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RESEARCH ARTICLE

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A new experience mining approach for improving low carbon city development

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Abstract

Developing low carbon city (LCC) has been widely appreciated as an important strategy for sustainable development. In line with this, an increasing number of cities globally have launched low carbon practices in recent years and gained various types of experience. However, it appears that existing studies do not present methods of how to use these valuable LCC experience in solving new problems. This study therefore introduces an experience mining approach to assist decision-makers in reusing previous experience when tailoring LCC development strategies. The mining approach consists of three processes, namely, collecting historical cases which have been experiencing LCC, establishing LCC experience base, and mining similar experience cases. This study innovates the existing experience mining approach by introducing a two-step mining process with considering the perspective of problem-based urban characteristics (PBUCs) and the perspective of solution-based urban characteristics (SBUCs). The application of the introduced mining approach has been demonstrated by a case study, where Shenyang's energy structure is adopted as the target problem. The new experience mining approach provides a valuable reference for decision-makers to retrieve similar cases for improving LCC development with the consideration of city characteristics.

KEYWORDS

city characteristics, experience mining, low carbon city, similarity measure, sustainable development

1 | INTRODUCTION

Urbanization is a double-blade for global sustainable development, which has aroused widespread attention, especially in the field of climate change (Song et al., 2018; Yao et al., 2018). Contrary to its contributions to economic growth, employment opportunities and technological innovation, urbanization has been causing rapid increase in fossil fuel consumption and carbon emissions (Ali, Bakhsh, & Yasin, 2019; Shuai et al., 2017; Shuai et al., 2018; Zhang et al., 2019). According to the United National Department of Economic and Social Affairs (UNDESA, 2019), the world's average urbanization rate increased from 29.6% in 1950 to 55% in 2018. This dramatically increase brought substantial increment of urban population and industrial activities, which are accompanied by large amount of carbon emissions. As reported by World Bank (2018), carbon emissions in the world have risen from 11.43 billion tons in

Abbreviations: AHP, Analytic hierarchy process; ANP, Analytic network process; CBR, Case-based reasoning; EI, Energy intensity; EO, Economic output; ES, Energy structure; IEA, International Energy Agency; IS, Industrial structure; LCC, Low carbon city; NAZCA, Non-state Actor Zone for Climate Action; NDRC, National Development and Reform Commission; P, Population; PBUC, Problem-based urban characteristic; SBUC, Solution-based urban characteristic; UNDESA, United National Department of Economic and Social Affairs; UNDP, United Nations Development Programme; UNEP, United Nations Environment Programme.

1965 to 36.14 billion tons in 2014, which has triggered global warming, an emerging challenge facing all countries globally. The United Nations (2014) further indicated that the gradual transition of the global population towards urban areas will rise from 50% in 2014 to 70% by 2050. This ever-increasing global urban population inevitably requires more energy consumption and thus generates sharp increase in carbon emissions. The International Energy Agency (IEA, 2008) warned that around 70% of global carbon emissions are originated from urban areas, and this proportion is expected to reach 76% by 2030. Therefore, urbanization highlights the dilemma between economic growth and carbon emission increase (Colenbrander et al., 2019; Qiao, Zheng, Jiang, & Dong, 2019b; Zhang et al., 2019). It is therefore important to explore a new urbanization development model characterized with low emissions, low pollution, and high energy efficiency for all countries (Cheng et al., 2019; Qiao, Peng, Sabri, & Rajabifard, 2019c; Shuai et al., 2019; Wang et al., 2016). In this context, the concept of low carbon city (LCC) emerged in response to tackling the challenge of climate change during the urbanization process.

The term LCC is seen as exemplifying urban sustainability by reducing emissions and promoting cleaner production at multiple scales (Fu & Zhang, 2017). On one hand, LCC is within the framework of sustainability, and benefits from sustainability guidelines for setting low carbon agenda and target plans for cities' low carbonization (Jensen, Bjerre, & Mansfeldt, 2016). On the other hand, LCC can contribute to the promotion of the sustainable pattern of city development, which focuses on reducing carbon emissions by changing citizen's behavior towards low carbon without harmful to their life quality (Dai, 2009). It is widely appreciated that the development of LCC is the most effective solution for enabling sustainable urbanization and tackling climate issues (Shen, Wu, Lou, et al., 2018; Shen, Wu, Shuai, et al., 2018). Therefore, the effectively improvement of LCC is of strategic essence across the globe.

There is a growing number of countries and international organizations having contributed efforts in improving the development of LCC. For example, the C40 Cities Climate Leadership Group, a network of the world's megacities taking action to reduce carbon emissions, has involved 96 cities in 2018. The Covenant of Mayors, launched in 2008 by the European Commission has involved 9,664 signatories to endorse and support the efforts of local authorities in implementing emission mitigation policies. The cities that joined the Non-state Actor Zone for Climate Action (NAZCA) launched in 2014 at the United Nations Climate Change Conference in Lima have adopted and implemented more than 2,500 actions to mitigate climate change. Su et al. (2013) reported that there are 1,050 cities in the United States, 40 cities in India, 100 cities in China and 83 cities in Japan have initiated a series of planning programs on low-carbon development. Furthermore, there are also many eco and low carbon city programs established in the world, which are demonstrations on sustainable urbanization and can offer new insights into the implementation plan for cities' low carbon development, such as Shenzhen's international low carbon city and Sino-Singapore Tianjin Eco-city (Zhan & de Jong, 2018).

The implementation of these LCC initiatives has generated large amount of experience and lessons for cities internationally on how to develop LCC. For example, Stockholm's progress in applying distributed energy supply and generating electricity by waste incineration are good examples for developing LCC, and have been adopted in London and other cities. The study by Khanna, Fridley, and Hong (2014) revealed that the experience of pilot LCCs in China serves as important models for further development of LCC in the whole country. Liu and Qin (2016) proposed that learning from the experience gathered from those forerunners is a smart and efficient strategy for the development of LCC, which may not only save resources but also bring technologies and investment from other countries. In order to reuse successful experience effectively, this study introduces the experience mining approach proposed by Shen et al. (2013) into the field of LCC development.

There are two objectives in this study: (a) developing a modified experience mining framework for LCC development, and (b) demonstrating processes of the new experience mining approach by conducting a comprehensive case study. In order to achieve the research objectives, the remainder of this paper first conducts a literature review to display the existing knowledge gap. Section 3 briefly illustrates the origins of experience mining principles, and portrays the modified framework of experience mining for developing LCC. Section 4 presents an empirical case on the application of experience mining for LCC. Section 5 provides the conclusions of this study.

2 | LITERATURE REVIEW

A number of studies have delved into improving the development of LCC, which mainly fall into three research streams. In the first stream, the improvement strategies are proposed based on analysis of carbon emission status (Cai et al., 2019; Liu et al., 2019), impact factors (Qin et al., 2019; Zhang et al., 2019), or indicator system (Yang, Wang, & Zhou, 2018; Ying & Yue, 2017; Zhou et al., 2015; Zhou et al., 2015). For example, Liu, Duan, et al. (2019) estimated carbon emissions for 30 cities in Northeast China, and based on which policy recommendations for carbon mitigation of these cities are provided. Qin et al. (2019) proposed several suggestions on how Chinese cities can improve LCC based on the understanding of the driving factors of carbon emissions. Yang et al. (2018) analyzed the low carbon development pathways of the pilot LCCs in China on the basis of an index system that quantitatively describes low carbon development. By evaluating the low carbon development level, Ying and Yue (2017) provided several insights to improve LCC, including legislative efforts, economic instrument, and energy-saving technology improvement. In the second research stream, many other scholars also pay attention to improving LCC in specific areas, such as low carbon energy (Hast et al., 2018; Ohnishi et al., 2018; Roberts et al., 2019), technological innovation (Wang, Engels, & Wang, 2018; Yin et al., 2019), and low-carbon industries (Dong et al., 2013; Wang et al., 2019; Zhang, Wang, & Da, 2014). In referring to the third research stream, improvement strategies for LCC are proposed without examining the factors or index system. For instance, Phdungsilp (2010) provided an insight into Bangkok's energy and carbon future and highlighted the steps required to promote sustainable LCC. Baeumler, Ijjasz-Vasquez, and Mehndiratta (2012) concluded that the low-carbon action plan of London city has provided an example of setting roadmap for LCC development, which includes four steps, namely, developing a baseline emission inventory, establishing an emission reduction goal, formulating policies and supporting actions, and monitoring and reporting of carbon emissions. Li et al. (2018) also suggested that developing LCC involves four key steps, including understanding city's carbon footprint, establishing city's emission goal, designing and implementing a LCC plan, and measuring LCC progress by evaluation indicator systems. Zhao, Gao, and Zuo (2019) reviewed low carbon policies of China and found out that the Chinese government mainly facilitates LCC development from the perspectives of planning guidance, building energy conservation, industrial development regulation, energy industry development and energy mix, economic measures, and supervision measures.

The above literature outlines some key profiles in improving LCC, but a few issues should be further addressed. First, most of the existing literature claimed to improve LCC by focusing on several impact factors, indexes, or sectors. However, LCC is a sophisticated system with multiple elements; thus, a sustainable development of LCC requires efforts from every factor, index, or sector, such as energy, multilayered governance, transportation, and building (Tan et al., 2017). Therefore, it appears that a holistic solution for improving LCC development is still absent (Li et al., 2018). Second, the existing improvement pathways are proposed for either individual cities or all cities but without the consideration of city characteristics. In fact, there are many differences between cities in multiple aspects such as economic development levels, energy mixes, and industrial structures (Liu, Duan, et al., 2019). Thus, different development pathways should be designed for different cities with the consideration of city characteristics. In summary, there is an urgent need to propose a holistic approach for guiding the improvement of LCC with distinctive city characteristics.

Few studies are attempting to apply experience mining approach to guide the development of LCC. Experience mining is first proposed by Shen et al. (2013), which is an effective approach to extract valuable experience from similar past practical cases as decision-making references to solve new problems. There are some scholars attempting to apply this approach in various areas. For example, Shen et al. (2017) introduced the measure of similarity into the experience mining approach for improving urban sustainability. Based on experience mining approach, Wang et al. (2019) presented a lessons mining system for searching references to support decision-making towards sustainable urbanization. Liu et al. (2019) established an experience mining framework based on case-based reasoning (CBR) for dispute settlement of international construction projects. Such studies demonstrate that experience mining approach can be applied in a wide range of experience-intensive problems due to the advantages such as its effectiveness for solving unstructured problems and convenience in updating the knowledge database (Liu, Li, et al., 2019). Shen, Yan, Zhang, and Shuai (2017) further pointed out that experience mining can ensure the mined cases are very similar to the target problem by considering local distinctive. Furthermore, the mined experience from this approach is characterized by continuous improvement as more and more cities devoted in low carbon transition, which will generate continuous experience for solving problems. In view of these circumstances, experience mining approach is suitable for guiding the improvement of LCC with distinctive city characteristics.

3 | RESEARCH DESIGN

3.1 | A modified experience mining framework

Experience mining approach is adopted in this study. The approach is originally built based on case-based reasoning (CBR), which involves five major components, namely, represent, retrieve, reuse, revise and retain (Finnie & Sun, 2003), as shown in Figure 1.

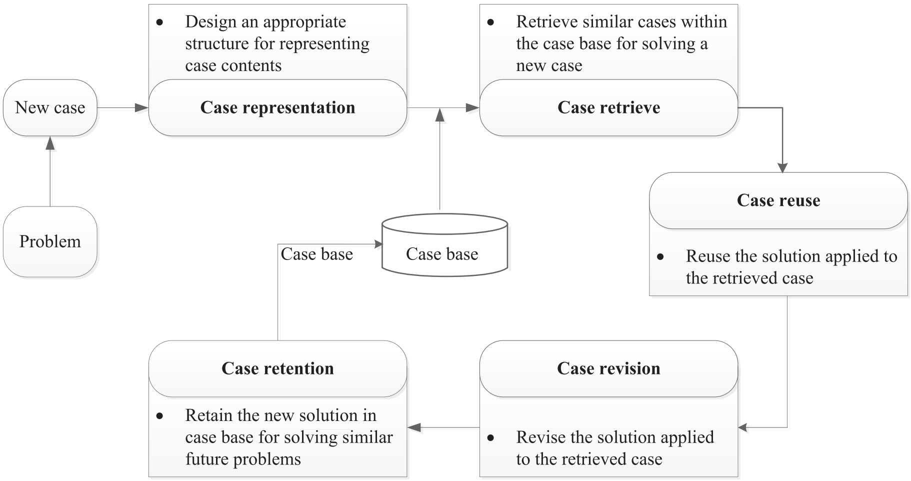
- Represent: Design an appropriate structure for representing case contents.
- Retrieve: Retrieve similar cases within the case base for solving a new problem.
- Reuse: Reuse the solution stored in the retrieved case as a reference to solve target problem.
- Revision: Revise the solution applied to the target problem.
- Retention: Retain the new solution in case base for solving similar future problems.

According to the 5R-schematic cycle in Figure 1, Shen et al. (2013) introduced experience mining approach which has three major components: a refinery process, a case base, and a mine-sweeper. The refinery process is to convert the practical cases or experience into individual experience modules, which are stored in a base, called case base. Mine sweeper is used to extract experience modules from the case base which are similar to the target case in order to solve the target problems (Shen et al., 2013). In other words, the three key contents in applying experience mining approach are collecting historical cases, establishing experience base, and mining or retrieving similar cases for references to solve new problems.

It is appreciated that the process of case retrieve plays most significant role for the application of experience mining as it directly affects the effectiveness of using the mined cases as references in solving new problems (Pereira & Madureira, 2013; Shen, Yan, Zhang, & Shuai, 2017). Shen, Yan, Zhang, and Shuai (2017) further pointed out that it is important to consider the level of similarity of the backgrounds between the target case and those to be mined from the case base when applying experience mining approach. In line with this, previous studies intend to add a similarity mechanism of case characteristics. For example, in referring to an urban case, typical characteristics include urbanization rate, development stage, climate zone, and landform (Huang, Fan, & Shen, 2019; Shen, Yan, Fan, et al., 2017; Shen, Yan, Zhang, & Shuai, 2017).

However, in applying experience mining approach for improving LCC development, the approach needs to be modified as the urban

FIGURE 1 Case-based reasoning cycle (Shen et al., 2017; Watson & Marir, 1994)



characteristics used in the existing approach for examining similarity convey limited information for describing cities' characteristics from both problem and solution perspectives. In fact, there are two types of urban characteristics for analyzing similarity between a target city and the stored cities, namely, problem-based urban characteristics (PBUCs) and solution-based urban characteristics (SBUCs). PBUCs are used to analyze problem background similarity which is the reference for mining similar cases from the case base. When the PBUCs between a target city and mined cities are similar, the solutions from the mined cities may be suitable for addressing the problem presented in the target city. In other words, mined cases may present a number of solutions. However, the effective implementations of these solutions will request for specific conditions. For example, promoting hydroelectric power is a key solution for optimizing energy structure, but the effectiveness of this solution will depend on the condition of rich water resources. For another example, the promotion of public bicycles is commonly appreciated as a good solution to improve low-carbon traffic, but this solution will not be suitable in the circumstance of mountain cities such as Chongqing in China. Thus, a further mining process is needed to examine which solutions are suitable for the target case. In other words, it is necessary to further mine preferred solutions by analyzing the similarity of solution-based urban characteristics (SBUCs) between the target case and the mined cases.

Based on the above discussions, this study extends the existing experience mining approach for improving LCC development by introducing a two-step mining process, as shown in Figure 2.

3.2 | Collecting historical cases for developing LCC

The collection of sufficient and appropriate cases in practicing LCC development is critical for mining effective LCC experience. Accordingly, a comprehensive literature review is conducted for collecting historical cases in this study. The sources used are as follows:

- Related database, such as Sustainable Cities: Best Practice Database (DAC, 2016) and Best Practices Database in Improving the Living Environment (UN-Habitat, 2016).
- Related books or journal papers, such as Baeumler et al. (2012), Tan et al. (2017), and Liu and Qin (2016).
- Official website, such as local governments, United Nations Development Programme (UNDP), United Nations Environment Programme (UNEP), World Bank, and C40 Cities Climate Change Group.

3.3 | Establishing an experience base of LCC

After collecting historical LCC cases, the experience information for each case needs to be properly structured so as to be effectively mined. It is considered that typical practice experience must contain three main elements, namely, specific problems, city characteristics, and solutions adopted for addressing corresponding problems (Huang et al., 2019; Wang, Shen, et al., 2019). As described in Figure 2, the LCC experience base will be presented by individual modules characterized with "problem-PBUC-SBUC," which is shown as Figure 3.

3.3.1 | Problem

In Figure 3, the representation of problems should be foolproof. Each problem needs to be addressed in order to develop LCC, for example, lack of low carbon technology, extensive consumption on fossil fuels, low use of renewable energies, and waste pollution (Chen & Zhu, 2013; Dong, Dong, & Dong, 2019; Dong, Dong, & Jiang, 2019; Huang et al., 2019; Wu, Tam, et al., 2019). Based on the theory of sustainable development, problems for developing LCC can be classified across economic, social, and environmental dimensions.

3.3.2 | Problem-based urban characteristic (PBUC)

In referring to LCC development, PBUCs can be city's emission characteristics, which are important references for taking LCC

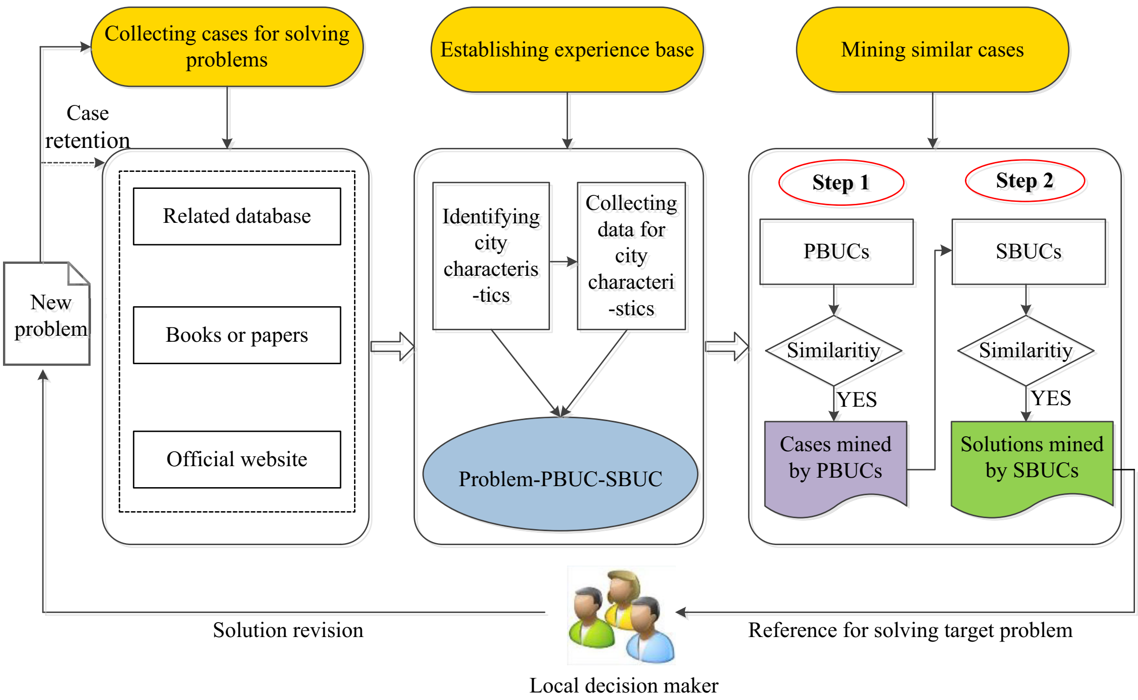


FIGURE 2 New experience mining approach for developing LCC: A two-step mining process [Colour figure can be viewed at wileyonlinelibrary.com]

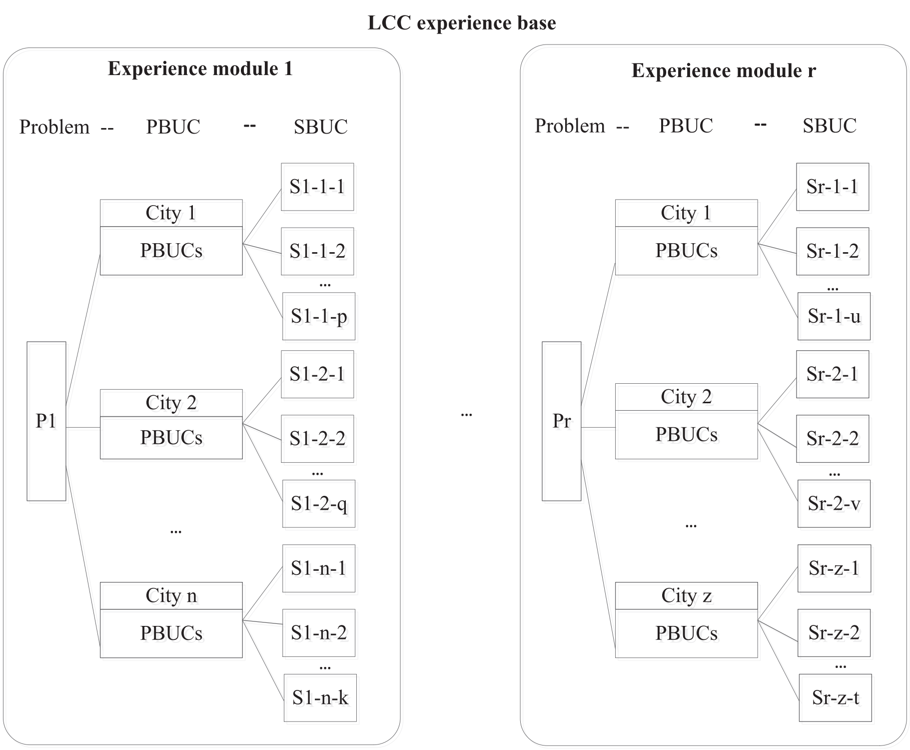


FIGURE 3 LCC experience base

improvement measures (Shen, Wu, Shuai, et al., 2018). It is considered that emission characteristics are to facilitate access to cities with the similar background in the LCC experience base. According to Shen, Wu, Shuai, et al. (2018), emission characteristics of cities can be decomposed by adopting an extended Kaya identity, which is shown as follows:

$$\sum C_i = \sum \frac{C_i}{E_i} \times \frac{E_i}{GDP_i} \times \frac{GDP_i}{GDP} \times \frac{GDP}{P} \times P = \sum ES_i \times EI_i \times IS_i \times EO \times P \tag{1}$$

In Model (1), C_i stands for carbon emissions of specific industry i, E is energy consumption, and P is the total population. In general, there are three typical types of industries (i = 1, 2, 3), namely, primary industry, secondary industry, and tertiary industry. Primary industry includes agriculture, forestry, animal husbandry, and fishery. Secondary industry consists of manufacturing industry and construction industry. Tertiary industry contains transport, storage and post, wholesale, retail trade, hotels, and other sectors (Ahmed, Ramli, & Yusup, 2016; Wang & Feng, 2017). In line with this, the following seven PBUCs are confirmed by referring Model (1):

1. *ES* (energy structure), which is measured by carbon emission per unit of energy consumption (X_1).
2. *EI* (energy intensity), which is measured by energy consumption per unit of GDP (X_2).
3. *IS* (industrial structure), which is measured by the ratio of industrial added value to GDP and can be decomposed as IS_1 (X_3), IS_2 (X_4), and IS_3 (X_5).
4. *EO* (economic output), which is measured by GDP per capita (X_6).
5. *P* (population), which represents the total population of a specific city (X_7).

3.3.3 | Solution-based urban characteristic (SBUC)

As described in the above section, SBUCs indicate the necessary conditions for the implementation of LCC solutions. According to previous studies, LCC solutions can be various, such as promoting low-carbon product certification, developing carbon trade pilots, compiling and verifying the emission inventories, defining the reduction baselines, and certifying emission-reduction credits (Liu et al., 2013; Wang et al., 2015). In referring to these sample solutions, a certain level of low carbon technology is an implementation condition, that is, a SBUC. There are various methods for determining SBUCs, such as literature review and interview.

3.4 | Mining similar cases for solving the problem presented in the target case

Mining is a process of searching the most similar cases for solving problems. In order to achieve this aim, the degree of similarity between a target city and the stored cities will be analyzed from the perspective of PBUCs and SBUCs, which has been shown in Figure 3.

3.4.1 | Similarity measure of PBUCs

There are various methods for measuring similarity, among which Euclidean distance is the most common type (Ahn et al., 2014). Euclidean distance is calculated as square root for the sum of squares of the arithmetical differences between the two objects, which is suitable for measuring the similarity of quantified attributes (Kwon et al., 2017). As all the seven PBUCs ($X_1, X_2, X_3, X_4, X_5, X_6, X_7$) are expressed by crisp numbers, this study adopts Euclidean distance for measuring the distance of each PBUC, denotes as $d_{XY}^{(w_j)}$, between a target city (X_j) and a stored city (Y_j). Due to the fact that the importance of these PBUCs may be different for the target problem, the weighted Euclidean distance between cities is employed to measure the general distance of the seven PBUCs, denotes as $d_{XY}^{(w_j)}$, which can be expressed in the following manner (Pal & Shiu, 2004):

$$d_{XY}^{(w_j)} = \sqrt{\sum_{j=1}^{f} (w_j)^2 \left(d_{XY}^{(j)}\right)^2} = \sqrt{\sum_{j=1}^{f} (w_j)^2 \left(X_{\text{std}}^{j} - Y_{\text{std}}^{j}\right)^2} \quad (2)$$

In Model (2), X_{std}^{j} and Y_{std}^{j} are the standard values of X_j and Y_j (j = 1,2,…,7) respectively. To eliminate dimensional influence of these seven characteristics, the standard values are used, which are converted by employing Z-score transformation:

$$X_{\text{std}}^{j} = \frac{X_j - \mu_X}{\sigma_X} \quad (3)$$

where μ_X and σ_X are the average value and standard deviation of X_j and Y_j during the surveyed period respectively.

w_j in Model (2) represents the weighting assigned to the jth PBUC, indicating the importance of this characteristic for developing LCC. There are various methods for determining weight of city characteristics, among which analytic hierarchy process (AHP) method is most commonly applied (Huang et al., 2019; Liu, Li, et al., 2019; Shen, Yan, Fan, et al., 2017). AHP is a hierarchic structured method for establishing the relative importance between a group of alternatives based on expert opinions by conducting pairwise comparisons (Saaty, 1988). However, this method does not consider the interactive relationships between PBUCs, which does not match with reality (Li et al., 2011). For example, cities with higher economic output (X_6) may have lower energy intensity (X_2), as they can afford to various advanced technologies in improving energy efficiency (Wu, Shen, et al., 2019). To address this limitation, this study adopts the advanced AHP method, namely, the analytic network process (ANP) method, to determine the weighting of city characteristics. ANP is a network and cluster structure, which has been widely proven effective for determining weightings by considering the mutual and interdependent relationships among variables (Liu et al., 2018; Wu et al., 2018).

Based on $d_{XY}^{(w_j)}$ in Model (2), the similarity of PBUCs between a target city and a stored city (denotes as $SM_{XY}^{(j)}$) can be defined as follows (Pal & Shiu, 2004):

$$SM_{XY}^{(j)} = \frac{1}{1 + d_{XY}^{(w_j)}} \quad (4)$$

The higher the value of $d_{XY}^{(w_j)}$, the lower the similarity between a target city X and a stored city Y. According to $SM_{XY}^{(j)}$, all the historical cities can be ranked, and the top N historical cities are mined from the experience base for further analyzing.

3.4.2 | Similarity measure of SBUCs

Different from the seven PBUCs measured by crisp numbers, the SBUCs cannot only be measured by crisp number but also other formats. For example, promoting the use of public bicycles can improve low-carbon traffic, but this solution is limited by landform, so landform is a SBUC. The landform characteristic is a crisp symbol with definite meanings, which can be expressed by hills, plains, mountains, plateaus (Huang et al., 2019). Different value formats of SBUCs should have different calculations for measuring similarity. In terms of SBUCs expressed by a crisp number (j^*), the similarity $SM_{XY}^{(j^*)}$ can be measured by using the Equations (2)–(4). For SBUC does not in the format of crisp number (j'), the similarity between the target city and stored cities can be measured by judging whether their conversion values are the same (Ahn et al., 2014; Kocsis et al., 2014; Shen, Yan, Zhang, & Shuai, 2017). For example, conversion value for landform characteristic of hills, plains, mountains, plateaus can be defined as 100, 200, 300, 400. When the conversion value for target city X and stored city Y is the same, the landform characteristic is similar. The equation is shown as follows:

$$SM_{XY}^{(j')} = \begin{matrix} 1, & \text{if } Q_X = Q_Y \\ 0, & \text{if } Q_X \neq Q_Y \end{matrix} \tag{5}$$

where Q_X and Q_Y represent the convert value of SBUC j' for target city X and stored city Y, respectively. Only if the similarity for SBUCs do not in crisp number are all equal to 1, the corresponding solution of the stored city is suitable for solving the problem presented in the target city, otherwise the solution is not applicable.

By integrating Equations (2)–(5), the general similarity of SBUCs between a target city and a stored city is obtained, which is defined as follows:

$$SM^{(J)} = SM_{XY}^{(j^*)} + \beta \times \sum_{j'=1}^{f} \delta_{j'} \times SM_{XY}^{(j')} \tag{6}$$

Equation (6) consists of two parts, which are used to measure the similarity of SBUCs expressed by crisp number (j^*) and other formats (j'), respectively. β is the weighting value of j' in comparing to j^*. $\delta_{j'}$ is the weighting value of each SBUC j'. As SBUCs are the necessary conditions for the implementation of solutions, this study considers that each characteristic has an equal importance on determining the effectiveness of solution implementation. In other words, SBUCs of a specific solution have equal weightings. The higher the value of $SM^{(J)}$, the more suitable of case solutions for solving problems presented in the target city.

4 | DEMONSTRATION OF THE NEW EXPERIENCE MINING APPROACH

4.1 | Defining a target problem

To demonstrate the proposed new experience mining approach in Figure 2, this study selects the energy structure of Shenyang city as a target problem for mining similar cases. It has been widely appreciated that there is an urgent need for the Chinese cities to optimize energy structure in order to reduce carbon emissions, as China is the largest carbon emitter in the world and characterized by coal-dominated energy structure (Chen et al., 2020; Qiao, Chen, Dong, & Dong, 2019a; Xu et al., 2019). The reasons why Shenyang is chosen as the case city mainly lie in the following two aspects. On one hand, Shenyang has been a typical heavy industrial city since the early 1900s, experiencing rapid economic growth and urbanization process, resulting in a large amount of coal consumption and carbon emissions (Xi et al., 2011). On the other hand, this city is located in central Liaoning province in Northeast China, which is one of the coldest regions in China, indicating substantial demand for coal-consumption heat supply in the cold of winter (Geng et al., 2013). Therefore, Shenyang is an emblematic city, which needs urgent action for optimizing energy consumption, and the mined experience of this city can be shared and promoted in many other cities.

4.2 | Establishing an experience base

As mentioned in section 3, an experience base for developing LCC is the basis for applying experience mining approach, which contains substantial cases. Considering that the statistical methods are quite different between China and other countries (Yang & Li, 2013), this study only takes the Chinese pilot LCCs into account for establishing the experience base. In order to promote the development of LCC, the National Development and Reform Commission (NDRC), China's top agency responsible for formulating and implementing national climate strategies, initiated a national low carbon pilot program since 2010, which encompasses 81 cities by 2017. These pilots have been at the leading edge in practicing LCC within China and launched many programs to achieve low-carbon targets, including the establishment of low-carbon institutions, formulation of greenhouse gas inventories, and the design of low-carbon development plans and lifestyles. According to the Tanpaifangjiaoyi Website, the annual average decrease rate of carbon intensity of pilot LCC (8.2%) is higher than that of the national level (6.6%). In this regard, pilots have achieved some progress, and their experience in developing LCC can be shared and learnt by other cities. For example, the low-carbon product certification system in Hangzhou and Chongqing, the low-carbon transportation pilots in Tianjin and Guangzhou, and real-time monitoring of public buildings in Shanghai are all well reported experience (Khanna et al., 2014; Wang et al., 2015). Therefore, the pilot LCCs are good representative cases for establishing an LCC experience base when optimizing energy structure of Shenyang city. Owing to the fact that the third-batch pilots are issued in 2017, their experience on LCC are limited and need to be further examined the effectiveness, and thus only 35 pilots in the two initial batches are surveyed in this study (Greater Khingan region is excluded due to data unavailability). The cities are Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding, Jinchen, Shijiazhuang, Qinhuangdao, Hulunbuir, Jilin, Suzhou, Huai'an, Zhenjiang, Ningbo,

TABLE 1 Relevant information of experience module for Beijing city

City	Year	PBUC X_1	X_2	X_3	X_4	X_5	X_6	X_7	Solution	SBUC	Reference
Beijing	2010	71,938	0.9	23.6	75.5	0.49	27.07	1,962	(1) Reducing coal consumption. For example, reducing coal for coking, power generation and heating gradually from industry to household, and improving the elimination of coal-fired power plants.	High economic development level; Alternative energy	"Beijing's energy development plan for the 13th five-year plan", "Beijing's clean air action plan 2013–2017", (Fan & Lei 2017; Wei et al. 2017)
	2011	75,566	0.8	22.6	76.6	0.46	24.16	2,019			
	2012	79,417	0.8	22.2	77	0.44	22.59	2,069	(2) Increasing the input of electricity. For example, expanding the scale of power transmission to promote "electricity generation coal," electrification and new energy vehicle projects.	High economic development level	
	2013	83,672	0.8	21.7	77.5	0.38	21.45	2,115			
	2014	88,237	0.7	21.4	77.9	0.36	18.16	2,152	(3) Increasing natural gas. For example, expanding the application of natural gas in heating, industry and refrigeration, improving the proportion of natural gas for heat supply reaches to 70%, and accelerating the improvement of urban and rural gas supply system.	Sufficient natural gas	
	2015	93,500	0.6	19.7	79.7	0.34	12.15	2,171			
	2016	99,766	0.4	19.3	80.3	0.321	8.67	2,173	(4) Improving the efficiency of renewable energy such as wind and solar. For example, accelerating wind power base facilities around Beijing, vigorously developing distributed energy sources such as solar, wind and natural gas.	Rich resource for wind and solar; Certain technology level	

TABLE 2 Weighting of each PBUC

PBUC	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Weighting	0.306	0.291	0.004	0.062	0.077	0.242	0.018

Wenzhou, Chizhou, Nanping, Jingdezhen, Ganzhou, Qingdao, Jiyuan, Wuhan, Guangzhou, Guilin, Guangyuan, Zunyi, Kunming, Yan'an, Jinchang, and Urumqi.

In order to mine experience of optimizing energy structure from the 35 LCC pilots, this study first conducts a comprehensive literature review for collecting experience on related databases, books or journal papers, and official websites according to the experience mining process presented in Figure 2. Second, city characteristics of each experience case, including PBUCs and SBUCs are identified. Thirdly, the data for city characteristics are collected from publicly available official sources, such as statistical yearbooks, energy statistical yearbooks, statistical communique of the national economic and social development. It is noting that the PBUC of energy structure (X_1) is represented by the proportion of coal consumption in total energy consumption in this study due to the data unavailability of carbon emissions at the city level, which is also appreciated by Zhou et al. (2017). To avoid inflation influence, the values of GDP are converted into constant prices measured in 2010. Through these three data retrieving processes, an experience base for optimizing energy structure can be established. As the volume of the experience base is too large, Table 1 only provides some relevant information of experience module for Beijing city.

4.3 | Mining experience cases by applying the similarity of PBUCs

By applying Equations (2)–(4), the similarity between Shenyang and the 35 stored cities for PBUCs can be obtained. As mentioned in section 3.4.1, before using Equation (2), the weighting of each PBUC will be determined by employing the ANP method. The data for processing ANP is collected through practical survey by judging the pairwise comparison between each characteristic. It is considered that there is no dependence between the seven PBUCs, and the ANP structure is interrelated. Based on this structure, the pairwise comparison of the PBUCs with respect to the goal is developed by using a 1–9 Saaty scale, which is shown in Table A1. To ensure the effectiveness of expert opinion, the research team conducted face-to-face interviews with 11 experts who have good knowledge of developing LCC, such as managers of Development and Reform Commission and the Ministry of Housing and Urban–Rural Development, researchers from Zhejiang University and Chongqing University. In case when there occur significant different judgements towards the pairwise comparisons, the research team will hold several collective discussions concentrating on the divergence until consensus has been reached. With the assistance of SuperDecision software, the relative

TABLE 3 Similarity results of PBUCs between Shenyang and stored cities

City	$d_{XY}^{(1)}$	$d_{XY}^{(2)}$	$d_{XY}^{(3)}$	$d_{XY}^{(4)}$	$d_{XY}^{(5)}$	$d_{XY}^{(6)}$	$d_{XY}^{(7)}$	$SM_{XY}^{(j)}$
Beijing	3.29	0.95	0.64	2.76	2.65	0.17	1.91	0.48
Tianjin	2.00	0.58	0.56	0.19	0.25	0.35	0.94	0.61
Shanghai	2.75	0.68	0.67	1.25	1.39	0.29	2.35	0.53
Chongqing	0.22	0.24	0.51	0.51	0.23	0.97	3.22	0.79
Shenzhen	1.75	0.78	0.75	0.55	0.83	0.98	0.39	0.61
Xiamen	1.28	0.72	0.62	0.26	0.48	0.09	0.68	0.69
Hangzhou	1.18	1.00	0.25	0.57	0.61	0.21	0.10	0.68
Nanchang	0.53	0.64	0.06	0.73	0.60	0.49	0.46	0.78
Guiyang	1.08	1.14	0.07	0.83	0.73	3.64	0.56	0.50
Baoding	0.62	0.54	1.35	0.46	1.09	1.30	0.42	0.71
Jinchen	1.09	2.24	0.06	1.22	0.98	0.85	0.89	0.57
Shijiazhuang	0.62	0.59	0.80	0.29	0.35	0.85	0.34	0.75
Qinhuangdao	0.62	0.18	1.49	1.10	0.27	0.94	0.78	0.76
Hulunbuir	1.08	0.31	2.09	0.49	0.84	0.68	0.86	0.72
Jilin	0.28	0.49	0.85	0.23	0.42	0.53	0.59	0.83
Suzhou	0.70	0.60	0.52	0.36	0.21	0.88	0.35	0.74
Huai'an	0.70	0.80	1.22	0.46	0.34	0.93	0.51	0.72
Zhenjiang	0.70	0.59	0.13	0.39	0.27	0.19	0.76	0.78
Ningbo	1.18	0.91	0.14	0.44	0.28	0.17	0.08	0.69
Wenzhou	1.18	0.96	0.29	0.19	0.21	0.92	0.14	0.66
Chizhou	0.31	0.63	1.49	0.28	0.69	1.20	1.02	0.73
Nanping	1.28	0.86	2.88	0.67	1.04	1.00	0.84	0.65
Jindezhen	0.53	0.40	0.44	1.05	1.10	0.97	0.99	0.75
Ganzhou	0.53	0.74	1.87	0.44	0.70	1.46	0.04	0.69
Qingdao	1.06	0.43	0.08	0.40	0.34	0.14	0.11	0.74
Jiyuan	0.24	1.01	0.04	2.25	1.86	0.28	1.13	0.73
Wuhan	0.57	0.28	0.21	0.33	0.35	0.15	0.30	0.82
Guangzhou	1.75	1.05	0.52	1.49	1.52	0.65	1.19	0.60
Guilin	1.22	0.39	2.13	0.41	0.95	1.15	0.50	0.67
Guangyuan	0.97	0.19	2.27	0.50	0.97	1.46	0.85	0.68
Zunyi	1.08	1.43	1.57	0.54	0.51	1.36	0.31	0.61
Kunming	0.21	0.19	0.07	0.50	0.39	0.81	0.25	0.82
Yan'an	0.52	0.51	0.62	1.97	1.98	0.66	0.90	0.75
Jinchang	1.15	1.61	0.33	2.00	1.88	0.36	1.17	0.62
Urumqi	0.83	1.21	0.56	1.10	1.20	0.50	0.73	0.68

weightings of the seven PBUCs are obtained, and the results are listed in Table 2.

By inputting the weightings and the data of PBUCs into Equations (2)–(4), the distance of each PBUC $d_{XY}^{(j)}$ and global similarity ($SM_{XY}^{(j)}$) between Shenyang and the 35 stored cities are calculated, as shown in Table 3. It can be observed from this table that, the stored city whose global similarity to Shenyang rank the top five is Jilin (0.83), Kunming (0.82), Wuhan (0.82), Chongqing (0.79), and Nanchang (0.78). In other words, the top five historical cases are mined, and their solutions can provide references for Shenyang city to optimize energy structure.

4.4 | Mining preferred solutions by applying the similarity of SBUCs

The above section has mined Jilin as the most similar case for reference to optimize energy structure in Shenyang. This study further conducts the similarity measurement of SBUCs between Shenyang and Jilin to select preferred solutions. Due to paper length, only typical solutions of energy structure optimization of Jilin are chosen to demonstrate the procedures of applying the new experience mining approach. The solutions and their SBUCs are shown in Table 4. It can be observed from Table 4 that the solutions of energy structure

TABLE 4 Solutions and corresponding SBUCs for optimizing energy structure in Jilin city

Solution number		Solution	SBUC	Reference
Coal reduction and cleanliness	S1	Formulating exit plan of inferior coal and supply system of clean coal, and carry out a special double random inspection on coal product production within the city	Governmental support (SU1)	"The 13th five-year plan for energy development and energy security system in Jilin city," "The 13th five-year plan to control greenhouse gas emissions in Jilin," "Implementation plan for controlling coal consumption in Jilin," "Clean air action plan for Jilin (2016–2020)"
	S2	Organizing coal-fired heating enterprises to build clean coal reserves and use high-quality coal and clean coal	Governmental support (SU1)	
	S3	Implementing coal reduction and replacement for new coal-consuming projects, and simultaneously building coal washing facilities to increase the rate of raw coal	Governmental support (SU1); Certain technology level (SU2)	
	S4	Increasing the elimination of backward production capacity, and strictly enforcing access to new coal-fired boilers	Governmental support (SU1); Certain technology level (SU2); Economic investment (SU3)	
Alternative energy increase	S5	Formulating a comprehensive plan for straw utilization in substituting wood technology and solidification molding, and carrying out special actions for straw energization	Governmental support (SU1); Certain technology level (SU2); Rich in crop resource (SU4)	
	S6	Accelerating the implementation of the "Gasification Jilin" project. For example, giving priority to natural gas utilization replacing coal combustion in residents' lives, developing high-efficiency utilization projects such as natural gas distributed energy	Governmental support (SU1); Certain technology level (SU2); Economic investment (SU3); Sufficient supply of natural gas (SU5)	
Clean energy development	S7	Improving the utilization of the Songhua River, accelerating the construction of pumped storage power station, and developing small hydropower stations	Governmental support (SU1); Certain technology level (SU2); Rich in water resource (SU6)	
	S8	Vigorously developing four major projects of biomass combustion for power generation, solidification molding fuel, biomass gasification, and fecal biogas	Governmental support (SU1); Certain technology level (SU2); Rich in biomass energy (SU7)	
	S9	Accelerating the development of wind power and solar power	Governmental support (SU1); Certain technology level (SU2); Economic investment (SU3); Rich in wind power and solar power (SU8)	

TABLE 5 Similarity results of SBUCs

Solution	S1	S2	S3	S4	S5	S6	S7	S8	S9
$SM^{(J)}$	1	1	1	0.88	1	0.91	0	1	0.91

optimization in Jilin mainly from the perspective of coal reduction and cleanliness, alternative energy increase, and clean energy development. To further identify preferred solutions, the similarities of SBUCs between Shenyang and Jilin are examined. In fact, Shenyang as the capital cities of Liaoning province, also has paid great attention on energy structure optimization, and has formulated a series of policies, such as "The 13th five-year plan to control greenhouse gas emissions in Shenyang," "Development plan of clean energy and renewable energy during 2016–2017 in Shenyang," and "Control plan for total coal consumption in Shenyang." These policies are also highly attached to promote clean energy technologies such as biomass energy, wind power and solar power. Therefore, it is considered that Shenyang can meet the implementation conditions of governmental support (SU1), certain technology level (SU2), rich in crop resource (SU4), sufficient supply of natural gas (SU5), rich in biomass energy (SU7), and rich in wind power and solar power (SU8) for solutions S1–S9. However, Shenyang is under limited water resource, and are not suitable for promoting hydropower generation on a large scale. Thus, the solution of S7 may not be adaptable in Shenyang city. By inputting the similarity value of the SBUCs into Equations (2)–(6), the global similarity values of the nine solutions (S1–S9) are shown in Table 5.

It can be seen from Table 5 that the mined solution S1, S2, S3, S5, and S8 share similar SBUCs with Shenyang. The high degree of similarity indicates that these solutions are valuable references for decision-making on the energy structure optimization of Shenyang. Although the similarity values of solution S4, S6, and S9 are less than 1, these solutions can still provide good references for assisting in solving the target problem.

The above case study in mining solutions for optimizing energy structure of Shenyang suggests that the new experience mining approach introduced in this study is applicable to mining solutions for addressing new problems towards LCC development. The mined city Jilin and the target city Shenyang are both located in Northeast China and have many similar city characteristics, such as climate and landform, thus it is considered that the mined solutions can be effectively adopted as references for Shenyang to formulate strategies for energy structure optimization. This indicates that the proposed new experience mining approach can help retrieve previous successful experience for reuse in addressing problems, and it consequently contributes to the development of LCC.

5 | CONCLUSIONS

This study introduces a two-step experience mining approach for developing low carbon cities (LCCs) by incorporating the perspectives of problem-based urban characteristics (PBUCs) and solution-based urban characteristics (SBUCs). In using the new mining approach, the cities with similar PBUCs will be first mined, and then the solutions presented in the mined cities will be further mined for solving target problems. The effectiveness of the new experience mining approach has been proven through a comprehensive case study.

The promotion of this new mining approach can break two limitations of previous studies on designing LCC roadmap. First, existing studies commonly present solutions for LCC development in fragmentation, while this new approach can organize the existing solutions systematically in the form of an experience base when solving new problems. Second, this approach enables the pathway for improving LCC more effectively as it allows decision-makers to design pathway for implementing LCC by considering city characteristics, including PBUCs and SBUCs.

The limitation of this study is that the effectiveness of the new mining approach is demonstrated only by few cases. Furthermore, other urban characteristics such as urbanization level and total areas should be further considered when determining PBUCs and SBUCs.

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APPENDIX A.

TABLE A1 Saaty's 1–9 scale of ANP (Saaty, 2013)

Intensity of importance	Definition
1	Equal importance
3	Weak importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2、4、6、8	Intermediate values