1994 to 2018 is presented in Fig. 5. By statistical analysis, we can attain the matching linear coefficient and $p$-value (coefficient = 0.48, standard error = 0.052, $t$-value = 7.158, $p$-value = $4.67\times10^{-7}$), which indicates a strong relationship between the number of articles and time of publication. Although the absolute quantity of articles is small, it demonstrates an increasing trend, from 1 in 1994 to a maximum of 13 in 2016. This trend indicates the increasing amount of attention the SD in the construction management field received from researchers. Interestingly, a slow growth trend occurred in the first decade 1994–2004, where only one article was published annually, except in 2001. Since 2005, SD has gradually been valued by construction management-related researchers and plays an important role in construction management.

As presented in Table 2, *JCEM*, *IJPM*, and *JME* published the highest number of SD-related articles in the construction management field from 1994 to 2018. *JCEM* published 15 SD-related articles, followed by *IJPM* (11), *JME* (10), *CME* (9), *JCP* (7), and *ECAM* (6). The remaining journals have five or less related articles, with a large number of journals published only one article in the past 25 years. Among all the journals listed in Table 2, SD-related articles published by *JCEM*, *IJPM*, *JME*, and *CME* account for roughly 43%.

### 4.2 Key journals, papers, and their contributions

The top 10 articles sorted by the number of citations per year according to Google Scholar are listed in Table 3. As shown, *IJPM* and *WM* published most of these articles. Although *WM* published only three SD-related articles, two of them are the most cited articles.

As presented in Table 3, several of the most frequently cited papers are related to waste management, construction change, and rework. Specifically, Yuan et al. (2012) proposed an SD model for simulating effects of different waste management strategies on construction and demolition waste reduction. As mentioned in this study, most previous studies usually overlook the interdependent and dynamic natures of the whole waste reduction system. The research provided innovation and contribution in the form of a new perspective for waste management from research methodology. Similarly, Yuan et al. (2011) developed an SD model that can serve as a platform for cost–benefit analysis of waste management. Moreover, SD was applied to analyze difficult-to-quantify social impact issues in waste management (Yuan, 2012).

The articles related to construction change and rework ranked third, seventh, eighth, and tenth. Love et al. (2002) employed an SD model to describe how construction change and rework can impact the project management system. This study was also the first to quantitatively analyze project management with SD. In addition, this research highlighted the importance of identifying project dynamics. Love et al. (2008) presented a forensic management approach on the basis of SD. The SD model developed in their study can determine how and why rework occurs. Motawa et al. (2007), on the other hand, integrated a fuzzy logic-based change prediction model with the SD model. They demonstrated the possibility of combining SD with other research methods. Love et al. (1999) first investigated construction rework on the basis of SD. This study highlighted the causal structure of rework influences. However, this research had explored the relationship among factors affecting project management on the basis of quantitative analysis. Therefore, the most effective rework prevention strategies cannot be identified.

The remaining three articles ranked second, sixth, and ninth. Zhang et al. (2014) developed an improved SD model for the assessment of construction project sustainability. Technological advancement and changes in the public perceptions are considered in the SD model. However, they did not consider the uncertainty of variables in the model. Rodrigues and Bowers (1996) first introduced SD in project management. They mentioned that each element of project is assumed to be isolated, and

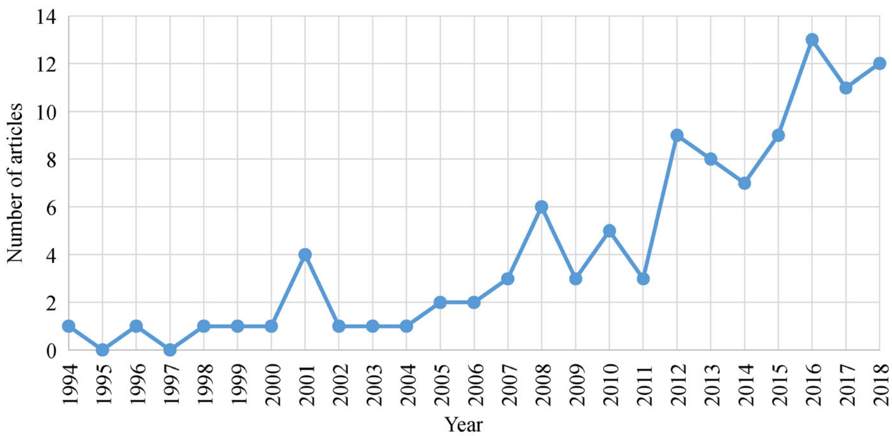


**Fig. 5** Number of SD-based construction management articles published annually from 1994 to 2018.

**Table 2** Number of SD-related articles in the construction management field published in different journals from 1994 to 2018

| Journals | Number |
|---|---|
| *JCEM* | 15 |
| *IJPM* | 11 |
| *JME* | 10 |
| *CME* | 9 |
| *JCP* | 7 |
| *ECAM* | 6 |
| *AC* | 5 |
| *Journal of Computing in Civil Engineering* | 5 |
| *Resources Conservation and Recycling* (*RCR*) | 4 |
| *International Journal of Civil Engineering* | 4 |
| *Safety Science* | 4 |
| *Accident Analysis and Prevention* | 3 |
| *Waste Management* (*WM*) | 3 |
| *Canadian Journal of Civil Engineering* | 2 |
| *Mathematical and Computer Modeling* | 2 |
| *Building and Environment* | 1 |
| *Computer-Aided Civil and Infrastructure Engineering* | 1 |
| *EJOR* | 1 |
| *IEEE Transactions on Engineering Management* | 1 |
| *Interfaces* | 1 |
| *Journal of Civil Engineering and Management* | 1 |
| *Journal of Enterprise Information Management* | 1 |
| *Journal of Environmental Engineering and Landscape Management* | 1 |
| *Journal of Industrial Engineering and Management* | 1 |
| *Journal of Operations Management* | 1 |
| *Journal of Professional Issues in Engineering Education and Practice* | 1 |
| *KSCE Journal of Civil Engineering* | 1 |
| *Production Planning & Control* | 1 |
| *Scientia Iranica* | 1 |
| *Technics Technologies Education Management* (*TTEM*) | 1 |
| Total | 105 |

this assumption made the model distant from the actual project. This study provided an overview of the project management areas that SD can be applied to. Lee et al. (2006b) combined SD model with network-based tools for the dynamic planning and control of construction project. They believed that SD holds the strength in strategic project management, rather than operational project management. Therefore, combining SD with other operational project management methods is necessary for effective project management. Under the guidance of this article, an increasing number of scholars have initiated investigating hybrid modeling.

## 4.3 Critical steps and issues when applying SD

### 4.3.1 Model boundary

The initial step in SD modeling is defining a clear model boundary. Factor or variable identification is the main method for researchers to do so. Factors or variables can be divided into three categories, namely, endogenous, exogenous, and ignored (Ogunlana et al., 2003). Endogenous variables (or factors) are determined by the SD model, whereas exogenous variables (or factors) are determined by the factors outside the SD model. Ignored variables (or factors) can affect the SD model but are not considered according to research aims. Explicitly defining endogenous, exogenous, and ignored variables is important. If the three kinds of variables are confused with one another, SD may fail in achieving the research aims (Sterman, 2000). Literature review, workshop, interview, and specific process are the four methods for researchers to define variables, which are often combined or merged simultaneously.

Statistically, 95 of the 105 reviewed articles have utilized literature review for identifying variables. A total of 23 articles have identified variables on the basis of specific process, 20 articles have conducted interview, and three articles have used workshop. Note that 16 of the 105 articles (15.24%) failed to mention variable identification but directly presented CLD or stock-flow diagram. Although these articles may consider variable identification in model development, they cannot prove that the SD model contains all the important variables. Researchers should elaborate on variable selection for readers to fully understand the model boundary.

### 4.3.2 Model development

In the construction management field, studies using SD have two kinds. One is qualitative analysis, and only CLD is used in this kind of research. For example, Love et al. (1999) used a CLD to determine the causal structure of rework influence. The other is quantitative analysis, which needs data for simulation. 97 of the 105 reviewed articles are quantitative analysis, indicating SD-based research with quantitative analysis is the focus in the construction management field. Regardless of whether the study is a qualitative or quantitative analysis, the CLD should be presented to illustrate the feedback structure of the system. However, 25 of the 105 reviewed articles (23.81%) failed to present the CLD. The most important thing in developing CLD is depicting the interrelations among identified variables. Literature review is the most popular method for studies to develop CLD (42 articles), followed by specific process (23 articles), interview (20 articles), and workshop (3 articles).

In most cases, only one method was applied to develop

**Table 3** Most-frequently cited papers

| Ranking | Author (year) | Journal | Document title |
|---|---|---|---|
| 1 | Yuan et al. (2012) | *WM* | A dynamic model for assessing the effects of management strategies on the reduction of construction and demolition waste |
| 2 | Zhang et al. (2014) | *IJPM* | A prototype system dynamic model for assessing the sustainability of construction projects |
| 3 | Love et al. (2002) | *IJPM* | Using systems dynamics to better understand change and rework in construction project management systems |
| 4 | Yuan et al. (2011) | *RCR* | A model for cost-benefit analysis of construction and demolition waste management throughout the waste chain |
| 5 | Yuan (2012) | *WM* | A model for evaluating the social performance of construction waste management |
| 6 | Rodrigues and Bowers (1996) | *IJPM* | The role of system dynamics in project management |
| 7 | Motawa et al. (2007) | *AC* | An integrated system for change management in construction |
| 8 | Love et al. (1999) | *CME* | Determining the causal structure of rework influences in construction |
| 9 | Lee et al. (2006b) | *AC* | Dynamic planning and control methodology for strategic and operational construction project management |
| 10 | Love et al. (2008) | *TTEM* | Forensic project management: An exploratory examination of the causal behavior of design-induced rework |

CLD. However, complete information cannot be attained by a single method (Sterman, 2000). Future research should draw CLD by using multi-methods. In the process of constructing CLD, researchers must apprehend a clear distinction between causality and correlativity. For instance, although the sales of ice cream and the murder rate are positively correlated, a causal chain from the sales of ice cream to the murder rate cannot be contained in the SD model because temperature leads to correlativity, as shown in Fig. 6. Researchers should ensure that correlativity is non-existent in CLD.

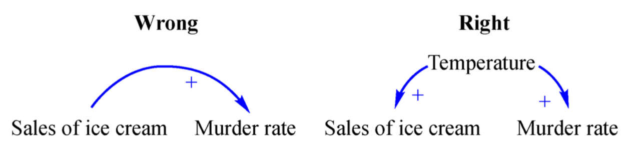


**Fig. 6** Causality and correlativity (Sterman, 2000).

Having defined CLD (structure of system), forming a stock-flow diagram is essential for the SD model to function on computers. Moreover, CLD and the stock-flow diagram are two different versions of the same model (Yuan, 2012). The difference is that the former is constructed in the hope of further understanding the structure of system, while the latter is in equations and computer code, which allows model simulation and quantitative analysis (Coyle, 1996). Therefore, equations and data are the core of a stock-flow diagram. The process of writing equations allows researchers to recognize vague concepts and contradictions that are not considered or discussed in CLD (Sterman, 2000). If researchers possess a deep understanding of the system boundary and the relationships among variables, constructing equations can be effortless. Compared with writing equations, collecting data for the SD model is difficult.

SD models in construction management have two kinds of variables. One is "hard" variable that is available as numerical data (Lee, 2017). The other one is "soft" variable that is descriptive, impressionistic, and has never been recorded (Sterman, 2000; Lee, 2017), such as "effectiveness of regulation execution", "safety awareness", "safety behavior", and so on. For "hard" variables, data can be collected from the real world, such as real projects. In articles conducting quantitative analysis, 95.88% (93 of 97) of studies have collected data from real projects. For "soft" variables, several methods have been used, including interview (85 of 97), questionnaire (9 of 97), on-site visit (11 of 97), and workshop (5 of 97). Given that "soft" variables are difficult to quantify, certain researchers suggest that a Likert-type scale structure can be applied for evaluating the performance of "soft" variables (Yuan et al., 2012; Wang et al., 2015). Evidently, no matter what method is applied, data reliability must be guaranteed. At the present stage, triangulated data sources can be a useful method to increase data reliability (Barratt et al., 2011).

#### 4.3.3 Model testing

According to strict testing standard, an SD model must pass both the model structure and behavior tests. However, certain previous studies focused only on behavior test and ignore the model structure test. Note that the model structure and behavior tests are equally important. The consistency test of model and real system behaviors becomes meaningful only when the confidence of the model structure is established.

Structure tests include direct structure tests and structure-oriented tests. Direct structure tests assess the validity of the model structure by comparing with knowledge on real system structure (Barlas, 1996), whereas structure-oriented tests assess the validity of the model structure by applying behavior tests on model-generated behavior patterns (Senge and Forrester, 1980). Direct structure tests contain structure-confirmation, parameter-confirmation, boundary adequacy, and dimensional consistency tests. The structure-confirmation test compares the causality and feedback of the model with the relationships that exist in the real system (Senge and Forrester, 1980). The parameter-confirmation test indicates the evaluation of the constant parameters against the knowledge of the real system in terms of conceptual and numerical confirmations (Senge and Forrester, 1980). Conceptual confirmation requires the model parameters to correspond with the elements in the real system, whereas numerical confirmation requires the sufficient accuracy of model parameters. The boundary adequacy test verifies whether the model contains all the important variables that affect the research objectives (Sterman, 2000). The dimensional consistency test verifies the right- and left-hand sides of each equation for dimensional consistency (Barlas, 1996).

Structure-oriented tests mainly include three tests. The first is the extreme-condition test, which compares the model-generated behavior with the anticipated behavior of the real system under several extreme conditions (Barlas, 1996; Balci, 1994). The second is the integral error test, which verifies whether the model behavior can change with the change in integration step (Sterman, 2000). The third is the behavior sensitivity test, which identifies the variables to which the model is sensitive by observing the change in model behavior through changing the variables in a reasonable range (Barlas, 1996). A sensitive variable must be highly accurate because its change can have an assignable effect on schedule.

Model behavior tests can then be conducted to measure how accurately the model can reproduce the behavior exhibited by the real system (Barlas, 1996). Numerous methods are used to measure the accuracy of model behavior, including $R$-square, mean absolute difference, mean absolute percentage error, mean square error, and Theil disequilibrium index. Analyzing the difference between model and real system behaviors is more crucial informing readers how accurate the SD model is.

By statistical analysis, the information of the model tests presented in the 97 articles conducting quantitative analysis is presented in Table 4. As shown, considerable existing research has not paid sufficient attention toward structure tests, especially toward integral error test. Due to the lack of historical data, 33 articles failed to conduct behavior test. To validate the SD model, these articles used expertise and literature to support the model. Note that the model test is a continuous process (Sterman, 2000). Researchers should constantly test the SD model to avoid considerable mistakes.

**Table 4** Issues related to SD model test

| Tested item | Number | Percentage (of 97) |
|---|---|---|
| Structure-confirmation test | 50 | 51.55% |
| Parameter-confirmation test | 45 | 46.39% |
| Boundary adequacy test | 47 | 48.45% |
| Dimensional consistency test | 44 | 45.36% |
| Extreme-condition test | 43 | 44.33% |
| Integral error test | 32 | 32.99% |
| Behavior sensitivity test | 44 | 45.36% |
| Behavior test | 64 | 65.98% |

#### 4.3.4 Model simulation

Once researchers have built confidence in the model structure and behavior, the SD model can be utilized to conduct a simulation. Under normal circumstances, SD model simulation is mainly used for designing and evaluating improvement policies and strategies. Among the reviewed articles, 53.61% (52 of 97) focus on policies and strategies simulation. Others concentrate on modeling dynamic performance of the real system (16.49%) and impact analysis (29.90%), which are the basis of policy and strategy simulation. Among the articles conducting such simulations, three articles are related to the structural adjustment of the SD model and six articles consider the combined effects of different policies and strategies. Sterman (2000) stated that policy and strategy designs do not only change model parameters but also create new model structures. In addition, interactions among different policies and strategies should be considered because the impact of comprehensive policies and strategies is not equal to the simple sum of each policy and strategy (Sterman, 2000).

### 4.4 Research topic areas that used SD

On the basis of the outcome of qualitative data analysis, nine topics are identified for the research interests of SD in this paper: (1) sustainable construction (and waste management); (2) design error, rework, and change management; (3) risk management; (4) resource management; (5) decision making, planning, and control; (6) hybrid modeling; (7) safety management; (8) PPP (Public–Private–Partnership) project; and (9) organization performance. The article entitled *The role of system dynamics in project management* is the first paper that systematically expounded the distinctive contribution that SD can provide to project management. This paper is considered critical in construction management and is not included in the nine research topics. The other articles are grouped under different main research topics. Notably, an article may cover more than one research topic. For