AQUA
Water Infrastructure, Ecosystems and Society

 AQUA – Water Infrastructure, Ecosystems and Society Vol 71 No 12, 1408 doi: 10.2166/aqua.2022.150

Research on pipe burst in water distribution systems: knowledge structure and emerging trends

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ABSTRACT

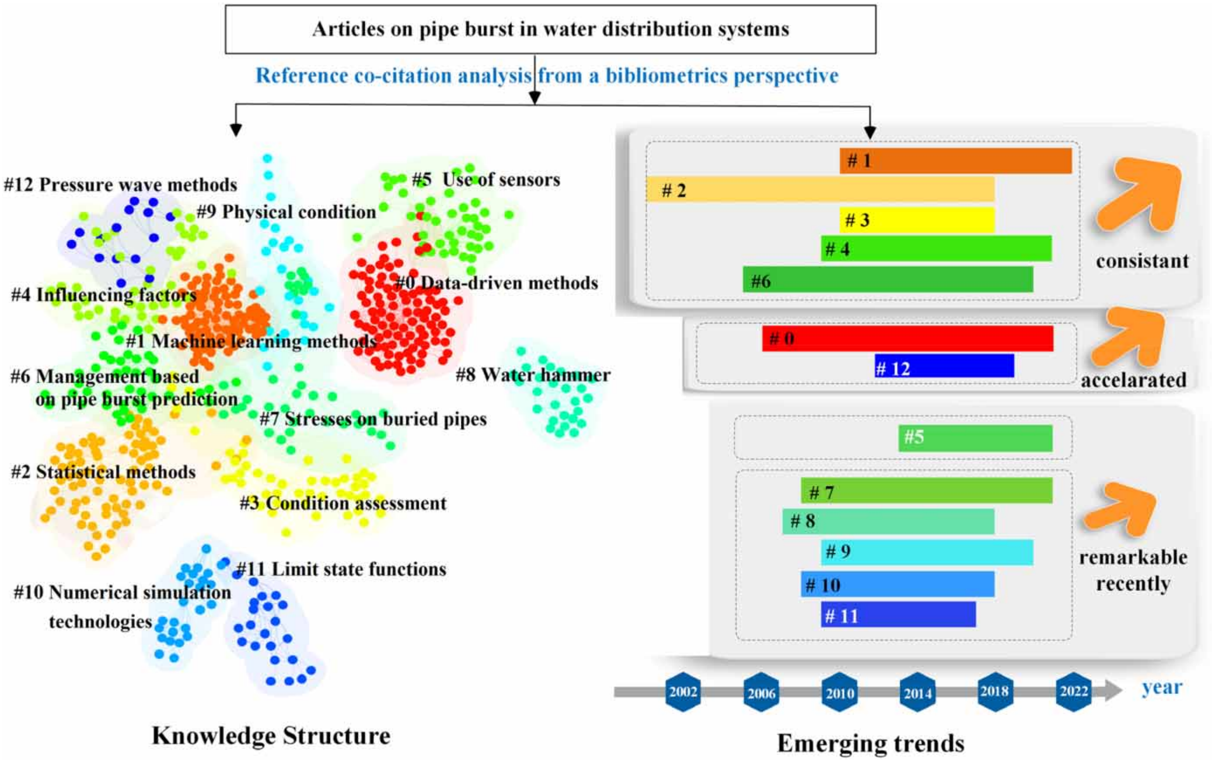
Pipe bursts in water distribution systems (WDSs) lead to large water losses, pollution risks, and public discontent, attracting widespread attention from researchers and water utilities around the world. This study provides insights into the knowledge structure and emerging trends of pipe burst research from a bibliometrics perspective. We used 845 original research and review articles on pipe bursts in the period of January 1991 – June 2022 that cited 16,813 references in the CiteSpace® software for reference co-citation analysis. The results indicate that the knowledge structure of pipe burst research is classified into four categories including pipe burst mechanism, pipe burst detection, pipe burst prediction, and use of sensors. The entire research on pipe bursts advances remarkably. First, pipe burst prediction is the core research category with continuous efforts to improve prediction performance. Second, pipe burst detection is likely to define new research focus to extend existing research focus on pipe burst prediction. Third, computer science and technology are widely and increasingly applied in burst process simulation and data pattern analysis to increase accuracy and effectiveness. This study grasps a full view of current achievements in pipe burst research and provides guidance for future research directions and technological development.

Key words: bibliometrics, emerging trend, knowledge structure, pipe burst, water distribution system

HIGHLIGHTS

- A full view of pipe burst research was provided from a bibliometrics perspective.
- The knowledge structure of pipe burst research consists of 4 research categories and 13 research topics.
- Research on pipe burst advances remarkably, especially in the area of burst prediction.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water distribution systems (WDSs) are municipal infrastructures to supply treated water for the functioning of societies. However, operational and environmental stresses continuously deteriorate water pipes and induce pipe bursts, which lead to large water losses, pollution risks, and public discontent (Rajani & Kleiner 2001; Folkman 2012). Consequently, it is significant to conduct research on pipe bursts in order to take effective measures for burst control in WDSs.

The basic mechanism of pipe bursts has revealed that stresses caused by internal/external loads are larger than pipe residual stresses. The process from pipe burying to pipe burst is often long in terms of time, and complex involving various factors, e.g., manufacturing quality, installation quality, pipe deterioration, temperature, soil condition, etc. Plenty of research articles are published on the process and control of pipe bursts in WDSs, and several review articles summarized the research progress on the mechanism, detection, and prediction of a pipe burst. With regard to the pipe burst mechanism, Rajani & Kleiner (2001) reviewed physical models used to calculate the frost load, total in-plane stress on pipes, pipe residual stress, and remaining wall thickness. Bergant *et al.* (2006) reviewed the research progress of water hammers on phenomenon discovery, danger recognition, numerical method development, and models used in commercial software packages. With regard to pipe burst detection, Li *et al.* (2015) divided burst detection methods into hardware-based and software-based methods and summarized their advantages and disadvantages. Wu & Liu (2017) classified data-driven approaches for pipe burst detection into classification, prediction-classification, and statistical approaches with performance discussion. With regard to pipe burst prediction, Kleiner & Rajani (2001) classified pipe statistical failure prediction models into deterministic and probabilistic models, and summarized governing equations, comparisons, and required data for implementing these statistical models. Nishiyama & Filion (2013) classified pipe failure prediction models into deterministic, probabilistic, and soft computing methods. Since differences exist in the development, adoption, and application of pipe failure prediction models, Scheidegger *et al.* (2015) presented a framework consisting of model assumptions, detailed data assumptions, and distinct types of probabilistic predictions to guide the selection of pipe failure prediction models. The burst consequences of large-diameter pipes are usually more severe and costly. Wilson *et al.* (2017) reviewed both statistical and mechanical failure prediction models for pipes with diameters larger than 500 mm. Dawood *et al.* (2020) reviewed statistical and machine learning models to predict pipe failure published from 2009 – 2019. Barton *et al.* (2019) summarized the factors affecting pipe failure, and provided advice for factor selection to build pipe failure prediction models.

The above reviews provided descriptions, comparisons, and critiques of the approaches to explore pipe burst mechanism, detection, and prediction. However, a comprehensive review of pipe burst research is lacking and the emerging trends in recent years are not summarized. Therefore, we aim to answer the following two questions in this study. (1) What is the knowledge structure of pipe burst research from 1991 to 2022? (2) How does pipe burst research evolve over time? This study can grasp a full view of current achievement pipe burst research and provide guidance for future research directions and technological development.

2. MATERIALS AND METHODS

Bibliometrics quantitatively analyse patterns in the scientific literature to understand the knowledge structure and emerging trends of a research field. CiteSpace®, which can produce visual interfaces in special structures as a bibliometrics software, has been widely used in review articles in various research fields. An effective function of CiteSpace® is reference co-citation analysis. Its basic assumption is that the references often cited together have a stronger bondage than others. They are picked up to form a cluster in which knowledge structure is described and emerging trends can be detected to some extent (Chen *et al.* 2010, 2012).

We input articles on pipe bursts into CiteSpace® (6.1 R3) for reference co-citation analysis. Articles published in the period of January1991 – June 2022 in the Web of Science core collection database with the term 'pipe burst' in titles, abstracts, or indexing terms were collected. Articles relevant to pipe burst, with the keywords 'pipe failure' and 'pipe break', were also included. Then, 845 original research and review articles with a total of 16,813 references were acquired and used in the subsequent analysis.

This study is unique in three aspects. First, the full view of the entire pipe burst research field, which has rarely been discussed, is explored. Second, the dataset to be analysed is constructed using 16,813 references of citation index-based expansion, which is always capable of tracking a more comprehensive development history than only 845 articles by keyword search. Third, the knowledge structure and emerging trends are identified by computer software in an objective manner, and professional opinions in a subjective manner.

3. THE KNOWLEDGE STRUCTURE OF PIPE BURST RESEARCH

The articles on pipe bursts were handled by the function of reference co-citation analysis of CiteSpace®. Figure 1 shows the co-citation network used to characterize the knowledge structure of pipe burst research, in which 13 clusters with sizes no smaller than 15 are demonstrated. Clusters distinguished by CiteSpace® are supposed to be the topics to constitute the knowledge structure of a research field (Chen *et al.* 2010). And those topics belong to four research categories as pipe burst mechanism, pipe burst detection, pipe burst prediction, and use of sensors. The labels of those research categories and topics were generated by professional opinions through the analysis of reference contents.

Detailed information on the 13 clusters of the pipe burst research is shown in Table 1. Size is the number of co-cited references in each cluster. The clusters with larger sizes usually indicate more articles published on these topics and are usually the core topics in the research field. Silhouette reflects the quality of the cluster homogeneity or consistency. All silhouettes of the 13 clusters are larger than 0.7, which is the standard value of high reliability. The mean year is the median publication year of all references in a cluster.

3.1. Pipe burst mechanism

The stresses acting on a pipe in the longitudinal direction are caused by thermal contraction, natural environment, operation, or human impact, while stresses in the transverse direction are caused by operation pressure, water hammer, soil cover load, traffic load, or expansion of frozen moisture (Rajani & Kleiner 2001). If the stresses exceed the limit of pipe residual ultimate strength, a burst would occur. Five clusters (i.e., research topics) are obtained in these research categories as follows.

3.1.1. Water hammer (Cluster 8)

A water hammer is formed by a hydraulic transient shock that was induced by the start-up or shutdown of pumps or valves. Considerable achievements have been reported on the concepts, causes, processes, and hazards of water hammer by

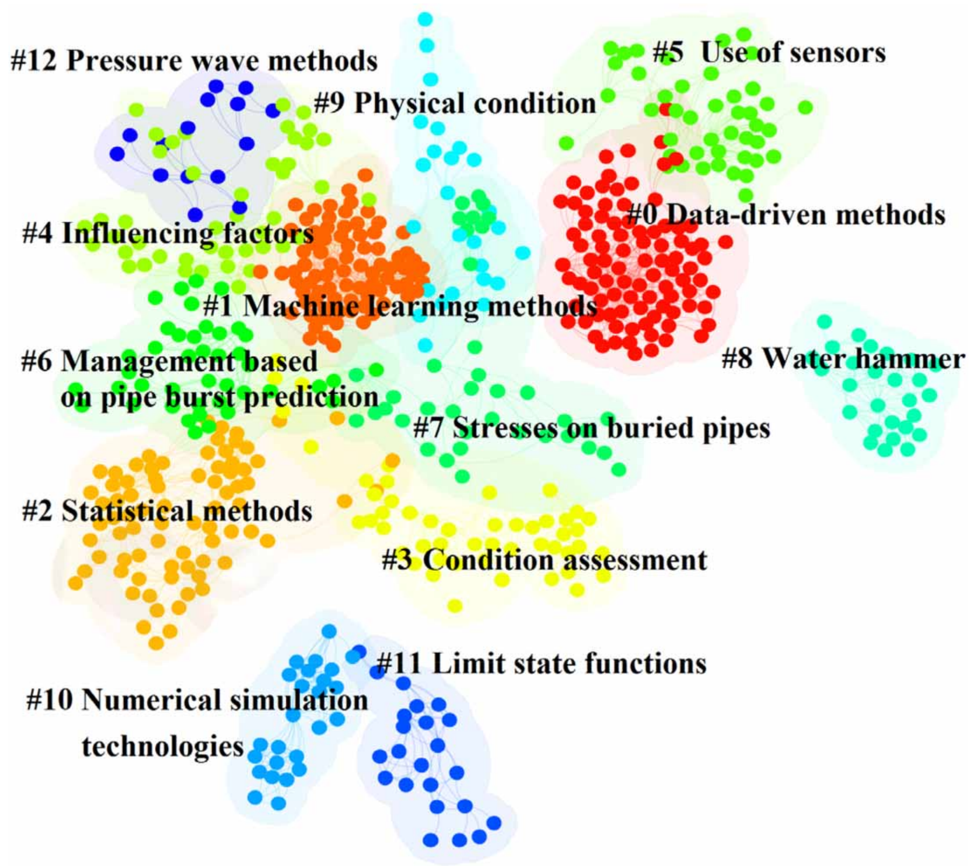


Figure 1 | Clusters of reference co-citation analysis of pipe burst research. Each node represents a reference; node size shows the number of citations; each link between nodes represents a co-citation relationship; and each colour represents a cluster. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/aqua.2022.150.

deducing analytical solutions, developing numerical models, establishing physical models, and formulating field tests (Bergant *et al.* 2006; Riedelmeier *et al.* 2014; Yao *et al.* 2016).

The main hazard of water hammers is pipe bursts due to high pressure. Other hazards, including joint loosening due to impact force and pipe wall erosion due to cavitation, deteriorate pipe physical condition and also increase pipe burst risk. Wang *et al.* (2014) presented a pipe burst risk assessment model based on a water hammer and identified risk factors

Table 1 | Clusters of reference co-citation analysis of pipe burst research

Category	Topic		Cluster ID	Size	Silhouette	Mean year
Pipe burst mechanism	Water hammer		8	27	0.974	2012
	Structural reliability analysis	Stresses on buried pipes	7	38	0.967	2015
		Numerical simulation technologies	10	25	0.999	2013
		Limit state functions	11	23	0.979	2013
	Physical condition		9	26	0.910	2013
Pipe burst detection	Data-driven methods		0	93	0.843	2013
	Pressure wave methods		12	15	0.956	2016
Pipe burst prediction	Machine learning methods		1	81	0.890	2016
	Statistical methods		2	78	0.904	2008
	Condition assessment		3	50	0.883	2014
	Influencing factors		4	45	0.905	2015
	Management based on pipe burst prediction		6	42	0.954	2012
Use of sensors	–		5	44	0.890	2017

such as maximum water pressure, maximum vacuum, maximum vapour volume, and maximum transient force. The relationship between water hammer and pipe burst is complex. Then, an in-depth analysis of the role played by the water hammer in a pipe burst is still required.

3.1.2. Structural reliability analysis (Clusters 7, 10, and 11)

Pipe structural reliability analysis estimates the stresses (e.g., deflection, buckling, and thrust by the pipe-soil system, traffic load, or pressure) acting on the pipe, and limit states of the pipe burst. Cluster 7 focuses on the estimation of stresses on buried pipes (Robert *et al.* 2022). Cluster 10 conducts structural reliability analysis using numerical simulation technologies (e.g., finite-element methods) to understand the pipe burst process (Hajali *et al.* 2016; Alzabeebee *et al.* 2018). Cluster 11 focuses on the construction of limit state functions (Rajani & Abdel-Akher 2012). Novel theories were introduced to measure the mechanical behaviour of stresses and establish burst limit states. Khemis *et al.* (2016) employed the subgrade reaction theory and first-order second-moment method to evaluate the effects of soil and structure properties on pipe critical buckling hoop force. Structural reliability analysis is useful to assess pipe burst risk, but the accuracy is limited due to the difficulty of accurate estimation of stress and pipe residual ultimate strength.

3.1.3. Physical condition (Cluster 9)

A pipe's physical condition deteriorates during its service time, and the deterioration process is influenced by various factors including corrosion, manufacturing techniques, pipe material, operating conditions, and environmental conditions (Rajani & Kleiner 2001). Basic mechanisms of the pipe deterioration process have been revealed such as corrosion growth, development of a crack, change in the pattern of pipe residual ultimate strength, and surface morphology of deteriorated metal pipe (Asadi & Melchers 2017; Wang *et al.* 2018). However, existing pipe deterioration models are not able to accurately simulate the actual complex process of a pipe burst. The pipe condition is difficult to monitor since WDSs are buried underground. Detailed information (e.g., pressure variation due to WDSs operation, temperature variation due to weather, and load variation due to traffic and soil) is not clear enough with existing monitoring technology. Then, the exact pipe physical condition is unavailable, which causes the parameter of laboratory experiments and numerical simulation not completely consistent with the actual situation.

3.2. Pipe burst detection

Pipe burst can be detected by hardware-based, data-driven, and pressure wave methods. Hardware-based methods, including listening rods, leak correlators, ground-penetrating radar, etc., are widely and effectively used worldwide (Li *et al.* 2015). Data-driven and pressure wave methods are the research topics obtained by the reference co-citation analysis and are briefly introduced as follows.

3.2.1. Data-driven methods (Cluster 0)

Data-driven pipe burst detection methods explore normal patterns of hydraulic data (pressure and flow) and distinguish outliers to indicate pipe bursts. According to the analysis object, data-driven methods can be classified into one-point and multi-point methods. One-point methods focus on a specific monitoring site and identify outliers by exploring the time series pattern of hydraulic data (Misiunas *et al.* 2006; Mounce *et al.* 2010; Ye & Fenner 2011; Palau *et al.* 2012; Bakker *et al.* 2014; Romano *et al.* 2014; Laucelli *et al.* 2016; Wu *et al.* 2021; Zhang *et al.* 2022). Multi-point methods analyse numerical relationships of hydraulic data among different monitoring sites and detect abnormal hydraulic relationships based on their topological locations (Farley *et al.* 2013; Kang & Lansey 2014; Wu *et al.* 2016; Zhou *et al.* 2019).

Some typical data-driven pipe burst detection methods are summarized in Table 2, which were confirmed to be effective from validation results and played an increasingly significant role as water supply management tools (Mounce *et al.* 2017). Two technical points require special attention to apply data-driven detection methods. First, an appropriate algorithm is required for data analysis to pick up outliers from hydraulic data. Characters of hydraulic data of diverse WDSs are influenced by factors such as water use habits, network structures, water supply conditions, and so on. Then, selecting the algorithm fit for data pattern analysis is the key technical point for the establishment of a data-driven pipe burst detection method. The second technical point is to reduce false warnings of pipe bursts. Random water use and acquisition fluctuation of sensors cause fluctuations in monitoring data, which may be mistaken for a sign of a pipe burst, and reduce the accuracy and practical value of burst detection methods. Most pipe burst detection methods in Table 2 were applied to DMAs, the hydraulic data patterns of which were simple due to simple network typologies. The reliability of methods was enhanced by testing data

Table 2 | Methods for pipe burst detection

Reference	Hydraulic data	Method	Validation
Zhang *et al.* (2022)	Pressure	One-point analysis: developed decision tree classification model through three pressure burst thresholds in different dimensions.	Validation was carried out in an actual case. The detection accuracy reaches 99.56%, with true positive rate and false positive rate being 96.65% and 0.35%, respectively.
Wu *et al.* (2021)	Flow	One-point analysis: identified high-flow and low-pressure data anomaly by statistical process control methods and deep machine learning.	Validation was carried out in an area with 328 km pipes. Detection rates were 84, 78, and 80% according to leak sizes from large to small.
Zhou *et al.* (2019)	Pressure	Multi-points analysis: compared actual pressure to pressure pattern.	Validation was carried out in a real network with 147 km pipes and 37 of 58 bursts were successfully located.
Wu *et al.* (2016)	Flow	Multi-points analysis: detected outlier by a clustering algorithm and confirmed the cause of abnormal fluctuation.	Validation was carried out in a district metered area (DMA) with a daily water demand of 8,000–11,000 m^3 and an area of 6.5 km^2. All three bursts were detected with a rate of 0.61%. Burst flow ranged from 13.3 to 23.1% of current inflow.
Laucelli *et al.* (2016)	Flow, pressure	One-point analysis: reproduced and predicted a WDS consumption by evolutionary polynomial regression.	Validation was carried out in a DMA with 500 commercial users, 2,640 domestic properties, and a pipe length of 24 km. The method was effective in detecting the presence of a large leak.
Kang & Lansey (2014)	Flow, pressure	Multi-point analysis: matched observation data with developed burst sensitivity tables.	Validation was carried out in a network constructed by EPANET* with 18 pipes, 9 nodes, 2 reservoirs, and 2 storage tanks. All two bursts simulated by applying emitter discharge coefficient at nodes were detected.
Romano *et al.* (2014)	Flow, pressure	One-point analysis: identified/ estimated significant discrepancies between observed and predicted data.	Validation was carried out in DMAs with residential properties between 409 to 3493 Twenty-nine out of 30 real-life bursts were detected, with a rate of 8%.
Bakker *et al.* (2014)	Flow, pressure	One-point analysis: analysed deviations between observed and predicted data.	Validation was carried out in three DMAs with connections of 130,920, 11,180 and 650 as well as detection probabilities of 7.8, 25.9, and 50.0%, respectively.
Farley *et al.* (2013)	Pressure	Multi-points analysis: calculated the sensitivity of potential pressure-instrument locations to leaks at different locations.	Validation was carried out in four DMAs with eight pipe burst events (simulated by hydrant openings), and six were detected.
Palau *et al.* (2012)	Flow	One-point analysis: synthesized information into a statistical model using principal-component analysis.	Validation was carried out in a DMA with 2,900 residential properties. The detection probability of a burst with approximately 5% of the average flow was between 30 and 95% depending on occurrence time.
Ye & Fenner (2011)	Flow, pressure	One-point analysis: used residual of Kalman filter to represent the amount of abnormal water use.	Validation was carried out to flow data of 10 DMAs and pressure data of four DMAs. The residuals of pressure were less sensitive to pipe burst events.
Mounce *et al.* (2010)	Flow	One-point analysis: compared observed and predicted data over time windows.	Validation was carried out to analyse 144 DMAs for 2 months, and 85% of alerts were related to some events.
Misiunas *et al.* (2006)	Flow	One-point analysis: detected increase in the inlet flow rate using modified cumulative sum.	Validation was carried out in a DMA with 108 pipes and 79 nodes. Five burst events with sizes between 5 and 20 L/s and duration from 1 to 8 min were detected.

*EPANET is a hydraulic solver for water distribution systems developed by the United States Environmental Protection Agency.

mean variation during a particular time (e.g., from midnight to 4 am) (Romano *et al.* 2014) or defining burst thresholds in different dimensions (Zhang *et al.* 2022).

Data-driven methods can detect pipe bursts by online pressure/flow data analysis, which is of low cost and used to trace historical conditions compared to hardware-based and pressure wave methods. Under the extensive construction of online hydraulic data acquisition systems, novel algorithms for data pattern analysis are continuously led into this research topic. Data-driven pipe burst detection methods show good development and application future.

It is worth noting that attention should be paid to the applicable conditions of data-driven methods. Specific instructions on the requirements of monitoring points, monitoring data characteristics, and the structure and scale of water distribution system should be given. It is helpful to speed up the application of pipe burst detection methods and to give guidance for other researchers to improve the existing methods.

3.2.2. Pressure wave methods (Cluster 12)

Pipe burst affects the transient trace of pressure wave, and additional reflections can be potentially used for pipe burst detection and localization (Chaudhry 2014; Rathnayaka *et al.* 2016). Colombo *et al.* (2009) summarized three types of methods for the identification and quantification of unusual pressure waves to indicate pipe bursts. The first was inverse-transient techniques that compared measured pressure waves between normal and burst conditions in the time domain. The second was frequency-domain techniques that utilized the changes in the frequency response of pressure waves to pipe bursts. The third was a direct transient analysis that aimed to isolate burst-induced unusual pressure waves in pressure trace. Pressure wave analysis is effective in detecting and locating pipe bursts, but has great limitations in practical use to real WDSs. The main reason is the huge investment in high-frequency pressure sensors.

3.3. Pipe burst prediction

The pipe burst process is complex due to randomly changing operation conditions (pressure, temperature, traffic load, etc.). However, it is feasible to predict the burst frequency of a pipe or burst rate of a WDS using appropriate prediction methods with project-acceptable accuracy. Five clusters (i.e., research topics) are obtained in this category as follows.

3.3.1. Condition assessment and influencing factors (Clusters 3 and 4)

Pipe condition assessment is to evaluate if a pipe can perform its function through analysis of relative physical, environmental, and operational factors (Grigg 2006). Physical factors include pipe age, diameter, pipe material, pipe vintage, wall thickness, dissimilar metals, type of joints, pipe lining and coating, and manufacturing processes. Environmental factors include groundwater presence, soil type, soil moisture, climate, pipe bedding, pipe location, trench backfill materials, stray electrical currents, seismic activity, and underground disturbances. Operational factors include water quality, water pressure, backflow potential, leakage, flow velocity, and operational and maintenance practices. Various methods have been used to calculate factor weights, such as assignment (Alegre *et al.* 2006), ANN (Al-Barqawi & Zayed 2006), and the Bayesian theory (Wang *et al.* 2010). Pipe condition assessment is useful for maintaining acceptable levels of service and providing appropriate maintenance plans. The American Society of Civil Engineers determines grades of the national WDSs every 4 years according to the actual condition and required investment (ASCE 2017).

Relationships between factors and their relative contributions to pipe burst are distinctive for different pipe materials, buried geographic region, and operation conditions (Barton *et al.* 2019). It is impossible and unnecessary to use all these relative factors in order to develop pipe burst prediction models. Therefore, proper factors as input parameters of the prediction models need to be determined first. Asnaashari *et al.* (2009) found pipe length and buried depth were the main factors for bursts in ductile iron and polyethylene pipes, and pipe wall thickness was one of the main factors for bursts in ductile iron pipes. Wols *et al.* (2019) proposed that pipe burst rates were higher for cast iron pipes at low temperatures and asbestos-cement pipes at high temperatures. With the in-depth study of the pipe burst mechanism, factors like diameter, material, temperature, etc. are more and more considered to develop pipe burst prediction models, which is helpful for the improvement of burst prediction accuracy.

3.3.2. Pipe burst prediction using machine learning methods (Cluster 1)

Machine learning methods automatically predict data tendencies using computers through experience (Jordan & Mitchell 2015). Breiman (2001) proposed the goal of machine learning was to improve prediction accuracy, which belongs to the algorithm modelling culture. Machine learning methods have advantages in pipe burst prediction owing to their self-learning to describe complex, distributed, and nonlinear systems and showed more reliable prediction accuracy or labor-saving than statistical pipe burst prediction models in some cases (e.g., Xu *et al.* 2011). Under the development of WDS information, construction, operation, physical, and environment data of WDSs have been greatly enriched, which provide preferential conditions of adequate and precise pipe burst record and factor data to apply machine learning methods. A large number of machine learning methods, such as genetic programming (Xu *et al.* 2011), Artificial Neural Network (ANN) (Tabesh *et al.* 2009; Jafar *et al.* 2010; Kutylowska 2015), boosted decision tree approach (Winkler *et al.* 2018), and evolutionary polynomial regression (EPR) (Berardi *et al.* 2008), are increasingly used to predict pipe burst in WDSs as efficient tools.

This kind of method skips mechanistic constraints and provides an effective and novel route for pipe burst research. However, they are highly dependent on monitoring data with noise, which need a burst mechanism to support model development (e.g., factor selection) and accuracy improvement.

3.3.3. Pipe burst prediction using statistical methods (Cluster 2)

Statistical methods can establish relationships between the pipe burst frequency (time) of an individual pipe or burst rate of a whole network and influencing factors. The statistical methods include Weibull distribution, Herz distribution, exponential regression, lognormal distribution, and time-linear regression, etc. (Scheidegger *et al.* 2015). They can be categorized into deterministic and probabilistic models. Deterministic models capture a definite burst pattern, and probabilistic models process pipe factor data to derive pipe burst likelihoods (Kleiner & Rajani 2001).

Statistical models have been applied to guide maintenance plans and future budgets as an effective burst control technique (Clair & Sinha 2012; Scheidegger *et al.* 2015). However, their accuracy is not very high generally, especially for individual pipes. Statistics derive empirical regularity of pipe burst frequency/time and make subsequent predictions based on the information of input factors. Model input factors cannot completely cover all influencing factors, since the existing monitoring system is incapable to collect the condition of all relative factors (e.g., pipe wall thickness). This demerit can be improved with the development of monitoring systems. Furthermore, there is the uncertainty of the pipe deterioration process due to random variations in operation and burial conditions. It is difficult to accurately predict pipe burst time even if the entire situation of a pipe is clear at present. This demerit can be improved with the introduction of novel methods to eliminate random variations. Consequently, there are common discrepancies between statistically derived predictions and the actual condition of an individual pipe. And burst prediction rate of a whole WDS usually has higher accuracy, since a large number of pipe samples can effectively reduce the impact of the randomness of an individual pipe sample. On the whole, pipe burst prediction using statistical methods is successful in the analysis of pipe burst trends, but there is still room for further improvement in accuracy.

3.3.4. Management based on pipe burst prediction (Cluster 6)

Water utilities face the challenge of how to optimize the maintenance plan of WDSs with limited funds. Pipe burst prediction helps address this challenge by identifying specific pipes that have high burst risk and need maintenance in priority positions (Kleiner & Rajani 2010). A number of systems, including pipeline asset and risk management systems (Burn *et al.* 2003) and KANEW software (Herz 1998), have been developed to formulate maintenance plans based on pipe burst prediction. With the development of water supply industry, it is of more interest to establish multi-objective maintenance plans. In addition to the aim of pipe burst reduction, the objectives of water quality safety, reasonable budget, and energy reduction are also incorporated by determining inspection interval, pipe replacement subsequence, and appropriate maintenance technologies (Prosser *et al.* 2015; Romaniuk 2018). The establishment of a maintenance plan for a WDS becomes more systemic and incorporated.

3.4. Use of sensors (Cluster 5)

Sensors collect hydraulic data of WDSs, forming the basis to comprehend the operation condition of WDSs. The design for use of sensors includes sensor installation position, construction convenience, sensor monitoring scope, investment, data storage convenience, and usable mode for data input and output. A certain number of research articles have studied the above areas for different WDSs in Cluster 5 (Simone *et al.* 2016; Qi *et al.* 2018). With the development of sensor manufacturing technologies and increasing requirements due to the construction of smart WDSs (Laramee *et al.* 2018), the depth and width of use of sensors continuously develop on how to use sensors to obtain precise and sufficient operating data in economical ways.

3.5. Distribution of authors and institutions

An overview of authors and institutions was obtained from our dataset. Twenty-four authors and 22 institutions who published most articles on pipe burst are shown in Figures 2(a) and 2(b), respectively. Nodes represent the authors or institutions. Node size is linearly related to the number of published articles in this area, and node colour represents the publishing year. The links between nodes represent the co-publishing relationships with link width representing the number of co-publishing articles and colour representing the publishing year. For the authors, Jayantha Kodikara, Chunqing Li, and Dragan Savic take the first three places, publishing 20, 18, and 17 articles, respectively. For the institutions, Exeter University has the largest number of 32 articles on pipe burst, followed by Monash University with 22 articles, and RMIT University with 21 articles. It can be seen that the links connecting to institutions and authors with most publications are generally more and wider, meaning that they have more collaborations. It should be noted that our analysis is based on the dataset of 845 articles with the keywords pipe burst, pipe failure, and pipe break published from January 1991 to June 2022 and the results are just valid for this situation. Different results may be obtained using datasets created by searching different keywords or for different periods.

4. EMERGING TRENDS OF PIPE BURST RESEARCH

We probed the emerging trends of pipe burst research through five indicators, namely the evolution of the clustering network, evolution of each cluster, references with high citation rates, references with the strongest citation bursts, and references with high betweenness centrality.

4.1. Evolution of clustering network

The annual number of articles published in pipe burst research was low and steady before 2007 but increased sharply since then (Figure 3), which indicates the development of pipe burst research.

We input articles on pipe bursts into CiteSpace® during different periods that began in 1991 and ended in 2016, 2017, 2018, 2019, 2020, and 2021, respectively, and clustering networks by reference co-citation analysis are shown in Figure 4. From 1991 to 2016, a total of six clusters were obtained, which belonged to three research categories of pipe burst mechanism (Clusters 7, 8, and 10), pipe burst detection (Cluster 0), and pipe burst prediction (Clusters 2 and 6). The co-citation clustering network continuously grew in two ways until 2022.

One way is the emergence of new clusters (research topics), which indicates the development of research width. New emerging topics in pipe burst mechanism include physical conditions (Cluster 9) and limit state functions (Cluster 11), which help to understand and simulate the pipe burst processes. A new emerging topic in pipe burst detection is the pressure wave method (Cluster 12), which extends the research width of pipe burst detection. New emerging topics in pipe burst prediction include machining learning method (Cluster 1) and influencing factors of pipe bursts (Cluster 4), which improve prediction accuracy. A new emerging research category is the use of sensors (Cluster 5) to acquire hydraulic data. The research contents

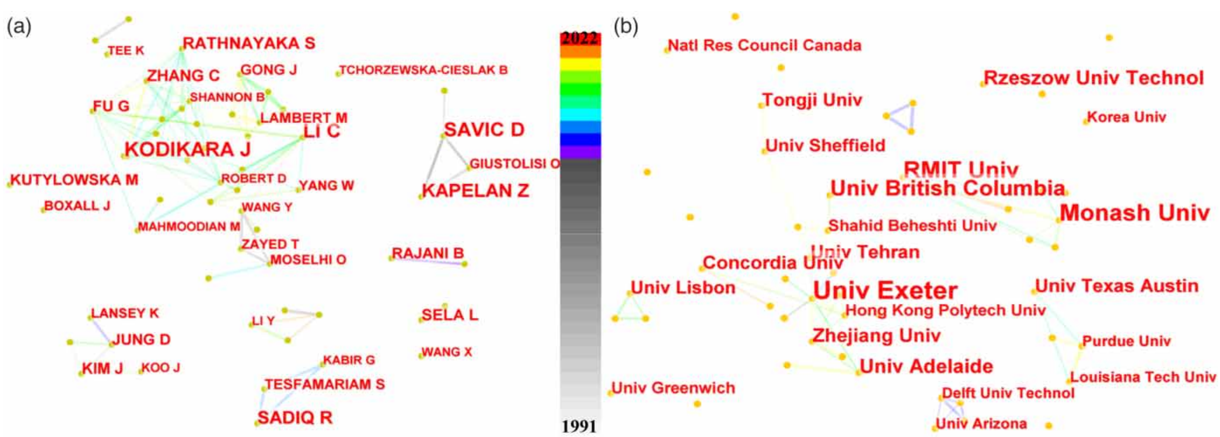


Figure 2 | (a) Authors and (b) institutions with most publications on pipe burst and their co-publishing relationships.

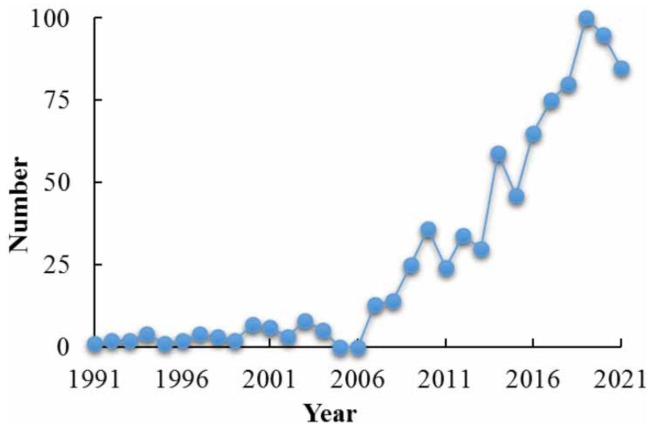


Figure 3 | Annual number of articles published in pipe burst research from 1991 to 2021.

of those new emerging clusters mainly aim to improve the effectiveness and accuracy of burst simulation, prediction, and detection.

The other way is the cluster size increase, which indicates the continuous expansion of related research topics in research depth. Cluster 0 had the biggest size increase compared to the other clusters, which indicates the research depth expansion of data-driven pipe burst detection. The evolution of clustering network provides additional visual aids to identify changes between adjacent years in a flexible way, which helps new researchers to find the research hotspots.

4.2. Evolution of each cluster

Figure 5 shows the timeline visualization of pipe burst research that how the co-citation clustering network is split into clusters. The vertical axis represents the clusters to which the node (reference) belongs, while the horizontal axis represents the reference publication time. Node on the horizontal axis represents landmark reference of each cluster. Node size is linearly related to citation number of the references. Node colour represents the year of citation occurrence. The links between nodes represent the co-citation relationship, while the colour represents the year of the first co-citation occurrence.

All clusters show bright development trends indicated by the recently appearing nodes. For the clusters in pipe burst detection (Cluster 0) and pipe burst prediction (Clusters 1, 2, and 6), the research is deeper and more systematic indicated by more landmark references and co-citation relationships than other clusters. Other clusters (Clusters 3, 4, and 12) in those two categories are under sustainable development indicated by persistent landmark references and co-citation relationships over the timeline. The categories of pipe burst mechanism (Clusters 7, 8, 9, 10, and 11) and the use of sensors (Cluster 5) have a short history and weaker systematicness indicated by shorter horizontal axis length, less landmark references, and less co-citation links. But those clusters have attracted research attention recently indicated by their considerable co-citation relationships among nodes in recent years.

4.3. Special references

Table 3 lists 10 references with high citation rates of the dataset in our study. Seven references are in the category of pipe burst prediction (Berardi *et al.* 2008; Clair & Sinha 2012; Li & Mahmoodian 2013; Kabir *et al.* 2015; Scheidegger *et al.* 2015; Wilson *et al.* 2017; Winkler *et al.* 2018). Three references are in the category of pipe burst detection (Mounce *et al.* 2010; Ye & Fenner 2011; Romano *et al.* 2014). It indicates those two categories obtained more attention in pipe burst research.

Table 4 lists 20 references with the strongest citation bursts of the dataset in our study. Citation burst analysis whether the citation of a reference has statistically significant fluctuations within 1991 to 2022. References with the strongest citation bursts suggest the activeness of relating research topics and the values of their strength indicate burst intensity (Chen *et al.* 2010, 2012). From 2007 to 2013, nearly all the references with the strongest citation bursts were in the category of pipe burst prediction. Two references used statistical methods to predict pipe burst (Pelletier *et al.* 2003; Yamijala *et al.* 2009), three references used machine learning methods to predict pipe burst (Berardi *et al.* 2008; Tabesh *et al.* 2009; Jafar *et al.* 2010), two references were on maintenance based on pipe burst prediction (Davis *et al.* 2008; Kleiner & Rajani

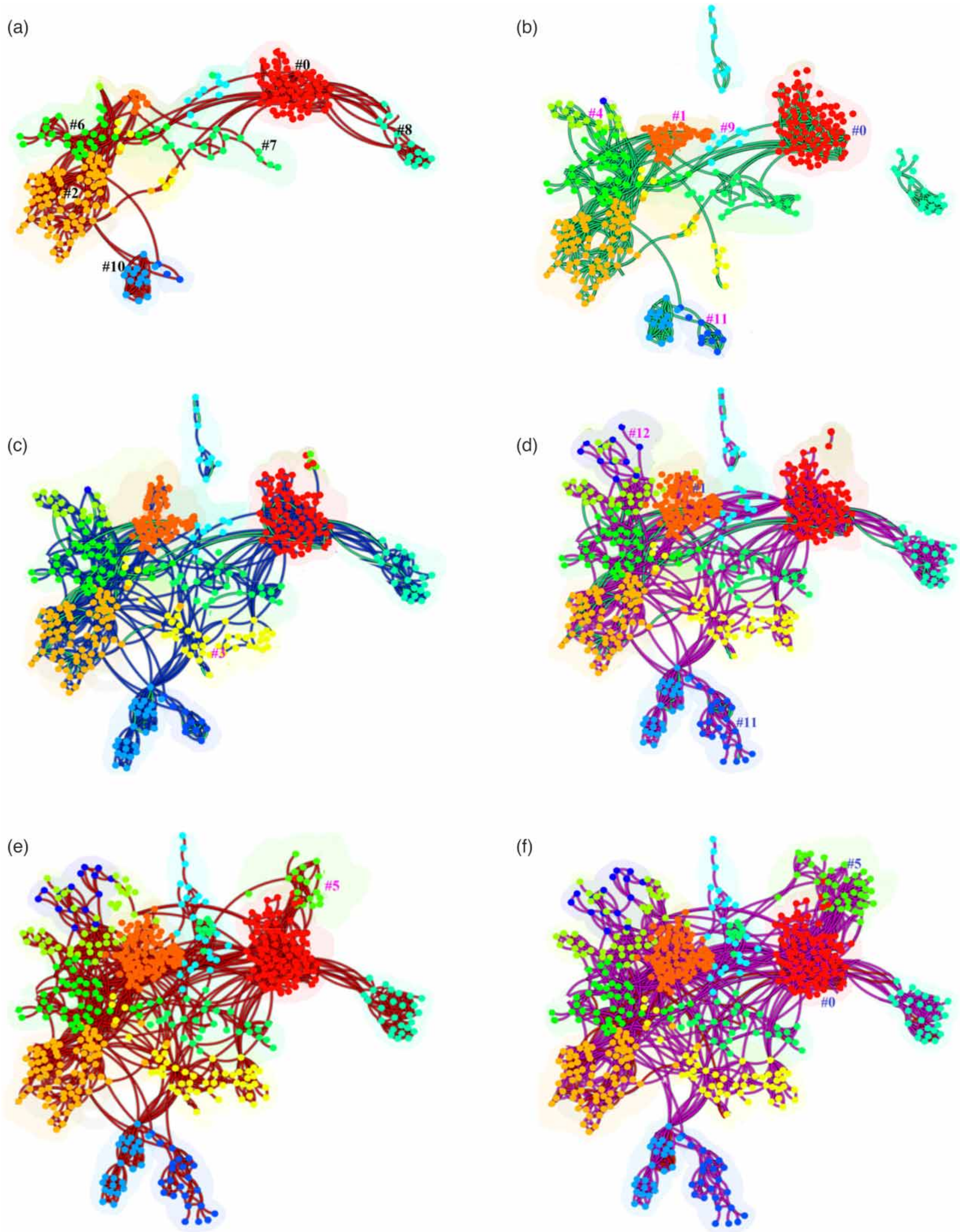


Figure 4 | Reference co-citation analysis of pipe burst research during different periods that began in 1991 and ended in (a) 2016, (b) 2017, (c) 2018, (d) 2019, (e) 2020, and (f) 2021. Purple label represents new emergence of the cluster, and blue label represents size increase of the cluster. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/aqua.2022.150.

2010), and one reference identified the predominant factors influencing asbestos-cement pipe burst (Hu & Hubble 2007). From 2014 to 2018, five references with the strongest citation bursts were in the category of pipe burst detection, which used the methods of the modified cumulative sum (Misiunas *et al.* 2006), transient-based detection (Colombo *et al.* 2009), principal-component analysis (Palau *et al.* 2012), artificial intelligence system (Mounce *et al.* 2010), and Kalman filtering

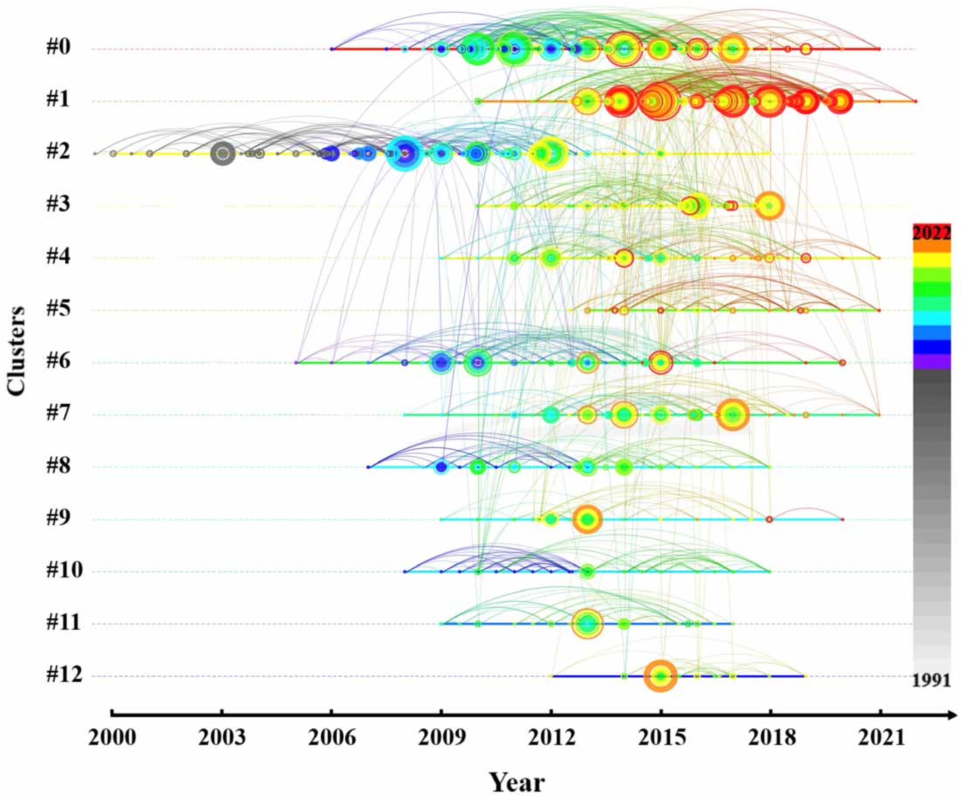


Figure 5 | Timeline visualization of co-citation clusters.

(Ye & Fenner 2011) to distinguish abnormal hydraulic data. From 2019 to 2022, four references were in the category of pipe burst prediction (Wilson *et al.* 2017; Winkler *et al.* 2018; Sattar *et al.* 2019; Snider & McBean 2020). To sum up, pipe burst prediction has always been a research hotspot and pipe burst detection also obtained research focus recently.

The betweenness centrality of a node measures the importance of the position in the co-citation network, which is a measure relating to the transformative potential of a scientific contribution. Nodes with high betweenness centrality

Table 3 | References with high citation rates (1991–2022)

Reference	Citation counts
Automated detection of pipe bursts and other events in water distribution systems (Romano *et al.* 2014)	27
Development of pipe deterioration models for water distribution systems using EPR (Berardi *et al.* 2008)	26
Statistical failure models for water distribution pipes-A review from a unified perspective (Scheidegger *et al.* 2015)	26
State-of-the-technology review on water pipe condition, deterioration and failure rate prediction models (Clair & Sinha 2012)	24
State-of-the-art review of water pipe failure prediction models and applicability to large-diameter mains (Wilson *et al.* 2017)	23
Pipe failure modelling for water distribution networks using boosted decision trees (Winkler *et al.* 2018)	23
Evaluating risk of water mains failure using a Bayesian belief network model (Kabir *et al.* 2015)	22
Development and verification of an online artificial intelligence system for detection of bursts and other abnormal flows (Mounce *et al.* 2010)	22
Kalman filtering of hydraulic measurements for burst detection in water distribution systems (Ye & Fenner 2011)	22
Risk based service life prediction of underground cast iron pipes subjected to corrosion (Li & Mahmoodian 2013)	21

Table 4 | References with the strongest citation bursts (1991–2022)

Reference	Strength	Lasting duration	
		From	To
Modelling water pipe breaks – three case studies (Pelletier *et al.* 2003)	9.5	2008	2011
Failure monitoring in water distribution networks (Misiunas *et al.* 2006)	4.5	2010	2014
Development of pipe deterioration models for water distribution systems using EPR (Berardi *et al.* 2008)	11.5	2011	2016
Factors contributing to the failure of asbestos-cement water mains (Hu & Hubble 2007)	5.2	2011	2015
Statistical models for the analysis of water distribution system pipe-break data (Yamijala *et al.* 2009)	4.9	2011	2017
Failure prediction and optimal scheduling of replacements in asbestos-cement water pipes (Davis *et al.* 2008)	4.7	2012	2016
Assessing pipe failure rate and the mechanical reliability of water distribution networks using data-driven modelling (Tabesh *et al.* 2009)	6.9	2013	2015
I-WARP: individual water main renewal planner (Kleiner & Rajani 2010)	5.8	2013	2015
Application of artificial neural networks (ANN) to model the failure of urban water mains (Jafar *et al.* 2010)	5.1	2013	2017
A selective literature review of transient-based leak detection methods (Colombo *et al.* 2009)	4.8	2013	2016
A review of methods for leakage management in pipe networks (Puust *et al.* 2010)	6.4	2014	2017
Development and verification of an online artificial intelligence system for detection of bursts and other abnormal flows (Mounce *et al.* 2010)	6.2	2014	2018
Burst detection in water networks using principal-component analysis (Palau *et al.* 2012)	6.0	2014	2017
Kalman filtering of hydraulic measurements for burst detection in water distribution systems (Ye & Fenner 2011)	4.8	2014	2018
Watermain break rates in the USA and Canada: a comprehensive study (Folkman 2012)	7.5	2015	2017
Watermain break rates in the USA and Canada: a comprehensive study (Folkman 2018)	5.2	2019	2022
Extreme learning machine model for water network management (Sattar *et al.* 2019)	6.2	2020	2022
Pipe failure modelling for water distribution networks using boosted decision trees (Winkler *et al.* 2018)	5.9	2020	2022
Improving urban water security through pipe-break prediction models: machine learning or survival analysis (Snider & McBean 2020)	4.5	2020	2022
State-of-the-art review of water pipe failure prediction models and applicability to large-diameter mains (Wilson *et al.* 2017)	4.5	2020	2022

scores are always highly connected to other nodes or positioned between different clusters (Chen *et al.* 2012). Table 5 shows seven references with high betweenness centrality (no less than 0.10) of the dataset in our study. It indicates pipe burst prediction and pipe burst detection contribute more to establishing connections among the knowledge structure and tend to be more systemic in our defined area of pipe burst research.

Table 5 | References with high betweenness centrality (1991–2022)

Reference	Centrality	Category
Reliability indicators for water distribution system design: comparison (Atkinson *et al.* 2014)	0.13	Pipe burst prediction
Application of artificial neural networks (ANN) to model the failure of urban water mains (Jafar *et al.* 2010)	0.11	
State-of-the-art review of water pipe failure prediction models and applicability to large-diameter mains (Wilson *et al.* 2017)	0.10	
State-of-the-technology review on water pipe condition, deterioration and failure rate prediction models! (Clair & Sinha 2012)	0.10	
Water distribution system burst detection using a nonlinear Kalman filter (Jung & Lansey 2015)	0.11	Pipe burst detection
Leakage fault detection in district metered areas of water distribution systems (Eliades & Polycarpou 2012)	0.10	
Reliability analysis of buried flexible pipe-soil systems (Babu & Srivastava 2010)	0.11	Pipe burst mechanism

5. CONCLUSIONS

This study shows that the knowledge structure of pipe burst research is classified into four categories as pipe burst mechanism, pipe burst detection, pipe burst prediction, and use of sensors. The entire pipe burst research is progressing remarkably, and computer science and technology show an important supporting role. The whole research tends to improve the effectiveness and accuracy of pipe burst prediction, detection, and simulation. Pipe burst mechanism and the use of sensors obtain remarkably increasing attention recently. Pipe burst detection has been attracting increasing attention with broad application prospects. Pipe burst prediction experiences deep and systematic research development, and provides evidence-based management suggestions for WDSs.

Reference co-citation analysis explores the evolution process of a discipline system from the perspective of citation relationships among articles, which is difficult to obtain through direct observations of researchers in a statistical manner. However, the process of discipline evolution is often characterized by multiple and heterogeneous components, complex structural relationships, and a variable and unpredictable external environment. Overdependence on co-citation analysis may lead to one-sided conclusions. Subjective understanding and judgement are still highly demanded for the analysis of knowledge structure and emerging trends.

ACKNOWLEDGEMENTS

This work was supported by the Ministry of Science and Technology of China (2019YFD1100105), the National Natural Science Foundation of China (52170105), and the Youth Innovation Promotion Association of the Chinese Academy of Sciences (2019043).

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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First received 24 August 2022; accepted in revised form 3 November 2022. Available online 16 November 2022