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REAL-TIME PIPE SYSTEM INSTALLATION SCHEDULE GENERATION AND OPTIMIZATION USING ARTIFICIAL INTELLIGENCE AND HEURISTIC TECHNIQUES

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SUMMARY: *Infrastructure systems in the United States are aging and considerable investment is needed to renew and replace a significant proportion of the existing systems. Piping systems, which are used in many infrastructure systems such as the distribution networks for utilities – water, sewage, gas, oil, etc., are very important in this regard. Real time scheduling is an important and necessary task in the planning and execution of construction projects. This is of particular importance in the installation of pipe systems, for which it is time consuming to plan and coordinate between team members the detailed requirements and information for the generation of practical installation schedules. During the installation stage, there can be delays or interference that could lead to the failure of the initial schedule plan. Current approaches are time-consuming, not automated and do not provide real-time schedules. Thus, the process is still fragmented and essentially manual, with inefficient information flow. To effectively improve the installation schedule, current knowledge of the installation site situation is important, with this knowledge being used to generate realistic schedules. Artificial intelligence (AI) maximizes the value of data by learning from previous cases and facilitates decision-making by making the process smarter and automatic. This paper proposes a new AI framework with machine learning (ML) and heuristic optimization techniques for automating practical pipe system installation schedule generation and optimization. A BIM model is used as reference to provide pipe system component information. A hybrid knowledge-based system is developed to integrate data-driven knowledge base and site-driven knowledge base on pipe system installation. K-Nearest Neighbor (KNN) and Graph Neural Network (GNN) ML techniques are adapted to map extracted components with the installation activities and their requirements for installation based on knowledge obtained from industry experts and piping codes. In addition, a heuristic algorithm is adopted to optimize the installation schedule. Finally, an optimal installation schedule that minimizes overlapping activities, time and cost is suggested.*

KEYWORDS*: Artificial Intelligence, Machine Learning, Automation, Pipe Systems, Schedule, BIM*

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1. INTRODUCTION

Across the United States, pipe-based infrastructure systems are aging and close to the end of their useful life. With water distribution systems, lead and corroded iron pipes are contributing to poor drinking water which is endangering public health [1]. The White House plans to 'Rebuild & Upgrade Water Infrastructure' to provide clean drinking water. The plan seeks to invest $111 billion in modernizing pipe system infrastructure [1]. Enhancing America's energy infrastructure, particularly for an abundant, reliable, and affordable natural gas, is one of the highest priorities of Advanced Research Projects Agency-Energy (ARPA-E) Administration. To keep up with growing energy industry, it is imperative to modernize and build out pipe infrastructures safely and efficiently [3]. To effectively plan pipe system infrastructure, careful planning and scheduling of pipe system installation are important and necessary tasks. Pipe system installation refers to laying and fitting of a pipe system to transport fluids or gases from the supply location to the demand location. Installation of pipe systems can be very challenging as it requires detailed planning, sequencing, coordination, and scheduling of pipe systems and components. To improve the operation and execution level of pipe system installation, automatic optimization and generation of real time installation schedule is important. A real time schedule incorporates the current situation on site and generates a plan based on available information that gives a list of tasks and the times at which each one should be undertaken. As such, real time installation schedule planning and execution are crucial aspects of the piping project in achieving efficient installation flow, high productivity, and completion of the project at a reduced cost and shorter duration. Many schedules have numerous conflicting features which are hard to discover during the planning stage and are only detected during the installation stage. Unanticipated conflicting constraints during pipe system installation can render initial planned schedules impractical and could result in mistakes, rework, additional costs, and schedule delays. As such, planning and generation of schedules based only on primary data/information may result in a redundant and infeasible schedule during the execution of the installation process on site. The real time correlation between various constraints such as, sequence of pipe system installation, resource availability, sudden delays or accidents is very important for robust, responsive and practical execution of pipe systems installation. Generation of real time installation schedules for pipe systems involves coordinating and integrating the pipe systems sequence with actual resource availability (workforce, machines, materials) and dealing with unanticipated constraints on site at a particular instance of time in an efficient way.

A piping project consists of numerous pipe systems having complex logic networks and containing various components such as: pipes, fittings, valves, etc. Various factors are considered in generating real time schedules for the installation of pipe systems. These include exact location of installation, availability of resources, unexpected delays, systematic installation process, time and space conflicts between pipe system components and other working resources, and the starting location for the installation. Adequate sequencing logic based on all constraints and real time information on all required data and resources is the basic premise behind efficient practical scheduling. A correct schedule should fulfil all the requirements and meet all the constraints and deadlines, whereas a wrong schedule could result in errors, risks, reworks, additional costs, and schedule delays. Therefore, realistic planning of schedules with a better understanding of the potential constraints, sequencing logic, and timely update of required information on pipe system installation can ensure an effortless installation process and generate the most appropriate practical schedule with reduced idle time and delays.

Traditional scheduling methods such as the Linear Schedule Method (LSM) (Harmelink 1995), Critical Path Method (CPM) (PMI 2017), Program Evaluation and Review Technique (PERT) (PMI 2017), Precedence Diagram Method (PDM) (El-Rayes and Moselhi 2001) have been widely applied for several decades. Traditional manual scheduling tools cannot produce optimized schedules and are ineffective with increased job complexity due to inconsistencies between the component breakdown structure of the model and the breakdown structure of the activities (Park and Cai 2015). The Last Planner System (Ballard and Howell 1994) and the Critical Chain Scheduling (CCS) method (Yang 2004) have been applied to the project management domain and can make schedule planning more effective than other traditional scheduling techniques. These scheduling methods require manual inputs, thereby taking substantial time and cost with lower levels of accuracy for bigger projects having complicated networks. Several commercial software such as: MS Project, Primavera, Mavenlink, etc. have considerably reduced the drawbacks of manual scheduling but require time-consuming preparation and significant human effort. Furthermore, they may not guarantee the generation of robust and realistic schedules as they are based on information fed to the system prior to schedule generation. Correlating timely information with complex pipe system networks and various constraints for practical schedule generation is complicated and time-consuming. Therefore, it needs to be automated and planned in a timely manner.

In recent years, Building Information Modelling (BIM) has offered substantial improvements in planning and scheduling in the construction industry. 4D BIM has been used and shows significant advantages in generating schedules (Kacprzyk and Kępa. 2014; Kim et al. 2013; Moon et al. 2014). The scope and capability, however, are limited and the link between design and scheduling still has room for further development (Wang and Azar 2018). Due to manual inputs required to pair and integrate the 3D BIM models with schedule related information such as installation procedure and activities, resources productivity, etc., it is time consuming to plan and coordinate between team members to understand the detailed requirements and information for the generation of practical installation schedules. In addition, limited studies are available on the application of 4D BIM for the generation of installation schedules for pipe systems. To effectively improve the installation schedule, continual learning of the installation site situation is important, with the learnt knowledge being used to generate realistic schedules. Liu et al. (2019) proposed Integrated Change and Knowledge Management System to manage changes and dependencies, track change histories, and capture lessons learned from changes. Artificial intelligence (AI) maximizes the value of data by continual learning from previous cases and other related knowledge database. In addition, AI facilitates decision-making which makes the process smart, automates repetitive, rule-based tasks, speeds up process and reduces errors. Moreover, it can also be trained to improve decision-making upon itself and take on broader task. AI can help in optimizing schedules by recommending information/knowledge based on historical data (Green 2016). To generate the practical installation schedule for pipe systems, information based on historic data as well as real-time knowledge of current site condition is important. Therefore, this study proposes a new AI framework with machine learning (ML) and heuristic optimization techniques for automating generation and optimization of practical installation schedule for pipe systems using BIM. 3D BIM model is used as reference to provide pipe systems components information. BIM enables automatic extraction of necessary geometric information (location of pipe systems, start and end point of the pipe systems) which are required to know the position of pipe system components and semantic information (project type, system type, pipe parameters) of piping project, to determine appropriate resource requirements for the efficient installation of pipe systems. Hybrid knowledge based system is developed to position pipe systems at the desired place considering both the data-driven knowledge base and site-driven knowledge base. K-Nearest Neighbor (KNN) and Graph Neural Network (GNN) ML techniques are adapted to integrate extracted information from the hybrid knowledge based system. Spatial constraint analysis is utilized to find the sequence of the whole pipe system minimizing overlapping activities. Since the built environment consists of several pipe systems with various components and logical constraints, exploration of the installation precedence sequences, and optimization of the installation schedule is computationally very demanding and NP-Hard. A heuristic algorithm, Simulated Annealing (SA), is adopted to generate the coordinated and optimized installation schedule in minimum time.

The rest of the paper is structured as follows. Related research work is reviewed in Section 2. Section 3 describes the proposed AI-based Framework for optimizing pipe system installation schedules. Section 4 presents an illustrative example to verify the practicability of the proposed framework. Conclusion and future work are discussed in Section 5.

2. RELATED WORK

Researchers and construction-related project participants have developed technologies related to Artificial Intelligence (AI) field to decrease the dependence level of expert in construction planning and schedule control (Liu et al. 2018). Various studies have focused on planning and optimization of practical schedules in diverse application areas. Pan et al. (2021) established an optimal real-time sequencing strategy based on simulation optimization approach with unbiased gradient estimators for appointment scheduling of patient. Ho and Yu (2021) applied KNN regression to ascertain optimal scheduling strategies for switching chillers and temperature settings of a chiller system in lowering its carbon emission. Kalathas and Papoutsidakis (2021) uses stored-inactive data from a company and uses data mining and applied machine learning techniques to create strategic decision support to generate maintenance schedules. Seccai et al. (2021) proposed a new efficient framework for solving the optimal TV promo scheduling problem by adopting machine learning (ML) models. Bandi and Gupta (2021) developed a framework to solve staffing and scheduling problems in operating rooms using historical case data. Kong et al. (2021) used greedy randomized adaptive search procedure for slot planning and truck scheduling. Zhao et al. (2020) optimized the construction duration and schedule for robustness based on the hybrid grey Wolf optimizer with a sine cosine algorithm. Hosseini et al. (2021) adopted pedestrian simulation model and GA for staged-evacuation schedule optimization. Amer (2020) adopted an active learning-based annotation workflow and tool for sequence labeling of construction schedules. Mawson and Hughes (2020) proposed and compared feed forward and recurrent deep neural networks to forecast manufacturing facility energy consumption and workshop conditions based on production schedules and other building information. Lafond (2021) employed model-based AI, heuristic methods, and discrete-event simulation to efficiently schedule project tasks while handling precedence constraints, resource constraints (labor, equipment) and capacity constraints. Mohamed (2021) developed a model for optimizing the project schedule and cost regarding overlap activities and their impacts. Tallgren et al. (2020) developed BIM-tool to enhance collaborative scheduling for pre-construction. Krause (2020) described AI-based discrete-even simulations for manufacturing schedule optimization. Sasikumar et al. (1997) proposed a knowledge-based heuristic approach for pipeline pumping schedule generation. Wati et al. (2021) discussed AI based Binary Particle Swarm Optimization for load scheduling of power plants to obtain minimum generation costs. Chen et al. (2020) developed real time human-robot collaboration for scheduling multiple tasks for factory production based on multi-threading method and Convolutional Neural Network (CNN). Case (Koo 2010) and knowledge (Mikulakova 2010) based methods are the common approaches to gather information for similar project schedule generation. These approaches require time-consuming manual and semi-manual efforts to extract the necessary information and generate the schedule (Wang and Azar 2018). Recently, AI methods have been used to solve scheduling problems in the manufacturing environment (Zhou et al. 2021). However, it is difficult for scheduling algorithms to process high-dimensional data in a distributed system with heterogeneous components

Although notable efforts have been carried out to optimize schedules, studies on schedule optimization for the installation of pipe systems are still lacking. The research mainly focused on optimization of conceptual schedule, but its application in generation of real-time practical schedules is limited. Few research (Sasikumar et al. 1997; Zhou et al. 2021; Kalathas and Papoutsidakis 2021) on practical schedules mainly discusses the planning of schedules based on historical data and information. The research methodology mostly involved a deterministic approach, which is unable to handle uncertainty in the original plan. However, they did not investigate the incorporation of onsite uncertainties in generating a realistic schedule. Moreover, the current research does not focus on developing a comprehensive strategy for extracting the details and information from the design model to generate and optimize the schedule. Thus the process is still fragmented and essentially manual, thereby making the process vulnerable due to lack of efficient information flow. To overcome these limitations, this paper proposes an AI-based automation framework to extract necessary information from a knowledge-based system for pipe system installation. Simulated Annealing (SA) is used to perform an extensive search to find a global optimum and provides comparable results relative to other prominent heuristic techniques but with lower computation cost and time (Mukhairez and Maghari 2015). As such, this research adopts SA to optimize the practical installation schedule for pipe systems.

3. AI-BASED FRAMEWORK FOR OPTIMIZING PIPE SYSTEM INSTALLATION SCHEDULES

The objective of the proposed AI-based framework is to automate and optimize realistic installation sequence and schedule of pipe systems with minimum time at a particular point in time accommodating all real-time installation constraints. The workflow of the proposed framework is shown in Fig. 1. The framework comprises four main units: 1) BIM Model Extraction, 2) Hybrid Knowledge Based System, 3) Spatial Constraint Analysis, and 4) Schedule Generation and Optimization. The framework extracts all the requisite piping project components information, process information (such as installation procedure, resource requirements details, etc.), and spatial constraint relationship information to formulate a practically favorable optimized schedule. The BIM model provides details of the geometry of the pipe systems, location, system type, and dimensional parameters (diameter and thickness), which are automatically extracted to configure the component breakdown structure. The Hybrid Knowledge Based System is developed considering both the data-driven knowledge base and site-driven knowledge base to provide the knowledge and information required to the position pipe systems at the desired location. KNN and GNN ML techniques are adopted to integrate the extracted components with the information required for installation from the hybrid knowledge based system. Spatial constraints are then analyzed to obtain the installation sequence minimizing overlapping activities and idle time among all the pipe system in 3D space. Optimization of the installation schedule is then done using SA based on a formulated time-minimizing objective function and installation precedence sequence as determined by spatial constraint analysis.

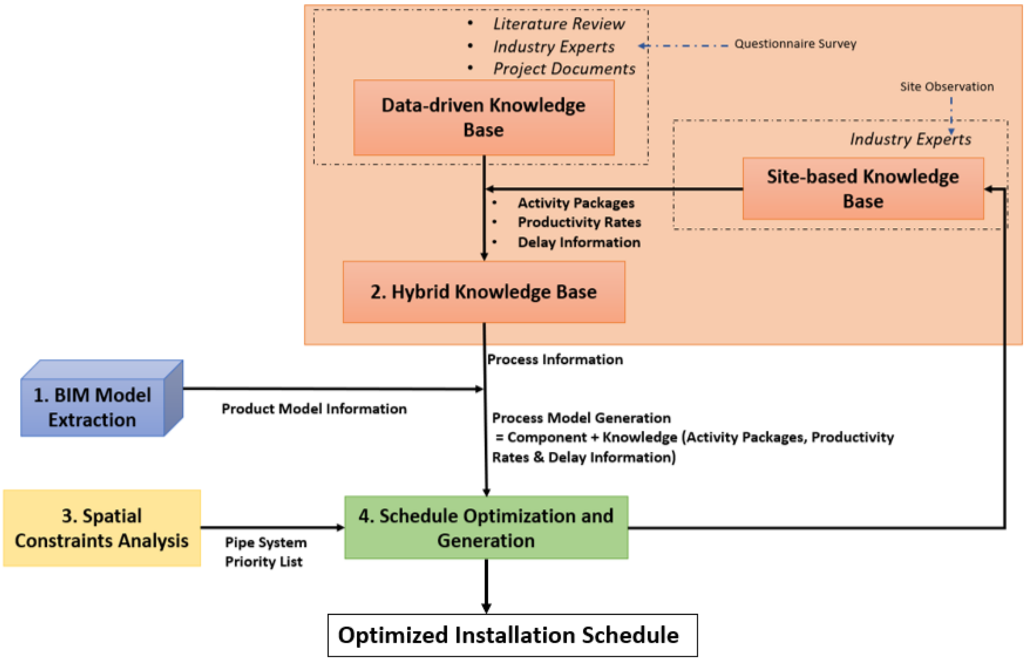


FIG. 1. Workflow of AI-based framework for practical schedule optimization.

3.1. BIM Model Extraction

A BIM model is used as a reference model to provide all the necessary geometric and semantic information required for the generation of an installation schedule for a piping project. All the detailed information (including connections) required for the installation schedule generation of the pipe systems are contained in the BIM model. The geometric information of the pipe system and its components include location, end coordinates, alignment (vertical, horizontal), etc. The semantic information relates to project types (residential, commercial, etc.), pipe system types (hot water, gas system, etc.), and pipe system component parameters (such as diameter, thickness, material, etc.). All the required information is automatically extracted from the BIM model and is stored in an external file (e.g., spreadsheet) for schedule exploration and optimization. After all the necessary details have been extracted from the BIM model, the information about installation procedure and resource productivity for the fitting of pipe systems and their components in the desired location is required. The exported information can also be used to preserve the pipe system information throughout the lifecycle of the project for operation and maintenance purposes.

3.2. Hybrid Knowledge-Based System

The framework includes a hybrid knowledge-based system based on ML to obtain necessary information for the optimization of the installation schedule for pipe systems. The hybrid knowledge-based system is developed considering both the data-driven knowledge base and site-driven knowledge base for continual up to date information and capturing of the experts' knowledge and installation site situation to generate realistic schedules, as shown in Fig. 2. The data-driven knowledge base consists of all the information based on literature reviews, industry experts, and historical project documents. The site-driven knowledge base accommodates all real-time information related to on-site activities such as, any changes in activity procedure, unavailability of resources, site reworks, unfortunate delays, and accidents. In this study hybrid knowledge-based system is responsible for the extraction of two important information items required for installation schedule optimization – these are installation activity packages and resource productivity rates. Installation activity packages refer to series of tasks to be followed to position and fix pipe system components. Resource productivity rates refers to the time taken by the concerned resource to perform a particular task. To select appropriate activity packages and resource productivity rates from the hybrid knowledge base, the list of attributes associated with respective information and weighting values (depending upon their importance in contributing to a particular information) are predetermined based on the knowledge of industry experts. Initially, the hybrid knowledge base consists of information from the data-driven knowledge base. Apart from summarizing the list of installation activity packages and resource productivity rates, the hybrid knowledge-based system also accounts for information related to different delay and set back occurring on site during actual installation of pipe systems. These information helps to generate real time practical schedule based on any delay for installation of the pipe system on site.

ML is used to extract the project associated necessary information from the hybrid knowledge base. In this study, KNN and GNN ML techniques are adapted to extract project specific activity packages and resource productivity rates required to generate and optimize the installation schedule. The extracted information from the hybrid knowledge based system is then combined with the pipe system BIM model to develop a process model (pipe system components + respective installation activity packages + related piping crew productivity information). After the installation is completed, the activity packages exercised, and productivity rates observed on site are mapped with recommended activity packages and productivity rates as per the hybrid knowledge base. If both the activity packages and productivity rates are distinct then the site observed values are added to the hybrid knowledge base for learning purposes. The approaches adopted for learning are discussed below:

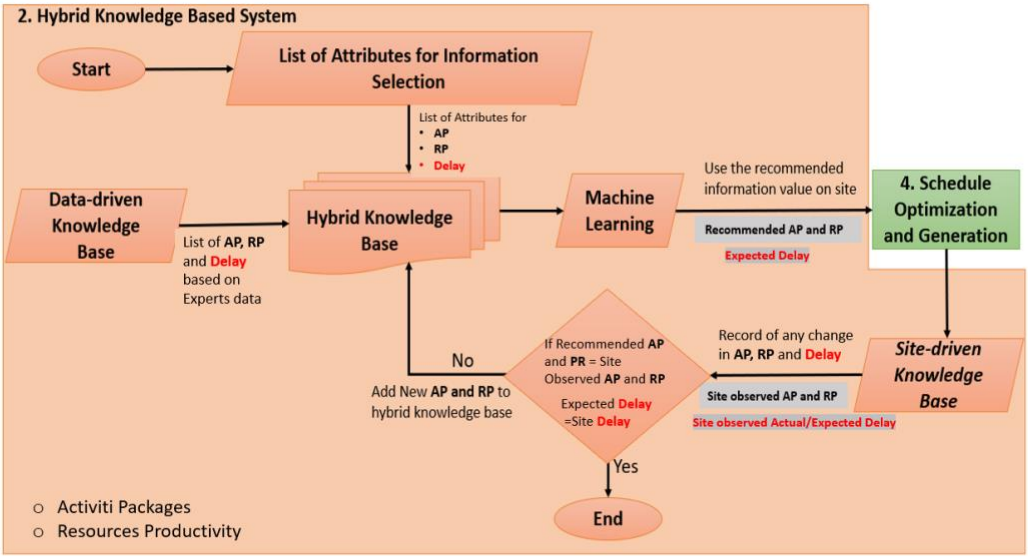


FIG. 2. Extraction information from hybrid knowledge based system

3.2.1. K-Nearest Neighbour (KNN)

KNN is a supervised learning technique which examines the similarity between different types of available cases and finds the most similar case for a particular category among the existing cases. This study examines the likeness between various available activity packages and resource productivity rates contained in the hybrid knowledge base to evaluate the most correlated activity packages and resources productivity rate. Fig. 3 shows different activity packages AP_1, AP_2, and AP_3 in terms of associated list of attributes such as diameter(D), project type (PT), pipe system type (PST), Weight (We) and adopting KNN to examine the similarity between different lists of attributes to find the most appropriate activity packages among those available.

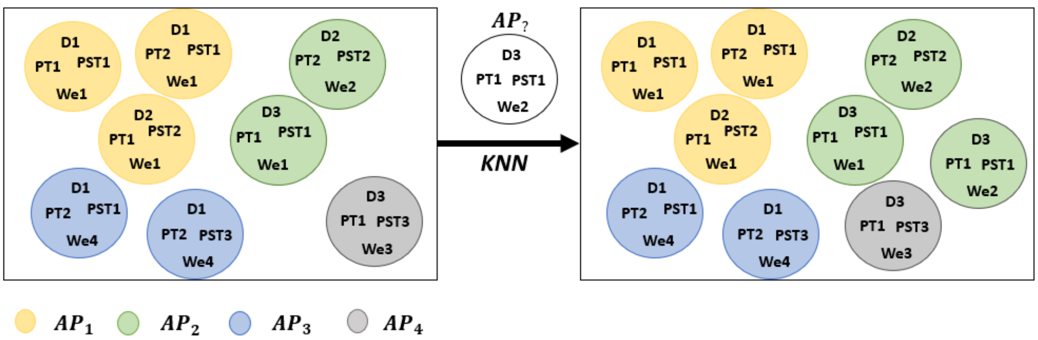


FIG. 3. Example of selection of activity package based on list of attributes

3.2.2. Graph Neural Network (GNN)

GNN is a category of deep neural techniques whose inputs are graphs of structured data. GNN have revolutionized the field of graph representation learning through effectively learned node embeddings and achieved state-of-the-art results in tasks such as node classification and link prediction (Ying et al. 2018). The general approach with GNNs is to view the underlying graph as a computation graph and learn neural network primitives that generate individual node embeddings by passing, transforming, and aggregating node feature information across the graph (Bruna et al. 2014). Graph is represented as (A, F). where $A \in \{0, 1\}$ n×n is the adjacency matrix, and $F \in R$ n×d is the node feature matrix assuming each node has d features. One of the first popular GNNs is the Kipf & Welling graph convolutional network (GCN) employing the message-passing architecture given by Eq. (1) (Ying et al. 2018).

$$H^{(k)} = M\,(A, H^{(k-1);}\ W^{(k)}) \qquad (1)$$

where $H^{(k)} \in R$ n×d are the messages computed after k steps of the GNN; M is the message propagation function, which depends on the adjacency matrix; $H^{(k-1)}$ message generated from the previous message-passing step; $W^{(k)} \in R$ d×d is a trainable weight matrix.

3.3. Spatial Constraint Analysis

Installation sequencing order of pipe systems based on spatial constraints is one of the major issues during the installation of pipe systems. Arbitrary installation of pipe systems and components with inappropriate sequence planning leads to delay, rework, higher installation costs, and congested sites.. Proper sequencing and adequate space for installation are significant to efficiently install a pipe system. Spatial constraint analysis is performed on pipe systems sharing common space by comparing the location of respective pipe systems and components. Spatial constraints occur when the space between nearby pipe systems is less than the minimum distance (D_{Buffer}) required for straightforward installation of both pipe systems simultaneously without any spatial clash or uneasy conflict during installation. To know whether components of pipe systems are sharing common space, this study formulated local boundary approach and determined if there is any overlap between local boundary of respective pipe system as shown in Fig. 4. The minimum and maximum 3D coordinates of a single pipe system is extracted, and a buffer value is added to them and local boundary box for each pipe system is drawn. After drawing local boundary box for pipe system, local boundaries are checked for any space clash and are then marked as overlapped boundary and pipe systems are determined as constraint pipe systems and are further evaluated for spatial constraint analysis.

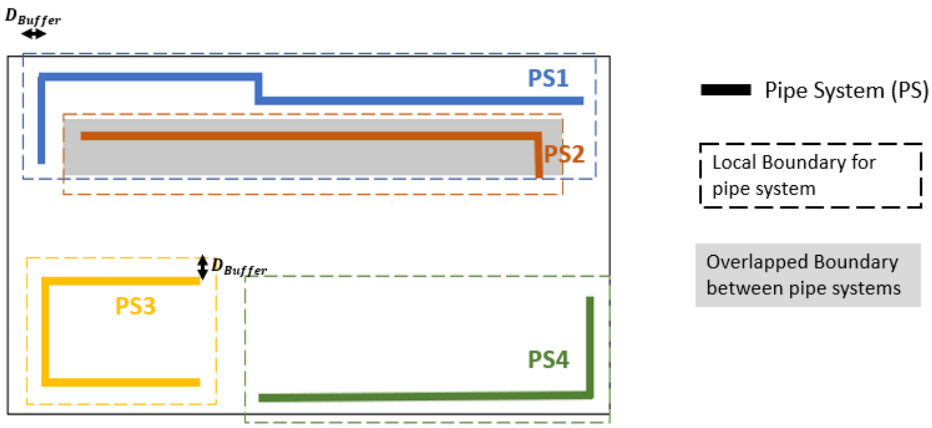
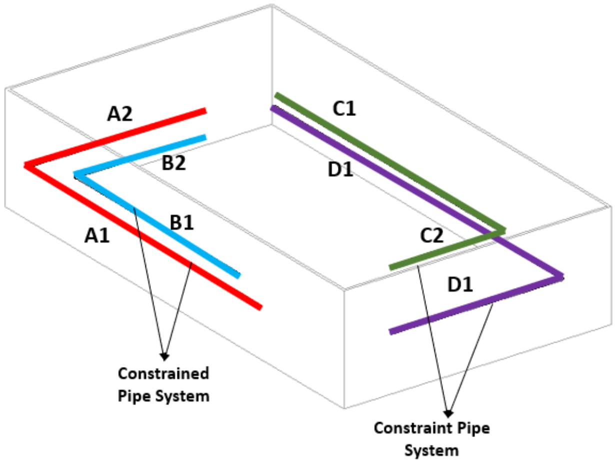


FIG. 4. 2D Example of local and overlapped boundary of pipe systems

In this approach, two major types of spatial constraint between pipe systems are considered and evaluated: *Higher to Lower* and *Outer to Inner* as shown in Fig. 5. *Higher to Lower spatial constraint* compares pipe systems lying vertically one over the other. Pipe systems which are at higher elevation (higher position) are installed before those at a lower elevation. *Outer to Inner spatial constraint* compares pipe systems lying alongside each other and are close to structural or architectural objects. The pipe system which is closer to the structural or architectural object (outer position) is installed prior to the other pipe system.



Higher to Lower	
Higher Position	***Lower Position***
C1	D1

Outer to Inner	
Outer Position	***Inner Position***
A1	B1
A2	B2

FIG. 5. Higher to Lower and Outer to Inner spatial constraints

3.4. Schedule Optimization and Generation Using Simulated Annealing (SA)

Installation schedule optimization is conducted based on spatial constraint requirements and availability of resources using simulated annealing (SA) to minimize the time required to install all the pipe systems in 3D space in a piping project. The total time to install all the pipe systems of a piping project is calculated as the sum of time taken to install pipe systems within available resources plus any delays that occurred during the installation process (Eq.1). SA is a probabilistic technique for finding global optimum of a given function. Prior to the start of optimization initial and final temperatures are set for the temperature cycle. At each temperature cycle, different schedules are generated and compared with each other and accepted using Boltzmann probability function (Eq. 2). The schedule selected at the end of the temperature cycle i.e., when final temperature is reached is adopted as the final and minimum optimized schedule.

$$\text{Min T} = \underset{1 \le pc \le N}{Max}[(n_{pc} * t) + (n_{pc} * t_{idle}) + (n_{pc} * t_{\text{delay}})] \tag{1}$$

where, T = total time required to install all the pipe systems, hours; pc = piping crew in-charge; N = total number of piping crew available for installation; $n_{pc} =$ total number of pipes and pipe fittings installed by piping crew pc; t = time taken by plumbing crew to install a single pipe, hours; t_{idle} = time taken by plumbing crew in waiting for installation, t_{delay} = time taken by plumbing crew due to delay

$$\text{P} = e^{\frac{(T_{old} - T_{new})}{K_b Temp}} \tag{2}$$

where, P = probability function of the acceptance criteria, T_{old} = initial time, T_{new} = new neighboring time, K_b = Boltzmann constant, Temp = current temperature

4. ILLUSTRATIVE EXAMPLE

To illustrate the proposed AI-based framework for realistic schedule optimization, a hypothetical piping project, which is based on real project but modified for ease of modeling and to enable consideration of a broad range of pipe system installation problems (Singh 2020) with 13 pipe systems is used (see Fig. 6, which shows the BIM model depicting a typical plant room). AI techniques help in optimizing practical schedules by utilizing knowledge relevant to the installation process of pipe systems based on historical data and real-time knowledge of current site condition. Dynamo for Revit (Autodesk 2021) was used to automatically capture all the necessary geometric and semantic information of the pipe systems and components from the BIM piping model as mentioned in Section 3, with the information stored in an MS Excel spreadsheet for further utilization. Table 1 shows geometric information about 3D space and dimension of information of structural and architectural components. The start and end points of all the pipe systems in 3D space are included in Table 2.

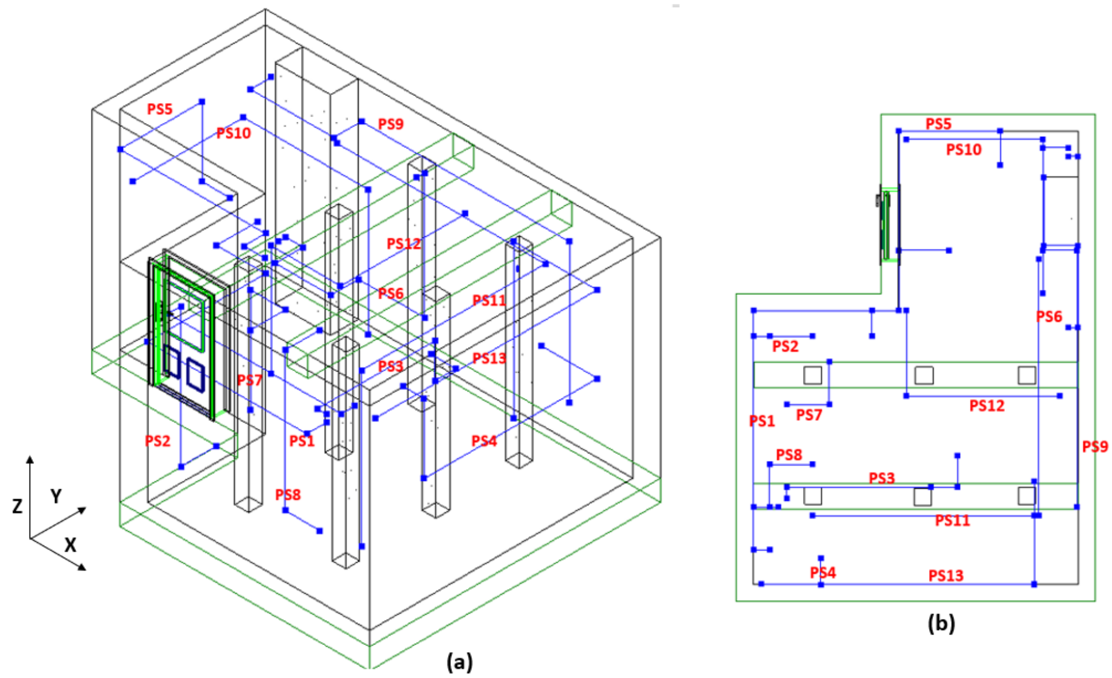


FIG. 6. Piping project BIM model (a) 3D View (b) Top View

TABLE 1. Geometric information of 3D space and objects

S. No.	Object	(X, Y, Z) Minimum Coordinate value (mm)	(X, Y) Middle Coordinated (mm)	(X, Y, Z) Maximum Coordinate value (mm)
1)	Plant room	(-13395, 3611, 0)	(-11295, 5311)	(-8095, 7411, 0)

S. No.	Object	(X, Y, Z) Minimum Coordinate value (mm)	(X, Y, Z) Maximum Coordinate value (mm)
2)	Column A	(-12855, 7011, 0)	(-12855, 7411, 3000)
3)	Column B	(-10638, 6711, 0)	(-10438, 6911, 3000)
4)	Column C	(-10638, 5491, 0)	(-10438, 5691, 3000)
5)	Column D	(-10638, 4211, 0)	(-10438, 4411, 3000)
6)	Column E	(-9235, 6711, 0)	(-9035, 6911, 3000)
7)	Column F	(-9235, 5491, 0)	(-9035, 5691, 3000)
8)	Column G	(-9235, 4211, 0)	(-9035, 4411, 3000)
9)	Beam H	(-10698, 3611, 2700)	(-10398, 7411, 3000)
10)	Beam I	(-9280, 3611, 2700)	(-8980, 7411, 3000)
11)	Door	(-12765, 5311, 0)	(-11825, 5311, 0)

TABLE 2. Start and end points of pipe systems

Pipe Systems	Supply Point (Start)	Demand Point (End)	Total number of pipes and fittings
PS1.	(-9000, 3900, 2000)	(-12000, 5900, 2000)	9
PS2.	(-8500, 3800, 2500)	(-11000, 4300, 500)	9
PS3.	(-9100, 4000, 2000)	(-9600, 6000, 1500)	9
PS4.	(-8400, 4400, 2500)	(-8900, 6900, 1500)	7
PS5.	(-11000, 5000, 2500)	(-13000, 6500, 1500)	11
PS6.	(-11100,7300,2300)	(-13100,7300, 500)	15
PS7.	(-10200,4000,2500)	(-10700,4500,1000)	5
PS8.	(-9500,4300,2700)	(-9000, 3800, 700)	5
PS9.	(-13200, 7300, 2500)	(-9000, 7400, 500)	9
PS10.	(-13300, 5400, 2100)	(-11500, 7000, 300)	5
PS11.	(-11900, 6950, 2500)	(-8900, 4300, 300)	5
PS12.	(-10300, 7200, 2300)	(-11300, 5400, 700)	5
PS13.	(-8100, 3700, 2600)	(-9300, 6900, 400)	5

After all the necessary details are extracted from the BIM model, the hybrid knowledge-based system was tested on deciding the suitable installation information about activity packages and resource productivity rates for the illustrated BIM model pipe systems. The list of attributes for activity packages selection with respective weighting values as assumed for this example are project type (7%), pipe system type (13%), weight of pipe material (50%), diameter of component (30%). The list of attributes for piping crew productivity rate selection with weighting values are project type (14%), pipe system material (15%), equipment type (33%), weight of pipe material (38%). The result for favorable installation activity packages and piping crew productivity rates with respective recommendation error as per the adapted KNN and GNN techniques are shown in Table 4 and Table 5 (Appendix). Recommendation error refers to the error associated with the recommendation of information (activity packages and productivity rates) depending on the list of attributes assigned for a particular project as per industry experts' knowledge. For this example, hybrid knowledge base consists of a total of seven activity packages AP_1 to AP_7, which account for a total of 14 combination lists and six productivity rates PR_1 to PR_6, with 23 combination lists based on the respective list of attributes are evaluated. The value of different productivity rates is $PR_1 = 0.32$, $PR_2 = 0.38$, $PR_3 = 0.42$, $PR_4 = 0.45$, $PR_5 = 0.3$, $PR_6 = 0.44$. The different activity packages and productivity rates are assumed to be only associated with pipes in pipe system while all pipe fittings are considered to have constant activity packages as AP_F and productivity packages as PR_F with value as 0.3 h. The predecessor-successor relationship between pipe system as per spatial constraint analysis is shown in Fig. 7(a). Fig. 7(b) and Fig. 7(c) show the waiting time required to install constraint pipe systems simultaneously following spatial constraint analysis rule using KNN and GNN techniques, respectively. The installation of successor pipe system must be done after predecessor pipe system completed installation of clashed component in pipe system. The waiting time refers to the time taken to install clashed component in predecessor pipe system for clash-free installation of the constraint pipe system.

The schedule for all 13 pipe systems as shown in the BIM model (Fig. 6) is calculated using SA as per the recommended activity packages and productivity rates of respective pipe system components as stated in Table 4 and Table 5 (Appendix) and spatial constraint analysis predecessor-successor relationship. The initial and final temperature for temperature cycle is assumed to be 0.1 and 5, respectively. The minimum schedule time using KNN to extract information from the hybrid knowledge-based system as generated by SA assuming there is no delay is 34.02 h when only one crew is available, 17.46 h when two crews are available and 11.74 h when three crews are available. The minimum schedule time using GNN to extract information form hybrid knowledge based system as generated by SA assuming there is no delay is 33.79 h when only one crew is available, 16.82 h when two crews are available and 11.72 h when three crews are available. Any sequnce following spatial constraint predecessor-successor relationship can be adopted for scheduling when one piping crew is available.

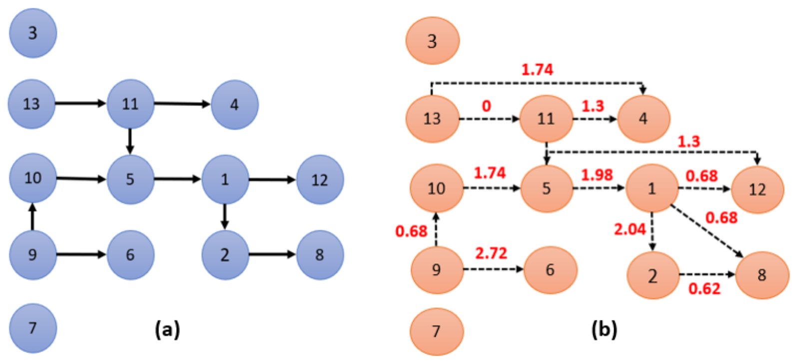


FIG. 7. Spatial constraint analysis (a) Precedence logic between pipe systems 1 to 13 (b) Waiting time (h) required to install constraint pipe system simultaneously based on KNN (c) Waiting time (h) required to install constraint pipe system simultaneously based on GNN

After comparing the schedule results from both KNN and GNN ML techniques, it was found that GNN gives shorter schedule times than KNN. GNN performs better than KNN and can have large discriminating power among options and produces high accuracy, if the GNN's aggregation scheme is highly expressive and has higher number of deciding attributes. The framework was also tested for any delays occurred on site. The delays occurring during the actual installation of pipe system on site tends to make original generated schedule as redundant. Therefore, new optimized installation schedule should be generated based on expected time required to fix delay and continue with the installation process of pipe system restricted due to delay. The expected time needed to overcome a particular delay can be considered as per developed hybrid knowledge data base. For illustration purposes, it was assumed that during the installation of pipe 3 of pipe system 1 (PS1), a hold up occurred due to unavailability of a component. The delay of 3 h is expected to occur while the installation is resumed. The delay will be affected to the PS1 and all other pipe systems which are successor to uninstalled PS1 components (pipes and fittings) in spatial constraint analysis predecessor-successor relationship. The next practical schedule with minimum time as generated by SA assuming the 3 h delay occurred due unavailability of component of PS1 is 36.79 h when only one crew is available, 18.5 h when two crews are available and 13.42 h when three crews are available. Table 3 shows the result of the proposed AI-based framework for realistic schedule optimization. The convergence time curve of the proposed framework is shown in Fig. 8.

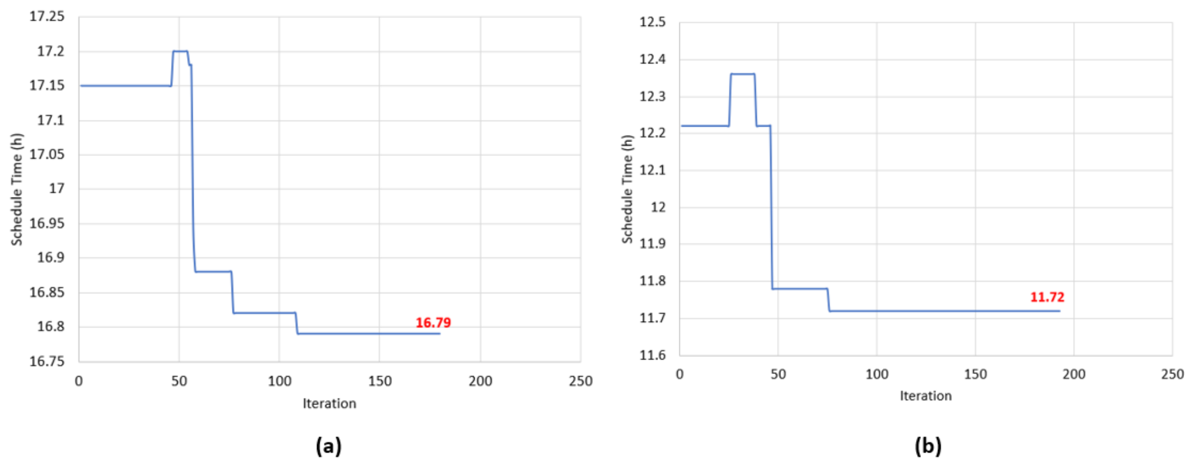


FIG. 8. Convergence time curve of the proposed framework

TABLE 3. Output of the proposed approach as per GNN technique

Number of piping crews	Installation schedule					
	Without Delay			**Delay**		
1	**Piping crew 1 – PS**			**Piping crew 1 – PS**		
	PS3, PS9, PS6, PS10, PS13, PS11, PS7, PS5, PS1, PS12, PS4, PS2, PS8			PS9, PS6, PS7, PS3, PS13, PS10, PS11, PS5, PS1, PS12, PS2, PS8, PS4		
	Optimal time hours = 33.79			**Optimal time hours = 36.79**		
2	**Piping crew 1 – PS(t)**	**Piping crew 2 – PS(t)**		**Piping crew 1 – PS(t)**	**Piping crew 2 – PS(t)**	
	PS9 (3.04) PS6 (5.08) PS4 (2.42) PS3 (3.1) PS12 (1.56) PS8 (1.59)	PS7 (1.68) PS13 (1.62) PS10 (1.92) PS11 (1.74) PS5 (3.78) PS1 (2.98) PS2 (2.98)		PS13 (1.62) PS11 (1.74) PS3 (3.1) PS6 (5.08) PS4 (2.42) PS12 (1.56) PS2 (2.98)	PS9 (3.04) PS7 (1.68) PS10 (1.92) PS5 (3.78) PS1 (5.98) PS8 (1.59)	
	Optimal time hours = 16.79			**Optimal time hours = 18.5**		
3	**Piping crew 1 – PS(t)**	**Piping crew 2 – PS(t)**	**Piping crew 3 – PS(t)**	**Piping crew 1 – PS(t)**	**Piping crew 2 – PS(t)**	**Piping crew 3 – PS(t)**
	PS13 (1.62) PS11 (1.74) PS4 (2.42) PS1 (4.02) PS12 (1.56)	PS9 (3.04) PS10 (1.92) PS6 (5.08) PS8 (1.59)	PS3 (3.1) PS7 (1.68) PS5 (3.96) PS2 (2.98)	PS13 (1.62) PS9 (3.04) PS6 (5.08) PS2 (3.68)	PS7 (1.68) PS11 (1.74) PS10 (1.92) PS5 (3.78) PS12 (1.56) PS8 (1.59)	PS3 (3.1) PS4 (2.42) PS1 (7.84)
	Optimal time hours = 11.72			**Optimal time hours = 13.42**		

PS = Piping System
T = time in h

Compared with traditional approaches, the proposed framework notably reduces the time for the generation of realistic schedule for installation of pipe systems on piping projects. An experienced engineer needs at least 150 minutes to generate the one schedule of 13 pipe system (Singh 2020), from extracting information, finding precise spatial sequence, and generating the installation schedule but without considering any site delay. However, the proposed automated framework took about 3 to 4 minutes, which represents 97% saving in time to generate realistic schedule. As the built environment contains numerous large pipe systems networks in 3D space, time savings in generating realistic installation schedules for pipe systems is of great significance. Moreover, traditional approach does not consider reliable knowledge data available and cannot guarantee optimal, sequential instillation schedule. The installation schedule generated using the proposed framework is optimal, sequential, and utilizes hybrid knowledge data based system to generate efficient and realistic installation schedule.

5. CONCLUSIONS AND FUTURE WORK

A practical installation schedule at any instance of time is a crucial aspect of the piping project in achieving efficient installation flow, high productivity, and completion of project at a reduced cost and shorter duration. Many schedules have numerous conflicting features which are only detected during the installation stage. Therefore, realistic planning of pipe installation schedules with a better understanding of the potential constraints, sequencing logic, and timely update of required information on pipe system installation is important. In this study a new AI-based framework with ML and heuristic optimizing techniques is proposed for automating the optimization of practical installation schedule for pipe systems using 4D BIM. The BIM model is used as a reference for providing necessary geometric and semantic information of pipe systems and components. KNN and GNN ML are adopted and compared to integrate extracted components with the appropriate activities and resources productivity rates for installation based on the developed hybrid knowledge based. GNN performed better than KNN giving shorter schedule times. The hybrid knowledge base considered both data-driven knowledge base and site-driven knowledge base. Spatial constraint analysis with local boundary search was developed to find a reliable clash-free installation sequence for pipe systems. SA algorithm was adopted to optimize the installation schedule based on spatial constraint analysis and information from the hybrid knowledge-based system. The framework was tested using a hypothetical piping model and the results show that the proposed

AI framework can generate realistic optimal and coordinated practical installation schedule for pipe systems with 97% saving in time to generate optimal schedule. Compared with traditional approaches, the proposed framework provides appropriate installation activities and productivity rates for installation schedule based on both data-driven knowledge and site-driven knowledge. With the utilization of historical data as well as real time site knowledge, the installation time of pipe systems can be reduced resulting in significant cost savings. However, there are certain limitations of this study. For example, no specific cost saving comparison was undertaken in this research. The duration of the pipe system installation was used as a proxy for cost, as longer duration activities usually cost more. Detailed quantification of cost savings based on the developed framework will be undertaken as part of future work. In addition, this study assumes that a data-driven knowledge base (from historical data) is readily available to generate optimal schedules for the installation of pipe systems. Future research could focus on combing data mining techniques with the schedule optimization to create the data-driven knowledge based system automatically, combined with the proposed AI-based framework to generate practical installation schedules for pipe systems.

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APPENDICES

TABLE 4. Recommended activity packages and productivity rates as per KNN technique

Pipe system (Pipe Number)	Recommended Activity Packages (AP)		Recommended Productivity Rates (PR)	
	AP	Error	PR	Error
PS1 (1)	AP4	0.13	PR2	0.38
PS1 (2)	AP3	0.43	PR2	0
PS1 (3)	AP3	0.43	PR2	0
PS1 (4)	AP4	0.13	PR2	0.38
PS1 (5)	AP4	0.13	PR2	0.38
PS2 (1)	AP1	0.3	PR1	0.38
PS2 (2)	AP4	0.3	PR2	0.38
PS2 (3)	AP7	0.13	PR3	0.38
PS2 (4)	AP1	0.3	PR3	0
PS2 (5)	AP4	0.3	PR1	0.38
PS3 (1)	AP7	0.13	PR2	0.38
PS3 (2)	AP6	0.2	PR3	0.38
PS3 (3)	AP1	0.13	PR3	0
PS3 (4)	AP1	0.13	PR1	0
PS3 (5)	AP1	0.13	PR2	0
PS4 (1)	AP1	0.13	PR2	0.38
PS4 (2)	AP1	0.13	PR2	0.38
PS4 (3)	AP4	0	PR2	0.38
PS4 (4)	AP3	0.43	PR2	0.38
PS5 (1)	AP2	0.2	PR2	0.38
PS5(2)	AP5	0.2	PR1	0.38
PS5 (3)	AP4	0	PR2	0.38
PS5 (4)	AP1	0	PR3	0.38
PS5 (5)	AP1	0	PR1	0
PS5 (6)	AP1	0	PR2	0
PS6 (1)	AP1	0	PR2	0
PS6 (2)	AP1	0	PR3	0
PS6 (3)	AP1	0	PR1	0.38
PS6 (4)	AP4	0.13	PR2	0.38
PS6 (5)	AP3	0.43	PR3	0.38
PS6 (6)	AP4	0.13	PR2	0.38
PS6 (7)	AP4	0.13	PR2	0.38
PS6 (8)	AP4	0.13	PR2	0.38
PS7 (1)	AP4	0.13	PR2	0.38
PS7 (2)	AP4	0.13	PR2	0.38
PS7 (3)	AP4	0.13	PR2	0.38
PS8 (1)	AP6	0.2	PR2	0.38
PS8 (2)	AP2	0.2	PR2	0

Pipe system (Pipe Number)	Recommended Activity Packages (AP)		Recommended Productivity Rates (PR)	
	AP	Error	PR	Error
PS8 (3)	AP2	0.5	PR2	0.38
PS9 (1)	AP5	0.5	PR2	0.38
PS9 (2)	AP6	0.2	PR2	0.38
PS9 (3)	AP7	0.13	PR2	0.38
PS9 (4)	AP6	0.2	PR2	0.38
PS9 (5)	AP4	0.13	PR2	0.38
PS10 (1)	AP3	0.43	PR2	0
PS10 (2)	AP4	0.13	PR2	0
PS10 (3)	AP2	0.2	PR2	0
PS11 (1)	AP5	0.2	PR1	0
PS11 (2)	AP3	0.43	PR2	0
PS11 (3)	AP2	0.5	PR3	0
PS12 (1)	AP5	0.5	PR1	0
PS12 (2)	AP2	0.5	PR2	0
PS12 (3)	AP5	0.5	PR2	0.38
PS13 (1)	AP2	0.5	PR2	0
PS13 (2)	AP5	0.5	PR2	0.38
PS13 (3)	AP7	0.13	PR2	0

TABLE 5. Recommended activity packages and productivity rates as per GNN technique

Pipe system (Pipe Number)	Recommended Activity Packages (AP)		Recommended Productivity Rates (PR)	
	AP	Error	PR	Error
PS1 (1)	AP1	0	PR2	0.33
PS1 (2)	AP4	0	PR1	0
PS1 (3)	AP3	0.13	PR1	0
PS1 (4)	AP6	0.13	PR2	0.33
PS1 (5)	AP3	0.13	PR2	0.33
PS2 (1)	AP6	0.13	PR2	0.33
PS2 (2)	AP1	0	PR2	0.33
PS2 (3)	AP4	0	PR2	0.33
PS2 (4)	AP1	0	PR3	0.33
PS2 (5)	AP4	0	PR1	0
PS3 (1)	AP1	0	PR2	0.33
PS3 (2)	AP4	0	PR2	0.33
PS3 (3)	AP7	0.13	PR2	0.33
PS3 (4)	AP1	0.13	PR2	0.33
PS3 (5)	AP4	0.13	PR2	0.33
PS4 (1)	AP7	0.13	PR2	0.33
PS4 (2)	AP3	0.13	PR1	0
PS4 (3)	AP6	0.13	PR2	0

Pipe system (Pipe Number)	Recommended Activity Packages (AP)		Recommended Productivity Rates (PR)	
	AP	Error	PR	Error
PS4 (4)	AP1	0.13	PR3	0.33
PS5 (1)	AP4	0.13	PR3	0.33
PS5(2)	AP1	0.13	PR2	0.33
PS5 (3)	AP4	0.13	PR2	0.33
PS5 (4)	AP1	0.13	PR2	0.33
PS5 (5)	AP4	0.13	PR2	0.33
PS5 (6)	AP1	0.13	PR2	0.33
PS6 (1)	AP4	0.13	PR2	0.33
PS6 (2)	AP1	0.13	PR1	0
PS6 (3)	AP4	0.13	PR2	0.33
PS6 (4)	AP1	0	PR2	0.33
PS6 (5)	AP4	0	PR2	0.33
PS6 (6)	AP3	0.13	PR2	0.33
PS6 (7)	AP6	0.13	PR3	0.33
PS6 (8)	AP2	0.13	PR3	0.33
PS7 (1)	AP5	0.13	PR1	0
PS7 (2)	AP1	0	PR2	0
PS7 (3)	AP4	0	PR2	0
PS8 (1)	AP1	0	PR1	0
PS8 (2)	AP4	0	PR4	0.33
PS8 (3)	AP1	0	PR1	0
PS9 (1)	AP4	0	PR2	0.33
PS9 (2)	AP1	0	PR1	0
PS9 (3)	AP4	0	PR2	0.33
PS9 (4)	AP1	0	PR2	0
PS9 (5)	AP4	0	PR1	0
PS10 (1)	AP1	0	PR2	0
PS10 (2)	AP4	0	PR2	0
PS10 (3)	AP1	0	PR2	0
PS11 (1)	AP4	0	PR3	0.33
PS11 (2)	AP1	0.13	PR3	0.33
PS11 (3)	AP4	0.13	PR2	0
PS12 (1)	AP3	0.13	PR1	0
PS12 (2)	AP6	0.13	PR1	0
PS12 (3)	AP1	0.13	PR1	0
PS13 (1)	AP4	0.13	PR1	0
PS13 (2)	AP1	0.13	PR5	0.33
PS13 (3)	AP4	0.13	PR1	0