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ORIGINAL ARTICLE

Automation in construction scheduling: a review of the literature

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Abstract Automating the development of construction schedules has been an interesting topic for researchers around the world for almost three decades. Researchers have approached solving scheduling problems with different tools and techniques. Whenever a new artificial intelligence or optimization tool has been introduced, researchers in the construction field have tried to use it to find the answer to one of their key problems—the "better" construction schedule. Each researcher defines this "better" slightly different. This article reviews the research on automation in construction scheduling from 1985 to 2014. It also covers the topic using different approaches, including case-based reasoning, knowledge-based approaches, model-based approaches, genetic algorithms, expert systems, neural networks, and other methods. The synthesis of the results highlights the share of the aforementioned methods in tackling the scheduling challenge, with genetic algorithms shown to be the most dominant approach. Although the synthesis reveals the high applicability of genetic algorithms to the different aspects of managing a project, including schedule, cost, and quality, it exposed a more limited project management application for the other methods.

Keywords Automation · Construction scheduling · Construction projects

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1 Introduction

Project schedule, specifically in construction projects, is a tool that helps project managers and project management teams handle several critical aspects of management. Through construction schedules, they manage time, cost, resources, and so on. Having the ability to ensure the sufficient availability of information to the management team makes the construction schedule one of the most, if not the most, vital gears for managing projects. Considering these facts about the importance of project schedules, their development should be done very carefully. The developer's background and experience play a very critical role in the creation of a construction schedule. In cases where the scheduler lacks a thorough understanding of the project and its scope, the supposedly helpful construction schedule will turn into a time- and cost-consuming tool, which will also mislead the project's workers. To solve the problem of insufficient information, researchers have been focusing on automating the process of generating schedules.

Research interest in automatically generating and optimizing construction schedules has been around for almost four decades, beginning in the early 1960s with Newell and Simon [65], who tried to find better ways to use computer-based algorithms and applications to ease the process of scheduling. Some researchers directly focused on using past accumulative construction as a database and scheduled new projects accordingly. Others have used project information models as input to reach the desired outcome. When expert systems were common as a research tool, some researchers tried to use advantages of these approaches, such as having high performance and reliability, to generate schedules. The introduction of neural networks opened another door for researchers in this field to mimic the way that human brains work regarding project scheduling. As a well-suited optimization tool, many researchers showed interest in optimizing project resource allocation and leveling using genetic algorithms (GAs). Different methods such as prediction market for predicting a project's future trends and using system dynamics for the process of program design are other computer-aided methods to enhance the development of project schedules.

Previous research studies are divided into the following sections: case-based reasoning and knowledge-based approaches, model-based approaches, GAs, expert systems, neural networks, and other approaches. Each of these methods will be explained in a separate section, and its previous applications in various research studies will be examined. This will be followed by a conclusion section, which will synthesize the collected data to provide a better understanding of the application of each of these methods.

2 Case-based reasoning and knowledge-based approaches

2.1 Definitions

Case-based reasoning (CBR), as an essentially different tool from the other major artificial intelligence tools, is able to exploit the specific knowledge of formerly practiced situations [1]. The CBR method remembers an earlier situation comparable to the present problem or situation and uses that earlier data to solve and explain the new problem. This method can adapt and use older situations (cases) to explain, critique, or cause new situations [45]. The main features of CBR can be summarized as below [80]:

- It does not need a specific domain model
- Its application is reduced to "identifying significant features that describe a case"
- It uses databases to handle huge amount of information
- It learns by receiving new knowledge in the form of new cases

2.2 Related research studies

In the late 1980s, Navinchandra et al. [64] described their GHOST network generator. The GHOST was able to take activities as input and develop a precedency network for those activities as output, by relying on knowledge about construction rules, basic physics, etc. Benjamin et al. [7] proposed a knowledge-based prototype for the purpose of planning and scheduling construction projects. Their prototype was aimed at generating schedules and also increasing the productivity of inexperienced schedulers. Their system helped schedulers identify precedence relationships and work breakdown structures (WBSs) by mimicking the process of an expert's decision making. Another group of researchers worked on a knowledge-based planning system (a.k.a. KNOW PLAN) in which the artificial intelligence (AI) and computer-aided design (CAD) are integrated for generating and then simulating construction schedules [59]. Echeverry et al. [14] listed the following four basic factors influencing the process of sequencing construction activities: physical relationships, construction trade interactions, interference-free paths of the objects, and code regulations. Then, they proposed their own knowledge-based prototype, which used some of the aforementioned factors to publish project-sequencing plans. Schirmer [68] integrated heuristic and CBR approaches for resource-constrained project scheduling problems. In his paper, he verified the proposed algorithm and described how to develop such a CBR system.

Muñoz-Avila and his team [62] started working on developing a CBR solution for generating construction schedules. As their first step, they introduced their novel case-based planning algorithm, named SiN. SiN was able to generate project plans using previously provided cases when an incomplete domain theory is given. Then, they focused on how to acquire proper cases from a project automatically or with minimum end-user efforts [61]. Their integrated plan retrieval model (as a CBR) served to help project planners create WBS more efficiently [44]. Later in 2003, they described how to use justification truth-maintenance system (JTMS) technology for further development of the algorithm [83]. By the use of this technology, along with a CBR module, they were able to create an interactive environment in which a user can either edit the project schedule or retrieve a case from the database to be reused in the scheduling process. They also presented their CBM-Gen+ algorithm that revised and edited the available cases in the database when there was a new solution [84]. With this revision on the existing case, the chance of inconsistency between the cases was reduced. Ultimately, their CBR solution, called Case-Based Project Management Assistant (CaBMA), was developed as an add-in extension for Microsoft Project [85]. This software was able to properly identify the cases from the project plans, reuse the previously captured cases to generate a new plan, and preserve the consistency of the entire project schedule [87]. They also worked on another software called Domain-Independent System for Case-Based Task Decomposition (DInCAD) that consisted of adding all the four main steps of CBR to the idea of reusing globalized cases to suit new problems [86]. This last research was also published in detail as a PhD dissertation [82].

König and his team [47] were also interested in this field of research. They presented a method to generate various task-ordering alternatives for a construction plan, along with an evaluation of each alternative. Their algorithm was able to automatically generate project schedules at any time and took advantage of using feature logic generic language [72] to associate existing constraints [74]. Later on, they used 3D model data in the form of Industry Foundation Classes (IFC) along with the cases from previous projects. When a new schedule for the given 3D model needed to be generated, their algorithm used feature logic to identify the cases in the 3D model, and CBR retrieved the most similar case(s) from the database using the proposed evaluation method. The solution to the scheduling problem would then be presented to the project manager and his/her final approval added to the database as a new case [54]. Therefore, they used a building information model (BIM) to identify the tasks to be scheduled through retrieving, reusing, revising, and retaining the learned experiences as CBR cases [55]. Summary and highlights of these pieces of research are shown in Table 1.

3 Model-based

Fischer and his team [27] showed interest in using project models as input for their algorithm to develop construction schedules. Based on their work in the Center for Integrated Facility Engineering (CIFE) at Stanford University, they extended the idea of automatic project schedules by adding models of construction methods. Their system, known as MOCA, used formalized construction method models to perform the scheduling based on product models. They defined the following five characteristics for each method: constituting activities, domain, constituting objects, resource requirements, and activity sequencing. These methods decomposed higher level activities of the schedule into lower level ones to ease the linking of the schedules with diverse level of details [25]. Then, they presented their constructability knowledge approach, which was tested for reinforced concrete structures. This approach was divided into the following five items: layout knowledge, application heuristics, dimensioning knowledge, exogenous knowledge, and detailing knowledge [26]. In their next step, they used component-based CAD models as their source of data. They discussed the shortcomings of common 4D (3D + time) models and showed planning support to be a requirement for CAD tools. Also, they proposed their own solution to the scheduling problem by generating 4D + x models for showing construction processes more accurately [53]. After a few years, they addressed the critical path method (CPM) limitations in rescheduling by defining a “constraint ontology” and “classification mechanism.” They implemented their method as a prototype that can quickly find out which tasks should be postponed to accelerate bottleneck tasks or critical milestones [48].

Firat [23], interested in automated solutions for scheduling problems, proposed the building construction information model (BCIM), including three submodels: building product model (BPM), building construction resource and cost model (BPRCM), and building construction process model (BCPM). These three submodels were focused on design objectives, resource objectives, and activity objectives, respectively [21]. Firat then used the location-based advanced line of balance (ALoB) as the output of his proposed methodology to show and solve the scheduling problem [22]. This model consisted of two processes; the first one generated a master schedule with the help of the aforementioned submodels, while in the second process, the project manager inputted detailed information to come up with an extended schedule based on the master schedule from the previous step [24]. Finally, Firat extended his model to be able to perform quantity takeoff in residential construction projects using his BCIM submodel along with the ALoB method [20].

Vriesa and Harink [77] presented their algorithm, which extracted the construction sequence from a 3D model of the building. They detected the adjacency inferences and used the approach of displacing objects downward to find intersecting

Table 1 Research highlights on case-based reasoning and knowledge-based approaches

Method/Tool	Contributors	Year	Remark
GHOST network	Navinchandra et al.	1988	Developing a precedency network, based on construction knowledge
Knowledge-based planning system (KNOW PLAN)	Morad and Beliveau	1991	Using artificial intelligence (AI) and computer-aided design (CAD)
SiN	Muñoz-Avila et al.	2001	Case-based planning algorithm
CBM-Gen+ algorithm	Xu and Muñoz-Avila	2003	–
CaBMA	Xu and Muñoz-Avila	2004	An extension for Microsoft Project
DInCAD	Xu and Muñoz-Avila	2005	–
BIM	Mikulakova E. et al.	2010	Using BIM as the source for data

components. Tulke et al. [76] addressed the common object-splitting problems of using BIM for scheduling and proposed their algorithm for BIM object boundary representations as defined in IFC. Kataoka [42] described his new way for automating construction simulations with the help of "construction method templates" stored as a knowledge base. Tauscher et al. [74] works described earlier could also be mentioned here as a model-based approach, since his team explicitly used IFC as 3D model input to their algorithm. Büchmann-Slorup and Andersson [8] reviewed the construction scheduling process, taking into account the BIM-based approaches. Weldu and Knapp [81] developed a "rule-based spatial reasoning" method that used the BIM components' topological relationships and automatically generated meaningful schedules for constructing the given 3D model. Table 2 shows highlights of the mentioned pieces of research.

4 Genetic algorithms

4.1 Definitions

The GA is an optimization tool that uses a heuristic search which mimics the natural evolutionary process [56]. Using a well-defined fitness function as the objective function or the core metric, the initial randomly generated genomes can evolve into optimized solution(s) for a given problem. This optimization is based on the objective(s) that is mathematically defined by the fitness function. The GA is known as a popular meta-heuristic optimization method that is mainly suitable for solving multi-objective problems [46] such as construction scheduling.

4.2 Related research studies

Davis [11] introduced the use of the genetic algorithm for optimizing job shop scheduling in the 1980s. A few years later, Wall [78] used GA for resource-constrained scheduling as his dissertation topic. He optimized the sequencing of job shop tasks by feeding the GA with more than 1000 different types of scheduling problems ranging from small job shop to project scheduling (10–300 activities, 3–10 resource types). Chan et al. [9] presented their work as the scheduling of resource-constrained construction projects using GA. They showed how their proposed GA-scheduler can optimize the resource utilization and perform resource leveling to come up with better project schedules compared to heuristic methods. Gonçalves et al. [28] continued this work by tackling resource-constrained multi-project scheduling. Murata et al. [63] introduced their multi-objective GA to reach Pareto fronts of flow-shop scheduling and described how their GA was developed.

Toklu [75] used genetic algorithms for scheduling of construction projects without resource constraints. He used a model to define the relationships between network activities (start to start or SS, start to finish or SF, finish to start or FS, and finish to finish or FF). Toklu simplified these relationships by defining basic mathematical equations; for instance, he defined the start-to-start relation between task i and task j as $T_i+L_{ssij}\leq T_j$, where L_{ssij} is the start-to-start time lag between task i and task j. Jaśkowski and Sobotka [37] described their evolutionary algorithm (also called GA), a system taking the relationship structure, available resources, and resource requirements of each task as input and finding the shortest duration of performing the project as output.

For multi-objective optimization of construction schedules, GA has been successfully used among engineering researchers [18]. In 1997, Feng et al. [18] introduced a GA methodology for optimizing time–cost relationship in construction projects. They also produced a computer application based on their methodology that could run the algorithm. Zheng et al. [88] also showed their interest in using GA for time–cost tradeoff optimization problems in construction projects. By comparing GA with other techniques, they showed that GA is capable of generating optimum results for time–cost optimization (TCO) problems in large construction projects. They also presented their own multi-objective GA using the adaptive weight approach, which was able to point out an

Table 2 Research highlights on model-based approach

Method/Tool	Contributors	Year	Remark
MOCA	Fischer	1994	Using formalized construction method models to perform the scheduling based on product models
Component-based CAD models	McKinneya and Fischer	1998	–
Building construction information model (BCIM)	Firat	2007	Including three models: building product model (BPM), building construction resource and cost model (BPRCM), and building construction process model (BCPM)
BIM for scheduling	Tulke et al.	2008	Based the algorithm on BIM objects
	Büchmann-Slorup and Andersson	2010	
Rule-based spatial reasoning method	Weldu and Knapp	2012	Using the BIM component topological relationships

optimal total project cost and duration [89]. Later, they showed that using niche formation, Pareto ranking, and the adaptive weighting approach in multi-objective GA could result in more robust TCO results [90].

In 2005, Azaron et al. [5] introduced their multi-objective GA for solving time–cost relationship problems specifically in PERT networks. In their research, they defined four objectives: minimizing project direct cost, minimizing mean of project duration, minimizing variance of project duration, and maximizing probability of reaching project duration limit. Another group of researchers developed their own multi-objective GA to reach a set of project schedules with near-optimum duration, cost, and resource allocation and embedded their algorithm inside MS Project as a macro [12]. In 2008, a multi-objective GA was introduced for scheduling linear construction projects; this focused on optimizing both project cost and time as its objectives [69]. Hooshyar et al. [35] presented a GA time–cost tradeoff problem solver with higher calculation speed than the Siemens algorithm. Senouci and Al-Derham [69] conducted similar research on this, focusing on multi-objective GA-based optimization. They implemented their algorithm for scheduling linear construction projects.

Abd El Razek et al. [2] developed an algorithm that used line of balance and critical path method concepts in a multi-objective GA. This proposed algorithm was designed to help project planners in optimizing resource utilization. This resource utilization optimization was conducted by minimizing cost and time while maximizing project quality by increasing resource usage efficiency. Late in 2011, Mohammadi [57] introduced his multi-objective genetic algorithm (MOGA) that generated Pareto front in its approach toward solving the TCO problem in industrial environments. In 2012, Lin et al. [50] designed and introduced their multi-section GA model for scheduling problems. They showed that the combination of that model with their proposed network modeling technique can provide automatic scheduling in the manufacturing system. In addition, Faghihi et al. [15] developed constructible project schedules using genetic algorithms and extended their ideas to optimize time, cost, and job-site movement of the crew. Main contributions and research highlights are listed in Table 3.

5 Expert systems

5.1 Definitions

An expert system, as a subset of artificial intelligence, is defined as a computer-based algorithm that imitates human decision-making skills [36]. Expert systems are generated for resolving complex and difficult problems by reasoning about knowledge. These systems are designed mainly using if–then structures instead of regular practical codes [52]. The initial development of expert systems occurred in the 1970s and matured in the 1980s [13].

5.2 Related research studies

Hendrickson and his team [52] started their work on using the expert system method for construction scheduling problems in the mid-1980s. In their first attempt, they evaluated how an expert system can control a project's cost, time, purchasing, and inventory by incorporating sample if-then structures. Then, they further developed their idea, as a prototype expert system, to estimate the duration of masonry construction projects, an attempt they called MASON [32]. In 1987, Hendrickson et al. [34] described their "prototypical knowledge intensive expert system," named CONSTRUCTION PLANEX and written on top of PLANEX, which can perform construction planning [91]. In construction planning, they only focused on developing project activity networks, cost estimating, and scheduling [33]. They used the proposed method to schedule the modular structural system of a high-rise building, including activities such as excavation and foundation [92]. They also developed a software package named Economic Optimization Module (EOM), aimed at minimizing the total cost of a concrete pour activity and considering time delay fines and material costs [66]. They also presented their prototype system, Integrated Building Design Environment (IBDE), to explore the communication- and integration-related issues common to the construction industry. The addressed issues were data organization, implementation, intercommunication, knowledge representation, and control [19].

Levitt et al. [49] attempted the use of AI in construction planning in 1988. They pointed out the limitations of planning

Table 3 Research highlights on genetic algorithm

Method/Tool	Contributors	Year	Remark
Job shop scheduling	Davis	1985	–
Resource-constrained scheduling	Wall	1996	–
Resource-constrained construction projects	Chan et al.	1996	–
Time–cost optimization in construction projects	Feng et al. Zheng et al.	1997 2002	–
Line of balance and critical path method	Abd El Razek et al.	2010	Optimizing resource utilization

tools and demonstrated the strength of AI for scheduling construction projects in their first step. Then, they introduced their “System for Interactive Planning and Execution (SIPE)” that was able to generate correct activity networks for multi-story office building projects [40]. An extension to the software, SIPE-2, was also able to develop hierarchical schedules for building a single-family house [41].

In 1990, Mohan [58] listed 37 different expert system tools that had been developed, focusing on the construction and management field of research, and predicted that the construction industry would use expert systems more in next few years. Moselhi and Nicholas [60] described their work as an integrated hybrid expert system that was produced using a relational database, traditional network analyzing software, and an interface written in the FORTRAN programming language. Their system was able to consider different productivity levels based on labor reassignment, site congestion, learning curves, and overtime. Shaked and Warszawski [70] presented their CONSCHED system that was able to perform quantity estimation, activity generation, activity time, resource allocation, and schedule determination. Then, they extended their knowledge-based expert system to take an object-oriented model of a high-rise building, along with the production functions, rules, and routines for developing construction schedules. Finally, they used algorithms to optimize resource allocation for managerial efficiency, minimal cost, or shortest duration [71]. Wang [79] developed an expert system with a knowledge-based programming technique, called ESSCAD, specifically for construction scheduling using information in CAD drawings. The outcome of the system was a primary construction project schedule, and as a test, a construction schedule of a reinforced concrete frame structure was generated from its AutoCAD drawings. A list of important contribution and pieces of research is summarized in Table 4.

6 Neural networks

6.1 Definitions

Artificial neural networks (ANNs), as computational models, are initially inspired by the brains of animals that are able to perform pattern recognition using the “all-or-none” (similar to mathematical binary language, 0 and 1) rule of the nerves.

McCulloch and Pitts [51] were stimulated by “all-or-none” characteristics of nervous functions and generated the first computational model defining neural networks using algorithms and mathematics. Then, Hebb [31] described a neural based learning theory known today as “Hebbian theory” or “Hebb’s rule.” In 1954, Farley and Clark [17] simulated a Hebbian network using so-called calculators as a computational machine at that time.

6.2 Related research studies

Sabuncuoglu [67] showed in his extensive literature review that although using ANN has been a tool for diverse scheduling problems (e.g., job-shop scheduling, single-machine scheduling, timetable scheduling, etc.), it was not used for construction sequencing and scheduling.

Adeli and Karim [3] started their work on using ANNs in the construction field of research. They introduced their mathematical formulation of construction scheduling and used their own developed ANN to optimize construction cost and ultimately cost-duration tradeoff by varying the project duration. Then, they extended their work and developed an object-oriented model [38]. Later, they implemented their work as software named CONSCOM that aimed to solve construction scheduling, change order management, and cost optimization problems [39].

Table 4 Research highlights on expert system

Method/Tool	Contributors	Year	Remark
MASON	Hendrickson, Martinelli, and Rehak	1987	Estimating duration for masonry construction projects
CONSTRUCTION PLANEX	Zozaya-Gorostiza, Hendrickson, and Rehak	1989	Prototypical knowledge-intensive expert system
Economic Optimization Module (EOM)	Phelan et al.	1990	Aiming to minimize the total cost of a concrete pour activity considering time delay fines and material cost
Integrated Building Design Environment (IBDE)	Fenves et al.	1990	Exploring the communication and integration-related issues in the construction industry
SIPE	Kartam and Levitt	1990	Generating correct activity network for multi-story office building projects
SIPE-2	Kartam, Levitt, and Wilkins	1991	Developing hierarchical schedules for building a single-family house
CONSCHED	Shaked and Warszawski	1992	Performing quantity estimation, activity generation, activity time, and resource allocation
ESSCAD	Wang	2001	Using information in CAD drawings

Table 5 Research highlights on neural network

Method/Tool	Contributors	Year	Remark
CONSCOM	Karim and Adeli	1999	Aiming to solve construction scheduling, change order management, and cost optimization problems
WBS generator	Hashemi Golpayegani	2007	Generating WBS of a given project
Single-machine scheduling	Rondon et al.	2008	Considering variables such as operation, deadline time, setup time, processing time, and due date

Hashemi Golpayegani [29] designed an ANN framework that could generate WBS of a given project. The entire solution consisted of five different ANN modules in three main categories: functional WBS, project control WBS, and relational WBS, each of which participated in developing the master WBS for their own section. Then, Hashemi Golpayegani extended the proposed system to a level such that the generated WBS could have simple finish-to-start relations leading to a workable project schedule at the end [30]. While he was working on this extension, another group of researchers showed their interest in developing WBS of the projects using ANNs [6]. They used four successively arranged neural networks rather than Hashemi's parallel structure. In 2008, Rondon et al. [4] introduced a neural network designed to schedule a single machine while considering variables such as the operation, deadline time, setup time, processing time, due date time, and other factors. Table 5 lists highlight pieces of research in this field.

7 Other methods

Kim et al. [43] designed a system dynamic (SD) model to find optimum program-level scheduling of sustainability projects on a university campus. The SD model was able to rearrange the projects in the given program to come up with a better sequencing of the projects in order to maximize cost savings. An extension of the same research investigated the combined interaction of human behavior modification and hardware improvement in monetary savings as well as timing and sequencing of the projects [16]. Damnjanovic et al. [10] developed a model of predicting a project's future and its milestones using prediction markets with the Hanson calculation method. By the use of that proposed tool, a project manager and his/her team can gain better insight into the project, helping them reschedule the project plan effectively.

8 Results

The literature review revealed the application of several methods to tackle scheduling problems, some more effective than others. The distribution of these methods is illustrated in Fig. 1. This figure clearly shows the dominant distribution of the genetic algorithm method as an optimization tool used by researchers to solve scheduling problems, specifically in the field of construction.

Each of these methods had different contributions to the construction field and represented different approaches to solving construction scheduling problems. These contributions are categorized into three different categories: time, cost, and quality. Figure 2 shows how each of the methods dealt with different aspects of construction scheduling. This figure also shows how genetic algorithms appeared instrumental in all the important aspects of construction management. An extended version of this figure is presented in Table 6, where the

Fig. 1 Distribution of methods (*NN* neutral networks, *GA* genetic algorithm, *KB* knowledge-based, *MB* model-based, *ES* expert system, *CB* case-based)

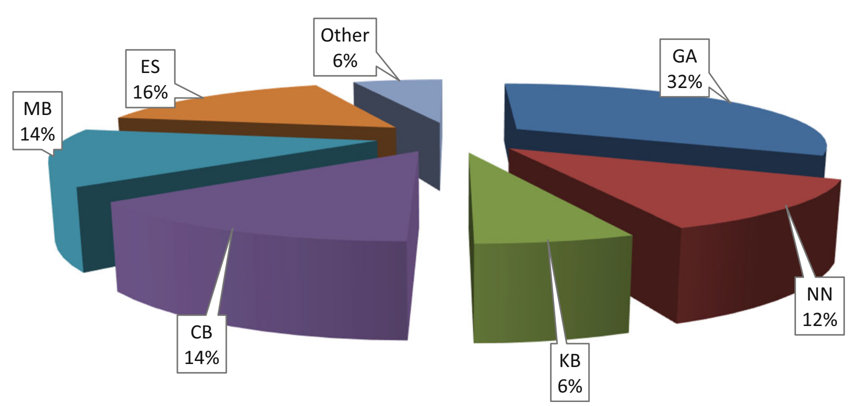
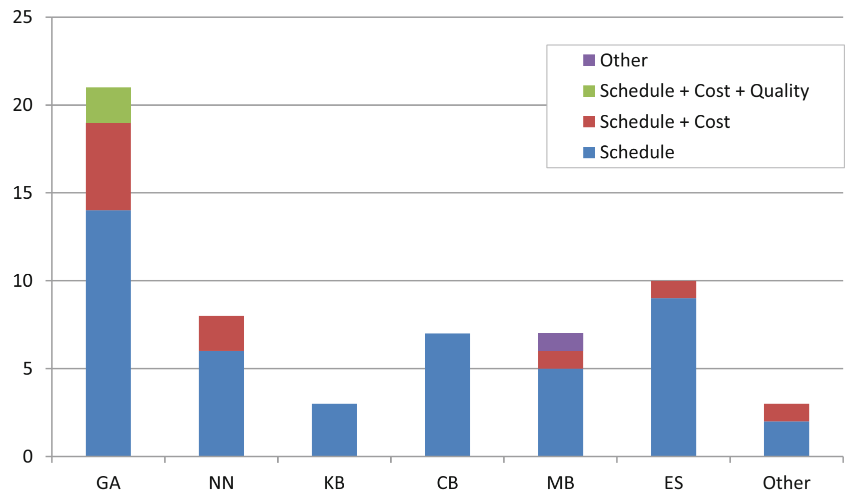


Fig. 2 Methods' contributions (*NN* neural networks, *GA* genetic algorithm, *KB* knowledge-based, *MB* model-based, *ES* expert system, *CB* case-based)



contribution of each study to the different aspects of construction management is specifically elaborated. The results show that the main focus of the researchers dealing with construction scheduling problems was on the time aspect of the project schedule, while the other two aspects (cost and quality) are equally important with not much attention from the researchers.

As previously elaborated, each of the current approaches targeted a unique aspect of the scheduling problem. While genetic algorithms are mainly focused on resource optimization and leveling by integrating the concepts of critical path method and line of balance, case-based reasoning and knowledge-based approaches are mainly dependent on utilizing similar historical data and developing knowledgebase to tackle the scheduling problem. On the other hand, while model-based approaches emphasize the development of rules for automating construction schedules such as spatial reasoning, artificial neural networks are mainly used to highlight the cost–schedule tradeoffs and perform cost optimization. Although there is an ample body of literature on the application of various tools to address the hassles associated with developing project schedules, there is still a lot to be carried out. This is mainly due to the fact that creating project schedules is highly reliant on a multitude of factors including but not limited to project planners' knowledge of a project's WBS, on-the-job experience, and planning capabilities. One of the remaining gaps to be bridged is a hybrid approach toward addressing multiple objectives associated with scheduling. An example is the need for a new hybrid tool that can automate schedules by ensuring the structural stability of the project while optimizing its schedule and cost. These hybrid approaches are both more feasible and more easily overcome mainly due to the prevalence of building information models, which can store all the required information needed to perform stability/structural analysis, especially their geometry and material properties.

9 Conclusion and suggestions

This paper summarizes the existing approaches to solve one of the most important problems in the field of construction management, that of project scheduling. Several different methods have been used by researchers to optimize project scheduling. As mentioned earlier, the method that has been used most often to cover all the aspects of scheduling is the genetic algorithm. This optimization tool has proven beneficial to optimizing project schedules with different objectives.

The recent introduction of BIM in the AEC industry opened a new aspect of integrating project information and data with its 3D model view. This new BIM can cooperate with any scheduling techniques and models that need project data, as a good source of project information to provide input for them. For the knowledge-based and case-based approaches, the BIM of the previous projects can be considered as the set of past knowledge and cases to be retrieved and reused. This article describes and lists some interests that have been raised to use BIM in the model-based approach section as a rich source of project data. Decompiling the embedded data from the 3D model can produce the relationship network for the project to be used as the basis for the GA fitness function.

This enriched source of data of the project elements and members increases the need to revisit some of the previous approaches while having the BIM in mind to find possibly more robust solutions for construction scheduling problems. For instance, using the embedded information in BIM can facilitate accessing precise geometry information for all the project elements. Also, having a digital 3D model of the entire project helps the scheduler to acquire a visual understanding of the project, as the plastic 3D model was used before the

Table 6 Detailed information on studies' contributions to construction scheduling problem

Research (alphabetical order)	Method*	Time	Cost	Quality	Benefits	Type of construction
R. H. Abd El Razek et al. [2]	GA	✓	✓	✓		
H. Adeli and A. Karim [3]	NN	✓	✓			
R.L. Avila Rondon et al. [4]	NN	✓				
A. Azaron et al. [5]	GA	✓	✓			
C. Benjamin et al. [7]	CB	✓				
R. Büchmann-Slorup and N. Andersson [8]	BIM	✓				
W. Chan et al. [9]	GA	✓				
L. Davis [11]	GA	✓				
N. Dawood and E. Sriprasert [12]	GA	✓				
D. Echeverry et al. [14]	CB	✓				
V. Faghihi et al. [15]	SD	✓	✓		Dynamic model	University campus
V. Faghihi et al., 2014 [16]	GA	✓	✓	✓	Developing schedule	
C. Feng et al. [18]	GA	✓	✓			
C. E. Firat et al. [22]	ES	✓				
C. E. Firat et al. [24]	MB	✓				
C. E. Firat et al. [20]	MB				Quantity takeoff	Residential
C. E. Firat et al. [23]	MB	✓				
M. Fischer et al. [27]	MB	✓	✓			
J.F. Gonçalves et al. [28]	GA	✓			Resource-constrained	
S.A. Hashemi Golpayegani and B. Emamizadeh [29]	NN	✓				
S.A. Hashemi Golpayegani and F. Parvaresh [30]	NN	✓				
C. Hendrickson et al. [33]	KB	✓				
C. Hendrickson et al. [34]	RB	✓				
B. Hooshyar et al. [35]	GA	✓	✓			
P. Jaśkowski and A. Sobotka [37]	GA	✓				
A. Karim and H. Adeli [38]	NN	✓	✓			
A. Karim and H. Adeli, 1999 (ASCE) [39]	NN	✓				
H. Kartam and R. Levitt [40]	ES	✓				Office building
H. Kartam et al. [41]	ES	✓				Single-family house
A. Kim et al. [43]	SD	✓	✓		Dynamic model	University campus
A. Konaka et al. [46]	GA	✓				
M. König et al. [47]	CB	✓				
B. Koo et al. [48]	MB	✓				
R.E. Levitt et al. [49]	ES	✓				
M. R. McGartland and C.T. Hendrickson [52]	ES	✓			Project monitoring	
K. McKinneya and M. Fischer [53]	MB	✓				
E. Mikulakova et al. [55]	KB	✓				
M. Mitchell [56]	GA	✓	✓			
G. Mohammadi [57]	ES	✓				
A. Morad and Y. Beliveau [59]	ES	✓				
S. Mukkamalla and Héctor Muñoz-Avila [61]	CB	✓				
H. Muñoz-Avila et al. [62]	GA	✓				
T. Murata [63]	CB	✓			GHOST	
A. Newell and H. A. Simon [65]	ES	✓	✓			Concrete pouring activity
I. Sabuncuoglu [67]	CB	✓				
A. Shrimmer [68]	GA	✓				Linear construction
A. Senouci and H. R. Al-Derham [69]	ES	✓				Modular construction
O. Shaked and A. Warszawski [70]	KB	✓				High-rise building
E.E. Tauscher et al. [73]	CB	✓				

Table 6 (continued)

Research (alphabetical order)	Method*	Time	Cost	Quality	Benefits	Type of construction
E.E. Tauscher et al. [74]	GA	✓			Resource constraint	

NN neural networks, *GA* genetic algorithm, *KB* knowledge-based, *MB* model-based, *ES* expert system, *CB* case-based, *RB* rule-based, *SD* system dynamic, *BIM* building information model

introduction of digital 3D models and lately with embedded information as BIM.

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