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A lessons mining system for searching references to support decision making towards sustainable urbanization

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ABSTRACT

The recurrence of similar problems caused by human errors in urbanization process is common throughout the world. However, the knowledge learnt from these problems should become lessons and important references for decision-making to avoid the recurrence of these problems, thus urban development can be sustainable. It is considered of imperative importance to incorporate the lessons experienced into the decision-making process in a way that can help foresee the potential problems and take proper measures for addressing the problems. There are few studies that have been conducted to investigate the similarity between the current scenario of urbanization practice and the previous context of lesson cases. The ignorance of this similarity presents a significant barrier for decision makers to learn from the existing lessons effectively thus to have references of how to make better decisions for future urbanization practices. This paper presents a Lessons Mining System (LMS) to assist in mining lessons experienced from previous practices. The establishment of LMS is based on Case-Based Reasoning (CBR) theory and the similarity matching principles. The system includes five components, namely, Lessons-case Representation, Lessons-case Store, Lessons-case Retrieval, Lessons-case Application, and Lessons-case Update. LMS can facilitate decision makers to understand what potential problems might occur from their current actions by referring to the lessons experienced previously in similar circumstances. This understanding can help decision makers take preventive measures against the potential problems. The use of LMS can send alarming messages to decision makers about what possible problematic consequence may occur, thus they can modify their actions before too late. A demonstration of Yangwu Town is presented to show the application of LMS, and the result shows that the lessons mined can provide valuable references for the government of Yangwu Town to improve their decision-making quality.

1. Introduction

Urbanization generally refers to both the process of population concentration in urban areas and the transformation of rural areas into urban areas (Street, 1997; UN, 2010), and it has become the driving engine for development in 21st century, particularly in those developing countries. The world is in the midst of the largest wave of urbanization in history (Hodson, 2016). The reason for this is that urbanization can bring benefits in multiple dimensions, such as more job opportunities and incomes, better education and health conditions, better social integration, and others (Dye, 2008; Dying, 2009). The presence of these benefits has been attracting constant flow of people from rural to urban areas. According to Undesa (2015), the proportion of urban population in the world increased from 29% in 1950 to 55% in 2015. It has been projected that this figure will reach 70% by 2050, indicating that 6.3 billion people will be living in cities (Ochoa et al., 2018). However, it has been widely appreciated that rapid urbanization has already induced various problems, such as air and water pollution (Li et al., 2017; Carrascal Incera et al., 2017; Sun et al., 2018), waste pollution (Wu et al., 2016; Golzarpoor et al., 2017), high energy consumption

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Abbreviations and notations

CBR	Case-Based Reasoning
LMS	Lessons Mining System
ULD	Urbanization Lessons Database
UI	User Interface
LGM	Local-Global Method
LLD	Lessons Learnt Database

(Akizu-Gardoki et al., 2018; Zhang and Bai, 2018), traffic congestion (Wang et al., 2017; Shen et al., 2018a), depletion of cultivated land (Marselis et al., 2017), habitat destruction (Malico et al., 2016), and other types of urban problems (Shaker, 2015, 2018; Zhang et al., 2018). These problems appear to be common throughout the world. It is considered that unless sustainable development principles are adopted in urbanization practices, the above urban problems will further hinder the urban sustainability (Ochoa et al., 2018; Alberti and Marina, 2009; Ren et al., 2018). Therefore, making progress towards sustainable urbanization is much more essential now than ever (Brown et al., 2018).

Nevertheless, it is not these problems themselves but their recurrences that attract concerns. Air pollution, for example, is a typical recurring event, which has been resulting in multi-types of health problems and the deaths of a large number of people around the world. Major air pollution events reported include the Meuse Valley fog incident caused by exhaust fume emissions from numbers of factories in Belgium in 1930 (Herrera-Mendoza et al., 2018), the Los Angeles photochemical smog episode caused by exhaust gas emissions from large number of cars and factories from 1943 to 1970 (Wang et al., 2016), the American Donora smog incident caused by harmful industrial emissions from factories in 1948 (Kamrin, 2014), the Great Smog incident of London caused by fume emissions from millions of coal stoves and local factories in 1952 (Shi et al., 2016). In fact, the problem of air pollution becomes worse rather than improved in many cities around the world.

Water pollution, for another example, is also a typical recurring problem and has been the major reason for multiple types of diseases and ecological problems. Major water pollution events reported include the oil-spill pollution in the Gulf of Mexico caused by inappropriate technical operation of British Petroleum Plc in 2010 (Arora and Lodhia, 2017), the severe pollution of Zarjub and Goharrud rivers in Rasht City of Guilan Province in northern Iran caused by improper location of industrial bases, hospitals, and poultry farms (Noorhosseini et al., 2017), the heavy metal pollution of water bodies in Pra Basin of Ghana caused by a large scale of illegal mining activities in the past 35–50 years (Duncan et al., 2018). There are still other types of urban problems occurring repeatedly to threat the sustainable development of cities, such as traffic congestion caused by improper urban planning, which has induced huge social, economic, and environmental costs in many cities around the world (Christidis and Rivas, 2012; Alam and Ahmed, 2013; Yu et al., 2017; Shen et al., 2018a).

The recurrence of these urban problems is highly associated with the poor decision quality caused by human errors. They have costed hugely to our societies, and the damages from some of these problems are irreversible. Unless these errors are learnt as lessons by decision makers and are incorporated to decision-making process for addressing new problems, the recurrence of problems cannot be reduced. Therefore, it is considered valuable to foresee whether a particular type of problem may reoccur in a specific urbanization process by referring to the existing lessons received in previous similar circumstances. The decision-making quality will be improved when these lessons are referred properly, consequently, the huge scale of costs for addressing the recurrences of the previous problems can be saved.

Previous studies have presented various techniques for understanding how past lessons can be used as valuable references to make better decisions. Reason (2000) proposed a model called Swiss Cheese Model to assist decision makers in foreseeing potential aviation problems by learning previous accident lessons. Servos et al. (2013) investigated the lessons from environmental problems by reviewing 58 Global Environmental Facility (GEF) projects and suggested measures for decision makers to foresee the recurrence of these problems. Mannan and Waldram (2014) pointed out that it is important to understand previous problems and the lessons received in the process of decision making for addressing similar problems, thus the recurrence of the problems can be avoided. Zhao et al. (2014) appreciated the importance of lessons learnt from past chemical accidents to help the chemical industry reduce the risk of catastrophic accidents in future. Ferjencik and Dechy (2016) concluded that the lessons learnt from the previous accidents in dynamite manufacturing plants could help prevent or mitigate those accidents that followed.

Several typical studies have examined how lessons can be learnt for foreseeing the potential problems in the context of construction project management. Paranagamage et al. (2012) pointed out that there is a lack of mechanism in contractors' practices for recording and reviewing lessons to foresee the mistakes of project management. Carrillo et al. (2013) opined that learning and capturing previous lessons can help understand potential problems and contribute to improvements in project management performance. Ferrada et al. (2014) argued that the potential problems in construction project can be better foreseen if people communicate and share effectively the lessons gained from unsuccessful projects, thus performance of future projects can be improved. Duffield and Whitty (2015) investigated the adaptation of Swiss Cheese Model by project management organizations and demonstrated how past project lessons can be learnt to help foresee the problems in implementing the current projects. Ferrada et al. (2016b) introduced the concept of lessons-learning in the discipline of construction management and suggested that construction companies can better understand the possible problems in committing future projects by learning previous lessons. There are still some other studies investigating the effectiveness of foreseeing potential problems by employing previous lessons (Drupsteen and Hasle, 2014; Labib and Harris, 2015; Eken et al., 2015; Labib and Read, 2015; Ferrada et al., 2016a; Love et al., 2016; Dash et al., 2016; Eric Stemna et al., 2017; Kim and Rhee, 2017; Suraji, 2003).

The above discussions demonstrate that the importance of incorporating the previous lessons for foreseeing the potential problems has been well appreciated. However, few studies have been conducted to investigate the similarity between current scenario of urbanization practice and previous context of lesson cases. The ignorance of the similarity has presented a crucial barrier to learn lessons effectively from previous urban problems. Consequently, the quality of decision making cannot be improved and the sustainability of urbanization practice will be sabotaged.

Therefore, this paper aims to develop an innovative lesson-learning mechanism to better address the similarity between current urbanization scenario and the context of previous lesson cases, namely, the Lessons Mining System (LMS). The system is expected to assist decision makers to mine lessons and help foresee the potential problems effectively in the urbanization practice. LMS system does not seek to inform decision makers 'what to do' but rather provide decision makers with an avenue for understanding 'what not to do' in the practice of pursuing sustainable urbanization.

2. Research method

In order to develop the Lessons Mining System (LMS), the Case-Based Reasoning (CBR) technique will be used as a reference tool. CBR is a method that extracts the effective solutions adopted previously in addressing certain type of problems, and these solutions are used as decision-making references to solve a new problem (Yang and Wang, 2009). The method has been widely used in many fields for decision making (Chen et al., 2016a; Zhang and Dai, 2018), problems diagnosis (Gu et al., 2017; Tung et al., 2010), products design (Yang and Chen, 2011; Shen et al., 2017a), and business management (Carmona et al., 2013; Sartori et al., 2016).

CRB is not a quantitative model, instead, it is composed of five functional actions, namely, Represent, Retrieve, Reuse, Revise, and Retain (5R), which form a cyclical model (Finnie and Sun, 2003), as shown in Fig. 1.

“Represent” is to structure the information about an existing case into three elements: problem, solutions and outcome. The information about these three elements needs to be organized and stored in a structured case base.

“Retrieve” is to mine from the case base the wanted cases that are most relevant to a concerned case (target case) through a matching process.

“Reuse” is to identify the solutions embodied in the retrieved cases, which will be adopted as most valuable references for making decision to address the problems presented in the target case.

“Revise” is to modify the solutions identified from the retrieved cases to ensure that the modified solutions can be implemented effectively in the target case.

“Retain” is to store the target case into the case base as a new case, which contributes to the development of the case base.

CBR mines the solutions from certain cases in the case base, and these cases are referred as solution cases which can be used as effective references for making decisions to solve new problems. However, the solution cases do not include lesson information for understanding what triggers the occurrence of the problem in these cases. Furthermore, these cases do not provide the information for investigating the similarity between a current scenario case and these solution cases. It shows that CBR focuses on seeking for resolution for existing problems but overlooks how to avoid the recurrence of these problems. CBR method therefore cannot help foresee the potential problems in on-going practices. Nevertheless, it is considered problem-avoiding is more important than problem-solving.

In this study, the CBR infrastructure will be reshaped into a new architecture, namely, LMS, in which case base is defined as lesson-case base. The structure of each lesson case in LMS is designed in three parts, namely, scenario feature variables, problem category, and the lessons learnt. Therefore, the novelty of the methodology adopted in this study can be highlighted as: 1) introducing the feature variables to describe lesson cases, 2) providing lesson information explored from each lesson case. A demonstration case is designated and used to show the application of LMS.

3. The architecture of Lessons Mining System (LMS)

Lessons are often defined as valid knowledge which is learnt from problems or failures (Dash et al., 2016; Pittman et al., 2014). There are two typical approaches to learn lessons from problems: by applying a quantitative lessons learning model (Reason, 2000; Duffield and Whitty, 2015; Labib and Read, 2015), or by creating a lessons-case database (Eken et al., 2015). The effectiveness of employing a quantitative model in generating lessons has been criticized (Pritchett, 1976), whilst learning lessons by creating a lessons-case database is considered feasible and effective (Mannan and Waldram, 2014).

By referring to the CBR infrastructure presented in Fig. 1, the LMS architecture is proposed, as shown in Fig. 2. LMS includes five elementary components: Lessons-case Representation, Lessons-case Store, Lessons-case Retrieval, Lessons-case Application, and Lessons-case Update.

3.1. Lessons-case representation

Lessons-case Representation in LMS is to define the way in which these lesson cases are organized. The specific activities of Lessons-case Representation are elaborated as follows.

3.1.1. Lessons-information collection

The establishment of LMS is based on the collection of sufficient lesson information associating with various problems in urbanization process. For this purpose, a comprehensive literature review was conducted on the sources where various lessons of urban problems are reported. The sources used in this study are listed in Table 1.

3.1.2. Lessons-information structure

The lesson information collected need to be properly structured.

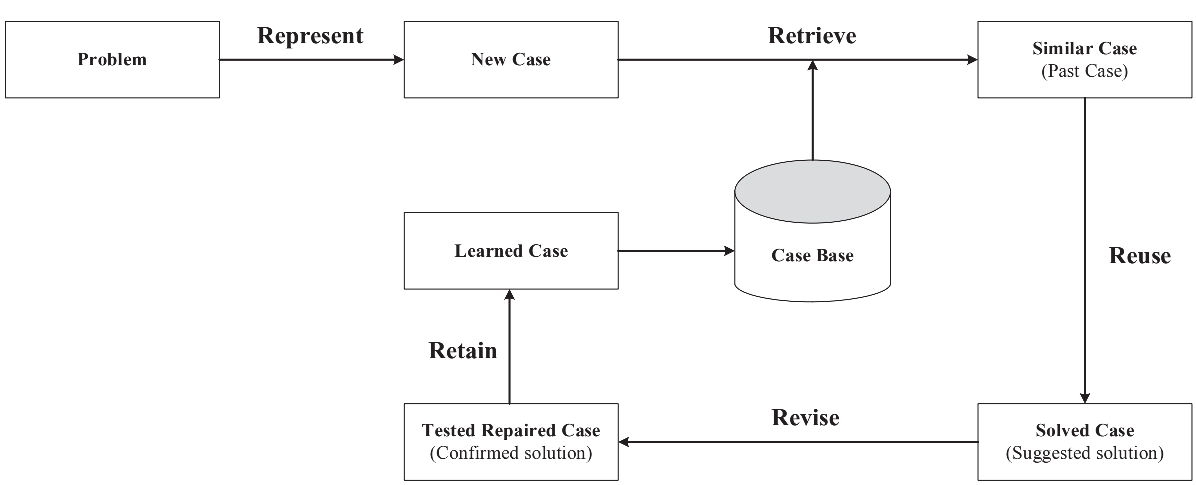

Fig. 1. 5R cycle of Case-Based Reasoning (CBR) method.

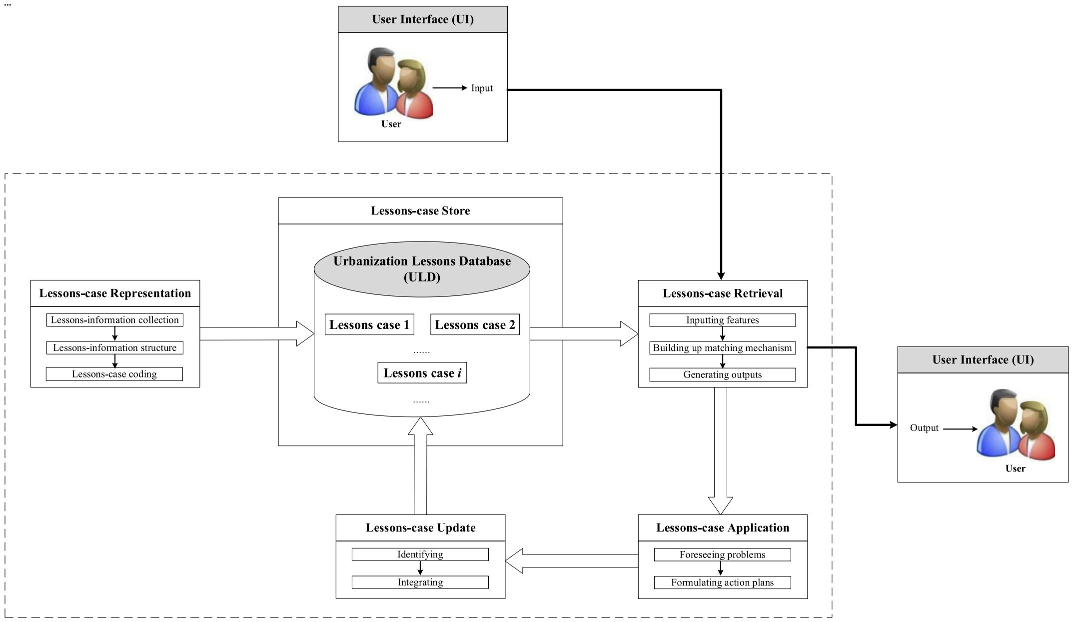

Fig. 2. The architecture of Lessons Mining System (LMS).

Table 1
The major sources for collecting lesson information associating with urban problems.

Sources	Details of information sources
Books	Ma et al. (2004); Barria and Thajchayapong (2011); Shapiro (2012).
Journal papers	Alam and Ahmed (2013); Black (2003); Brook (2008); Cao et al. (2011); Chen et al. (2016b); Chen et al. (2013); Christidis and Rivas (2012); Contreras and Ferri (2016); Dockery et al. (1993).
Regional reports	European Commission (Revel, 2011).
National reports	The Government of China (Xinhua, 2017), the Central Pollution Control Board in India (Bhawan and Nagar, 2015).
City reports	Xingtai City in China (Zhang et al., 2015), Mexico City (Moreno et al., 2008), Ulaanbaatar City in Mongolia (Amarsaikhan et al., 2014), Tirana City in Albania (Mandija and Zoga, 2012), Delhi City in India (Singh and Peshin, 2014).

The information for describing a lesson case must be accurate and concise, and the redundant information must be removed. Each lesson case is structured into three types of information: (1) a scenario description of the lesson case; (2) a description of the category of the problem encountered; and (3) a description of the lessons learnt from the problem. The three components of a lesson case are highlighted in Fig. 3.

The description of the lesson scenario is to reveal the context in which the problems occurred. The scenario will be expressed by using a set of principal feature variables and their corresponding values. These feature variables can be selected from in the International Urban Sustainability Indicators List (IUSIL) (Shen et al., 2011). For example, as shown in Fig. 3, the feature variables for describing a lesson case include four dimensions, namely, environmental characteristics such as landform and climate; economic performance such as income and finance; social development such as public education and health; and governance performance such as policy transparence and accountability (Shen et al., 2011, 2017b, 2017c, 2018b; Zhang, 2016; De Jong et al., 2015; Shaker and Sirodoev, 2016). These four-dimension feature variables are defined by four types of formats, including crisp symbol, crisp number, interval number, and fuzzy linguistic variable (Shen et al., 2017b). For example, “Crisp number” is used to measure urban population by a definite value of “2000 thousand”.

The description of problem category is to facilitate the access to each individual lesson case in the case base. Typical problems associated to urbanization are classified, for example, as shown in Fig. 3, waste pollution, air and water pollution, high energy consumption, traffic congestion, depletion of cultivated land, habitat destruction (Wu et al., 2016; Li et al., 2017; Carrascal Incera et al., 2017; Sun et al., 2018; Marselis et al., 2017; Malico et al., 2016; Akizu-Gardoki et al., 2018).

The lessons learnt from the occurrence of problems should be described in the way that can reveal the human errors triggering the problems and alert decision makers not to commit the errors again. The representation of these lessons should enable effective learning about those human errors committed previously. For example, as shown in Fig. 3, these lessons can be insufficient government investment, excessive acquisition of farming land, inadequate assessment on urban carrying capacity, housing shortage for rural-urban migrants, inappropriate urban planning (Den Hartog et al., 2018; Chan et al., 2018; Wen et al., 2018; Bayulken and Huisingh, 2015; Puppim DE Oliveira, 2013; Hu et al., 2016; Fenton et al., 2015).

3.1.3. Lessons-case coding

Whilst the representation of a lesson case is guided by the three-components structure shown in Fig. 3, each component will be indexed by the corresponding parameters, which are named as scenario parameter, problem parameter, and lessons parameter. Fig. 4 demonstrates the parameter-coding structure in LMS.

In Fig. 4, each type of parameters is defined by a group of feature

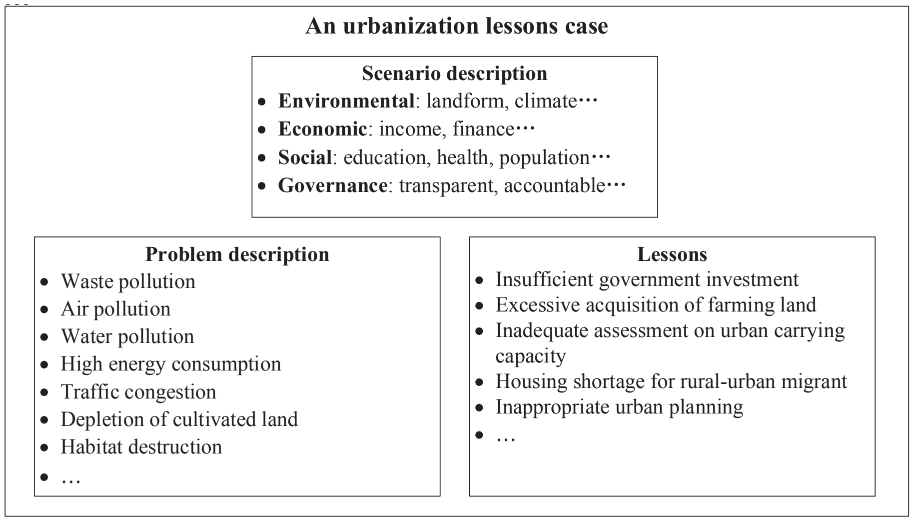

Fig. 3. The three-structured components of a lessons case.

variables. For example, the scenario parameter (P1) is defined by the feature variables of environmental characteristic, landform and climate, and others. Each feature variable corresponds to a unique code, for example, environmental characteristic is denoted by the code P1-1, landform and climate is denoted by the code P1-2. The level of performance by each feature variable will be linked to the indicators that measure urbanization performance in different perspectives, as shown in Fig. 4. The urbanization performance indicators are coded as I1, I2, … I*m*.

3.2. Lessons-case store

In referring to Fig. 2, the second elementary component of LMS is to store the represented lesson cases in Urbanization Lessons Database (ULD). These represented lesson cases were standardized by indicators, parameters, semantic relations, and index pointers in ULD, as shown in Fig. 5. Specific lesson cases in ULD can be indexed according to the values of indicators and parameters.

There are four types of indexes in Fig. 5:

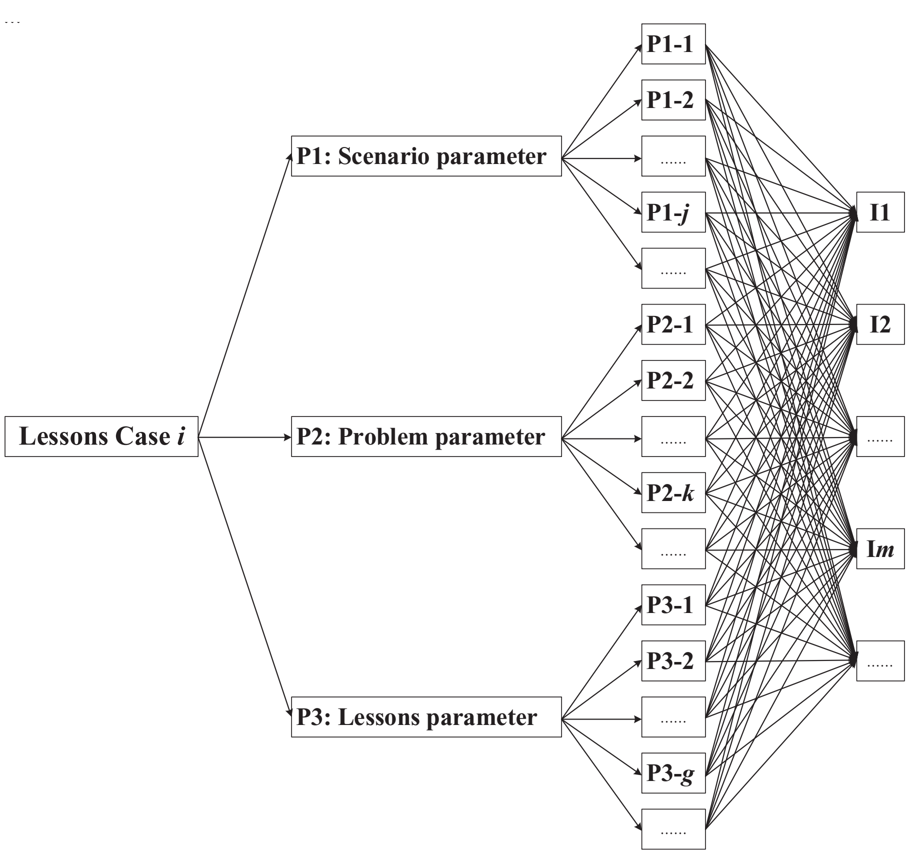

Fig. 4. Parameter coding structure in LMS

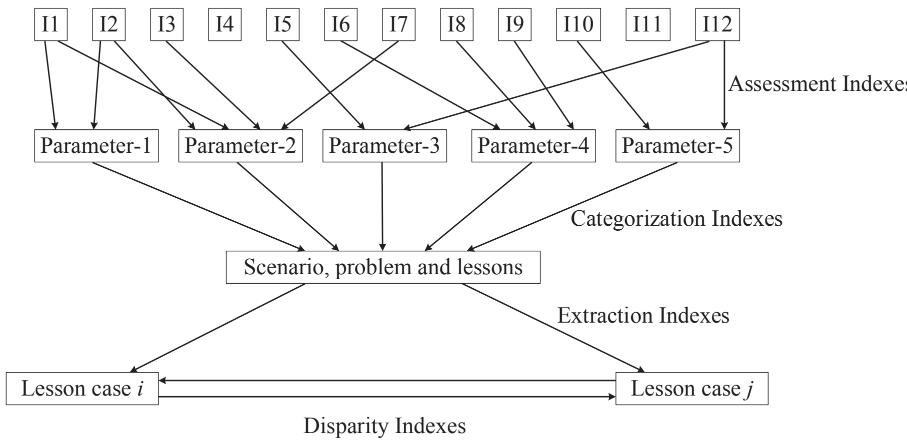

Fig. 5. Lesson-case index structure of ULD adapted from Shen et al. (2013).

(1) links from the performance indicators to parameters, named “assessment indexes”;
(2) links from parameters to scenario, problem and lessons, named “categorization indexes”;
(3) links from scenario, problem and lessons to the stored lesson cases, named “extraction indexes”;
(4) links between the lesson cases, called “disparity indexes”.

By using the four types of indexes, similar types of lesson cases can be grouped into one category by a group name. The individual cases within a same group form a hierarchy according to the degree of their memberships in the group. Different groups are interlinked by a semantic network. The indexed structure of LMS can interpret a lesson case in semantic and pragmatic criteria, instead of purely syntactic ones.

3.3. Lessons-case retrieval

Lessons-case Retrieval is to mine lesson cases by establishing a matching mechanism between the stored lesson cases in ULD and the target case specified by the LMS user (decision maker). According to Fig. 2, Lessons-case Retrieval includes three processes, namely, inputting features, building up matching mechanism, and generating outputs.

3.3.1. Inputting features

In the process of inputting features, the LMS user will refer to the target scenario and confirm the feature information of the scenario. The target scenario is a specific practice for which the LMS user wants to foresee the potential problems from the practice. The target scenario is described by feature variables and the values of these feature variables are given or defined by the user through the User Interface (UI). By following the UI, the user will be asked to select specifications of the feature variables that can best describe the scenario. For example, the value of landform can be hills, plains, plateaus, basins, etc.

3.3.2. Building up the matching mechanism

Matching mechanism is to help match the target scenario with the lesson cases in ULD. In order to establish this matching mechanism, there are two research activities: the calculation of global similarity between the target scenario and all the stored lesson cases, the designation of matching coefficient for filtering out those lesson cases which have lower similarity to the target scenario.

Local-Global method (Cheng and Ma, 2015) is used to calculate the global similarity. For this purpose, firstly, the local similarity between target scenario and all individual lesson cases in ULD will be calculated in referring to each feature variables which are described in crisp symbol (Guo et al., 2011; Castro et al., 2009), or interval number format (Slonim and Schneider, 2001), or fuzzy linguistic format (Shiu and Pal, 2004). Secondly, the global similarity between target scenario and each individual lesson cases will be calculated by applying the weighted local similarities (Shen et al., 2017a).

Furthermore, a matching coefficient (α) needs to be designated for selecting the useful lesson cases from ULD. The designation of α is based on the user's preferences and specific circumstance. Those individual lesson cases whose global similarity values with the target scenario are less than the designated matching coefficient (α) will not be shown on the User Interface (UI).

3.3.3. Generating outputs

By applying the matching coefficient, the lesson cases that the user wishes to refer to will be mined and generated. There may be a number of lesson cases mined, thus it is necessary to establish the ranks between these mined cases in order to differentiate the suitability between the mined cases. The rank will be established according to the global similarity, and the top cases are considered to be able to provide more valuable references for making decisions in response to the target scenario. On the other hand, the number of mined cases should be sufficient in order to provide effective information, and this can be achieved by adjusting the value of matching coefficient.

3.4. Lessons-case application

According to the model Lesson-case Application in Fig. 2, the mined lesson cases will provide users with two major functions:

3.4.1. Foreseeing potential problems

Following the Lessons-case Retrieval process in section 3.3, a number of urbanization lesson cases will be mined and ranked in referring to the features of the target scenario. These mined cases have experienced various types of problems, coded by P2 in LMS. The LMS user can foresee whether these problems will occur to the target scenario for which he is addressing. In the context of urbanization practice, the LMS can help decision makers or practitioners in a specific urban environment to foresee the potential problems, if any. This assessment will allow the decision makers implement precautionary measures to avoid the reoccurrence of these problems.

3.4.2. *Formulating action plans*

The lessons learnt from each mined lesson case provide important references for the LMS user to make better decisions, thus these problems embodied in the mined cases will not occur in the target scenario. As these mined lessons are different in nature, such as human errors, natural disasters and others, the user can formulate different action plans. As these action plans are designated based on the lessons learnt from previous cases which have similar circumstances to that faced in the target scenario, their effectiveness in application is expected. In other words, the implementation of these action plans can reduce the possibility of the reoccurrence of problems in the future urbanization development.

3.5. *Lessons-case update*

According to the model in Fig. 2, the function of Lessons-case Update is to integrate new lessons into ULD. When new problems are encountered in future practices, the lessons from these new problems should be properly examined and described for the inclusion in ULD. In order to avoid the repetition of similar lesson cases in ULD, it is necessary to filter these new lesson cases before integrating them into the database by using parameter indexes. Only these lesson cases which have different values in these parameters are stored as new lesson cases. Accordingly, ULD will be updated.

4. Demonstration

In this section, a demonstration is used to show the procedures of applying the introduced LMS by users (decision makers). In applying LMS, the users can foresee the potential problems by referring previous lesson cases and implement proper actions for avoiding the reoccurrence of the related problems. The process of the demonstration is illustrated in Fig. 6, in which the target scenario is named Yangwu Town (C_0), located in Guizhou province in China. The scenario case has abundant natural resources, such as land resources, and various kinds of agricultural and forestry products. The local government is developing the township by infrastructure construction and industrial upgrading, and wishes to know the potential problems if any from such development.

4.1. *The inputs of feature variables*

According to the description of lesson scenario in section 3.1, four dimensions are used to describe the scenario of a lesson case:

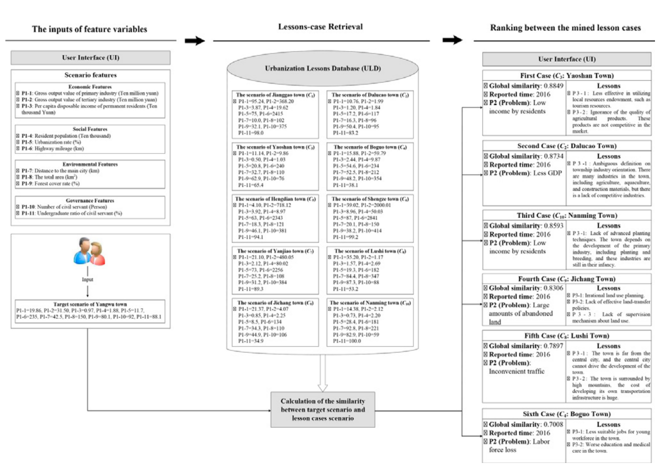

Fig. 6. Lessons-mining demonstration for supporting decision-making of Yangwu Town.

environmental, economic, social and governmental dimensions, as shown in Fig. 6. Each dimension is described by multiple scenario parameters. In this demonstration, eleven feature variables are identified in four dimensions, and coded accordingly, as shown in Fig. 6. For example, the feature variable "gross output value of primary industry" is coded as P1-1, "gross output value of tertiary industry" is coded as P1-2, "per capita disposable income of permanent residents" is coded as P1-3, etc. The values of these variables need to be provided by the user (the government of Yangwu Town (C_0)). For demonstration, the values of these variables are set as: P1-1 = 19.86, P1-2 = 31.50, P1-3 = 0.97.

4.2. *Lessons-case retrieval*

In Fig. 6, the Lessons-case Retrieval process is conducted by matching the target scenario Yangwu with all the stored lesson cases in ULD. In this demonstration, ten lesson cases are stored in ULD, including Jianggao Town (C_1), Dalucao Town (C_2), Yaoshan Town (C_3), Boguo Town (C_4), Hengdian Town (C_5), Shengze Town (C_6), Yanjiao Town (C_7), Lushi Town (C_8), Jichang Town (C_9), Nanming Town (C_{10}). The values of the feature variables for each lesson cases are illustrated in Fig. 6. All the eleven feature variables are measured in the format of crisp number. According to the methods described in Section 3.3, the local similarity between the target scenario and lesson cases in ULD is measured by calculating the distance between the values of the two crisp numbers. The shorter the distance, the more similar the lesson case is considered to the targeted scenario. The local similarity can be obtained through the following formula (Guo et al., 2011; Castro et al., 2009):

$$Sim\,(P_{ij},\ P_{0j}) = 1 - \left|P_{ij} - P_{0j}\right| / (\beta - \alpha), \quad P_{ij},\ P_{0j} \in [\alpha,\ \beta] \tag{1}$$

where $Sim\,(P_{ij},\ P_{0j})$ is the similarity between lesson case C_i and targeted case C_0 in regard to the feature variable P_j. α and β are the lower and upper bounds of the range, respectively.

The global similarity between the target scenario and lesson cases in ULD can be obtained by integrating local similarity of all features:

$$Sim\,(C_i,\ C_0) = \frac{1}{11}\sum_{j=1}^{11} w_j\, Sim(P_{ij},\ P_{0j}) \tag{2}$$

where $Sim\,(C_i,\ C_0)$ denotes the global similarity between the lesson case C_i and target case C_0. w_j denotes the weighting value of feature P_j. The weighting of each feature variable in this demonstration will be determined by using the Equal Weight (EW) method. The calculation results on similarity are listed in Table 2.

For demonstration, the value of the matching coefficient α is designated as 0.7. By applying this matching coefficient, those lesson cases whose global similarity to Yangwu Town is less than 0.7 will not be shown on the User Interface (UI). As a result, the following six lesson cases are mined and shown to the user: C_2 ($\alpha = 0.8734$), C_3 ($\alpha = 0.8849$), C_4 ($\alpha = 0.7008$), C_8 ($\alpha = 0.7897$), C_9 ($\alpha = 0.8306$), C_{10} ($\alpha = 0.8593$).

4.3. *Ranking between the mined lesson cases*

The six mined cases are ranked according to their global similarity degree with the target scenario, and the results ranking are shown in Fig. 6. For example, Yaoshan Town (C_3) ranks first with the global-similarity value of 0.8849. Yaoshan Town is a small mountain town, which is located in Southwest China. The traffic of Yaoshan is not convenient, it is difficult for tourists to enjoy holiday

Table 2
The global similarity between target scenario and all the lesson cases in ULD.

Similarity	Lesson cases										
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Local similarity $Sim\ (P_{ij},\ P_{0j})$	**P1-1**	0.1729	0.9002	0.9044	0.9563	0.8271	0.7899	0.9874	0.8316	0.9834	0.9399
	P1-2	0.8316	0.9852	0.9892	0.9858	0.6565	0.0152	0.7756	0.9848	0.9863	0.9852
	P1-3	0.6576	0.9730	0.9441	0.8368	0.6513	0.0559	0.8641	0.9286	0.9864	0.9714
	P1-4	0.7754	0.9995	0.9893	0.8998	0.9103	0.3907	0.0108	0.9898	0.9953	0.9959
	P1-5	0.1936	0.9299	0.8841	0.4545	0.3439	0.0408	0.2191	0.9032	0.9592	0.7873
	P1-6	0.1997	0.9567	0.9982	0.9996	0.2263	0.0433	0.2581	0.9805	0.9629	0.9801
	P1-7	0.6075	0.6836	0.8816	0.8792	0.7041	0.7283	0.7886	0.4988	0.8973	0.3925
	P1-8	0.8175	0.7935	0.8470	0.7639	0.8891	1.0000	0.8394	0.2436	0.8472	0.7285
	P1-9	0.1429	0.4714	0.6941	0.4386	0.3929	0.2500	0.1250	0.8750	0.3732	0.9482
	P1-10	0.2028	0.9915	0.9549	0.2620	0.1859	0.0930	0.1775	0.9887	0.9606	0.9071
	P1-11	0.8464	0.9232	0.6467	0.2320	0.9078	0.8310	0.9846	0.4624	0.1843	0.8157
Global similarity $Sim\ (C_i,\ C_0)$		0.4953	0.8734	0.8849	0.7008	0.6087	0.3853	0.5482	0.7897	0.8306	0.8593

life here. Yaoshan has a low level of urbanization and is far from central city, and it cannot share the benefits of urbanization of China. Although the residents of Yaoshan mainly rely on agriculture, there are no major competitive agricultural products for sale in this town, the residents therefore have low incomes.

5. Discussion

The above demonstration suggests that the introduced system LMS is applicable and can assist decision-makers in foreseeing the potential problems if any from the current urbanization practice by referring the previous lessons mined. These lessons are important references for designing better decisions to promote sustainable urbanization. The key procedures in using the system can be highlighted as follows:

Building up an adequate database. The demonstration case highlights the importance of building up an adequate Urbanization Lessons Database (ULD) where there must be sufficient number of lesson cases recorded. This way can ensure that valuable information will be mined for decision references. The lesson cases can be selected from official databases, reports, and journal papers. For example, they can be extracted from the Lessons Learnt Database (LLD) designed for construction companies and projects (Ferrada et al., 2016a; Eken et al., 2015).

Selecting appropriate feature variables to describe the scenario of lesson cases. In order to mine valuable lessons for references in implementing current urbanization practice, the system should be able to describe accurately the context of previous lesson cases. It is considered of imperative importance that multi-dimensional feature variables should be selected to present the major characteristics of the circumstances where the lesson are received, these variables can be selected from the International Urban Sustainability Indicators List (IUSIL) (Shen et al., 2011). For example, in the demonstration case, the Yangwu town government must be clear about the scenario it encounters and input accurate values of the selected feature variables, such as gross output value of primary industry, gross output value of tertiary industry, per capita disposable income of permanent residents, resident population, urbanization rate, etc.

Establishing the matching mechanism between the target scenario and all the recorded lesson cases in the database ULD. For establishing the proper matching mechanism, the key issue is to ensure the adequacy of similarity calculation. The calculation in this study is based on the Local-Global method. It is therefore considered that the matching process built in LMS is reliable.

Foreseeing the potential problems and designing proper actions. The mined lesson cases are important references for decision makers to foresee the potential problems from the urbanization practices they are implementing. For example, in the above demonstration, the major problems experienced by the top-three mined cases is related to weak performance of economy, such as low income by township residents in Yaoshan Town and Nanming Town, and less GDP in Dalucao Town. Therefore, it is considered that these problems are likely to occur in the target scenario of Yangwu as well. By referring to the problems in Yaoshan, the government of Yangwu Town should be aware that the low-income problem may lead to serious consequences, such as poverty by the residents, and fiscal deficit by the local government. Furthermore, the lessons received by the mined lesson cases would facilitate Yangwu Town to take proper measures for addressing the problems foreseen in its own town. The lessons received from the top-three mined lesson cases include “Less effective in utilizing local resources endowment, such as tourism resources”, “Ignorance of the quality of agricultural products”, “Ambiguous definition on township industry orientation”, and “Lack of advanced planting techniques”. It is considered that Yangwu Town would be presented with the problem of weak economy if similar kinds of human errors are committed. Therefore, the government of Yangwu Town is advised to implement proper policies in advance, such as enabling the effective utilization of resources endowment, recruiting experts to help famers in agricultural production, attracting talents to assume the role of consultants for making better township planning and adjusting the local industry structure, and developing township jointly with external investors.

6. Conclusions

This paper introduces the Lessons Mining System (LMS) as a new mechanism for foreseeing the potential problems in a specific urbanization practice by referring to the previous lessons learnt. The application of LMS will generate valuable lessons learnt previously thus can support decision-making process in developing better actions for practicing sustainable urbanization. In other words, the decision produced by applying LMS has better quality in producing measures to ensure that the previous problems will not happen again in the on-going practice because that the decision is based on the lessons learnt. Without this lessons-mining mechanism, previous lessons cannot be truly learnt, consequently many problems have been recurring in practice. The demonstration case applied in the paper tells that the system LMS is effective and applicable.

It is considered that the Lessons Mining System (LMS) opens a door to lessons sharing on the problems and failure practices during the urbanization process. And it represents an innovative mechanism in conducting research in the discipline of sustainable urbanization. This mechanism enables to carry out more efficient analysis on a wide range of past lesson practices, thus obtain valuable information to assist decision-makers in formulating better actions to improve the sustainability of the future urbanization practice.

The limitations of LMS in its current stage are implicit in its Urbanization Lessons Database (ULD), including limited number of lesson cases for empirical evidence. It is also appreciated that the outcome in new scenario from applying the solutions generated through the application of LMS cannot be received in short time. It is therefore the intention of this research team to extend the research to empirical study in future.

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