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A SCIENCE MAPPING APPROACH BASED REVIEW OF MODEL PREDICTIVE CONTROL FOR SMART BUILDING OPERATION MANAGEMENT

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Abstract. Model predictive control (MPC) for smart building operation management has become an increasingly popular and important topic in the academic community. Based on a total of 202 journal articles extracted from Web of Science, this study adopted a science mapping approach to conduct a holistic review of the literature sample. Chronological trends, contributive journal sources, active scholars, influential documents, and frequent keywords of the literature sample were identified and analyzed using science mapping. Qualitative discussions were also conducted explore in details the objectives and data requirements of MPC implementation, different modeling approaches, common optimization methods, and associated model constraints. Three research gaps and future directions of MPC were presented: the selection and establishment of MPC central model, the capability and security of processing massive data, and the involvement of human factors. This study provides a big picture of existing research on MPC for smart building operations and presents findings that can serve as comprehensive guides for researchers and practitioners to connect current research with future trends.

Keywords: model predictive control (MPC), building operation management, science mapping, literature review.

Introduction

Buildings constitute one of the largest sectors of energy consumption and account for 20–40% of energy usage in the world (Pérez-Lombard et al., 2008). In the meanwhile, buildings also serve as one of the most important infrastructures that influence human lives by providing a comfortable living environment, especially considering the large amount of time for human indoor activities (US Environmental Protection Agency [EPA], 1989). It poses challenges in building operations to both create a comfortable indoor environment for occupants and maintain building energy efficiency, because managing the indoor space to be in optimal conditions is usually energy-consuming. Furthermore, the increasing penetration of renewable energy also introduces new requirements in building operations, which are critical to support the future smart grid with improved system integration and resilience (Pazheri et al., 2014).

To support smart building operation, the model predictive control (MPC) arises as one of the most promising building technologies and continuously grows with increasing attention from both the academic community and industry experts these years (Hilliard et al., 2016). Specifically, the MPC is the control technique that utilizes central models to forecast future building status with different control signals and solves optimization to generate optimal building control sequence for predictive control under user-specified constraints (Serale et al., 2018). As the key components of MPC, central models usually require measured system status (e.g., indoor temperature) and forecasted disturbance (e.g., outdoor weather, occupant activity) as inputs (Zhan & Chong, 2021). Thanks to the wide adoption of sensing techniques and building management systems, continuous stream of sensing data further empowered the development of MPC to be mature and applicable with consistent and satisfactory performance in practice. Employed as the supervisory control of buildings, MPC has been developed and applied to achieve smart building operation with various purposes, such as improved energy efficiency and thermal comfort (Yang et al., 2020), demand response to support reliable

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grid operation (Bianchini et al., 2016), and a healthy living environment for occupants (Ganesh et al., 2019). MPC has become a critical component for enhanced building intelligence.

Given the increasing popularity of MPC for smart building operation management, previous researchers have conducted various qualitative reviews in this field. Serale et al. (2018) summarized the formulation of MPC and Afram and Janabi-Sharifi (2014) investigated principles and influential settings in MPC application. Other works summarized the MPC technique for smart building operation management from various detailed technical perspectives, such as usable models in MPC (Rockett & Hathway, 2017), optimizations in MPC development (Mariano-Hernández et al., 2020), data requirements and incorporation in MPC setup and formulation (Zhan & Chong, 2021; Mirakhorli & Dong, 2016), and AI-support MPC (Merabet et al., 2021). In addition to technology, researchers have also summarized relevant works from purpose perspectives, including for building-integrated microgrids operations (Fontenot & Dong, 2019), for renewable energy (Sultana et al., 2017), and for building energy flexibility (Kathirgamanathan et al., 2021).

These previous reviews (Afram & Janabi-Sharifi, 2014; Rockett & Hathway, 2017; Mariano-Hernández et al., 2020; Mirakhorli & Dong, 2016; Merabet et al., 2021; Fontenot & Dong, 2019; Sultana et al., 2017; Kathirgamanathan et al., 2021) have made valuable contributions to the current body of knowledge, but they are manual and qualitative reviews. Few works have adopted a scientometric analysis approach to conduct a systematic review. Additionally, none of them has utilized any graphic representation to discover the inherent relationships among those research works. Motivated by the fact that humans present strong visual processing abilities and are therefore better at discovering domain knowledge when it is presented in graphical forms (Felizardo et al., 2011; Keim, 2002), we utilized a science mapping approach to conduct a review of MPC for smart building operation management to complement existing qualitative reviews.

This paper is organized as follows. Section 1 outlines the research methodology and literature discovery and retrieval strategy. Results of science mapping analysis together with different knowledge graphs are presented in Section 2. Section 3 provides qualitative discussions and insights of the analytical results and discusses research themes, gaps, and trends. Final section draws the conclusions. The findings in this research are expected to provide researchers and practitioners with a thorough understanding of the status quo and evolving trends of MPC for smart building operation management research and facilitate future studies in this domain.

1. Methodology

This section discusses the review methodology adopted in this research: literature search, science mapping, and qualitative discussion. Detailed research workflow is illustrated in Figure 1.

1.1. Literature-based discovery

Web of Science was chosen as the literature-based discovery (LBD) and information retrieval database, because of its wide literature coverage and good compatibility with different science mapping tools (Van Eck & Waltman, 2014). Both the backward expansion method and query-based lexical search method were utilized to generate an initial list of papers that fit the scope of this review. Backward expansion starts from recently published reviews by domain experts (Chen & Song, 2019), and query search complements the document list by incorporating papers of most recent years (2018–2021) that may have not been covered by existing reviews. The search was carried out using the query of "(model predictive control) AND (building energy)" for topic search in the Web of Science Core Collection database.

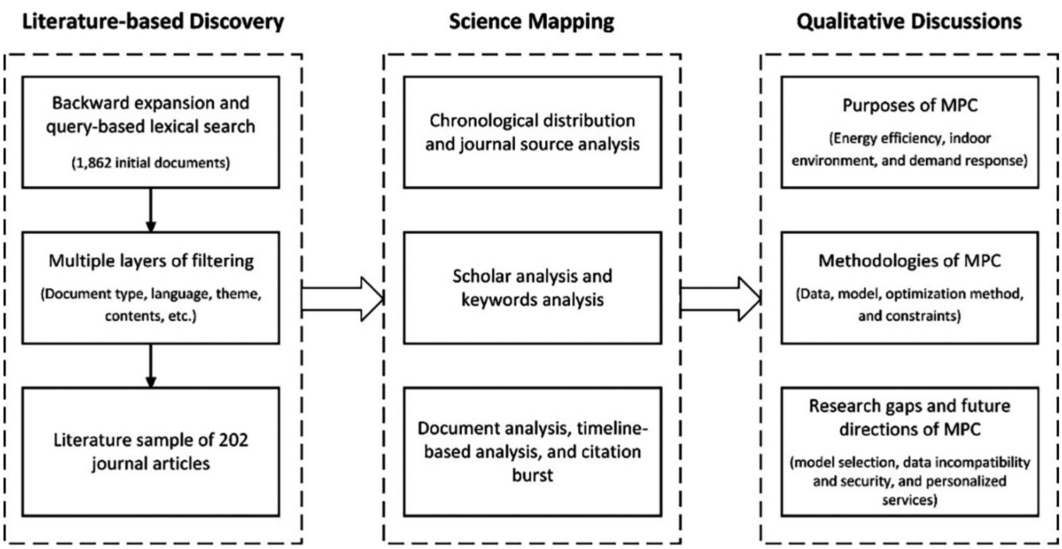


Figure 1. Detailed workflow of the proposed research

From the initial list of 1,862 documents, proceeding papers, reviews, and book chapters were removed and 1,390 journal articles published in English remained. Titles and abstracts of the remaining articles to were manually reviewed to conduct further screening, and articles that are not related to MPC but related to various other topics were excluded. Since this review focuses on the applications of MPC on building operation, studies relevant to the application of MPC in other fields, such as microgrid operation (Craparo et al., 2017; Menon et al., 2016), were excluded. Besides, articles that focus only on building modeling approaches but do not contain any control designs (Zhu et al., 2019; De Coninck et al., 2016) were also removed from this review to make the target of this review specific to MPC. Eventually, a total of 202 journal articles were selected to the best of our knowledge to be the literature sample for the following science mapping and qualitative discussions in this study.

1.2. Science mapping

Science mapping is a generic process of domain analysis and visualization (Chen, 2017), and it has been broadly applied to facilitate systematic literature reviews of scientific research both within the scope of smart building operations (Sepasgozar et al., 2020; Kim et al., 2021) and within other different fields (Jin et al., 2019; Martínez et al., 2015; Hallinger & Kovačević, 2019). Two prominent science mapping tools were utilized in this research: VOSViewer (Van Eck & Waltman, 2010) and CiteSpace (Chen, 2006). VOSViewer leverages a distance-based approach to visualize bibliometric networks of units (represented as nodes), including source journals, authors, organization, countries, keywords (Van Eck & Waltman, 2014). The distances between those nodes reflect the relatedness of those units measured in different metrics, such as co-authorship, shared references, co-occurrence, etc. However, VOSViewer is not good at handling timeline-based analysis, which is a critical step of conducting bibliometric analysis. Since each publication can be linked to a specific point in time based on its publication date, timeline-base analysis is useful for understanding temporal relations among existing research topics and identifying the emergence of new research topics (Morris et al., 2003). Fortunately, CiteSpace has a strong focus on timeline-based visualization and can facilitate insights on how bibliometric networks evolve over time (Van Eck & Waltman, 2014). It also provides users with the flexibility of using different text-clustering algorithms to generate visualization results. Considering the analytical results of VOSViewer and CiteSpace can complement each other, we decided to use both tools in this research for different analytical purposes.

1.3. Qualitative discussions

Finally, in-depth discussions were made to explore research works on MPC for smart building operation management from different perspectives. Objectives of such discussions include summarizing ongoing main research topics, categorizing purposes of MPC, setting out procedures of MPC methodology, pointing out existing research gaps, and suggesting future research directions.

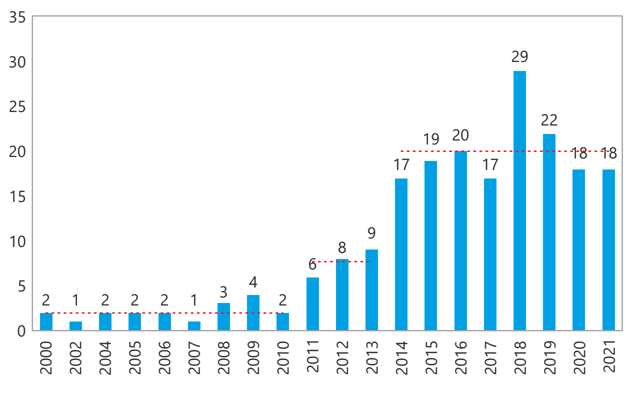
2. Science mapping

This section contains various results of the science mapping analysis and corresponding discussions, all of which were conducted based on the entire literature sample of all 202 journal articles. It starts with the chronological distribution of the literature sample, and then journal source analysis, scholar analysis, keywords analysis, and document analysis were carried out using VOSViewer. Finally, timeline-based analysis and citation burst analysis was conducted using CiteSpace to explore research topic evolution over time.

2.1. Chronological distribution and journal source analysis

We first summarized the literature sample according to their publication year, and displayed their chronological distribution in Figure 2. Based on the number of publications of each year, we divided the entire timespan into three stages: stage one (2000–2010), stage two (2011–2013), and stage three (2014–2021). In stage one, fewer articles were published and the average number of articles was only 2.11. Stage two worked as a short interim period between the other two stages, where the average number climbed up to 7.67. In stage three, the number of publications significantly surged and the average number of articles had increased to 20.13 per year. The number of articles published in this stage accounted for 79% of the literature sample, indicating that MPC for smart building operation management had drawn increasing attention in academia in recent years.

Next, we summarized the literature sample according to their journal sources. After setting the minimum number of documents of a journal source at 2 in VOSViewer, 16 out of 24 journal sources remained and were displayed in Figure 3. Each note represents a journal source and the size of the note denotes the number of documents from



Note: 1. Blue histogram denotes the number of articles published in each year; 2. Red dotted line denotes the average number for each stage.

Figure 2. Chronological distribution of journal articles

that journal source. The distance between two nodes approximately reflects the number of times they cite each other (Van Eck & Waltman, 2014). The color of a node demonstrates the cluster to which the node has been assigned, and each cluster contains a set of closely related nodes that are automatically determined by VOSViewer using a smart local moving average algorithm (Van Eck & Waltman, 2014; Waltman et al., 2010; Waltman & Van Eck, 2013). Figure 3 shows that *Energy and Buildings* has made the biggest contribution in terms of the number of publications, followed by *Applied Energy*, *Building and Environment*, and *Energy*. It also shows that *Energy and Buildings*, *Applied Energy*, and *Energy* have been classified into the same cluster, because they have been actively citing each other and are therefore more closely related.

Table 1 summarized the quantitative measurement of the top journal sources based on the number of publications. Publications from *Energy and Buildings*, *Applied Energy*, and *Building and Environment* had accounted for more than 60% of the literature sample and had received the most average citation. To adjust for the fact that older documents have had more time to receive citations than more recent documents, VOSViewer introduced and implemented the measurement of normalized citation, which equals the number of citations of a document divided by the average number of citations of all documents published in the same year (Van Eck & Waltman, 2020). Publications from *Applied Energy* and *Sustainable Cities and Society* have received the highest average normalized citation. According to the average publication year, documents of *Building and Environment* were published at an earlier stage, and documents of *Sustainable Cities and Society*, *Energies*, and *Journal of Process Control* are more recent.

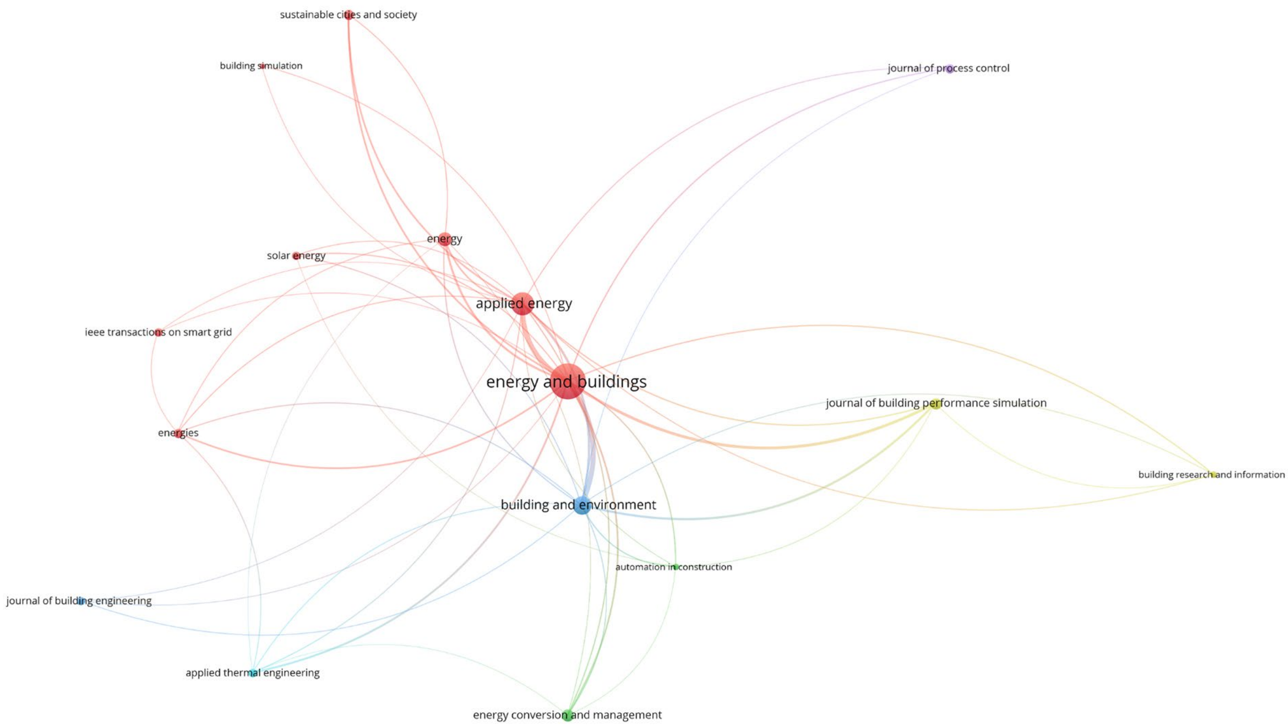


Figure 3. Visualization of journal sources that publish MPC for smart building operation management research

Table 1. Top journal sources in terms of number of publications

Journal Source	Number of publications	Total citation	Average publication year	Average citation	Normalized citation	Average normalized citation
Energy and Buildings	74	4058	2015	54.84	63.23	0.85
Applied Energy	32	1629	2017	50.91	51.79	1.62
Building and Environment	20	1243	2012	62.15	18.65	0.93
Energy	11	481	2017	43.73	9.58	0.87
Energy and Conversion Management	9	205	2016	22.78	7.01	0.78
Journal of Building Performance Simulation	8	231	2015	28.88	4.26	0.53
Sustainable Cities and Society	6	142	2019	23.67	6.93	1.16
Energies	5	4	2020	0.80	0.28	0.06
Journal of Process Control	5	53	2020	10.60	4.28	0.86

2.2. Scholar analysis and keywords analysis

Besides journal sources, we also summarized the literature sample according to their authors. After setting the minimum number of documents of an author at 2 in VOSViewer, 120 out of 596 scholars remained and were displayed in Figure 4. Each note represents a scholar and the size of the note denotes the total number of citations that scholar has received. More related scholars are located closer and their in-between distance approximately denotes the number of times they cite each other. Table 2 summarized the impacts of the top twenty scholars sorted by their number of citations. It is seen in Table 2 that Oldewurtel F., although with only two articles, has achieved

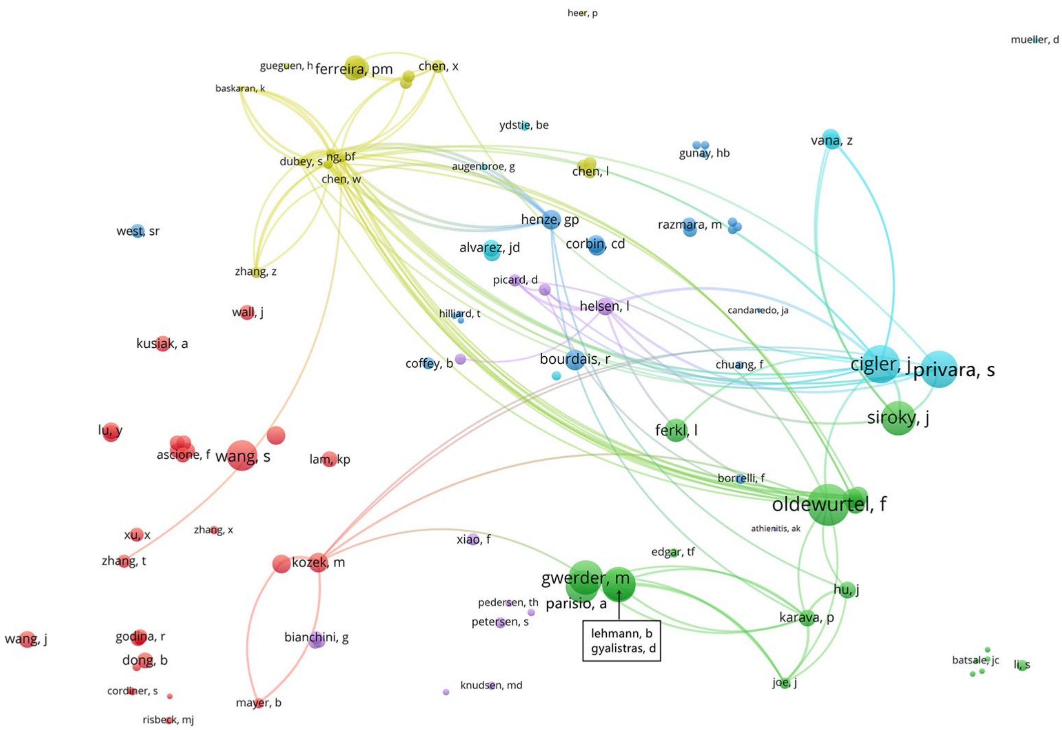


Figure 4. Visualization of scholars in the field of MPC research

Table 2. Top twenty scholars in terms of the number of citations

Scholar name	Number of publications	Total citation	Average publication year	Average citation	Normalized citation	Average normalized citation
Oldewurtel, F.	2	1032	2012	516.00	6.4	3.20
Cigler, J.	6	866	2012	144.33	6.13	1.02
Privara, S.	4	804	2012	201.00	4.88	1.22
Siroky, J.	3	692	2012	230.67	4.29	1.43
Gwerder, M.	3	679	2013	226.33	5.04	1.68
Gyalistras, D.	2	660	2013	330.00	4.64	2.32
Lehmann, B.	2	660	2013	330.00	4.64	2.32
Parisio, A.	2	608	2017	304.00	3.85	1.93
Wang, S.	7	543	2011	77.57	8.94	1.28
Ferkl, L.	2	320	2012	160.00	1.95	0.98
Bourdais, R.	3	246	2013	82.00	2.14	0.71
Ferreira, P. M.	2	239	2014	119.50	2	1.00
Ruano, A. E.	2	239	2014	119.50	2	1.00
Silva, S.	2	239	2014	119.50	2	1.00
Ghiaus, C.	3	235	2013	78.33	1.81	0.60
Hazyuk, I.	3	235	2013	78.33	1.81	0.60
Penhouet, D.	3	235	2013	78.33	1.81	0.60
Henze, G. P.	5	219	2015	43.80	3.81	0.76
Kozek, M.	5	218	2016	43.60	5.7	1.14
Killian, M.	4	199	2016	49.75	5.21	1.30

the highest total citation, average citation, as well as average normalized citation. In terms of the number of publications, Wang, S., Cigler, J., Henze, G. P., and Kozek, M. are most productive. In terms of both average citation and average normalized citation, Oldewurtel, F., Gyalistras, D., and Lehmann, B. are on the top of the list. It is also interesting to find that the average publication year of most researchers listed in Table 2 is between 2012 and 2013, and Parisio, A., Kozek, M., and Killian, M. are more active in recent years.

Keywords, including both Author Keywords that authors believe best represent the context of their paper (Li et al., 2009) and Keywords Plus that appear frequently in the titles of an article's references and not necessarily in the title of the article or as Author Keywords (Garfield, 1990; Garfield & Sher, 1993; Zhang et al., 2016), are critical textual information for scientific publications. Before conducting keyword analysis using VOSViewer, a critical step of textual data pre-processing is needed because different written expressions can semantically mean the same thing. Most textual analysis tools, including VOSViewer, however, would treat them differently if no data pre-processing is conducted. In the context of this research, for example, "model-predictive control", "model predictive control (mpc)", and "mpc" all equal to "model predictive control". This step can be done by sorting all keywords in alphabetical order and manually unifying those different written expressions. After setting the minimum number of occurrences of a keyword at 5 in VOSViewer, 62 out of 840 keywords were selected and visualized in Figure 5. Each note denotes a keyword, the size of the note represents the number of occurrences of that keyword, and the distance of two keywords approximately demonstrates the number of co-occurrences of the two keywords. Top ten keywords are model predictive control (113), optimization (50), system (44), thermal comfort (34), management (28), performance (28), demand response (28), energy (26), simulation (25), predictive control (20), where the numbers in parentheses denote occurrences.

Figure 5 shows that from a methodology perspective, "model predictive control" usually relies on "simulation" to achieve the "predictive control" and "optimization" (methods including "genetic algorithm" and "particle swarm optimization") and to find the optimal solutions in building management. Currently, "model predictive control" has already been applied to both "commercial buildings" and "residential buildings", especially to smartly control the "hvac system" or "heating system". For the purpose of MPC, it has been most widely utilized to achieve improved "thermal comfort" and "energy efficiency". With the trend of emerging renewable energy, recent studies further extended MPC to "demand response" and "demand-side management", such as the utilization of "energy flexibility", "thermal energy storage", "mass" in buildings, and "microgrid" support. In addition to the energy, thermal comfort criteria, such as "predicted mean vote", is also an important dimension to consider in the MPC formulation.

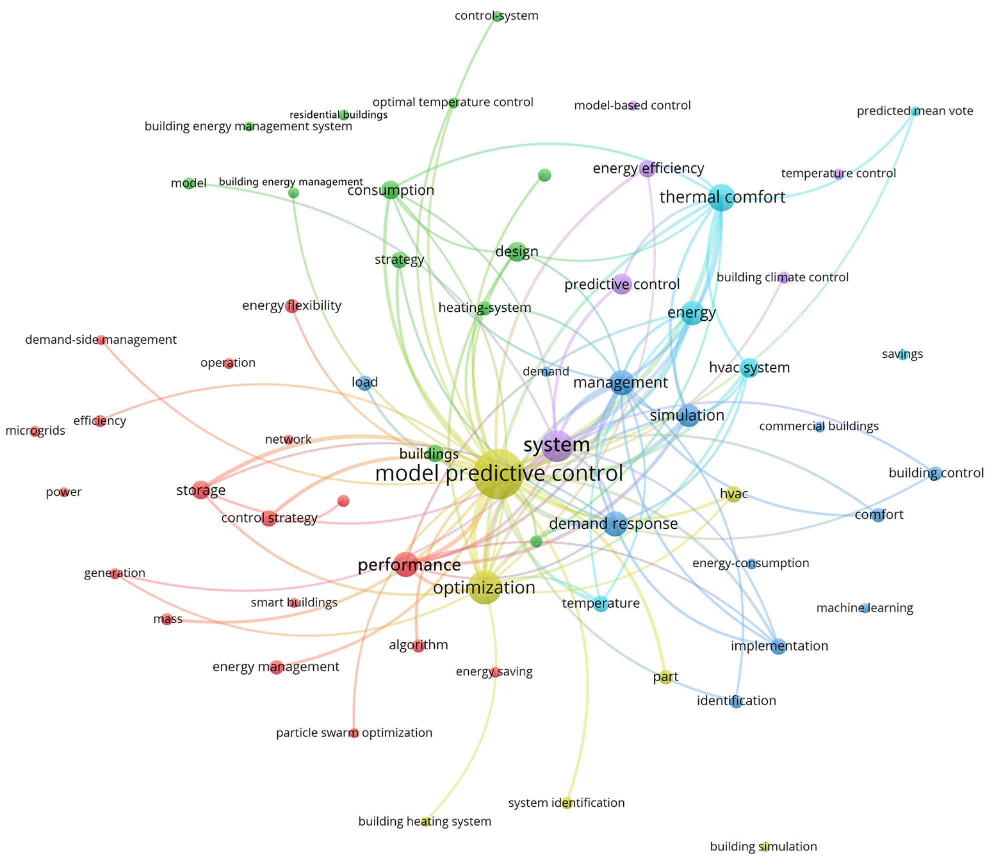


Figure 5. Visualization of highly occurred keywords

2.3. Document analysis, timeline-base analysis, and citation burst

Besides keywords, we also summarized the relationship between each document. After setting the minimum citations of a document at 50 in VOSViewer, 60 connected documents were selected and displayed in Figure 6. Each note represents a document and the size of the note denotes the total number of citations that the document has received. More related documents are located closer and their in-between distance approximately denotes the number of references they share.

Table 3 summarized the impacts and contents of the top twenty most-cited documents sorted by their number of citations. Energy efficiency and thermal comfort are two of the most important dimensions in building control, and most relevant papers have proposed MPC with either multi-objective optimization to simultaneously achieve energy-efficient operation and improved thermal comfort (Ferreira et al., 2012; Hazyuk et al., 2012; Ascione et al., 2016), or a single objective to enhance energy efficiency or thermal comfort without compromising the other in the MPC formulation (Oldewurtel et al., 2012; Privara et al., 2011; Freire et al., 2008; Fong et al., 2006; Maasoumy et al., 2014). These highly cited articles also demonstrated that MPC could be utilized to optimize indoor air quality (IAQ), such as the CO_2 concentration, by controlling the heating, ventilation, and air conditioning (HVAC) air supply (Wang & Jin, 2000; Mossolly et al., 2009; Kolokotsa et al., 2009). With the increasing penetration of renewable energy resources, researchers have applied MPC to improve building and renewable energy (e.g., photovoltaic) integration (Shakeri et al., 2017) and to minimize the energy cost during building operation (Chen et al., 2013; Avci et al., 2013). It is worthy to note that energy cost saving does not necessarily stem from building energy efficiency measures. Although improving energy efficiency could help save energy cost, the energy cost saving could also be achieved through considering dynamic electricity pricing in the MPC formulation, as demonstrated in Chen et al. (2013) and Avci et al. (2013). In MPC operation, uncertainties (Maasoumy et al., 2014), optimal utilization of thermal mass (Privara et al., 2011; Ferreira et al., 2012), and occupancy (Dong & Lam, 2014) are all important dimensions to be considered. Besides being deployed as a central control strategy, distributed MPC has also been developed to regulate indoor thermal conditions (Moroşan et al., 2010). Finally, these highly cited articles also present the validation of MPC in real building settings (Široký et al., 2011; Ferreira et al., 2012), which could serve as important evidence for the applicability of MPC in practice.

CiteSpace enables timeline-based analysis by analyzing the cited references of selected articles, and two types of timeline analysis were conducted in this review: timeline-based document clustering and citation burst. After selecting the top 5% of most cited references from each year, we kept 295 documents to be classified into different clusters and had them visualized in a timeline-based manner as shown in Figure 7. Clusters and corresponding labels were automatically identified and generated by CiteSpace using the log-likelihood ratio algorithm based on the keywords of each document. Documents belonging to "distributed model predictive control" first appeared in 2005, followed by those belonging to "energy efficiency" and "multi-objective optimization". Other clusters, including "smart buildings", "demand response", "building automation and control" and "energy flexibility" are more recent ones as shown in Figure 7.

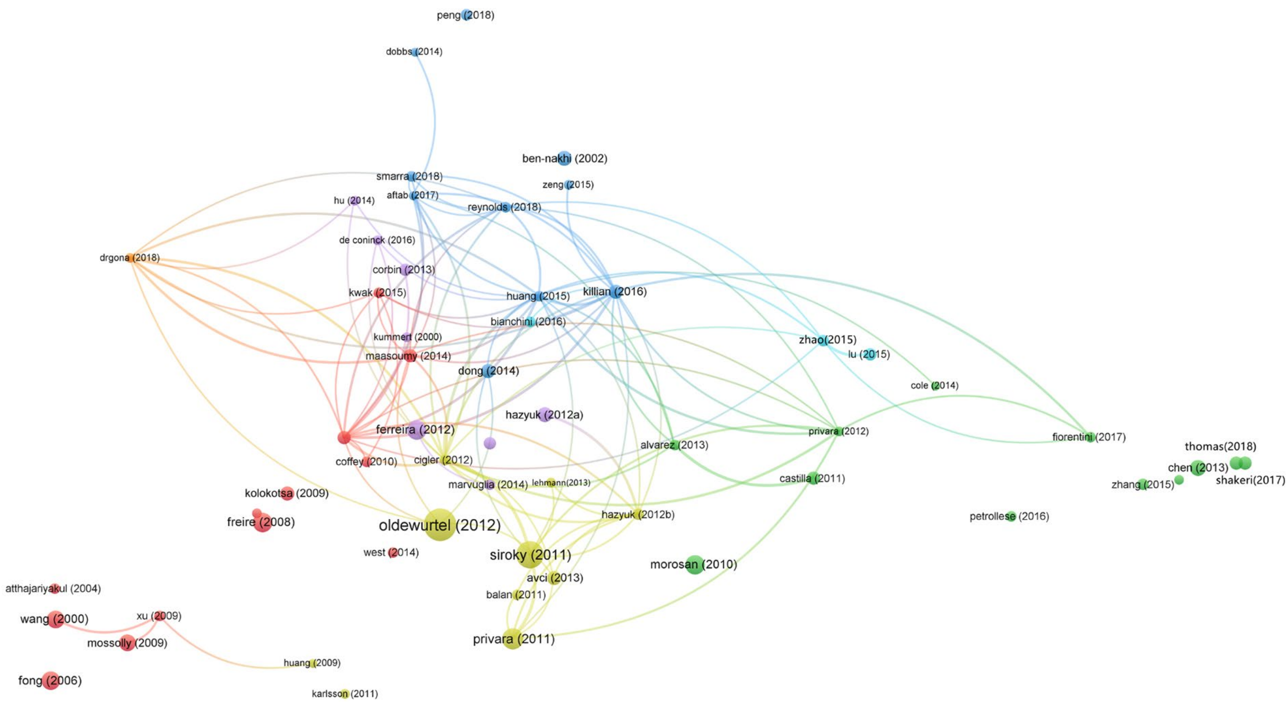


Figure 6. Visualization of highly cited articles

Table 3. Top twenty highly cited articles in the literature sample

Article	Title	Total citation	Normalized citation
Oldewurtel et al. (2012)	Use of model predictive control and weather forecasts for energy efficient building climate control	608	3.85
Široký et al. (2011)	Experimental analysis of model predictive control for an energy efficient building heating system	424	2.56
Privara et al. (2011)	Model predictive control of a building heating system: The first experience	255	1.54
Freire et al. (2008)	Predictive controllers for thermal comfort optimization and energy savings	223	2.41
Moroşan et al. (2010)	Building temperature regulation using a distributed model predictive control	216	1.51
Ferreira et al. (2012)	Neural networks based predictive control for thermal comfort and energy savings in public buildings	214	1.35
Fong et al. (2006)	HVAC system optimization for energy management by evolutionary programming	202	1.54
Wang and Jin (2000)	Model-based optimal control of VAV air-conditioning system using genetic algorithm	173	1.49
Mossolly et al. (2009)	Optimal control strategy for a multi-zone air conditioning system using a genetic algorithm	168	1.69
Chen et al. (2013)	MPC-Based Appliance Scheduling for Residential Building Energy Management Controller	154	2.36
Hazyuk et al. (2012)	Optimal temperature control of intermittently heated buildings using Model Predictive Control: Part I – Building modeling	133	0.84
Ben-Nakhi and Mahmoud (2002)	Energy conservation in buildings through efficient A/C control using neural networks	132	1.00
Avci et al. (2013)	Model predictive HVAC load control in buildings using real-time electricity pricing	122	1.87
Dong and Lam (2014)	A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting	113	2.40
Killian and Kozek (2016)	Ten questions concerning model predictive control for energy efficient buildings	112	2.89
Kolokotsa et al. (2009)	Predictive control techniques for energy and indoor environmental quality management in buildings	111	1.12
Maasoumy et al. (2014)	Handling model uncertainty in model predictive control for energy efficient buildings	109	2.32
Ascione et al. (2016)	Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort	105	2.71
Thomas et al. (2018)	Optimal operation of an energy management system for a grid-connected smart building considering photovoltaics' uncertainty and stochastic electric vehicles' driving schedule	105	4.01
Shakeri et al. (2017)	An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid	105	2.86

Citation burst analysis, which detects publications that have a surge of citations over certain periods of time (Cipresso et al., 2018), was also conducted with the help of CiteSpace that uses Kleinberg's algorithm (Kleinberg, 2003). The top-ranked document by bursts is Oldewurtel et al. (2012) in Cluster #0, with burst strength of 8.46. The second is Privara et al. (2011) in Cluster #0, with burst strength of 8.43. The third is Široký et al. (2011) in Cluster #0, with burst strength of 7.76. The fourth is Moroşan et al. (2010) in Cluster #0, with burst strength of 6.59. The fifth is May-Ostendorp et al. (2011) in Cluster #0, with burst strength of 4.85. The sixth is Ferreira et al. (2012) in Cluster #0, with burst strength of 4.54. The seventh is Pérez-Lombard et al. (2008) in Cluster #0, with burst strength of 4.41. The eighth is Ma et al. (2012) in Cluster #0, with burst strength of 4.39. The ninth is Freire et al. (2008) in Cluster #8, with burst strength of 4.14. The tenth is Afram and Janabi-Sharifi (2014) in Cluster #0, with burst strength of 4.01. Results showed that most top articles in the citation burst analysis belong to Cluster #0, indicating the significant importance of 'energy efficiency' in this field. Table 4 displays the results of citation burst analysis sorted by chronological order.

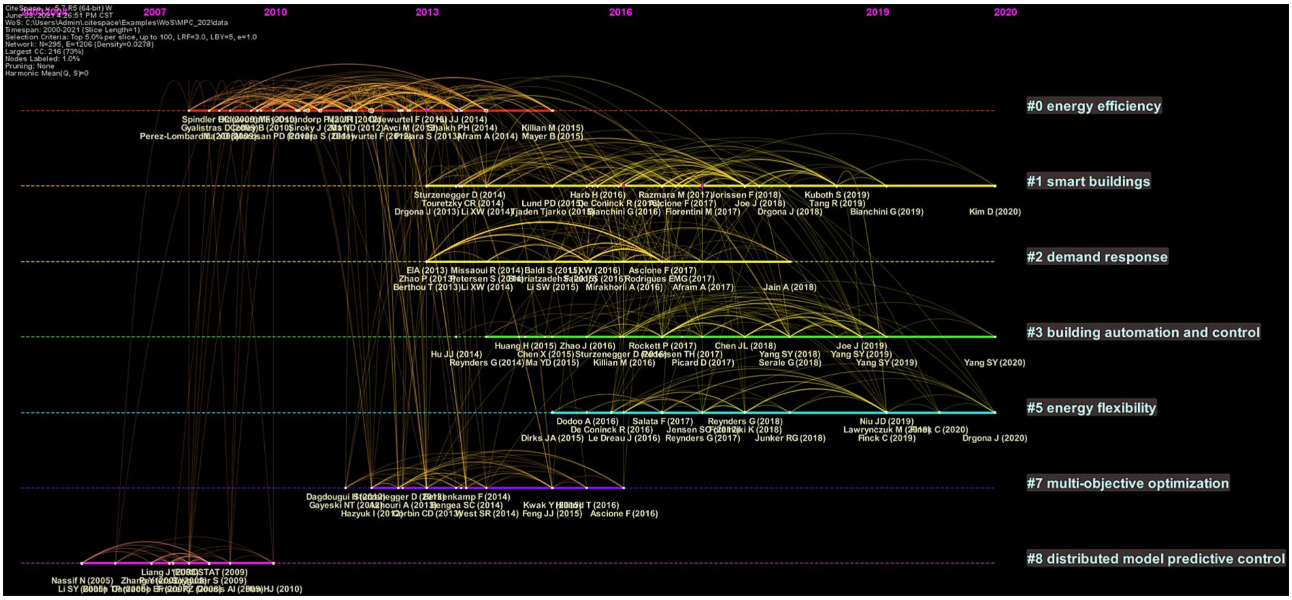


Figure 7. Visualization of reference documents clustering in a timeline-based manner

Table 4. Top ten articles popped up in the citation burst analysis sorted chronologically

References	Title	Strength	Begin	End	2000–2021
Freire et al. (2008)	Predictive controllers for thermal comfort optimization and energy savings	4.14	2010	2013	
Moroşan et al. (2010)	Building temperature regulation using a distributed model predictive control	6.59	2011	2015	
Pérez-Lombard et al. (2008)	A review on buildings energy consumption information	4.41	2011	2013	
Privara et al. (2011)	Model predictive control of a building heating system: The first experience	8.43	2012	2016	
Široký et al. (2011)	Experimental analysis of model predictive control for an energy efficient building heating system	7.76	2012	2016	
Oldewurtel et al. (2012)	Use of model predictive control and weather forecasts for energy efficient building climate control	8.46	2013	2017	
May-Ostendorp et al. (2011)	Model-predictive control of mixed-mode buildings with rule extraction	4.85	2014	2016	
Ferreira et al. (2012)	Neural networks based predictive control for thermal comfort and energy savings in public buildings	4.54	2015	2017	
Ma et al. (2012)	Model Predictive Control for the Operation of Building Cooling Systems	4.39	2015	2017	
Afram and Janabi-Sharifi (2014)	Theory and applications of HVAC control systems – A review of model predictive control (MPC)	4.01	2016	2019	

3. Qualitative discussions

Following previous bibliometric analysis and science mapping results, this section provides in-depth qualitative discussions of research works on MPC for smart building operation management. Compared to previous reviews, the paper not only provided the most up-to-date summary for typical application of MPC on smart building operation, but also detailly reviewed critical components in MPC, including the objectives and data requirements of MPC implementation, specific modeling approaches, optimization methods, and associated constraints. Research gaps and corresponding future directions of MPC were also presented in this section.

In summary, MPC has been widely used to improve both energy efficiency and building indoor environment and increasingly applied to facilitate building and renewable energy integration. White-box and grey-box building modeling usually serve as the central model in MPC operation, while data-driven modeling have gained popularity in recent years due to the enhanced data availability. Depending on the nature of the problem, linear or nonlinear programming, evolutionary algorithms, and stochastic optimization are mainstream optimization methods in MPC. Thermal comfort and physical capacity of systems are typically formulated as constraints in solving the optimization problem. The selection and establishment of MPC central model, the capability and security of processing massive data, and the involvement of human factors constitute the major research gaps for the advancement of MPC techniques. These findings with details below will provide a comprehensive overview to facilitate the understanding of current status of MPC development from the holistic view to detailed components.

3.1. Purpose of MPC

3.1.1. Improve energy efficiency and indoor environment

Improving building energy efficiency will reduce operation costs and greenhouse gas emissions, and it is therefore of significant importance with environmental, economic, and social benefits. In the meanwhile, buildings are designed and operated to maintain a comfortable indoor environment for building occupants as one of the basic requirements. Thus, for the purpose of the application, MPC is mostly developed to achieve improved energy efficiency and at the same time ensure a comfortable indoor environment with respect to either thermal comfort or IAQ (Privara et al., 2011; Mossolly et al., 2009; Ascione et al., 2016). The settings of HVAC systems, such as on/off status (Chen et al., 2018), supply air temperature and airflow rate (Fontenot & Dong, 2019) indoor temperature setpoints (Aftab et al., 2017), are optimally adjusted according to the control aims. The control aim can be reflected in the objective functions of MPC control, of which simultaneous optimization of energy efficiency and indoor environment status (Cigler et al., 2012; Chen et al., 2015), minimization of energy consumption while maintaining thermal comfort (Ferreira et al., 2012; Dobbs & Hencey, 2014; West et al., 2014) or IAQ (Ganesh et al., 2021), and optimized thermal comfort (Freire et al., 2008; Castilla et al., 2011) are commons ones in MPC for smart building operation. Reducing the environmental impacts, such as minimizing CO_2 emission (Knudsen & Petersen, 2016) could also be incorporated into the control objective function as well.

3.1.2. Meet demand response

In addition to enhancing energy efficiency and the indoor environment, the increasing adoption of renewable energy resources poses new challenges to building operation, i.e., requiring buildings to shift from reactive to active roles in power management to ensure stable power system operations. Hence, to compensate for the intrinsically intermittent and variable nature of electricity generation from renewable energy, MPC was also widely used to support demand response, when buildings are operated to curtail or shift electricity to respond to grid signals and financial incentives. Lower peak load and better load balancing (Shakeri et al., 2017) are aims of smart building operations to be achieved by MPC (Biyik & Kahraman, 2019). Still, building HVAC systems are a major energy flexibility resource utilized by MPC in demand response (Vedullapalli et al., 2019). Building thermal mass is considered as another important thermal storage in buildings to absorb or release heat in smart building operation, despite the challenges in accurately modeling system coupling and thermal dynamics of buildings (Kathirgamanathan et al., 2021; Hu et al., 2019). Currently, demand response is usually implemented in commercial buildings (Vedullapalli et al., 2019). These years, MPC for demand response in residential buildings has become a possibility as the growing acceptability and the deployment of smart home energy management (Oldewurtel et al., 2012; Godina et al., 2018). If buildings have distributed renewable energy (such as PV panels) deployed on site, the variable generation from these renewable energy resources should be considered to ensure the load balancing and reduced grid impacts of buildings in the smart building operation (Thomas et al., 2018; Wanjiru et al., 2017).

3.2. Methodology of MPC

3.2.1. Data

Data is the basis for smart building operation. It is not only necessary to build the central model of MPC, but also a critical component in the control feedback loop so that building operations can be optimized in a real-time manner. Overall, usable data in MPC include both static data, such as the building construction details for the central model establishment, and dynamic data that reflects building operation and environment status, such as metered energy consumption, indoor temperature and activities, weather conditions, and HVAC operation status (Zhan & Chong, 2021). To support smart building operation, data needs to be collected at different intervals (e.g., 15 minutes, half an hour, hourly, or daily) and spatial resolutions (building, system, and component level), and different MPC application scenarios impose different data requirements in practice. For example, building construction information is heavily used in white box modeling to serve as the central model of MPC (Ascione et al., 2016; Li & Malkawi, 2016). Room temperature is usually required in the identification of greybox modeling approaches (Andriamamonjy et al., 2019; Arroyo et al., 2020). Historical energy consumption can be acquired for energy management system development with MPC (Bartolucci et al., 2019). Information of occupant thermal comfort could be collected as feedback of MPC decision makings (West et al., 2014). To support smart building operations with MPC, the most frequently collected data include indoor and outdoor environmental variables (e.g., indoor and outdoor air temperature, indoor relative humidity, and air velocity) and occupant relevant information (e.g., thermal comfort, occupancy status) (Merabet et al., 2021).

3.2.2. Model

Central building models are one of the most critical components in MPC. These central models predict the required building energy and indoor thermal dynamics, and they both serve as the optimization inputs to generate optimal building operation decisions in the control horizon. Hence, an accurate and reliable central model in MPC is crucial to ensure the applicability of MPC in practice. Existing building models in MPC applications include white-box (physics-based) modeling, black-box (data-driven) modeling, and grey-box (combination of both) modeling.

3.2.2.1. White-box modeling

White-box modeling is physics-based and it relies on physics principles to describe the fundamental heat and mass balance of buildings. With decades of development, white-box modeling has become relatively mature with several well-developed simulation engines, such as EnergyPlus (Crawley et al., 2001) and TRNSYS. Based on complex physics laws, white-box modeling could accurately model building thermal dynamics and simulate energy consumption of different types of building systems. On the other hand, however, a massive number of model inputs can be required in model establishment based on engineering experience or actual measurement. This makes the white-box modeling process expertise-demanding and error-prone, resulting in deviations of simulation results. It is common to observe missing input parameters during the model establishment process. The complexity of white-box modeling also makes it computational-intensive, thus introducing another major barrier that hinders its usability in the MPC framework since repetitive computation is required in the optimization process. To counteract the side effects of complex physics-based modeling, model reduction techniques, such as iterative approaches (De Rosa et al., 2019) and Balanced Truncation (Robillart et al., 2019), have been utilized to reduce the model complexity while preserving the model structure, to minimize the accuracy loss of physics-based simulation.

Several previous works have utilized white-box modeling for MPC. For example, Salakij et al. (2016) developed the building energy analysis model (BEAM) for building heat and moisture transfer prediction, which was incorporated into MPC to optimally adjust HVAC setpoints for energy efficiency and building load reduction. Schirrer et al. (2016) developed high-fidelity building models to support MPC in heating and cooling control considering energy efficiency and thermal comfort. Bianchini et al. (2019) utilized white-box modeling for a large commercial building and integrated it with a two-stage optimization strategy to optimize heat pump and electricity operation considering PV generation. For residential buildings, Ruusu et al. (2019) demonstrated significant savings of housing operations using the developed energy management system with MPC and detailed building models as the core. Physics-based models for buildings and HVACs along with micro-scale concentrated solar power were established to support MPC aiming to reduce building operation costs (Toub et al., 2019).

3.2.2.2. Black-box modeling

The advancement of computational power and increasingly wide adoption of IoT infrastructure have opened opportunities for continuous sensing data collection and big data analysis to enable improved decision-making. As one application of using data to support decision making, data-driven building modeling has become a rising technique that attracted attention from both the research community and industry these years (Sun et al., 2020). Instead of relying on building physics, data-driven models utilize mathematical modeling to represent building dynamics (Bourdeau et al., 2019). To train such models, building indoor environmental conditions such as the indoor temperature and system sensing data such as airflow rate measurement and outdoor weather data are commonly used as model inputs (Li & Malkawi, 2016). On the other hand, indoor temperature and building energy consumption are usual model outputs to be utilized in the MPC (Huang et al., 2015a; Bünning et al., 2020). Black-box modeling is computationally much less intensive compared to white-box modeling, offering great advantages in the MPC optimization process. Once the framework for model training is established, it is easy to automate the training process across different types of buildings, and such a process would require much less domain knowledge or engineering efforts compared with white-box modeling. However, since data-driven approaches only rely on data in the model training process, data quality is critical in determining model robustness. A massive amount of data covering diverse scenarios of building operations would be required to train an effective data-driven building model usable in building prediction. Feature identification is important to establish a robust data-driven building model as well. Another drawback of applying data-driven modeling is its "black-box" nature, i.e., the model parameters are unexplainable with physics meanings, affecting the credibility of its application in practice. Building robust data-driven models will require relevant computer science knowledge that could be out of the expertise of building engineers.

Despite the advantages and disadvantages of data-driven building modeling, various data-driven methods have been deployed in MPC to support optimal decision-making in building energy management. Among those works, neural network is one of the most widely used machine learning algorithms in modeling building dynamics.

Chen et al. (2018) developed a neural network model as the central model of MPC to smartly operate mechanical and natural ventilation of buildings, aiming to optimize building energy efficiency while maintaining comfort. Similarly, Chaudhuri et al. (2019) proposed a framework that uses neural network to predict building HVAC consumption and locate the optimal operating state such that the energy consumed to maintain indoor comfort is minimized. Kusiak et al. (2014) have employed a multilayer perceptron neural network to predict building HVAC energy consumption and indoor environment and applied interior-point method to generate optimal HVAC control sequence. Neural Network can also be employed to forecast renewable energy generation to facilitate the smart operation of zero-energy buildings with MPC (Megahed et al., 2019). In addition to neural network, various other methods have been adopted to support black-box modeling in MPC. Ríos-Moreno et al. (2007) evaluated the usability of linear autoregressive models to model indoor temperature for intelligent building operation support. Auffenberg et al. (2017) utilized the Bayesian network to establish a personalized thermal comfort model and further integrated it into an optimal HVAC control algorithm to minimize energy consumption. Random forest was utilized to infer indoor temperature of buildings in the next 24 hours under different HVAC control schedules (HVAC On/Off) to optimize the building heating and cooling energy efficiency in real building settings (Manjarres et al., 2017). Similarly, the subspace modeling approach was used to represent building dynamics and integrated into MPC to achieve heating energy saving for a campus building (Privara et al., 2011). Support vector regression was applied to model HVAC systems and used as part of MPC for optimal HVAC control (Xi et al., 2007). Long short-term memory (LSTM) with attention mechanism was utilized as the central model for indoor temperature in a data-driven MPC to minimize energy, peak power, and discomfort in a multi-zone building (Mtibaa et al., 2021).

3.2.2.3. Grey-box modeling

Grey-box modeling, as a combination of white-box and black-box modeling, is another type of building modeling technique widely used to support MPC decision making. Grey-box models are formulated as reduced-order physics-based models with physical meanings in model parameters. In the model training process, optimization methods, such as least square optimization, are applied to identify the optimal set of model parameters that can most representatively depict building dynamics in terms of energy consumption and indoor environment. Specifically, the Resistance-Capacitance (RC) model is the most used grey-box model in MPC. The RC model uses the analogy of electric circuits, including resistors and capacitors, to represent the heat transfer process as building dynamics (Yang et al., 2018). Different types of RC models, such as 2R1C (Fux et al., 2014) and 3R2C (Lee & Braun, 2008) exist in the application. Compared with white-box modeling, an advantage of grey-box modeling is its computation efficiency. Selecting the appropriate model complexity and avoiding parameter overfitting or underfitting in the model parameter identification process are all significant when using grey-box modeling for MPC support (Bacher & Madsen, 2011).

Using RC models to model the thermal response of buildings, Zhuang et al. (2018) developed the MPC with a feedforward structure to minimize building energy consumption, which was validated with real site deployment. To enable demand response, Biyik and Kahraman (2019) developed the predictive control strategy including the lumped mathematical model to describe transient zonal thermal dynamics, modeling of energy storage, and renewables. Li et al. (2015) utilized grey-box modeling to capture the dynamics of integrated systems, involving building HVAC and solar collectors to achieve the optimal solar energy usage in high-performance buildings. The hybrid model predictive control (HMPC) scheme based on simplified grey-box building models and inverse neural network model was proposed for the smart operation of HVAC systems in commercial buildings (Huang et al., 2015b).

3.2.3. Optimization method

The optimization method used in MPC differs according to various formulations of MPC problems. A computationally efficient optimization algorithm is crucial to ensure the timely and optimal delivery of building operation decisions as MPC outputs. In general, the optimization problems in MPC could be solved by several methods, including linear or nonlinear programming (Sun & Yuan, 2006), evolutionary algorithms (Deb et al., 2002), and stochastic optimization (Schneider & Kirkpatrick, 2007). If both the objective function and constraints were linear, the optimization in MPC would have become a linear programming problem, which could be easily solved with the global optimum (Ma et al., 2011). However, considering the complexity and non-linear nature of building dynamics, optimization in MPC is more likely to be a nonlinear programming problem (Široký et al., 2011; Privara et al., 2011) that is hard to solve, especially if it is non-convex. Mixed-integer programming problems, as one type of non-linear programming problem, is commonly seen in optimization of MPC for smart building operation if the control output is the signal for HVAC on/off (Chen et al., 2018). To solve complex non-linear optimization problems, dynamic programming is another flexible approach that provides a guarantee to reach the global optimum (Xi et al., 2007; Candanedo & Athienitis, 2011; Henze et al., 1997). The principle of dynamic programming is breaking down the optimization problem into smaller subproblems to ensure the sub-optimality, and hence, the overall optimality of the solution.

In addition to solving optimization with classic approaches guaranteed to find global optimum, meta-heuristics methods, which are a set of methods designed to search through a large population of candidate solutions, have also been widely used in MPC optimization (Wang &

Jin, 2000; Reynolds et al., 2018). With less required computational efforts, meta-heuristics methods could find a relatively optimal solution in reasonable time, although the global optimum solution of the problem is not guaranteed. Although solution quality is compromised, this feature is especially helpful when the solution set is huge and it would be impractical to perform a thorough search. Among different meta-heuristics methods, particle swarm optimization (PSO) and genetic algorithm (GA) are the two most used approaches. In PSO, the solution to the optimization problem is continuously updated based on mathematical settings of algorithms such that the solution will gradually move towards the optimal place in the objective function space (Corbin et al., 2013). Similarly, GA will initialize a set of solutions and then evolute these solutions through mutation, crossover, and selection to reach an optimal set of solutions (Vose, 1999). For example, Hu and Karava incorporated PSO into the MPC for mixed-mode cooling control of buildings to reduce cooling load (Hu & Karava, 2014). Reynolds et al. (2018) developed an artificial neural network to predict building energy consumption and indoor environment status and then coupled with GA to achieve energy saving. Mtibaa et al. (2021) developed data-driven MPC with GA as the optimizer for building HVAC system control. Wang and Jin (2000) utilized GA to solve online optimization for smart control of the variable air volume system. A multi-agent control system was proposed for indoor energy and comfort management using PSO as the optimization algorithm (Wang et al., 2012).

Finally, given the uncertain nature of building operation, stochastic optimization is another optimization approach for optimal building control decision making while accounting for existing random variables in the optimization process (Rahmani-Andebili, 2017; Chen & Hu, 2019). In optimization, probability density functions of those random variables are established and incorporated into the problem formulation and solving. Despite its computational intensity, stochastic optimization is beneficial for the robustness of designed control algorithms by taking uncertainties into account.

3.2.4. Constraints

Setting constraints in MPC is important to ensure the performance and applicability of smart building operations. In general, these constraints could stem from either performance requirements or physical constraints of systems. Among performance constraints, thermal comfort is one of the most important constraints that are widely encoded in MPC formulations since the thermal comfort of occupants should be maintained as minimum requirements of building operation regardless of what control aims to be (Chen et al., 2015). These constraints could either be represented by predictive mean votes/predicted percentage of dissatisfaction (PMV/PPD) (Cheung et al., 2019; Fanger, 1970) or indoor temperature of buildings. In past works, energy-saving from MPC is achieved with PMV as constraint (Ferreira et al., 2012; Chen et al., 2015). In addition, another type of constraint commonly seen in MPC formulation is the physical constraints of building systems, such as the capacity limit of systems, the limit of system changing rate, etc.

3.3. Research gaps and future directions of MPC

Despite the advancement of MPC, it is still not widely adopted in real building operations due to model selection trade-offs between model complexity and robustness, data incompatibility and data security issues, and limitation in providing occupants with more customized services.

First, the central model selection and establishment is one of the most crucial components that determine MPC performance in application. With different types of building energy models used in MPC, it is still not clear about what levels of model complexity are appropriate to achieve satisfactory control performance in practice (Blum et al., 2019; Picard et al., 2017; Foucquier et al., 2013). Considering the existing trade-off among model complexity, model accuracy, and computational time, choosing the appropriate central model, and determining its corresponding data requirements to support MPC operation is the first and foremost step in MPC development (Zhan & Chong, 2021). In the meanwhile, ensuring the quality of the established model in MPC is another important dimension to further increase the reliability and adoption of MPC. A robust central model in MPC would not only require model robustness under various scenarios and be therefore usable in different building operation conditions, but also need to be adaptive over time to capture the changing building dynamics. Hence, to further increase the validity of the central model in MPC, it is critical to first understand the required modeling accuracy to serve different purposes of MPC applications. Mechanisms should be built to verify the adaptability and validate the model applicability under actual building operating conditions to ensure the robustness of central building model.

In addition to the modeling challenges in MPC, the increasing number of sensing deployments and the massive amount of sensing data collected to reflect building operation open new opportunities but also challenges for smart building operation with MPC (Carli et al., 2020). These sensing data, such as controlled indoor temperature, airflow status, and water flow rates could come from heterogeneous sources in various formats (Naji et al., 2019). The massive amount of data introduces challenges of data communication, analysis, and labeling as required for different purposes. It also puts new requirements for data storage with the fast-growing collected data volume. The building MPC should have the capability to reflect on real-time building operations and make timely adjustments. In the meanwhile, in the future of smart building operation, information from building sensing networks could contain sensitive information, such as occupant activities collected by occupancy sensing techniques (Blum et al., 2019). Although the information is beneficial to the decision-making of MPC, this raises new concerns of data security and privacy in building operations (Fernandes et al., 2016). To tackle with these issues, advanced computing methods, such as deep learning along with data storage (e.g., non-SQL database) should be increasingly deployed to increase the model intelligence and efficiency of massive data processing. The improvement of cybersecurity for information of smart buildings and occupants inside should be established at different levels, including hardware, middleware, and software to preserve the information security in data communication (Fernandes et al., 2017). Applying edge computing as distributed information techniques will also benefit both data processing efficiency and privacy conservation in future smart building operation.

Finally, the building MPC should better incorporate human factors into account, which could be reflected as (1) making use of collected human information for smart building operation and improved occupant service; and (2) handling the uncertainties introduced by human behaviors in control decision making. Former research has demonstrated that the building operation based on thermal comfort models of groups of populations such as PMV/PPD cannot guarantee satisfactory building operation performance (Brager & Baker, 2009). The advancement of sensing (participatory sensing) (Jazizadeh et al., 2013) and HVAC techniques have made personalized indoor environment adjustment possible by further involving humans in the loop. Occupancy information could also be utilized for demand-driven ventilation achieved by MPC as energy-efficient building operation (Peng et al., 2017). However, this information is still lacking and not considered in current HVAC control loop. Hence, further development of human-building interaction frameworks, i.e., the channels to collect and process individual information, will be beneficial for building systems to understand perceptions of indoor environment by occupants and make adjustments based on identified needs. Low-cost sensing networks could also be deployed for automatic information collection. In the meanwhile, the uncertainties of occupant behaviors could result in stochasticity, hence, unexpected outcome of building decision-making by MPC (Goyal et al., 2012). Accounting for these uncertainties in the MPC decision making will increase the robustness of MPC application in real building settings.

Conclusions

This study conducted a holistic review of 202 journal articles in the domain of model predictive control for smart building operation management. Different from existing reviews in this field, it adopted review methods that combined both the science mapping approach and qualitative discussions. A three-stage increasing trend of relevant studies was captured by analyzing the chronological distribution of the number of publications since 2000. Results of the science mapping analysis were summarized below.

From the journal source perspective, *Energy and Buildings*, *Applied Energy*, and *Building and Environment* have contributed to most of the publications and achieved the highest number of citations per publication. On the scholar analysis side, *Wang*, *S.*, *Cigler*, *J.*, *Henze*, *G. P.*, and *Kozek*, *M.* are among the most productive scholars with the highest numbers of publications, and *Oldewurtel*, *F.*, *Cigler*, *J.*, *Privara*, *S.*, and *Siroky*, *J.* are among the most influential scholars with the highest numbers of citations. The keywords analysis summarized that MPC usually relies on "simulation" and "optimization" to achieve "predictive control" and find optimal control on "hvac system", "heating system", and other building operations, for the purpose of "energy efficiency", "thermal comfort", and "demand response". Articles were classified into different clusters based on their keywords and were presented in chronological order: "distributed model predictive control", "energy efficiency", "multi-objective optimization", "smart buildings", "demand response", "building automation and control" and "energy flexibility". Finally, articles receiving the highest citation and highest normalized citation were identified and articles with the strongest citation burst strength were captured.

Following the science mapping results, in-depth qualitative discussions were conducted to outline ongoing main research topics, summarize MPC purposes and methodologies, point out research gaps, and suggest future research directions. Improving energy efficiency, enhancing the indoor environment (IAQ and thermal comfort), and satisfying demand response are three common purposes of applying MPC for smart building operation management. The advantages and disadvantages of three different modeling techniques for MPC – white-box modeling, black-box modeling, and grey-box modeling – as well as the data needed for each model are outlined. As for optimization, mixed-integer programming, dynamic programming, and meta-heuristics methods such as PSO and GA are often utilized to solve the nonlinear optimization problem in MPC. Stochastic optimization can be another optimization approach, given the uncertain nature of building operations. Such optimization problems need to be solved under certain constraints, such as performance requirements (e.g., thermal comfort) and physical constraints of systems (e.g., capacity limit of systems or limit of system changing rate). Finally, research gaps and corresponding future directions of MPC works were pointed out in three folds: unclear central model selection criteria and procedure, insufficient data processing capability and security, and lack of personalized occupant satisfaction.

This review-based study provides a holistic review of research works related to applying MPC to smart building operation management, by combining the novel science mapping approach and traditional in-depth discussion. Both the academic community and industry practitioners could benefit from this study by grasping an overview of relevant research works from both visual and textual perspectives and by following up research gaps and future directions outlined in this study. It should also be pointed out that this review is limited to the literature sample selected from Web of Science, and only English journal articles were included.

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