the protection of the ecological environment and adheres to the basic concept of sustainable development. Relevant indicators of resource management mainly include environmental monitoring, greening of the park and utilization of recyclable resources.

Environmental monitoring (C_{21}): The environment in the park should be under monitoring, including real-time monitoring and publication of noise, air quality and other information. If one function is realized, 1 point will be obtained.

Greening in the park (C_{22}): The higher the greening ratio in the park, the better the protection effect of the ecological environment will be.

Recyclable resources utilization (C_{23}): the utilization rate of recyclable resources in the park. The higher the ratio, the better the utilization effect of recyclable resources in the park, and the more conducive to the sustainable development of the park.

2.1.3. Relevant indicators of economic benefits

Economic benefit is the ultimate goal of smart industrial park construction. Relevant indicators of economic benefits mainly include innovation and entrepreneurship, digital investment attraction and park output value.

Innovation and entrepreneurship (C_{31}): There should be clear preferential measures to support innovation and entrepreneurship enterprises in the park. The larger the data, the greater the support of the park for innovation and entrepreneurship enterprises.

Digital investment attraction in the park (C_{32}): The smart industrial park should build an investment attraction management system to achieve the functions of qualification review of investment attraction objects, settlement approval, customer relationship management of investment attraction objects, online house inspection, decoration formalities handling, online enterprise rent-release, settlement statistics, and so on. If one function is achieved, 1 point can be obtained.

Park output value (C_{33}): The park output value is the most direct manifestation of the park's economic benefits. The higher the output value, the better the economic benefits driven by the park.

2.1.4. Relevant indicators of operation and maintenance efficiency

The informatization and intellectualization of the smart industrial park should serve the needs of daily work and life, improve efficiency, and facilitate the operation and maintenance of production and life in the park. Relevant indicators of operation and maintenance efficiency mainly include intelligent management, living facilities and organizational system.

Intelligent management (C_{41}): The smart industrial park should build an intelligent management system, and use physical cards, virtual cards, face recognition and other methods to realize the all-in-one card management functions of personnel access, vehicle access, elevator use, and internal consumption in the park. If one function is achieved, 1 point will be obtained.

Life supporting facilities (C_{42}): the degree of intelligence of the application scenarios related to life in the park, such as whether there is a smart canteen, whether there is software in the parking lot that can dynamically feedback the parking information in the park, whether the main office space in the park covers unmanned retail supermarkets and intelligent lockers, whether there are express delivery robots in the park, etc., and 1 point will be obtained if one function is achieved.

Organization system (C_{43}): the perfection of the organization system. The park should establish complete management systems that match the construction content of the smart industrial park, have clear business processes and task decomposition, have a sound smart industrial park management organization with clear structure, clear responsibilities, and can match the management system. The higher the degree, the more perfect the organizational system.

2.2. Determination of weight

2.2.1. Hesitant fuzzy language set description

The evaluator is an expert with relevant experience in the construction of smart industrial parks. It is necessary to determine the importance of each indicator, so that the corresponding indicator weight can be obtained. Various experts have certain differences in their work and experience, and their understanding of indicators is also different. They can put forward specific suggestions from their own perspective [8]. When these experts are not sure about a certain indicator, the answer given may be in a certain range rather than a certain value. For example, the organizational system of the smart industrial park is between important and very important, or the innovation and entrepreneurship of the park is between important and extremely important, which is a very important probability; If the indicators are relatively certain, an exact answer will be given. Therefore, the hesitant fuzzy language set [9] is introduced in the description of expert evaluation. In this way, all semantic information can be retained, and it is flexible enough to truly reflect the views and opinions of various experts, thus providing an accurate basis for the follow-up evaluation.

hesitant fuzzy language set is expressed as S={$S\alpha$ | α = -τ, ..., -1, 0, 1, ..., τ}. If we choose a 7-level evaluation, there are seven levels of importance, specifically expressed as: S={S_{-3}, S_{-2}, S_{-1}, S_0, S_1, S_2, S_3}={Extremely unimportant, very unimportant, unimportant, moderately important, important, very important, extremely important}. In the harmonic function, each language value corresponds to a value between [0,1]. The above language sets were used in this study. As the length of may be different, it must be extended to the same length in order to ensure comparability. h^+ and h^- are the maximum and minimum values of the language set, and $\bar{h} = \eta h^+ + (1-\eta)h^-$. In this study, all experts are considered neutral, so $\eta = \frac{1}{2}$ [10]. When an expert does not make an evaluation, the evaluation will be extended by the value of other experts.

2.2.2. Determination of experts' weights

In fact, it is difficult to determine the weight of experts directly. Although many scholars have carried out relevant studies, most of the studies still set the same weight for each expert, which often has a certain deviation from the real situation. In view of the above problems, an optimization model is designed to minimize the degree of expert divergence in this study, which improves the accuracy of expert weight determination.

First of all, it is necessary to effectively describe the expert judgment. In this process, the hesitant fuzzy language set is mainly used. In this way, the corresponding hesitant fuzzy number can be obtained. The formula is as follows:

$$h_{mk} = \{h_{mk}^l \mid l = 1, \cdots, L, \quad m=1, \cdots, n, \quad k=1, \cdots, p\} \tag{1}$$

The divergence degree of two experts m and u is described and calculated by Euclidean distance. The specific formula is as follows:

$$d(h_{mk}, h_{uk}) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\sum_{m=1}^{n}\sum_{u=1, u\neq m}^{n}(h_{mk}^l - h_{uk}^l)^2} \tag{2}$$

The hesitant fuzzy number with expert weight is expressed as: $\{w_m^V h_{mk}^l \mid l = 1, \cdots L\}$, the weighted sum of the Euclidean distance of m and u is as follows:

$$\bar{d}(h_{mk}, h_{uk}) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\sum_{m=1}^{n}\sum_{u=1, u\neq m}^{n}(w_m^V h_{mk}^l - w_u^V h_{uk}^l)^2} \tag{3}$$

In the above process, it is necessary to ensure that the divergence degree of the weighted hesitant fuzzy number is small enough to maximize the group consensus degree. The corresponding optimization model can be obtained as follows:

$$\begin{cases} \min_{w_m^V} D = \sum_{k=1}^{p}\sum_{m=1}^{n}\sqrt{\frac{1}{L}\sum_{l=1}^{L}\sum_{m=1}^{n}\sum_{u=1,u\neq m}^{n}(w_m^V h_{mk}^l - w_u^V h_{uk}^l)^2} \\ h_{mk} = \{h_{mk}^l \mid l=1,\cdots,L,\quad m=1,\cdots,n,\quad k=1,\cdots,p\} \\ h_{uk} = \{h_{uk}^l \mid l=1,\cdots,L,\quad m=1,\cdots,n,\quad k=1,\cdots,p,\quad u\neq m\} \\ \sum_{m=1}^{n} w_m^V = 1 \\ w_m^V \geq 0, m=1,\cdots,n \end{cases} \tag{4}$$

Based on the above model (4), the best value can be calculated to ensure the minimum divergence.

2.2.3. Determination of indicators weights

The importance of indicators is judged according to the hesitant fuzzy evaluation of experts, and its evaluation is expressed as h_{mk}, and then the weight of indicators is further determined. In this process, the weighted average algorithm is mainly used, and the specific steps are as follows:

Step 1. First extend the hesitant fuzzy evaluation value to make the length consistent, which can be expressed as:

$$h_{mk} = \{h_{mk}^l \mid l=1,\cdots,L,\quad m=1,\cdots,n,\quad k=1,\cdots,p\}$$

Step 2. Calculate the weight to obtain the corresponding hesitant fuzzy evaluation value, which is specifically expressed as:

$$\bar{h}_{mk} = \{w_m^V h_{mk}^l \mid l=1,\cdots,L,\quad m=1,\cdots,n,\quad k=1,\cdots,p\}$$

Step 3. The parameters of the weighted average algorithm are calculated as follows:

$$\bar{u}_k = \sum_{m=1}^{n}\bar{h}_{mk}^1, \tag{5}$$

$$\bar{v}_k = \sum_{m=1}^{n}\frac{1}{T-2}(\bar{h}_{mk}^2 + \bar{h}_{mk}^3 + \cdots + \bar{h}_{mk}^{L-1}), \tag{6}$$

$$\bar{\pi}_k = \sum_{m=1}^{n}\bar{h}_{mk}^L \tag{7}$$

Step 4. After the above operations are completed, convert the hesitant fuzzy evaluation value and get the triangular intuitionistic fuzzy number, which is similar to the original weighted average operator of intuitionistic fuzzy number. The weight of the k-th index can be calculated as:

$$w_k^C = \frac{\bar{u}_k + \bar{\pi}_k(\frac{\bar{u}_k}{\bar{u}_k + \bar{v}_k})}{\sum_{k=1}^{p}[\bar{u}_k + \bar{\pi}_k(\frac{\bar{u}_k}{\bar{u}_k + \bar{v}_k})]} \tag{8}$$

From the above steps, the weights of different indicators can be calculated.

2.2.4. Aggregation method based on TOPSIS

TOPSIS takes advantage of the proximity of PIS and NIS in the sorting process [11]. The basic process of this method is as follows:

Step 1. Calculate the normalized decision matrix and apply vector normalization to calculate g_{ik}, where i represents the i-th smart industrial park:

$$g_{ik} = \frac{x_{ik}}{\sqrt{\sum_{i=1}^{r} x_{ik}^{2}}}, i = 1, 2, \cdots, r \tag{9}$$

Step 2. The weights w_m^V (m = 1, 2, ..., n) and w_k^V (k = 1, 2, ..., p) can be determined by the methods in 2.3.2 and 2.3.3.

Step 3. Construct the weighted and normalized comprehensive evaluation matrix V of the smart industrial park.

$$V = \begin{bmatrix} w_{11}^{C} g_{1,11}^{l} & \cdots & w_{43}^{C} g_{1,43}^{l} \\ \vdots & \ddots & \vdots \\ w_{11}^{C} g_{r,11}^{l} & \cdots & w_{43}^{C} g_{r,43}^{l} \end{bmatrix} \tag{10}$$

Step 4. The optimal value and the least optimal value in the comprehensive evaluation index of the smart industrial park are respectively expressed as A^+ and A^-, then:

$$A^{+} = \{\max_{r} v_{ik} \mid k = 11, \cdots, 43\} = (v_{11}^{+}, v_{12}^{+}, v_{13}^{+}, v_{21}^{+}, v_{22}^{+}, v_{23}^{+}, v_{31}^{+}, v_{32}^{+}, v_{33}^{+}, v_{41}^{+}, v_{42}^{+}, v_{43}^{+}) \tag{11}$$

$$A^{-} = \{\min_{r} v_{ik} \mid k = 11, \cdots, 43\} = (v_{11}^{-}, v_{12}^{-}, v_{13}^{-}, v_{21}^{-}, v_{22}^{-}, v_{23}^{-}, v_{31}^{-}, v_{32}^{-}, v_{33}^{-}, v_{41}^{-}, v_{42}^{-}, v_{43}^{-}) \tag{12}$$

Among them, $v_k^+ = \max v_{i,k}, k = 11, 12, \cdots, 43.$ $v_k^- = \min v_{i,k}, k = 11, 12, \cdots, 43.$

Step 5. Calculate the Euclidean distance between each smart industrial park to be evaluated and A^+:

$$S_i^{+} = \sqrt{\sum_{k=11}^{43} (v_{i,k} - v_k^{+})^2}, i = 1, 2, \cdots, r \tag{13}$$

Similarly, calculate the Euclidean distance between each smart industrial park to be evaluated and A^-:

$$S_i^{-} = \sqrt{\sum_{k=11}^{43} (v_{i,k} - v_k^{-})^2}, i = 1, 2, \cdots, r \tag{14}$$

Step 6. The relative closeness between the smart industrial park to be evaluated (i) and the optimal value is calculated as follows:

$$R_i^{+} = \frac{S_i^{-}}{S_i^{-} + S_i^{+}}, 0 < R_i^{+} < 1, i = 1, 2, \cdots, r \tag{15}$$

Step 7. R_i^+ is the evaluation score. By comparing the evaluation scores, the comprehensive evaluation of the smart industrial park can be ranked. The higher the value of $R_i^+ (i = 1, 2, \cdots, r)$, the higher the degree of intelligence of the smart industrial park.

3. Examples and analysis

As shown in Table 1, it is necessary to first convert the experts' evaluation into hesitant fuzzy number:

Table 1 Experts' evaluation on the importance of indicators for smart industrial parks

Indicators	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
C11	(0.83)	(0.5)	(0.33,0.5)	(0.67)	(0.5,0.67)
C12	(0.67,0.83)	(0.67)	(0.33,0.5)	(0.5)	(0.33,0.5)
C13	(0.5)	(0.83)	(0.67)	(0.83)	(0.67,0.83)
C21	(0.67)	(0.5)	(0.67)	(0.33,0.5,0.67)	(0.67,0.83)
C22	(0.5)	(0.67)	(0.67,0.83)	(0.5,0.67)	(0.83,1.0)

C23	(0.33,0.5,0.67)	(0.33,0.5)	(0.67)	(0.67)	(0.5,0.67)
C31	(0.33)	(0.5,0.67)	(0.83)	(0.83)	(0.5,0.67)
C32	(0.67,0.83)	(0.67)	(0.67)	(0.83)	(0.67,0.83)
C33	(0.17,0.33)	(0.33)	(0.5,0.67)	(0.33,0.5,0.67)	(0.33,0.5,0.67)
C41	(0.67)	(0.5)	(0.83)	(0.83)	(0.67,0.83)
C42	(0.33)	(0.33,0.5)	(0.33)	(0.33)	(0.5,0.67)
C43	(0.67,0.83,1.0)	(0.5)	(0.5,0.67)	(0.5,0.67)	(0.5,0.67,0.83)

According to the model (4), the weights of five experts are obtained as w_m^V ={0.2001,0.2277,0.1968,0.1888,0.1866}, and the weighted divergence degree of the group is $\overline{d}(h_{mk,}h_{uk})=1.412$. If their weights are set to $w_m^{'V}=0.2$, m=1,..., 5, then the weighted divergence degree of the group $\overline{d}'(h_{mk,}h_{uk})=1.5006$ can be obtained. According to the above analysis, $\overline{d}(h_{mk,}h_{uk})<\overline{d}'(h_{mk,}h_{uk})$ and divergence is smaller when different weights are set, so the method proposed in this study is reasonable and effective.

The corresponding weights of indicators are 0.0835, 0.0764, 0.1022, 0.0849, 0.0945, 0.0756, 0.0878, 0.1029, 0.0538, 0.1008, 0.0545 and 0.0832.

Suppose there are three smart industrial parks, i.e., A, B and C, and the corresponding scores of each indicator are shown in Table 2.

Table 2 Scores of various indicators of three smart industrial parks

Indicators	A	B	C
C11	2	5	6
C12	3	6	2
C13	1	3	2
C21	2	3	6
C22	80%	70%	60%
C23	20%	45%	35%
C31	2	5	3
C32	5	8	10
C33	1000	2300	1500
C41	2	5	6
C42	1	3	4
C43	5	4	8

After aggregation by TOPSIS method, the scores of A, B and C are 0.1364, 0.6634 and 0.6262 respectively. According to the comprehensive score, the star level of the smart industrial park is divided into 0~0.2 as one star, 0.2~0.4 two stars, 0.4~0.6 three stars, 0.6~0.8 four stars, 0.8~1 five stars. Therefore, A is one star, B and C are four stars, and B's score is higher than that of C. Through comparison, it can be seen that A has done the best in greening the park, but at the same time, it should improve the utilization rate of recyclable resources, further enhance the support for innovation of enterprises in the park, and improve the total output value of the park; C has done a good job in energy management and operation and maintenance efficiency, and the further improvement lies in the greening construction of the park and the improvement of the park output value. Although the score of B is the highest, it can still be further improved in terms of digital investment attraction and organizational system improvement in the park.

4. Conclusions and suggestions

This paper studies the comprehensive evaluation method of smart industrial park based on hesitant fuzzy theory. The application of this method will help improve the semantic flexibility of the evaluator. At the same time, the weights of experts and indicators are set according to the designed minimum divergence model. On this basis, three smart industrial parks A, B and C are taken as examples to verify the effectiveness of the proposed method in evaluating the comprehensive capacity of smart industrial parks, and can provide decision-making suggestions for different parks to improve the comprehensive capacity of smart industrial parks. The evaluation method proposed in this paper has certain applicability and can provide certain reference for other multi-criteria decision-making problems.

References

[1] Lazaroiu, G.C., Roscia, M., 2012. Definition methodology for the smart cities model. Energy 47, 326–332.

[2] Pan, M., Sikorski, J., Kastner, C.A., Akroyd, J., Mosbach, S., Lau, R., Kraft, M., 2015. Applying industry 4.0 to the Jurong Island eco-industrial park. Energy Procedia 75, 1536–1541.

[3] Zhu, F., Zhong, P., Sun, Y. Multi-criteria group decision making under uncertainty: Application in reservoir flood control operation[J]. Environmental Modelling & Software, 2018(100):236-251.

[4] Ma, J., Lu, J., Zhang, G. Decider: A fuzzy multi-criteria group decision support system[J]. Knowledge-Based Systems, 2010(23):23-31.

[5] Heravi, G., Fathi, M., Faeghi, S. Multi-criteria group decision-making method for optimal selection of sustainable industrial building options focused on petrochemical projects[J]. Journal of Cleaner Production, 2017(142):2999-3013.

[6] Li, Z., Liang, X., Yin, H. A multi-criteria group decision making method for elevator safety evaluation with hesitant fuzzy judgments. Applied and Computational Mathematics, 2017(16):296-312.

[7] Li, Z., Zhang, Q., Liao, H. Efficient-equitable-ecological evaluation of regional water resource coordination considering both visible and virtual water[J]. Omega. 2018(83): 223-235.

[8] Boschetti, F., Richert, C., Walker, I., Price, J, Dutra, L. Assessing attitudes and cognitive styles of stake-holders in environmental projects involving computer modeling[J]. Ecological Modelling, 2012(247):98-111.

[9] Liao, H., Xu, Z, Herrera-viedma, E., Herrera, F. Hesitant fuzzy linguistic term set and its application in decision making: a state-of-the-art survey[J]. International Journal of Fuzzy Systems, 2018, 20(7):2084-2110.

[10] Liao, H., Xu, Z., Zeng, X-J. Distance and similarity measures for hesitant fuzzy linguistic term sets and their application in multi-criteria decision making[J]. Information Sciences, 2014(271):125-142.

[11] Xu, Z. Intuitionistic fuzzy aggregation operators[J]. IEEE Transaction of Fuzzy Systems, 2007(15):1179-1187.