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PLANNING MUNICIPAL DRAINAGE INFRASTRUCTURE MAINTENANCE OPERATIONS WITH FINITE AVAILABLE CREWS: PRAGMATIC OPTIMIZATION APPROACH

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Abstract. This paper proposes a streamlined approach to addressing the problem of allocating finite crew resources to concurrent jobs in the context of municipal drainage infrastructure maintenance. The problem was defined from the perspective of a project manager involved in planning such operations on a day-by-day basis. The problem statement was then transformed into a simplified Integer Linear Programming optimization model. Performance metrics were devised to evaluate the optimization model's effectiveness. A heuristic algorithm representing the decision-making process by a seasoned planner in the partner company was also developed. Both methods were applied to a case study and contrasted based on the same performance metrics. The findings underscored substantial optimization benefits in rendering decision support in resource-constrained drainage construction operations planning. In conclusion, this research presents an alternative strategy for navigating the complexities inherent in finite crew resource allocation on multiple concurrent drainage projects; lends a cost-effective optimization solution to improving the utilization of finite available crews while satisfying service demands from multiple clients to the largest extent possible.

Keywords: municipal infrastructures, crew allocation, optimization, drainage maintenance scheduling, multiple scattered sites, short-term planning.

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1. Introduction

The allocation of limited resources to a multiple set of concurrent jobs is a significant challenge in various applied domains, such as civil engineering and management, project management, production planning (e.g., job shop or flow shop planning), transportation planning in supply chain management, and healthcare professionals planning in hospitals (Goli et al., 2022a; Sarker et al., 2012). The importance of addressing this problem cannot be overstated, as it can significantly impact the efficiency, cost, and quality of subsequent execution processes. As a result, extensive research has been conducted to tackle this problem in various applied scenarios across diverse domains, where operations research is found to play a predominant part and has resulted in numerous intricate mathematical models, optimization techniques, and solution algorithms (Goli et al., 2023; Goli & Keshavarz, 2022; Guo & Zhang, 2022). On the other hand, the construction industry is notorious for it's one-of-a-kind project nature and constant changes in the project development environment. In order to deal with dynamic changes, project management requires careful planning, coordination, and execution to deliver projects on time, within budget, and to the satisfaction of all the stakeholders. Beyond project management, stakeholder engagement, technology integration, and compliance with legal and regulatory requirements, safety management, institutional governance, labour provision and performance are all identified as critical to the successful delivery of construction projects (Dikmen et al., 2022; Ninan et al., 2021; Qiu et al., 2019).

Deploying complex mathematical models into construction project planning could be counterproductive, considering the inherently dynamic nature of construction projects coupled with a lack of comprehensive datasets. This factor would potentially amplify the intricacy of making decisions in connection with project management due to the models' computational demands and the difficulty of integrating them into practical project management processes. Addressing the identified problem warrants a thorough comprehension of the planning processes along with the predominant environmental conditions, while keeping the sufficiency and relevance of these models to accommodate real-world constraints.

Consequently, a notable divergence between research and practical implementation of mathematical modeling and optimization techniques in planning construction projects can be observed in reality. Addressing this issue necessitates developing optimization models that are adaptable to changing project conditions by efficiently adhering to any existing and emerging constraints. As such, the resulting optimization models can be integrated into current project management workflows and the obtained optimization solutions can be communicated to project stakeholders as effective decision support. Ultimately, the individual organization or the whole industry can improve project management practices through optimizing resource utilization and service provision.

This research deliberately prioritizes simplicity to ensure practical applicability and accessibility while keeping the problem definition sufficient from the practitioners' perspective. This simplicity lends a straightforward yet effective solution to tackle a complex project management problem in the real world, which is characteristic of operating utility service call centers where crews are dispatched for maintenance or repair services at the customers' premises. Although this optimization model was developed to improve municipal drainage services, it can be adapted and expanded to other similar applications.

In the remainder of this paper, the problem is first defined from the perspective of a project manager involved in planning such operations on a day-by-day basis. The problem statement is generalized, and relevant literature is reviewed for allocating finite crew resources to concurrent jobs in the context of municipal drainage infrastructure maintenance. Next, the problem statement is transformed into a simplified Integer Linear Programming (ILP) optimization model. For concept proof using case data from the partner company, a computer program was coded with interfaces in MS Excel, and performance metrics were devised to evaluate the optimization model's effectiveness. A heuristic algorithm based on the decision-making process by a seasoned planner in the partner company was also developed. Both methods were applied to a case study and contrasted on the same performance metrics. The findings underscore substantial optimization benefits in applying resource-constrained drainage construction operations planning. Ultimately, the conclusions were drawn by recapitulating research findings and addressing limitations and future extensions.

2. Problem statement

In this section, we describe the limited resource allocation and operations planning problem in drainage services project management through a practical investigation involving a collaboration between the University of Alberta and an industry partner in Edmonton, Alberta, Canada. The partner company operates extensive networks of the city's water and sewer lines. The first type of job in rendering drainage services is *service connection*, including new installations, repairs, and replacements, mainly in response to customer demand. Such jobs feature deadlines often mandated by regulations or customer demands. In addition, maintenance crews inspect and monitor the network to identify any issue that demands immediate attention, resulting in the triage of routine jobs by various priorities and the confirmation of emergencies (such as collapsed or broken pipes, sewer backups, lost services, and unexpected floods). Limited professional construction crews perform these jobs within a restricted time period at specific locations. Each job is unique in terms of the client, location, site circumstance, required duration, and varied priority. Notably, the required timeframe for a typical job is generally dictated by the time allowed for a work permit and temporary road closure, even though a certain amount of float time could have been factored in the time duration so as to account for any risks associated with the jobs.

Therefore, the challenge inherent in current work planning practice pivots primarily around prioritizing, sequencing, and allocating jobs to the crews, aiming to complete as many jobs as possible by committed deadlines while utilizing available crew resources efficiently (Hegazy & Kamarah, 2022). Job prioritization is subsequent to the commonly practiced risk management process by implementing systematic analytical procedures to rate the event's likelihood or consequence effectively and producing a *job priority index*. It is noteworthy that risk management is not the focus of this study, but its outcome serves as an input in the optimization formulation described in the subsequent sections.

With a large number of jobs (ongoing, planned, and newly added) subject to tight constraints on the availability of crews (weekends off, leaves, or holidays) and job deadlines, the current project management practice requires trial and error in order to arrive at a practically feasible solution. In particular, balancing various crews' workloads while ensuring high resource utilization ratios would present a daunting task, let alone any attempt to optimize the scheduling for all the relevant jobs to meet their priorities and client service goals. Notably, the current practice of project planning rarely allows for the opportunity to devise and assess better alternatives. Far from the optimum, the planning solution is, at best, practically feasible. Often, the solution would not satisfy many job deadline constraints. In reality, this would lead to missed opportunities for performance improvement and incurring unnecessary tangible and intangible costs such as negative impact on social equity, business losses, and client dissatisfaction (Lu et al., 2008; Siu et al., 2016).

3. Literature review

The optimized allocation and scheduling of construction crews in planning drainage services projects represent a complex problem in operations research (OR), specifically categorized under "routing and scheduling problems". The complexity arises from the need to coordinate service delivery across multiple geographic locations in the optimization of the path (routing) and timing (scheduling) of crew assignments (Altuwaim & El-Rayes, 2021). The intricacy of routing decisions encompasses the strategic movement of crews to various work sites, while scheduling emphasizes the temporal aspect of service delivery at these locations. The origin of this dual-focus planning problem can be traced to the Traveling Salesperson Problem (TSP) and the Vehicle Routing Problem (VRP) in OR.

Over recent years, a continuous evolution of TSP and VRP has been attributed to significant advancements in solution algorithms, including meta-heuristic algorithms, such as Genetic Algorithms (GAs), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO). For instance, the work by Goli et al. (2022b) on a two-echelon electric vehicle routing problem introduced a moth-flame meta-heuristic algorithm, showing the potential of such nature-inspired algorithms in solving VRPs with environmental considerations. Tan and Yeh (2021) provided a comprehensive overview and classification of VRP and its variants, focusing on literature published between 2019 and August 2021. The authors utilized a taxonomic framework to categorize VRP models into customer-related, vehicle-related, and depot-related, while solution algorithms were grouped into exact, heuristic, and meta-heuristic algorithms. The paper highlighted the NP-hard nature of VRPs under real-world constraints such as time windows, traffic conditions, and fleet heterogeneity. In addition, VRP models focus on how to route vehicles efficiently with constraints often related to vehicle capacities and routing logistics. The objective function typically aims to minimize travel costs or distances. However, crew scheduling in construction projects is concerned with the optimal allocation of finite crew resources to tasks over time with constraints on crew availability, skill sets, task times and task dependencies, aimed at meeting project deadlines, minimizing labor costs, or maximizing resource efficiency.

Previous related research regarding water and sewer service operations scheduling and crew allocations by exploiting optimization techniques is reviewed as follows. Draude et al. (2022) formulated the sewer maintenance scheduling problem as a multi-objective optimization problem with three objectives: minimizing the total maintenance cost, minimizing maintenance teams' travel times, and maximizing the job's priority score, all over a pre-defined scheduling horizon. Then, they solved the optimization problem using the Nondominated Sorting Genetic Algorithm-II (NSGA-II) optimization method. Elmasry et al. (2019) introduced a multiobjective optimization model to weigh on time, cost, and the number of inspected sections for inspecting deteriorated sewer pipelines using mixed integer linear programming (MILP). They used the general algebraic modeling system (GAMS) to reduce the computational complexity of the suggested optimization model. Osman et al. (2017) presented a simulation-based multiobjective optimization model to schedule repair crews across water network break sites in an urban setting. They used a Genetic Algorithm (GA) to minimize the time and cost to complete all the breaks and the cumulative impact of all break incidents on road users and water customers. Zaman et al. (2015) presented the formulation of a combinatorial optimization problem for drainage operations activities' scheduling to improve productivity, where the objective was to minimize end-of-shift unused (waste) time and travel time; notably, they applied a greedy heuristic algorithm in a case study. Navab-Kashani et al. (2015) investigated how to apply the TSP as a traveling path optimization technique for daily closed-circuit television (CCTV) inspections on sewer mainlines in a Canadian city. Poser and Awad (2006) developed a methodology based on a genetic algorithm for solving the TSP and finding the best route for collecting solid waste in cities. Salman et al. (2013) presented a more complicated method for optimized scheduling of rehabilitation of water distribution networks. They utilized unsupervised neural networks to cluster water mains into groups according to locations and rehabilitation methods. Then, they used mixed-integer nonlinear programming (MINLP) to determine the number of rehabilitation contract packages and the generation of optimized scheduling of those packages.

It is worth mentioning that this study differs from previous related work by utilizing mathematical programming to materialize a simplified and intuitive approach to allocating finite crew resources over concurrent jobs in the context of municipal drainage infrastructure maintenance. The goal is to avoid unnecessary complications associated with mathematical programming, thereby making the optimization solution sufficiently acceptable and practically scalable.

4. Model formulation

This section outlines the developed short-term crew allocation optimization model for drainage installation and repair operations under practical constraints. The model assumptions are explained first, followed by the problem formulation.

- Based on the following premises, the model does not consider travel times between sites.
  - Construction personnel return to their residences after daily operations and commute to an ongoing or new site at the start of the following day. The travel time for crew members is primarily limited to intra-urban commuting, which is integrated into commuting to work before the beginning of the workday.
  - Additionally, job durations are estimated using discrete integer intervals, typically daily, with a marginal proportion of time added to operational tasks relative to the time expended on crew transition. The frequency of required inter-site travels would be considered inconsequential. As such, the

model does not account for fractional job durations as time allocations for crew transition.

Therefore, the model excludes crew travel time between sites, while the crew members commute directly to the designated construction site at the start of each work period.

The crews are identical, and the quantity of available crews is deterministic, resulting from strategic staffing decisions informed by company-wide projections of work requirements. Nonetheless, the actual availability of these crews may exhibit variability due to factors such as holidays or instances of illness.

- Jobs are independent of each other, and they have deterministic duration considering the predictability with a high confidence level for drainage service job types and the short-term planning window (e.g., planning for the next two weeks). However, jobs do not necessarily have equal duration. Therefore, depending on job type classification, a specific range (or options of integers) is randomly sampled as the job duration in this research. For instance, water line replacements may take one or two days, but sewer line replacement takes two or three days.
- Job preemption is not allowed. These types of jobs are categorized as small projects with short duration. They have a high setup time compared to their duration. As a job starts, the job needs to be finished at the earliest due to inconvenience and disturbance to traffic and business around the job location.

With the above assumptions made, the problem is generalized as follows.

There is a set of n independent jobs to be constructed by m number of crews. Each crew can handle one job at a time; therefore, each job can be assigned at most to one crew. The mathematical formulation is based on Integer Linear Programming (ILP) and solved by Analytic Solver, resulting in an optimal crew allocation plan. Note, that the Analytic Solver is an MS Excel-based optimization tool (Frontline Systems Inc.), which utilizes branch and bound algorithms for tackling ILPs. It is a more advanced version than the free Solver available in MS Excel. The problem was represented in a spreadsheet (MS Excel) so that the job and crew attributes could be registered in the model. Jobs data include site index, unique job number (i.e., work order), location, type, released (received) date, estimated duration, and priority index. Crew attributes comprise crew availability within the planning horizon, calendar, and non-working days.

It is worth mentioning that the problem definition was confirmed to be realistic and sufficient by involved practitioners, which was instrumental in devising pragmatic optimization and arriving at optimum solutions with significance in the real world. Moreover, the problem formulation can be represented as a generalized assignment and Multiple Knapsack Problem (MKP) (Chekuri & Khanna, 2005) which is generally much more complex and associated with higher computational loads than TSP or VRP. Before elaborating the model formulation, two special terms are defined with implications clarified herein.

Slack time (*ST*): which is the amount of time from the date a job is received to the job specific deadline, deducting the expected job duration, as displayed in Figure 1. The slack time is a buffer to account for the time required for planning and administrative work (such as obtaining permits, crew preparation and mobilization).

The priority index (*PI*) is scaled on the range [0.1, 0.5] to denote various priority levels, as shown in Table 1.

Below, the notations used in the model are listed with explanations:

- T: length of the planning horizon, usually defined as a weekly or biweekly plan period. However, the model can be applied to more extended periods with a much larger set of jobs to be planned;
- a_i: crew i availability within T;
- n: total number of jobs to be scheduled;
- m: total number of crews;
- i, j: crew and job indices respectively;
- (d_j, dl_j, dr_j) denotes (construction duration, deadline, date received), respectively, for job j;
- Slack Time for job j: $\mathrm{ST}_j = dl_j - dr_j - d_j$, where $j = \{1, 2, ..., n\}$;
- PI_j: priority index job j.

The problem is formulated as follows:

$$\text{Maximize}\, z = \sum_{i=1}^{m}\sum_{j=1}^{n} PI_j \;(1 - (ST_j / \sum_{j=1}^{n} ST_j)).x_{ij} \quad (1)$$

Subject to:

$$\sum_{i=1}^{m} x_{ij} \le 1, \;\; \text{where } j = \{1, ..., n\}; \quad (2)$$

$$\sum_{j=1}^{n} d_j.x_{ij} \le a_i, \;\; \text{where } i = \{1, ..., m\}; \quad (3)$$

$$x_{ij} \in \{0,1\}, \;\; i = \{1, ..., m\}, j = \{1, ..., n\}, \quad (4)$$

where $x_{ij} = 1$ if crew i is allocated to job j, and $x_{ij} = 0$ otherwise. To avoid trivial cases, we also demand that:

$$\min_{i=1,\dots,m} a_i \ge \min_{j=1,\dots,n} d_j, \sum_{j=1}^{n} d_j \ge \operatorname{Max}_{i=1,\dots,m} a_i, \sum_{j=1}^{n} d_j \ge \sum_{i=1}^{m} a_i. \quad (5)$$

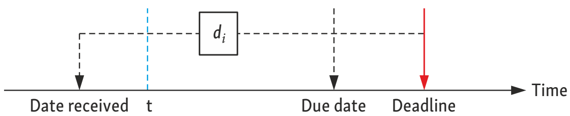


Figure 1. Slack time representation

Table 1. Priority indices implications

Scaled PI	Implication
0.5	Highest Priority (no longer routine job; emergency)
0.4	Higher Priority (must complete by deadline)
0.3	High Priority (need to complete by deadline)
0.2	Lower Priority (Better to keep deadline)
0.1	Lowest Priority (OK to pass deadline)

The model's objective function (Eqn (1)) is to maximize the number of jobs with higher priority and less slack time over the planning horizon. Note that the objective function is the multiplication of two terms: (1) priority index and (2) normalized job's slack time, which is one minus the slack time of the job divided by the summation of all jobs' slack times. The second term is intended to select jobs with less slack time so as to perform jobs within job deadlines as much as possible. The set of constraints (2) declares that no more than one crew can be allocated to any job, or at most, one crew is allocated to each job. The set of constraints (3) restricts each crew's utilization to its availability, meaning that each crew can be assigned within its total availability. Constraint (4) defines the type of decision variables. Finally, in the set of constraints (5), the first assumption ensures that each crew's availability exceeds the minimum job durations. If this inequality is violated, we may remove the corresponding crew from the optimization model for that specific planning horizon. Also, the second assumption avoids a trivial solution where all jobs can be performed by one crew. Additionally, the last inequality in the constraints (5) denotes that the summation of the job durations is greater than or equal to the total crews' available work days. If this inequality is violated, the model still generates the solution but with crews idling time (though it is not desired).

It is noteworthy that the formulated simplified model resembles the characteristics of MKP. However, the model represents a novel job scheduling problem under constraints of resources, priorities, and deadlines, which significantly differs from MKP. In other words, the presented problem allocates crews to the jobs while in MKP, there are *n* given items that should be packed in *m* knapsacks with distinct capacities (Chekuri & Khanna, 2005). Furthermore, in the present problem, not exceeding the maximum job duration subject to the maximum crew availability is intrinsic and does not require extra constraints. In contrast, the summation of the job durations should be greater than or equal to crews' total availability.

5. Plan performance metrics

In this section, *Plan Performance Index* (PPI) is defined in order to measure the optimization model performance, which also serves as a comparison index among alternative solutions being evaluated. PPI compares the number of planned jobs from the model to the estimated number of jobs that could be completed, given the full crew days available. The calculation of PPI is also exemplified in the case study.

$$\text{PPI} = \frac{\text{Total number of jobs planned}}{\text{Estimated number of potential job completions}}, \quad (6)$$

where:

$$\text{Total number of jobs planned} = \text{total numbers resulting from optimization model}; \quad (7)$$

$$\text{Estimated number of potential job completions} = \frac{\text{Total crew days available}}{\text{Mean of sample jobs duration}}. \quad (8)$$

Note that the numerator in Eqn (8) represents the sum of the crews' availabilities $\left(\sum_{i=1}^{m} a_i\right)$ within the planning horizon (T), and the denominator is the mean(average) value of the job duration factoring in all the jobs in the pool ready to be planned. Consequently, the fraction outcome estimates the maximum number of jobs that can be allocated. It is noted that the estimated number of potential job completions does not consider the priorities and slacks of the jobs. Another metric to measure the plan's performance is the *Customer Satisfaction Index* (CSI) specific to the generated plan. CSI is herein defined against each job's planned deadline. As all the jobs are constructed in compliance with regulations and standard quality codes, quality assurance is not deemed relevant in this case; instead, abiding by deadlines and incurring the least inconveniences during construction are the primary customer satisfaction concerns in the present problem. CSI is equal to 100% for a particular job if the planned job completion date is within the imposed deadline; otherwise, CSI is set as zero. Hence, CSI mainly gauges customer satisfaction regarding meeting job deadlines. Notably, in the model formulation, preemption in construction is not allowed; once the job starts, its assigned crew does not stop the ongoing job to work on another job.

Finally, the average crew utilization planned (CUP) is calculated against the crews' availability. In this context, crew utilization is determined by measuring CUP for each crew and then averaging them as the average crew's utilization planned (Eqn (9)). The CUP over 100% indicates over-allocation, and CUP under 75% means under-allocation. The optimization goal is to achieve 100% CUP. Herein, it is pointed out that CUP only considers crew idle time between executing different jobs; it does not account for the crew's non-working time while performing on jobs. Modeling detailed crew operations on a particular job is beyond the current scope of research.

$$\text{Crew utilization planned (CUP)} = \frac{\text{Crew working days planned}}{\text{Crew working days available}}. \quad (9)$$

6. Case study

We conducted case studies in collaboration with the industry partner. Table 2 shows samples of the job attributes registered for the case studies. The planner considered eight crews employed on a full-time basis. Each crew works five working days a week except statutory holidays, as shown in Table 3, which serves as a template for bi-weekly registered crew availability. Note Crew "Cr-215" has one workday off over the two-week job planning window in contrast with other crews, which will be factored in the optimization solution.

Table 2. Jobs registration format in the optimization model

Site index	Work Order	Received	Deadline	Priority	Duration	Slack
1	207823.1	19-4-2022	17-5-2022	0.3	2	26
2	207843.2	02-5-2022	31-5-2022	0.4	2	27
3	206905.1	01-4-2022	29-4-2022	0.1	3	25
2	208061.3	24-4-2022	23-5-2022	0.3	2	27
3	208412.5	02-4-2022	06-5-2022	0.2	2	32

Table 3. Crews' availability within two weeks

Crew code	Availability	Crew code	Availability
Cr-214	10 days	Cr-230	10 days
Cr-215	9 days	Cr-231	10 days
Cr-217	10 days	Cr-232	10 days

The model resorts to the Frontline Solvers Excel_ Analytic Solver (Analytic Solver Optimization V2017: 020ASOP-TIM) in deriving optimum solutions. Note the Analytic Solver implements the branch and bound method to tackle this type of problem (FrontlineSolver, 1990). One selected sample solution is demonstrated herein. We set the optimization to run 100 times based on the standard LP/Quadratic Engine from the Analytical Solver package. On a desktop Intel(R) Core (TM) i7 computer, CPU time was recorded to be less than one minute in all samples with fewer than 100 jobs and less than two minutes for samples between 100 and 250 jobs. Table 4 summarizes the results of applying the optimization model to selected case studies.

As seen in Table 4, in all the cases, PPI is greater than one, which confirms the outperformance of the optimization method over the manual planning practice based on heuristic rules (as it is described in the following section), not to mention the time required to apply tedious and error-prone manual procedures.

After obtaining an optimized solution for each case sample, the result can be visualized effectively through a Gantt chart and communicated to the field supervisors.

Table 4. Several samples' attributes and results of the optimization model with 8 crews and 100 runs

No	Samples Attributes				Optimization Results				
	# Jobs	Crew Capacity	Horizon	Run time(S)	# Planned Jobs	# Delayed	PPI	CSI	CUP
1	45	77 d	2 w	11.25	40	0	1.05	100%	100%
2	62	79 d	2 w	16.78	42	0	1.10	100%	100%
3	85	116 d	3 w	19.38	66	0	1.13	100%	100%
4	100	118 d	3 w	65.23	67	0	1.12	100%	100%
5	200	120 d	3 w	91.84	81	0	1.33	100%	100%
6	250	156 d	4 w	95.47	104	0	1.32	100%	100%

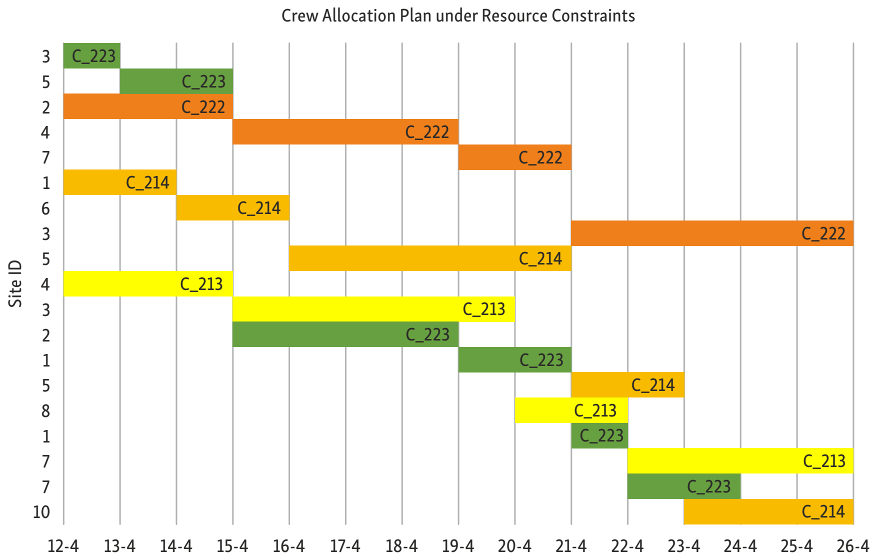


Figure 2. Snapshot of a Gantt chart based on the optimization model solution

For instance, based on the sample with 45 jobs, part of the Gantt chart shown in Figure 2, depicts the obtained crew allocation plan across multiple scattered sites and job start and completion dates. The graph's vertical axis indicates Site ID, and the bar chart visualizes job start and finishes time with the allocated crew. These color-coded bars distinguish the jobs distributed between various crews. Each crew's work continuity can be traced with a specific color denoting that crew.

It can be inferred from the obtained results that all the jobs are scheduled to be completed before their deadline (i.e., 100% meeting clients' deadlines), which are evenly distributed subject to crew availability constraints being imposed. In short, it would be practically impossible for a human planner to manually account for all the constraints and make a feasible plan as optimal as the one automatically generated by the proposed optimization solution. The prototype computer program provides an analytical decision support tool in the practical context of planning municipal drainage network repair and maintenance. Additionally, the heuristic method is generalized based on current practice, as presented in the ensuing section.

7. Heuristic algorithm

This section proposes a heuristic algorithm to address the crew allocation and scheduling problem. The approach mimics the decision-making process of a seasoned planner and has undergone validation via empirical case studies in collaboration with the industry partner. The presented method was applied in several test scenarios to cross-validate the optimization method.

- **Step 1:** Sort the list of jobs by their deadline in ascending order. That means the jobs with the shortest deadlines first appear in the list.
- **Step 2:** Sort the jobs with the same deadline according to their priority. That means jobs with higher priority first appear in the list with the same deadline.
- **Step 3:** Assign jobs from the list resulting from the step (2).
- **Step 4:** Calculate the *remaining crew availability* (RCA) for each crew. Initially, RCA for each crew is equal to the crew's availability within the planning horizon. After assigning each job, the job duration is deducted, yielding the updated RCA for the crew.
- **Step 5:** Iterate through steps (3) and (4) until RCA equals zero.

In the last iteration, one should consider comparing the RCAs with the durations of the candidate jobs when matching and assigning the jobs to the crews.

The optimized plans resulting from the mathematical model were cross examined against those from the heuristic method. In all the cases, the optimized solution plan outperformed the heuristic method in terms of more planned jobs and no tardy jobs passing deadlines. The Appendix exhibits the input data and optimization solution for the case of 85 jobs and Figure 3 displays the generated plan for this case study by applying the heuristic method. Notably, 59 out of 85 jobs were scheduled based on the heuristic method, in contrast to 66 planned jobs based on the optimization model. The heuristic method resulted in five tardy jobs that would miss deadlines, as bolded in Figure 3, whereas no tardy jobs were found in the optimized solution.

Crew(1)					RCA_1
Site ID	Job ID	d_j	C_j	dl_j	15
3	210225.0	1	09-03-2022	15-03-2022	14
4	210215.0	3	12-03-2022	17-03-2022	11
9	210203.0	1	13-03-2022	19-03-2022	10
9	206226.6	3	16-03-2022	20-03-2022	7
1	219908	1	17-03-2022	20-03-2022	6
10	206723.2	2	19-03-2022	21-03-2022	4
8	**210664**	**3**	**22-03-2022**	**21-03-2022**	1
8	210598	1	23-03-2022	23-03-2022	0

Crew(2)					RCA_2
Site ID	Job ID	d_j	C_j	dl_j	15
5	207823.1	1	09-03-2022	16-03-2022	14
3	210682.0	2	11-03-2022	17-03-2022	12
8	206741.2	2	13-03-2022	19-03-2022	10
7	202594.0	3	16-03-2022	20-03-2022	7
8	210504	3	19-03-2022	20-03-2022	4
2	**219526**	**3**	**22-03-2022**	**21-03-2022**	1
1	**210502**	**1**	**23-03-2022**	**21-03-2022**	0

Crew(3)					RCA_3
Site ID	Job ID	d_j	C_j	dl_j	15
6	210790.0	1	09-03-2022	16-03-2022	14
4	210076.2	3	12-03-2022	18-03-2022	11
10	210224.0	2	14-03-2022	19-03-2022	9
3	210358	2	16-03-2022	20-03-2022	7
9	210304	1	17-03-2022	20-03-2022	6
5	210286	1	18-03-2022	21-03-2022	5
3	210718	3	21-03-2022	21-03-2022	2
4	**210340**	**2**	**23-03-2022**	**22-03-2022**	0

Crew(4)					RCA_4
Site ID	Job ID	d_j	C_j	dl_j	14
4	206683.1	3	11-03-2022	17-03-2022	11
6	210754.0	2	13-03-2022	18-03-2022	9
7	210196.0	2	15-03-2022	19-03-2022	7
6	210646	3	18-03-2022	20-03-2022	4
1	210430	1	19-03-2022	20-03-2022	3
7	210466	1	20-03-2022	21-03-2022	2
5	210610	2	22-03-2022	22-03-2022	0

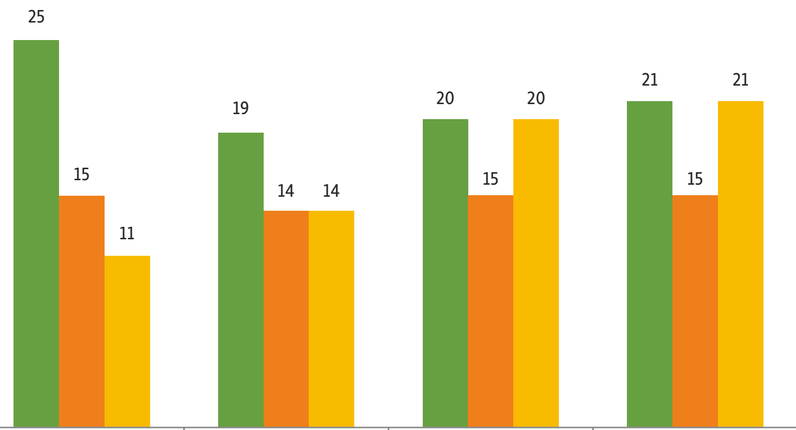
Crew(5)					RCA_5
Site ID	Job ID	d_j	C_j	dl_j	14
3	210808.0	2	10-03-2022	17-03-2022	12
4	210844.0	1	11-03-2022	18-03-2022	11
4	210628.0	3	14-03-2022	19-03-2022	8
5	206801.3	2	16-03-2022	20-03-2022	6
10	208512.3	1	17-03-2022	21-03-2022	5
6	210556.0	2	19-03-2022	21-03-2022	3
7	210700.0	3	22-03-2022	22-03-2022	0

Crew(6)					RCA_6
Site ID	Job ID	d_j	C_j	dl_j	13
7	207843.1	1	09-03-2022	17-03-2022	12
8	206701.2	1	10-03-2022	18-03-2022	11
1	207577.1	3	13-03-2022	19-03-2022	8
2	210214.0	2	15-03-2022	20-03-2022	6
7	206459.2	3	18-03-2022	21-03-2022	3
4	206701.8	2	20-03-2022	21-03-2022	1
9	210520.0	1	21-03-2022	22-03-2022	0

Crew(7)					RCA_7
Site ID	Job ID	d_j	C_j	dl_j	15
3	206876.3	3	11-03-2022	17-03-2022	12
6	206905.1	1	12-03-2022	19-03-2022	11
2	210412.0	1	13-03-2022	19-03-2022	10
9	2062765.3	3	16-03-2022	20-03-2022	7
10	210484.0	2	18-03-2022	21-03-2022	5
3	210448.0	2	20-03-2022	21-03-2022	3
4	**210934**	**3**	**23-03-2022**	**22-03-2022**	0

Crew(8)					RCA_8
Site ID	Job ID	d_j	C_j	dl_j	15
7	206317.5	1	09-03-2022	17-03-2022	14
9	206848.1	2	11-03-2022	19-03-2022	12
5	210880.0	3	14-03-2022	19-03-2022	9
9	206768.5	1	15-03-2022	20-03-2022	8
2	206800.9	3	18-03-2022	21-03-2022	5
1	206752.5	1	19-03-2022	21-03-2022	4
3	208061.1	3	22-03-2022	22-03-2022	1
7	206538.7	1	23-03-2022	23-03-2022	0

Figure 3. Heuristic algorithm results for planning of 85 jobs



	PI(0.1)	PI(0.2)	PI(0.3)	PI(0.4)
Sample Data	25	19	20	21
Heuristic Technique	15	14	15	15
Optimization Solution	11	14	20	21

Figure 4. Heuristic and optimized solutions compared on the number of assigned jobs in various priorities: the case of 85 jobs

Out of 59 clients served in the plan derived from the heuristic method, five were associated with CSI = 0%, which means an average CSI = 91.5% compared to the CSI = 100% based on the optimization solution. Both approaches resulted in the same crew work continuity (CUP equal to 100%) in the current case. Further, a critical comparison is made between the optimized vs. heuristic methods regarding the number of jobs planned under each priority category. As shown in Figure 4, the optimization model planned all the higher-priority jobs (i.e., PI = 0.3 and 0.4). In comparison, the heuristic method scheduled more jobs with lower priority (e.g., fifteen "PI = 0.1" jobs by the heuristic method compared to eleven "PI = 0.1" jobs by the optimization model).

These results served as the evidence to confirm that the optimization model outperformed the heuristic method in terms of scheduling more jobs for the available crews in the planning time window without exceeding job deadlines, not to mention the considerable time and effort required to perform the heuristic method manually (it took at least four hours on each scenario in contrast with one to two minutes to run the optimization model). Furthermore, the model was validated by presenting the derived plans from the two methods to the subject matter experts via face validation, who confirmed the superiority and effectiveness of the optimization model in lending analytical decision support.

8. Conclusions

In dynamic application settings in the real world, cost-effective optimization methods are desired for utilizing available resources, making construction schedules, and ensuring the timely delivery of services. This study highlights the challenges in managing municipal drainage infrastructure projects in terms of allocating limited crews against many jobs scattered on various sites, each with distinct priorities and deadlines. The dynamic nature of these operations is largely characterized by extensive installation or repair tasks, prioritization, and adherence to strict deadlines. Our investigation has revealed the inadequacy of existing planning practices, which are primarily reliant on trial and error to cope with the dynamically changing project environment under the constraints of crew availability and deadlines. In reality, this would lead to missed opportunities for improvement and unnecessary direct and indirect project costs, including negative impact on social equity, business losses, and client dissatisfaction.

Through collaborative research with an industry partner, we aimed to (1) develop effective and flexible planning methods utilizing affordable and user-friendly tools for optimization of scheduling crews in job execution and (2) enable a finite number of crews to perform the routine jobs by their respective deadlines, address high priority or emergency jobs on time, and maximize the number of jobs scheduled over a given planning horizon. Therefore, this has resulted in a practical and efficient Integer Linear Programming model tailored to the mentioned problem statement. Case studies were conducted to mimic practical scenarios for planning drainage services in specified time windows, encompassing job pools ranging from twenty-five to two hundred fifty jobs. A heuristic method – which represented how an experienced planner in practice tackles the defined problem – was also applied in a case study. Notably, three performance metrics were defined to compare the optimization model solutions against the heuristic ones. In all the cases, the optimization model outperformed the heuristic method in terms of more planned jobs and no tardy jobs past deadlines. Hence, the study has delivered a streamlined optimization model featuring tractability, flexibility, and speed, which lends a significant advantage to practice, given the need for frequent replanning and model updating due to delays and changes. The model has streamlined the planning and scheduling processes while avoiding computational intensity and algorithmic complexity. The close collaboration with the industry partner has underscored practicality and relevance to the stakeholders who would be the ultimate beneficiaries of the applied research. To the involved industry partners, this would potentially yield direct cost savings, and keep more clients satisfied, while maximizing resource efficiency and indirect cost savings. It is worth mentioning that the proposed optimization solution has also eliminated the need for expensive optimization computing by making it possible to leverage inexpensive and open-source solver engines (such as MS Excel Solver).

To sum up, this research has contributed to the body of knowledge regarding planning multi-concurrent construction projects:

- Streamlining the crew planning problem of multi-concurrent small projects scattered over distinct site locations without compromising the sufficiency of the real-world problem definition.
- Avoiding the computational burden of complex models by simplifying the model into a straightforward ILP, which leads to solving the problem of practical complexity and size in a matter of seconds.
- Generating the optimal solution for crew planning and scheduling via a user-friendly Excel spreadsheet program that suits the dynamic environment of multi-project planning.
- Providing the basis for updating the plan in case of emergencies or unexpected job delays in the execution phase, thanks to the short turnaround time required for updating the plan.

Lastly, this planning problem is characteristic of operating utility service call centers where crews are dispatched for maintenance or repair services at the customers' premises. Not limited to the described municipal drainage services planning problem, the proposed optimization model can be extended to other application contexts in further research (for instance, considering crew travel times between job locations and worker locations and workers' skillsets). This method also serves as the foundation for developing agile updating processes tailored to such a dynamic domain of planning multi-concurrent projects.

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Disclosure statement

The authors strongly state that there are no competing financial, professional, or personal interests from other parties.

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APPENDIX

In this section, you'll find the input data and optimized solution for a case that involves 85 jobs. SiteID refers to different site numbers, each of which can have several unique work orders. The notations used here have been explained in the Model formulation section. The binary number one that appears under each crew's code indicates that the corresponding crew has been assigned to the job based on the optimal solution.

SiteID	Work Order	d_{rj}	d_j	dl_j	Pl_j	ST_j	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
3	210225.0	01-03-2022	1	15-03-2022	0.2	13	0	0	0	0	0	1	0	0
5	207823.1	01-03-2022	1	16-03-2022	0.1	14	0	0	0	0	1	0	0	0
6	210790.0	01-03-2022	1	16-03-2022	0.1	14	0	0	0	0	1	0	0	0
4	206683.1	01-03-2022	3	17-03-2022	0.4	13	0	0	0	0	1	0	0	0
3	210808.0	02-03-2022	2	17-03-2022	0.3	13	0	0	0	0	0	0	1	0
7	207843.1	03-03-2022	1	17-03-2022	0.2	13	0	0	0	0	0	0	1	0
3	206876.3	03-03-2022	3	17-03-2022	0.2	11	0	0	0	0	0	0	0	0
7	206317.5	03-03-2022	1	17-03-2022	0.1	13	0	0	0	0	1	0	0	0
4	210215.0	03-03-2022	3	17-03-2022	0.1	11	0	0	0	0	0	0	0	0
3	210682.0	03-03-2022	2	17-03-2022	0.1	12	0	0	0	0	0	0	0	0
4	210076.2	04-03-2022	3	18-03-2022	0.4	11	0	1	0	0	0	0	0	0
6	210754.0	04-03-2022	2	18-03-2022	0.3	12	0	0	0	0	0	0	1	0
4	210844.0	03-03-2022	1	18-03-2022	0.2	14	0	0	0	0	0	0	1	0
8	206701.2	01-03-2022	1	18-03-2022	0.1	16	1	0	0	0	0	0	0	0
6	206905.1	05-03-2022	1	19-03-2022	0.4	13	1	0	0	0	0	0	0	0
9	206848.1	04-03-2022	2	19-03-2022	0.4	13	0	0	0	0	0	0	1	0
9	210203.0	03-03-2022	1	19-03-2022	0.4	15	0	0	0	0	0	0	0	1
8	206741.2	04-03-2022	2	19-03-2022	0.3	13	0	0	0	0	0	0	1	0
10	210224.0	02-03-2022	2	19-03-2022	0.3	15	0	0	0	0	0	0	1	0
7	210196.0	05-03-2022	2	19-03-2022	0.3	12	0	0	1	0	0	0	0	0
4	210628.0	05-03-2022	3	19-03-2022	0.3	11	0	0	0	1	0	0	0	0
1	207577.1	05-03-2022	3	19-03-2022	0.2	11	0	0	0	0	0	0	0	0
2	210412.0	02-03-2022	1	19-03-2022	0.2	16	1	0	0	0	0	0	0	0
5	210880.0	01-03-2022	3	19-03-2022	0.2	15	0	0	0	0	0	0	0	0
9	206226.6	04-03-2022	3	20-03-2022	0.4	13	0	0	0	1	0	0	0	0
7	202594.0	06-03-2022	3	20-03-2022	0.4	11	0	0	0	1	0	0	0	0
3	210358.0	06-03-2022	2	20-03-2022	0.4	12	0	0	1	0	0	0	0	0
6	210646.0	02-03-2022	3	20-03-2022	0.4	15	0	1	0	0	0	0	0	0
5	206801.3	04-03-2022	2	20-03-2022	0.3	14	0	0	0	1	0	0	0	0
2	210214.0	04-03-2022	2	20-03-2022	0.3	14	0	0	0	0	1	0	0	0
9	2062765.3	02-03-2022	3	20-03-2022	0.2	15	0	0	0	0	0	0	0	0
9	206768.5	01-03-2022	1	20-03-2022	0.2	18	1	0	0	0	0	0	0	0
1	219908.0	01-03-2022	1	20-03-2022	0.1	18	0	0	0	0	0	0	0	1
8	210504.0	01-03-2022	3	20-03-2022	0.1	16	0	0	0	0	0	0	0	0
9	210304.0	06-03-2022	1	20-03-2022	0.1	13	1	0	0	0	0	0	0	0
1	210430.0	03-03-2022	1	20-03-2022	0.1	16	1	0	0	0	0	0	0	0
10	208512.3	03-03-2022	1	21-03-2022	0.4	17	0	0	0	0	0	0	0	1
7	206459.2	01-03-2022	3	21-03-2022	0.4	17	0	0	1	0	0	0	0	0
10	210484.0	07-03-2022	2	21-03-2022	0.4	12	0	0	0	0	0	1	0	0
2	206800.9	01-03-2022	3	21-03-2022	0.3	17	0	0	0	0	0	0	1	0
10	206723.2	02-03-2022	2	21-03-2022	0.3	17	0	0	1	0	0	0	0	0
2	219526.0	07-03-2022	3	21-03-2022	0.3	11	0	0	0	0	0	1	0	0
5	210286.0	05-03-2022	1	21-03-2022	0.3	15	0	0	0	0	0	0	0	1
7	210466.0	06-03-2022	1	21-03-2022	0.3	14	0	0	0	0	0	0	0	1
6	210556.0	07-03-2022	2	21-03-2022	0.3	12	0	0	1	0	0	0	0	0

SiteID	Work Order	d_{rj}	d_j	dl_j	Pl_j	ST_j	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
4	206701.8	05-03-2022	2	21-03-2022	0.2	14	0	0	0	0	0	1	0	0
3	210448.0	07-03-2022	2	21-03-2022	0.2	12	0	0	0	0	0	1	0	0
1	206752.5	01-03-2022	1	21-03-2022	0.1	19	0	0	0	0	0	0	0	1
1	210502.0	07-03-2022	1	21-03-2022	0.1	13	1	0	0	0	0	0	0	0
8	210664.0	05-03-2022	3	21-03-2022	0.1	13	0	0	0	0	0	0	0	0
3	210718.0	07-03-2022	3	21-03-2022	0.1	11	0	0	0	0	0	0	0	0
9	210520.0	07-03-2022	1	22-03-2022	0.4	14	0	1	0	0	0	0	0	0
7	210700.0	02-03-2022	3	22-03-2022	0.4	17	0	0	0	1	0	0	0	0
4	210934.0	05-03-2022	3	22-03-2022	0.3	14	1	0	0	0	0	0	0	0
3	208061.1	02-03-2022	3	22-03-2022	0.2	17	0	0	0	0	0	0	0	0
5	210610.0	03-03-2022	2	22-03-2022	0.2	17	0	1	0	0	0	0	0	0
4	210340.0	05-03-2022	2	22-03-2022	0.1	15	0	0	0	0	0	0	0	0
7	207732.1	07-03-2022	2	23-03-2022	0.4	14	0	1	0	0	0	0	0	0
8	210598.0	03-03-2022	1	23-03-2022	0.4	19	0	0	0	0	0	0	0	1
3	206706.8	06-03-2022	2	23-03-2022	0.3	15	0	0	1	0	0	0	0	0
3	216990.0	06-03-2022	3	23-03-2022	0.3	14	0	0	0	0	1	0	0	0
7	206538.7	07-03-2022	1	23-03-2022	0.2	15	0	0	0	0	0	0	0	1
9	210916.0	05-03-2022	1	23-03-2022	0.2	17	0	0	0	0	0	0	0	1
6	206709.3	06-03-2022	3	23-03-2022	0.1	14	0	0	0	0	0	0	0	0
8	206724.1	04-03-2022	1	23-03-2022	0.1	18	0	0	0	0	0	0	0	1
4	210574.0	06-03-2022	1	23-03-2022	0.1	16	1	0	0	0	0	0	0	0
9	210736.0	07-03-2022	3	23-03-2022	0.1	13	0	0	0	0	0	0	0	0
8	210826.0	05-03-2022	2	24-03-2022	0.4	17	0	0	1	0	0	0	0	0
6	210862.0	04-03-2022	2	24-03-2022	0.4	18	0	1	0	0	0	0	0	0
10	208395.0	04-03-2022	1	24-03-2022	0.2	19	0	0	0	0	0	0	0	1
9	210250.0	04-03-2022	1	24-03-2022	0.2	19	0	0	0	0	0	0	0	1
7	210538.0	04-03-2022	1	24-03-2022	0.2	19	0	0	0	0	0	0	0	1
6	205954.1	07-03-2022	3	24-03-2022	0.1	14	0	0	0	0	0	0	0	0
6	210206.0	05-03-2022	2	24-03-2022	0.1	17	0	0	0	0	0	0	0	0
7	210592.0	06-03-2022	3	25-03-2022	0.3	16	0	0	0	0	0	1	0	0
8	210898.0	06-03-2022	3	25-03-2022	0.3	16	0	0	0	0	1	0	0	0
5	210772.0	08-03-2022	1	25-03-2022	0.2	16	1	0	0	0	0	0	0	0
4	210268.0	06-03-2022	3	26-03-2022	0.3	17	1	0	0	0	0	0	0	0
7	208412.1	08-03-2022	2	26-03-2022	0.1	16	0	0	0	0	0	0	0	0
2	210322.0	07-03-2022	3	26-03-2022	0.1	16	0	0	0	0	0	0	0	0
10	210477.0	07-03-2022	1	27-03-2022	0.4	19	0	0	0	0	0	0	0	1
1	210394.0	07-03-2022	3	27-03-2022	0.1	17	0	0	0	0	0	0	0	0
8	206723.8	08-03-2022	1	28-03-2022	0.4	19	0	0	0	0	0	0	0	1
10	210376.0	08-03-2022	2	28-03-2022	0.4	18	0	1	0	0	0	0	0	0
2	210232.0	08-03-2022	3	28-03-2022	0.1	17	0	0	0	0	0	0	0	0