

**Enhanced Constraints Representation and MTSP Schedule Optimization
for Repetitive Projects Considering Environmental Sustainability**

by

Fam Saeed

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	NAME: Mazdak Nik-Bakht Title: Associate Professor & Associate Dean of Research & Innovation, Gina Cody School of Engineering & Computer Science, Concordia University
Supervisor	NAME: Tarek Hegazy Title: Adjunct Professor, Civil and Environmental Engineering University of Waterloo
Internal Member	NAME: Carl Haas Title: Professor, Civil and Environmental Engineering University of Waterloo
Internal Member	NAME: Mahesh Pandey Title: Professor, Civil and Environmental Engineering University of Waterloo
Internal-External Member	NAME: Ramadan El-Shatshat Title: Associate Professor, Electrical and Computer Engineering University of Waterloo

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

ABSTRACT

The Canadian construction industry is facing serious challenges regarding project delays (affecting 25% - 50% of large infrastructure projects), cost overruns (totaling around \$91 billion between 2017 and 2023), and contributing nearly 39% to Canada's annual Green House Gas emissions. Most of the infrastructure projects, e.g. bridges, highways, and multi-school rehabilitation, involve tasks that are repetitive in nature. Thus, repetitive scheduling techniques offer multiple benefits, including economy of scale and learning curve savings. However, planning such projects remains complex, particularly when units are not identical in size and multiple crews are being involved to fast-track the project. In response, this research developed novel Multi-Travelling Salesman Problem (MTSP)-based schedule optimization model(s) offering an enhanced constraints representation for optimizing key repetitive construction projects. The proposed research framework incorporates three modules to handle various types of repetitive projects (linear and scattered). It also provides more sustainable schedules by integrating environmental impacts into the optimization process. Unlike existing models, the proposed modules formulate the scheduling problem as a MTSP where crews move across units to complete their assigned tasks while meeting time and budgetary constraints. One of the modules also quantifies, monetizes and incorporates key environmental impacts into the optimization process, accounting for variations in construction methods and materials and their effects on time, cost, and sustainability. The optimized schedules are then visualized through legible charts, GIS maps, and intuitive construction simulations. This modules formulation is unique. Its novelty beyond existing repetitive scheduling models stems from: (1) handling multiple crews simultaneously by incorporating crew routing sequences as key scheduling variables through a MTSP formulation; (2) introducing adjacency constraints to maintain, for all crews, both work continuity and unit linearity, if needed, while accounting for

transition times between units; (3) adding new criteria to the multi-mode construction scheduling models where each task can be executed using optimal alternative methods and materials affecting time, cost and environmental considerations; and (4) generating sustainable construction schedules by quantifying and integrating environmental impacts into the optimization process. The proposed model is validated against previous models in the literature through several case studies. Not only do these modules provide more efficient computational performance, but they also demonstrate significant improvements across various optimization objectives, such as project duration, crew transition-time, crew idle-time, environmental impacts, total cost, and various combinations. The proposed research framework provides significant benefits as a scalable and adaptable solution for managing complex repetitive projects, enhancing the delivery of infrastructure projects and offering substantial benefits to the multi-billion-dollar construction industry.

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Dedication

To my beloved father,

I have fulfilled my promise — your son is now called Dr. Fam.

Rest in peace.

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Chapter 1

Introduction

1.1 General

The construction industry is a major contributor to the Canadian economy, generating about 162 billion dollars annually accounting for 7.50 % of the Gross Domestic Product (GDP), and employing more than 1.6 million people (Canadian Construction Association 2025). The industry is growing steadily (Figure 1.1), with total construction spending amounting to approximately \$368.8 billion in 2023 and expected to exceed \$445 billion by 2028 (Statista 2024). Similarly, within the North American context, the U.S. construction industry exceeded 2,000 billion worth of new construction expenditures by the end of 2024 (U.S.A. Statista 2025).

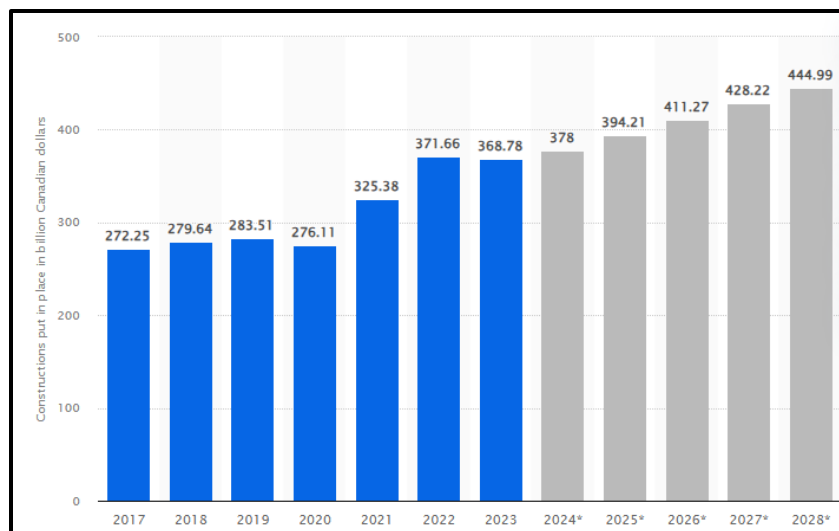


Figure 1.1 Construction spending in Canada from 2017 to 2028 (Statista 2024)

However, the Canadian construction industry is currently facing serious challenges in terms of project delays (affecting 25% - 50% of large infrastructure projects), cost overruns (totaling around \$91 billion between 2017 and 2023), and labor shortage (with over 93,000 unfilled jobs nationwide) (Sixth Annual Report - CRUX Insights 2023; Statistics Canada 2025). These

challenges are hindering the industry's ability to meet growing demands for housing and infrastructure projects. Most of these projects, particularly large infrastructure projects, involve tasks that are repetitive in nature. Thus, repetitive scheduling techniques can bring multiple benefits, including economy of scale and learning curve savings. However, planning such projects remains complex, particularly when units are not identical in size and multiple crews are being involved to fast-track the project (Saeed et al. 2024a).

At a more detailed level, repetitive projects are categorized into Vertical Repetitive Projects (VRPs) (e.g. high-rise buildings), Linear Repetitive Projects (LRPs) (e.g. water/sewer pipelines and highways), and Scattered Repetitive Projects (SRPs) (e.g. multi-bridge or multi-school rehabilitations) (Nguyen et al. 2022; Tran et al. 2022). In an ideal repetitive schedule, crews move across units with an optimal order of execution that helps to meet time and budgetary constraints. Typically, VRPs have a rigid order of execution, starting from the first unit (floor) and moving up to the next units towards the last unit in a sequential order (Gouda et al. 2017). In LRPs, where the project units are geometrically linear, crews must move from one unit to an adjacent unit, etc. The scheduling for these two types of projects (VRPs and LRPs) can be straight forward when the units are identical in size and a single crew is being used, thus moving from unit 1 to 2, to 3, to n.

However, the scheduling process for LRPs gets more complex when the unit sizes are not identical and multiple activity crews are employed to fast-track the project. In these scenarios, each crew must start from a specific unit and then move to an adjacent unit, to maintain both work continuity and unit linearity. To do so, the scheduling and crew assignment do not follow a rigid 1 to n sequence and must follow a flexible (soft logic) approach, adding more complexity to the scheduling problem. SRPs, on the other hand, require even more flexibility to suit the dispersed locations of units (e.g., schools or bridges) and the time and cost to move crews among units, while maintaining efficient resource utilization (Podolski and Sroka 2019). Thus, traditional scheduling

techniques (e.g., CPM, LOB) exhibited severe computational and visualization challenges on repetitive projects.

In addition, planning for repetitive construction projects needs to consider an additional dimension (variable) that addresses environmental impacts by determining which construction mode keeps environmental impacts to a minimum. This is needed because the construction industry is a major contributor to environmental issues. Globally, construction activities are responsible for 32% of the world's resource depletion and 40% of the solid waste sent to landfills (Sanchez et al. 2019). In Canada, the construction sector is responsible for more than 4 million tonnes of waste per year, representing an estimated 1.8 million tons of embodied carbon (Racine et al. 2021), which in turns represents 39% of the annual Green House Gas (GHG) emissions (Ansah et al. 2021; The Delphi Group 2021). The construction sector and its building materials alone are responsible for one-third of the construction emissions, while the building operations sector is responsible for the reminder (Figure 1.2).

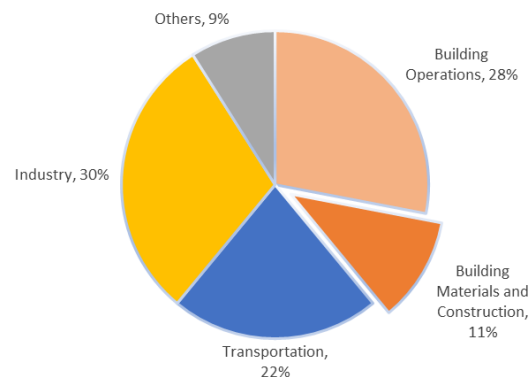


Figure 1.2 GHG emissions by sector in Canada (The Delphi Group, 2021)

Additionally, the growing scale of projects and the demand for faster and more cost-effective delivery increase the complexity of managing these projects. Scheduling becomes exponentially more challenging as the number of repetitive activities grows, which must observe certain logical relationships, and may involve different crew sizes and unit sequences than its

predecessors and successors. Given all the abovementioned challenges, there is an immense need to develop a flexible yet comprehensive framework with an environment-sustainable feature to efficiently deliver such projects while meeting their constraints.

1.2 Research Motivation

This research aims to provide a more practical representation of the constraints controlling the repetitive projects scheduling through developing novel schedule optimization model(s), tailored specifically to LRPs and SRPs. The study has been motivated by challenges in existing repetitive scheduling techniques, the need to consider environmental impacts in construction planning, and the need for a scheduling tool with simulation and legible visualization abilities. The developed model needs to consider key constraints such as resource limits, crew work continuity, site conditions, and environmental factors. These challenges and needs are described in more detail below:

1.2.1 Need for flexible schedule optimization model for SRPs

Optimizing schedules for Scattered Repetitive Projects (SRPs) involves synchronizing the activities of multiple crews across diverse locations while considering time, budgetary, resource, and environmental constraints (Han et al. 2020). In such circumstances, challenges can arise, such as resource overallocation, project delays, reduced productivity, gaps in schedule, and the need to resort to costlier construction methods to meet deadlines. Thus, multi-crew routing algorithms, such as Multi-travelling Salesman Problem (MTSP), can enhance crew assignment for SRPs, exploring a variety of work constraints and work dynamics (i.e., interactions among locations, crew-unit assignments, and crews' skills/learning/fatigue) on repetitive scheduling computations. Additionally, such MTSP algorithms can formulate a flexible optimization framework for SRPs by minimizing construction duration under a strict deadline, where the site order is a key scheduling variable that adds to the complexity of the optimization process. Despite extensive

research efforts over the past decades, no comprehensive model exists for optimizing the routing of multiple crews while simultaneously accounting for crew-specific characteristics, spatial characteristics of units, crew mobilization and travel constraints, construction sequence, and variation in work quantities.

1.2.2 Challenges in existing scheduling techniques for LRPs

Existing scheduling methods struggle to maintain crew-work continuity along the repetitive units. This is particularly so when the repetitive units are not identical in size and multiple crews are involved to fast-track the project. Typical linear methods schedule the tasks one after the other and end up with long schedules that exceed deadlines. The permutations of assigning each crew to a group of adjacent units (to maintain linearity) are extremely large, which means arriving at an optimal schedule is a huge challenge. Accordingly, a need exists for a novel formulation that does not force linearity using constraints between the finish of a predecessor unit and the start of a successor unit. This traditional constraint representation is complex to model generically and is difficult to produce optimum schedules. Additionally, as repetitive units may require mobilization or preparation times, crew transfers between units consume both time and cost. Therefore, the impact of crew transitions on repetitive project scheduling needs to be considered. Lastly, to address real-life situations, multiple objectives need to be optimized simultaneously (e.g., total project duration, crew transition time, and crew idle time).

1.2.3 Need to consider the environmental impacts in construction planning

Construction activities result in significant environmental impacts, which includes carbon emissions, depletion of natural resources, and the generation of massive amounts of waste sent to landfills. Only few studies have considered these environmental impacts while planning for construction projects and even fewer have considered the environmental impacts for repetitive projects. However, changes in units' execution order, construction methods, material utilization,

and crew selection can result in varying environmental impacts across different scenarios. Quantifying and monetizing these impacts are crucial for decision-makers to promote sustainable construction practices. Therefore, when planning repetitive projects, schedules should be optimized to prioritize environmental impacts that foster eco-friendly and sustainable construction management practices.

1.2.4 Need for scheduling tool with simulation and legible visualization abilities

Lastly, to improve repetitive scheduling, a user-friendly tool is needed that streamlines the management of complex information, including unit sequences, non-identical durations, several activities, multiple crews and execution timings. This tool should offer a clear visualization of the schedule to all participants such as crews, asset owners, and project managers. The desired features of such a tool include: (1) Does not require deep learning curve and able to provide a near-live simulation of the construction process; (2) Able to manage individuals (crews), consumable resources (materials) and equipment across project units; (3) Incorporates precise spatial information of units and traffic data to optimize scheduling decisions; and (4) Provides real-time updates on the state of activities (Started, Working-on, or Finished) and crew state (Working, Idle, or Travelling). Such a tool could foster better communication among project stakeholders, reducing labour losses, conflicts between departments, and material waste. Additionally, this tool could improve machinery and equipment utilization, leading to more efficient project delivery.

1.3 Research Objectives and Scope

This research presents a flexible yet comprehensive framework for scheduling repetitive projects, to meet budgetary and resource constraints while minimizing their environmental impacts. The proposed framework incorporates innovative MTSP formulations with enhanced constraints representations to generate optimal repetitive schedules. The detailed objectives of this research are as follows:

1. Investigate the constraints governing the scheduling of repetitive projects to overcome their current challenges and provide more practical representations of these constraints.
2. Analyze the environmental impacts associated with construction projects and explore potential scenarios for mitigating these impacts through the scheduling process.
3. Develop an optimization model integrating crew arrangements, cost, duration, and associated environmental impacts to generate feasible yet sustainable schedules.
4. Validate the proposed model through multiple case studies comparing its performance and novel features against existing models from the literature.
5. Promote efficient communication among project stakeholders through legible charts, GIS maps, and intuitive construction simulations.

The outcome of this research is intended to provide project managers with a decision support system to systematically generate near-optimal schedules for repetitive projects, such as bridges and multi-school rehabilitation. This decision support system will facilitate efficient communication among project stakeholders and lead to savings in time, cost, and environmental impacts while ensuring comprehensive control over project execution.

1.4 Research Methodology

The proposed research methodology to meet the research objectives is described in the following steps:

- a. Literature Review: Conduct an extensive review of the recent scheduling optimization approaches for repetitive projects.
- b. Software Survey: Analyse commercial software for repetitive scheduling to identify their challenges and assess their features.
- c. Routing Algorithms: Explore routing algorithms (i.e., MTSP) to determine their applicability in optimizing schedules for repetitive projects.

- d. Sustainability: Investigate the environmental impacts associated with construction projects and current methodologies for quantifying and monetizing these impacts.
- e. MTSP-based Scheduling: Develop a MTSP formulation to handle multiple crews simultaneously by incorporating crew routing sequences as key scheduling variables.
- f. CP-based Scheduling: Introduce a more holistic scheduling module with novel constraints representation to maintain, for all crews, both work continuity and unit linearity, if needed, while accounting for transition times between units.
- g. Sustainable Scheduling: Formulate a multi-mode construction scheduling module where each task can be executed using alternative methods and materials affecting time, cost and environmental considerations.
- h. Schedule Visualization: Visualize the optimized schedules through legible charts, GIS maps, and intuitive construction simulations.
- i. Testing and Validation: Validate the developed modules against case studies from literature to assess their practicality and flexibility.
- j. Integration and Vision: Discuss the integration of the developed scheduling modules within the vision of Infrastructure Ontario, aiming for its adoption by municipalities as a comprehensive and efficient scheduling solution for infrastructure projects.

1.5 Proposed Framework Components

The proposed research aims to propose an enhanced constraints representation for optimizing repetitive projects while meeting time, budgetary, and environmental constraints. The proposed framework proceeds through four main steps (Figure 1.3). Step 1 takes the project data inputs regarding units (e.g., tasks, durations, precedencies, etc.), crews (e.g., availabilities, skills, etc.), and any other constraints.

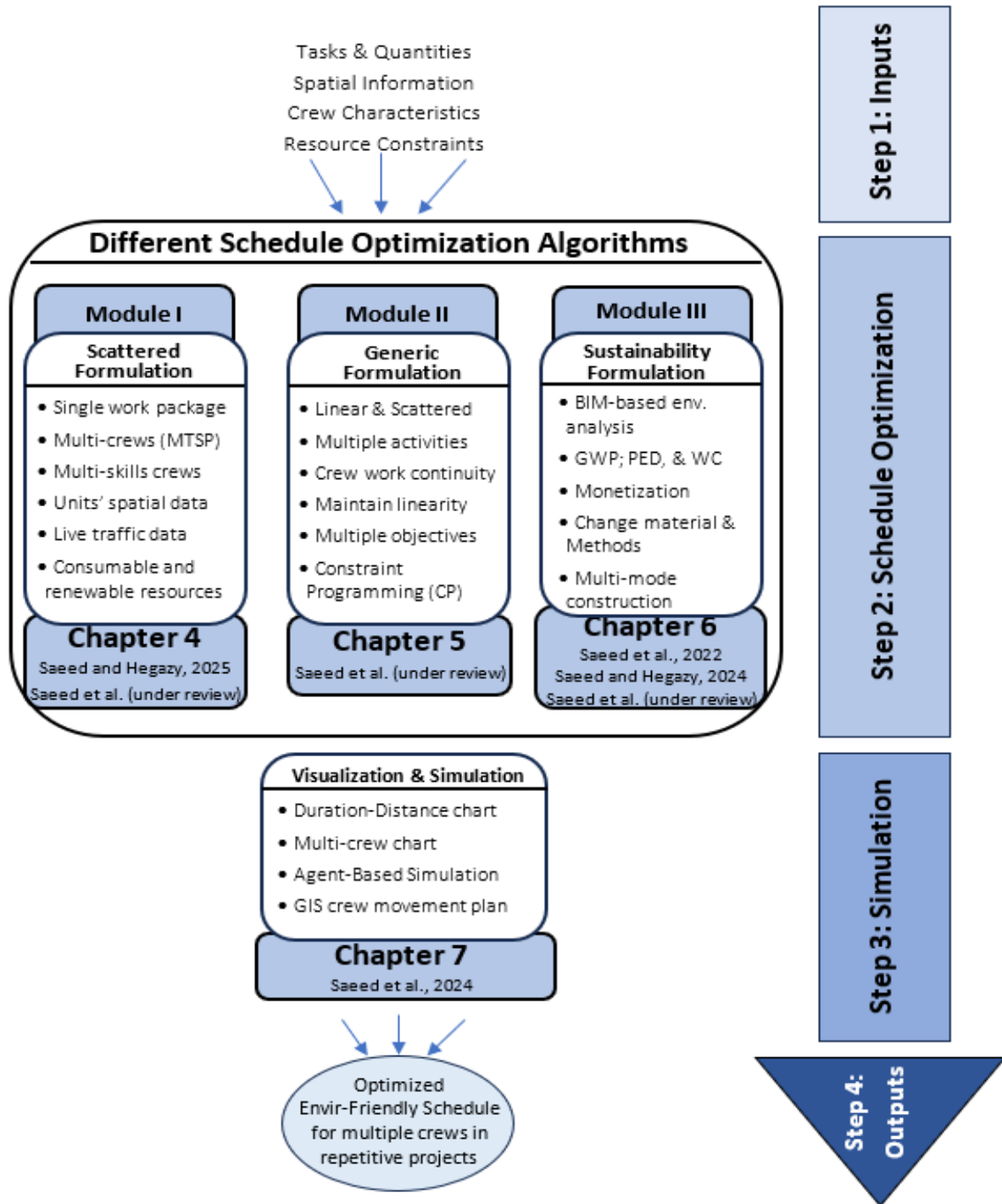


Figure 1.3 Proposed research framework components

Step 2 introduces three novel schedule optimization modules, allowing the end-user to select the most suitable one based on the specific needs of their project. **Module I** introduces a scheduling algorithm based on the Multi-Travelling Salesman Problem (MTSP) to determine

optimal crew routing across scattered units. **Module II** develops a more holistic CP-based scheduling model for optimizing both linear and scattered projects. **Module III** quantifies, monetizes and incorporates the environmental impacts into the schedule optimization process, accounting for variations in construction methods and materials and their effects on time, cost, and sustainability. Once optimization is complete, Step 3 simulates the resulting schedule to assess their feasibility. Lastly, Step 4 generates the optimized environment-friendly schedules and presents them through legible charts, GIS maps, and intuitive construction simulations to facilitate interpretation and decision-making.

1.6 Thesis Organization

The remainder of this thesis is organized as follow:

Chapter 2 presents a comprehensive literature review to highlight the unique characteristics of both scattered and linear repetitive projects and drawbacks of current scheduling techniques, as well as recent advancements in Simulation and Constraint Programming techniques and their applications within the scheduling domain. Recent environmentally conscious practices aimed at generating more sustainable construction schedules are also discussed.

Chapter 3 analyzes the key commercial software systems for repetitive scheduling, compares their features (through hands-on experimentation), identifies their persistent challenges, tests their flexibility, ease of use, and their ability to model practical conditions.

Chapter 4 presents Module I of the proposed framework for optimally scheduling multiple crews among scattered repetitive units. The proposed model incorporates crew routing orders as a key scheduling variable for SRPs and formulates a MTSP optimization problem to handle multiple crews simultaneously. The chapter also presents a real-life application and validation results of the developed optimization module.

Chapter 5 introduces Module II of the proposed framework that is a novel CP Optimization Model for both linear and scattered projects to maintain, for all crews, both work continuity and unit linearity, while accounting for transition times between units. The chapter also presents the model's validation through several case studies from literature.

Chapter 6 presents Module III of the proposed framework which includes two main parts. Part 1 quantifies and monetizes the environmental impacts to be integrated into the schedule optimization model. Part 2 introduces the multi-mode construction scheduling model which incorporates these quantified impacts into the scheduling scenarios.

Chapter 7 presents an Agent Based Simulation Model (ABSM) to simulate the generated repetitive schedules. The ABSM synchronizes the work of multiple crews across units modelling scheduling for the high level of complexity and resource allocation in repetitive projects.

Chapter 8 summarizes the presented research, highlights its contributions, and provides recommendations for future research.

Chapter 2

Literature Review

2.1 Introduction

This section provides a comprehensive literature review on: (a) scheduling techniques for repetitive projects, with focus on SRPs and LRPs; (b) adapting the site order as a key scheduling variable; (c) routing algorithms and TSP research and their applications in the scheduling domain; (d) recent CP-based schedule optimization models; (e) sustainability and environmental impact integration into project scheduling; and (f) applying Geographical Information System (GIS) and Simulation technologies for repetitive scheduling. This section ends with highlighting the research gaps that this study aims to fill.

2.2 Repetitive Scheduling for Construction Projects

All types of repetitive projects require the schedule to meet a variety of constraints (maintaining crew-work continuity, handling limited resources, meeting strict deadlines, etc.). Despite extensive efforts in the field of repetitive scheduling, each study focuses on a specific objective, typically either reducing project duration or project cost for a specific type of repetitive projects. Also, each study addresses some but not all the applicable construction constraints. Studies that focus on reducing project duration include the work of Hegazy et al. (2021) which dealt with the repetitive schedule as a game of Tetris and introduced useful time-saving geometric manipulations. Meanwhile, Ammar (2019) developed a non-linear programming formulation of the Line-Of-Balance (LOB) technique to optimize project duration, considering work interruption constraints. However, neither Hegazy et al. (2021) nor Ammar (2019) incorporated limited resource constraints in their models. Moreover, Ammar's (2019) study and other studies (e.g., Altuwaim et al. (2018) and Zou and Zhang (2020)) focused only on the easier case of projects with identical

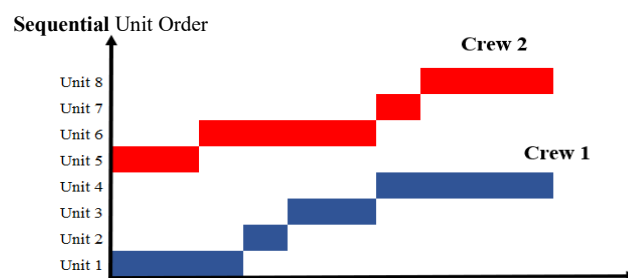
units. To consider the more general/complex case of non-identical units, recent efforts include Tran et al. (2022) who employed a Fuzzy Clustering Artificial-Bee-Colony approach that can deal with multiple resources considering task priorities. However, their model was designed for linear projects only. In another study, Tomczak and Jaśkowski (2022) employed a particle swarm algorithm in a multi-objectives model that can optimize project duration and the resource idle time, with the relative importance of these criteria set by the decision-makers.

Various other studies focus on minimizing project cost. Podolski and Sroka (2019) applied simulated annealing to minimize total project cost (direct, indirect, penalties, and crew's idle-time cost), while Huang et al. (2016) and Altuwaim et al. (2018) each employed Genetic Algorithm (GAs) for a similar purpose. Monghasemi and Abdallah (2021) developed a linear optimization model to generate near-optimal schedules focusing on minimizing interruption costs. Other cost-reduction efforts focused on improving work continuity for general contractor crews through subcontracting Tomczak and Jaśkowski (2020) or utilizing off-site prefabrication methods to handle resource constraints (Liu et al. 2018). Additional interesting studies such as Tomar and Bansal's (2022) considered the production rates for the crews to estimate duration; however, they assumed constant production rates for all task crews. Regardless of adopting time or cost reduction objective, assigning multiple crews to the units remains a key challenge in all models, with limited efforts focusing on SRPs or incorporating stakeholders' preferences in their formulations.

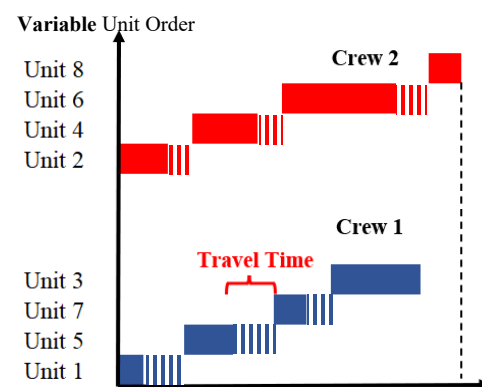
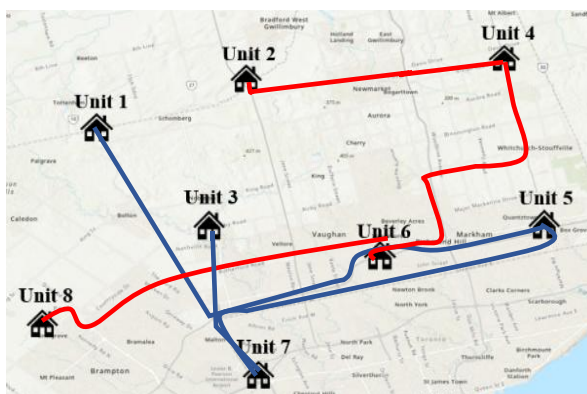
2.3 Execution Order in Scattered Repetitive Projects (SRPs)

In an ideal repetitive schedule, crews move across units (or sites) with an optimal order of execution that helps to meet delivery deadlines. The utilized unit's execution order affects the execution time, travel distance/time, and overall cost (Hegazy and Kamarah 2022). Typically, LRPs such as highways have a semi-rigid order of execution, starting from the first unit and moving to adjacent units towards the last unit (Gouda et al. 2017). In the linear schedule (Figure

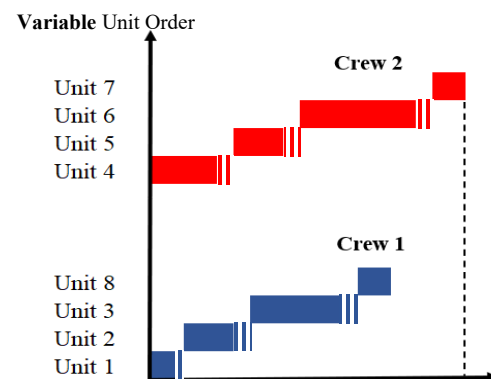
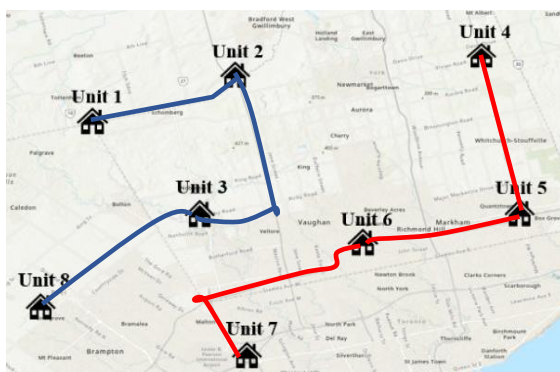
2.1 a), each crew moves to adjacent units in sequential order (crew1 moves along 1-2-3-4, while crew2 moves along 5-6-7-8). However, other studies such as Dolabi et al. (2014) have introduced alternative non-sequential scheduling approaches that allow multiple crews to execute tasks non-sequentially (Crew 1 may work on units 1-3-5-7, while Crew 2 handles units 2-4-6-8), demonstrating extra flexibility. The two options in Figure 2.1 b, c illustrate how the crew assignments and the order of units for each crew significantly influence crew travel time across the units, and project duration.



(a) Linear schedule for two crews along 8 units.



(b) Scattered repetitive schedule with inefficient site orders.



(c) Scattered repetitive schedule with proper site orders reduces project duration.

Figure 2.1 The difference between the schedules in linear and scattered projects

A limited number of studies investigated the use of varying unit orders, which offers an additional degree of freedom for SRPs (first column of Table 2.1, as illustrated in Figure 2.1b, c). Among existing efforts, Podolski and Sroka (2019) determined a near-optimal execution order among repetitive units in the case of a single task crew with a fixed productivity rate across the units of a task. To avoid this limitation, the model by Monghasemi and Abdallah (2021) applies practical fatigue and learning effects to the crews and thus has been adopted in the present study. Recently, Hegazy and Kamarah (2022) proposed a comprehensive model to optimize the allocation of multiple crews among non-identical scattered sites while considering crew moving time/cost.

Table 2.1 Recent models for scheduling scattered repetitive projects (SRPs).

Reference	Order of Execution	Multiple Crews	Different Crew Productivity Rates	Non-identical Units	Fatigue and Learning Effects	Adopted Model
Hegazy and Kamarah (2022)	√	√		√		Modified FCFS*
Podolski and Sroka (2019)	√		√	√		Simulated Annealing
(Huang et al. 2016)	√			√		Genetic Algorithm
Monghasemi and Abdallah (2021)	√			√	√	Linear Optimization
Mostafa et al. (2022)	√	√		√		Enhanced CPM/LOB**
Gad et al. (2023)		√		√		Agent-based Simulation

* FCFS: First-Come-First-Served

** CPM/LOB: Critical Path Method/ Line of Balance

The key advantage of Hegazy and Kamarah (2022)'s model is that the activities use multiple crews and independent execution orders among the units. However, one limitation is that the model estimates travel times among units roughly by dividing travel distance by a fixed moving speed. Overall, only limited studies such as Gad et al. (2023) allow multiple activity crews with pre-specified skill sets, although fixed among all crews. To the author's knowledge, however, no

model has considered crews' capacity to load/unload/refill consumable resources during work or during moving from one unit to another.

2.4 Repetitive Scheduling for Linear Projects

On the other hand, LRPs, such as highways, bridges, and pipelines, are usually constructed by a group of crews, each one of which moves from one unit to an adjacent unit, etc. The scheduling in this case can be straight forward when the units are identical in size and a single crew is being used, thus moving from unit 1 to 2, to 3, to n. The scheduling process becomes extremely more complex when the unit sizes are not identical and with multiple activity crews being employed to fast-track the project. In this case, each crew must start from a specific unit and then move to an adjacent unit, to maintain both work continuity and linearity. As such, the scheduling and crew assignment do not follow a rigid 1 to n sequence and must follow a flexible (soft logic) approach, which adds another layer of complexity to the scheduling problem. This situation of a linear activity with non-identical units and more than one crew is illustrated in Figure 2.2, with 10 units. Unit 5 is smaller in size, while unit 6 is larger in size. Three crews are employed in this activity. Figure 2.2 shows two possible schedules for this linear activity, resulting from assigning the crews to different units. Although both schedules observe the work-continuity and linear work sequence of each crew, their crew-to-unit assignments are different, resulting in the right-side schedule being shorter in duration (12 vs. 14). This example demonstrates that there can be many possibilities to schedule each activity, let alone scheduling all the activities in the project. Each schedule will have different end duration, crew transition time, and resource profile. Thus, it is a great challenge to arrive at a near-optimal schedule.

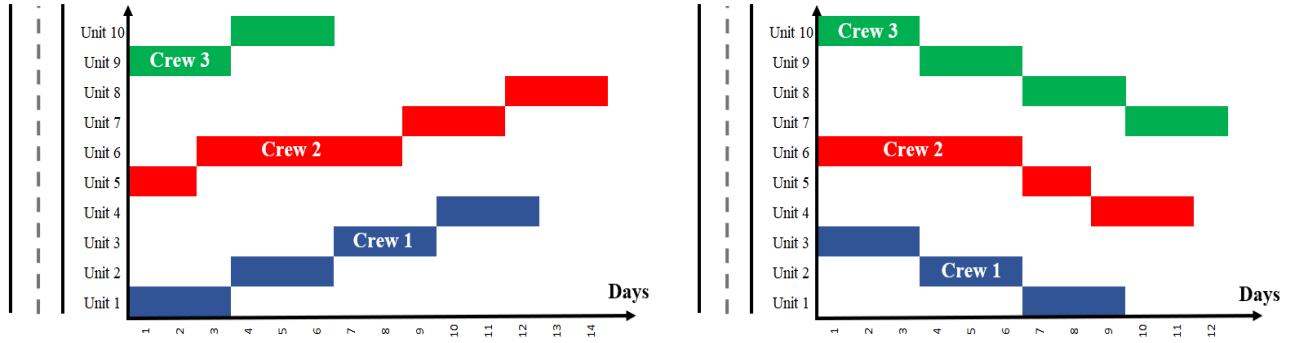


Figure 2.2 Alternative schedules of a linear activity, both observing work continuity and unit linearity for all crews.

The complexity of scheduling increases exponentially with the number of repetitive activities in the project, which must observe certain logical relationships, and each activity can have a different number of crews, and a different sequence of units than its predecessors and successors. For example, a carpentry crew could opt for a unit sequence of $(1 \rightarrow 2 \rightarrow 3 \rightarrow 4)$ among four units, while the successor painting crew could select another sequence $(1 \rightarrow 3 \rightarrow 4 \rightarrow 2)$. Each crew selects the optimal sequence to manage its resources. Determining the optimum sequence for each crew in each task—while respecting work continuity, unit linearity, project deadlines, resource limits and cost constraints--creates considerable challenges for an optimization model.

2.5 Recent Scheduling Models for Linear Projects

Over the past decades, extensive research has been conducted on the scheduling of linear projects using the Line Of Balance (LOB) method and its variations (Table 2.2). Hu et al. (2025b) developed a LOB-based integer linear programming model to optimize linear projects. However, their model overlooks the needed linearity constraint among the units and was focused only on minimizing the total project duration. In another model, Tran et al. (2022) proposed a Fuzzy Clustering Artificial Bee Colony approach (FABC) that models only Finish-Start relationships

without lag/lead among the activities and focuses on minimizing total project duration. In contrast, Altuwaim and El-Rayes (2021) proposed a multi-objective schedule optimization model that generates optimal trade-offs among project duration, work interruptions, and overtime use, although using only a single crew per task.

Table 2.2 Recent scheduling techniques and their features for linear and scattered projects

	Study	Linear Projects	Multiple crews	Transition time	Soft Logic Const.	Adjacency constraint	Non-identical	Work Continuity	4-Precedence Re.	Time Objective	Cost Objective	Multiple-Objective	Technique
1	Hu et al. (2025b)	√	√	√			√	√	√	TD			ALNS
2	Tran et al. (2022)	√	√				√		FS	TD			FABC
3	Altuwaim and El-Rayes (2021)	√					√		√	√	√	√	GA
4	(Huang et al. 2016)	√			√		√		FS	PD	√	√	GAs
5	Hu et al. (2023)	√	√				√		√	√	√	√	GAs
6	Moos et al. (2022)	√	√			√			FS		√		CP
7	Hegazy et al. (2021)	√	√	√			√	√	FS	PD			ASAP
8	Liu et al. (2021)	√	√				√	√	√	IT			CP
9	Tang et al. (2018)	√	√	√			√	√	√			√	LSM

In a series of efforts, Hegazy et al. (2020) introduced computational and geometrical enhancements to the LOB method which schedules the tasks one after the other, to generate more tightly packed repetitive schedules. Hegazy et al. (2021) introduced further improvements although still overlooks the linearity constraints for linear projects. In another direction, (Huang et al. 2016) highlighted the importance of adopting soft logic in the schedule optimization process to allow for more optimized schedules in terms of project duration and/or cost. However, their model can only be applied to cases of one crew per task.

2.6 Routing and TSP Research

With SRPs encompassing scattered units, the assignment of crews to units becomes a form of routing problem, for which the TSP technique can be applied. TSP algorithm tries to determine the optimal route for a vehicle or a salesman to visit a number of (n) cities while minimizing travel time (Mazidi and Damghanijazi 2017). This problem is easy to describe, but it is still hard to find an optimal solution. Thus, it is referred to as a Non-deterministic Polynomial (NP)-hard problem with an exponential increase in complexity as the number of cities increases (Labadie et al. 2016). When the problem involves multiple vehicles moving across a set of cities, it is referred to as a Vehicle Routing Problem (VRP) or Multiple-TSP (MTSP) in the case of salesmen (Toth and Vigo 2014). Depending on the application context, the MTSP salesmen can be ground vehicles such as trucks/crews or flying vehicles such as Unmanned Aerial Vehicle (UAV) known as drones. The ‘cities’ to be visited by the ‘salesmen’ would be seen as the assets requiring rehabilitation or customers waiting for product delivery.

2.6.1 Routing problem constraints and variants

TSP has a wide range of variants, resulting from the various problem characteristics and the constraints that are specific to each domain. The general problem characteristics include salesmen, a depot, an optimization objective, problem constraints, and an implementation approach. Based on the analysis of several papers, an anatomy of the key variables that can describe any routing problem has been summarized as shown in Figure 2.3. A discussion of the problem characteristics and associated variables are as follows:

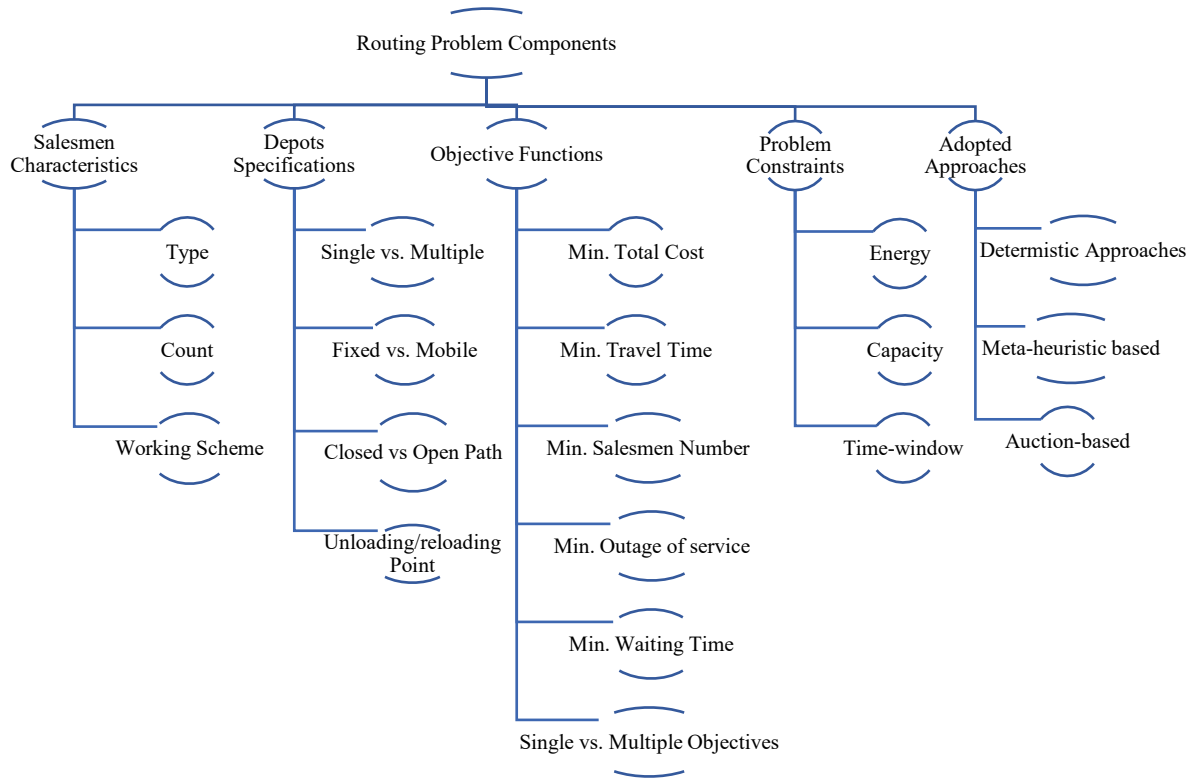


Figure 2.3 Key components of the routing problems

Salesmen characteristics:

- Salesman type: Depending on the application context, examples of salesmen include vehicles (Erdelić and Carić 2022), humans (e.g., healthcare providers (Euchi et al. 2020)), or robots (Wang et al. 2022).
- Number of salesmen: A key variable in the optimization process (Moussavi et al. 2019) that adds to the complexity of the problem.
- Working scheme: Whether the salesmen can work cooperatively in the same location (Xu et al. 2022) or independently as one salesman per site.

Depot Specifications:

- Single or multiple depots: The routing problem can include only one depot (Cokyasar et al. 2022) or multiple depots (Ceselli et al. 2021) from where the salesmen can start their route and return to it.
- Fixed or mobile depot: The depot in routing problems is usually fixed; however, certain applications introduce the possibility of a mobile depot. A mobile depot could be a truck from which UAVs embark on and conclude their tours (Euchi 2021).
- Closed or open path: In the classical routing problem, the salesman's route path adheres to a closed trajectory, necessitating the initiation and conclusion of their tour from the same depot position (Liu et al. 2021b). Conversely, in specific applications, the salesman may opt not to return to the depot, remaining in the last visited city. Alternatively, salesmen might choose to initiate their route from their own depot (Malagodi et al. 2021). Furthermore, when multiple depots are considered, the salesman has the option to connect with any existing depot, potentially different from the initial one (Ramos et al. 2020).
- Unloading/reloading point: When refuelling is allowed, it can be performed either at the depots (Erdelić and Carić 2022) or some additional refuelling positions (Cokyasar et al. 2022).

Objective functions:

Typical TSP algorithms try to minimize travel time/distance to visit n cities. However, its variants showed the ability to deal with other single or multiple objectives. These objective functions must therefore be formulated to minimize parameters such as: total cost (Shahnejat-Bushehri et al. 2021), mission time (Cokyasar et al. 2022), number of salesmen (Erdelić and Carić 2022), cost of client dissatisfaction in the case of service outages (Rashidnejad et al. 2018), customers' waiting time (Euchi et al. 2020), or routing risk when transporting hazardous materials (Wang et al. 2018).

Problem constraints:

Besides typical constraints related to number of salesmen and any pre-set sequence among some locations; the literature showed a growing interest in considering additional constraints such as:

- **Energy consumption:** Depending on the application context of the routing problem, the salesman may be assumed to consume energy while moving among cities. Vehicles such as electric cars (Ceselli et al. 2021) have limited range. Hence, without refuelling option, the planned tour will be constrained by the limited range of the vehicle.
- **Capacity constraint:** During its mission, the salesman may carry parcels or data. Thus, the capacity constraint on carrying these items needs to be considered (Erdelić and Carić 2022).
- **Time window constraint:** This constraint corresponds to the time interval during which the salesman needs to visit a given target. In some applications (e.g., home health care), the salesman must pick up some products from one place, carry them, and then deliver them to another destination within a limited time window (Shahnejat-Bushehri et al. 2021).

Implementation approaches:

- **Deterministic approaches:** also known as exact methods, these approaches can attain an optimal solution for small-size problems. Generally, they are time-consuming due to the intricate calculations needed, leading to limited adoption in a few studies. This category encompasses, but is not restricted to, Integer Programming (Rashidnejad et al. 2018), Branch and Cut Algorithm (Ceselli et al., 2021), etc.
- **Meta-heuristic approaches:** each approach within this category can be seen as a class of local search methods based on natural selection rules among individuals of consecutive generations to solve a problem. Commonly utilized meta-heuristic algorithms in the literature include Genetic Algorithms (Rashidnejad et al. 2018), Ant Colony Optimization (Wang et al. 2022),

Practical Swarm Optimization (Wei et al. 2020), Artificial Bee Colony techniques (Kaya et al. 2022), and Clustering Algorithm (such as K-means, Nearest neighbour).

- Auction-based approaches, also known as market-based, these approaches can be either centralized, involving a central auctioneer (Koubâa et al. 2016) that receives bids and assigns the cities to the salesman with the lowest cost, or distributed (Kivelevitch et al. 2013), where the bidding process is shared among various salesmen.
- Hybrid approaches: hybrid algorithms involve the simultaneous operation of two or more algorithms that complement each other, producing a harmonised effect. These well-designed hybrids, such as Hybrid of Ant-Colony and Genetic Algorithms (Jiang et al. 2020), often outperform their non-hybrid counterparts.

2.6.2 Applications and potential benefits in construction scheduling

The applications of vehicle and salesman routing problems have a rich history that is too vast to fully elaborate here. Recent resource management and scheduling studies are of special interest in this research. In these respects, TSP and other related variants have been applied to a wide range of applications, such as scheduling UAVs for power inspection process in remote regions (Lu et al. 2022); planning optimal school bus routes (Boonperm et al. 2019); optimizing supply chain planning and scheduling (Aguirre et al. 2018); scheduling home-healthcare staff routing (Sinthamrongruk et al. 2017); determining proper travel schedules for tourists (Supithak et al. 2021; Yu 2022); solving multi-ship scheduling problem in maritime transportation (Mahmoodjanloo et al. 2020); planning of drone-based delivery of goods (Mbiadou Saleu et al. 2022); and planning inventory routing for hazardous materials (Hu et al. 2020).

Furthermore, TSP techniques play a vital role in the maintenance scheduling of systems in geographically scattered facilities. Applications include the operation and maintenance scheduling

of heating networks (Rodrigues et al. 2022), utilities in commercial buildings (Allaham and Dalalah 2022), networked infrastructures (e.g., power transmissions, telecommunications, etc.) (Pourjavad and Almeshdawe 2022), offshore wind farms (Mostajeran et al. 2017) and global outsourcing networks (leasing and maintenance services) (Xia et al. 2021).

Focusing more on construction-related applications, diverse studies have shown the multiple benefits that TSP brings to the industry with applications such as on-site equipment utilization (Han et al. 2021; Tarhini et al. 2021), inspection and maintenance (Pourjavad and Almeshdawe 2022), and supply chain optimization (Mbiadou Saleu et al. 2022). One main observation, however, is that only very few studies (10% of related publications) apply TSP to construction project scheduling (Saeed et al. 2024a). Podolski and Sroka (2019) developed a cost optimization model for repetitive projects and used simulated annealing to choose the near-optimal execution order of the units. However, their model does not allow activities to use multiple crews and uses fixed productivity rates for the activities throughout the project. In another effort, Monghasemi and Abdallah (2021) developed a mixed-integer optimization model for scheduling repetitive projects with non-identical units. Their model formulates the order of execution of units as VRP to optimize the schedule. However, similar to the model of Podolski and Sroka (2019), Monghasemi and Abdallah's (2021) model assumes that only one crew executes each activity, and its productivity rate is fixed throughout the project. Furthermore, the unit order optimization did not consider the spatial information of the units.

Based on the above literature, the MTSP technique has great potential to be utilized in the context of repetitive scheduling as it has enough flexibility to deal with the practical constraints of repetitive projects across scattered units. However, the few research efforts that have applied TSP in the construction scheduling of SRPs have simplified assumptions and limitations; thus, have not fully benefited from the power of the TSP algorithm. The main assumptions and limitations are:

- Each activity uses only one crew.
- Each activity has a fixed productivity rate.
- The order of execution is the same for all activities.
- Variable durations and costs from one unit to another are disregarded.
- Priorities are not assigned for the order of execution of some units.
- Each unit has different work conditions, thus affecting productivity.
- Spatial and traffic information are not considered in unit order optimization.

Additionally, the schedule optimization of repetitive projects involves multiple non-identical units, several activities per unit, and multiple crews working across these units, resulting in a massive number of possible crew-to-unit assignment permutations. Applying TSP algorithms to such large-scale scheduling scenarios introduces additional computational complexity. To handle such large-scale optimization problems, Constraint Programming (CP) has been successfully used to solve combinatorial problems and constraint satisfaction problems (Liu et al., 2021). Its powerful optimization engine combines operational research, artificial intelligence, and computer science, making it a perfect option for construction industry applications.

2.7 Constraint Programming (CP)

To overcome the limitations of traditional scheduling techniques (e.g., LOB) that schedule activities one after the other, Constraint Programming (CP)-based scheduling models have gained significant attention due to their ability to handle large-scale projects with complex constraints (Liu et al., 2021). CP proved to be a powerful tool that combines operations research and logic programming techniques and has been successfully applied to solve complex combinatorial problems in a wide variety of domains (Zou & Zhang, 2020). In literature, various researchers reported the advantages of CP in scheduling problems (e.g., (Liu et al. 2021a; Zou and Zhang 2020)). Efforts include but are not limited to Gedik et al. (2017) for crew assignment problem with time windows; Tang et al. (2014) for resource leveling in linear projects; Liu & Wang (2012) for

scheduling linear projects with multi-skilled crews; and Tang et al. (2018) for solving a multi-objective optimization problem in linear projects.

In more recent efforts, Zou & Zhang (2020) developed a CP-based model to optimize the cost of the project while not exceeding the project deadline. Their model introduced the soft logic among the units across activities; however, it only applies to scattered not linear projects. Furthermore, Moos et al. (2022) produced a CP-based schedule optimization model for linear projects and successfully considered the linear nature during crew assignments to the units. However, this model works on the simple case of identical activity segments and forces linearity through equality constraints between the finishing of a predecessor unit and the start of a successor and uses only Start-to-Start and Finish-to-Finish relationships among the activities.

Despite recent research advances, the current body of literature still suffers from several key limitations that restrict the practical application of these scheduling models in practical linear environments. The key complexity in linear projects occurs when multiple crews are used to fast-track projects with non-identical units, which are practical conditions. In this case, linear schedules require not only crew-work continuity to be maintained, but also each crew to work on adjacent units, to maintain linearity and reduce travel time. The latter requirement is not easy to achieve. Scheduling models that assign crews consecutively to units and schedule tasks one after the other like Tetris (e.g., Hegazy et al. 2021) end up with long and less-optimum schedules that have time gaps. Optimization models, on the other hand, schedule only identical tasks together and force crews to work in adjacent units by adding constraints between the finish of a predecessor unit and the start of a successor unit. These limitations exacerbate the difficulty in producing optimum schedules that are generically modeled and satisfy all constraints.

2.8 Sustainable Scheduling and Environmental Impacts

The global construction industry is responsible for approximately 32% of the worldwide resource depletion and 40% of the solid waste sent to landfills (Sanchez et al. 2019). In Canada, the construction sector produces over 4 million tons of waste per year, contributing an estimated 1.8 million tons of embodied carbon (Racine et al. 2021), accounting for nearly 39% of the annual Green House Gas (GHG) emissions (Ansah et al. 2021; The Delphi Group 2021). Given the substantial environmental impacts and energy consumption associated with the construction sector, there is increasing attention on improving construction projects' energy efficiency and advancing sustainable practices.

Sustainability in construction covers three primary dimensions: social, economic, and environmental (Khaled et al. 2022). While social sustainability, which relates to human well-being and community impact, remains challenging to define and falls outside the scope of this study, this study focuses on economic and environmental sustainability. In practice, stakeholders often prioritize economic objectives, as minimizing costs and schedules directly contributes to market competitiveness and organizational growth. This economic dimension represents the traditional approaches to scheduling construction projects where planners focus on minimizing project total duration and cost (discussed in earlier sections). In contrast, environmental sustainability goals target reducing transportation needs, minimizing energy consumption and related greenhouse gas emissions, reducing waste generation, and promoting material reuse and recycling (Dasović and Klanšek 2022). This section reviews two key aspects of: (1) recent research efforts that have integrated environmental objectives into construction project scheduling optimization, and (2) the development of multi-mode construction scheduling models and their potential to advance sustainability in repetitive project contexts.

2.8.1 Recent studies on sustainable scheduling

Traditionally, the economic dimension of construction project scheduling (such as cost and duration) and environmental impact assessments have been conducted separately. This separation has proven problematic given the large scale and complex nature of construction projects. That's so because integrating the environmental goals into project planning can negatively impact project timelines and resource utilization efficiency (Hussain and Hussain 2023). Additionally, while modern buildings are often designed to minimize energy consumption during their operational phase, sustainability considerations during the construction phase are often overlooked in both literature and practice (Dasović and Klanšek 2022).

Over the past two decades, increasing attention has been directed toward incorporating environmental impacts into project planning and control processes. For example, Barrientos et al. (2016) presented an in-depth analysis of railroad infrastructure construction projects, by incorporating carbon footprint and water consumption calculations, as well as economic and social indicators into scheduling decisions. Using a genetic algorithm (GA), their model generated alternative execution strategies to facilitate multi-criteria decision-making. However, it treated the project as a single unit, limiting its general applicability beyond railroad projects. Similarly, Zheng et al. (2016) presented a hybrid GA model to minimize project time, penalty costs, and environmental impacts, demonstrating the feasibility of simultaneously optimizing sustainability criteria across multiple projects.

Yi et al. (2018) extended this perspective by introducing a scheduling model for technical tender evaluation, considering project completion time, cost, build quality, and environmental impact. While their approach enhanced bidder selection and informed contractual negotiations, it did not directly optimize resource utilization or project duration. In contrast, Panwar and Jha (2019) proposed a multi-objective optimization model implemented in MATLAB that

simultaneously minimized duration, cost, and greenhouse gas emissions by evaluating different execution modes for each activity. This approach quantified environmental impacts as CO₂-equivalent emissions, advancing the integration of sustainability in construction scheduling.

More recently, Ali Banihashemi and Khalilzadeh (2023) addressed the trade-off between time, cost, quality, and environmental performance by evaluating alternative activity execution modes. Applied to a water supply project, their approach successfully identified execution strategies that achieved high construction quality at minimal cost while reducing environmental impacts. However, they also noted the challenges of gathering accurate data on time, cost, quality, and emissions for all potential execution alternatives. Other studies have applied similar multi-criteria optimization frameworks to different domains, including sustainable pavement maintenance Naseri et al. (2024) and bridge construction scheduling Shrivastava and Singh (2025).

Parallel to these efforts, research has increasingly focused on integrating environmental impacts into resource-constrained scheduling problems (RCSP), evolving into enhanced multi-mode formulations. For instance, Aramesh et al. (2023) developed a multi-mode RCSP model that explicitly included reducing CO₂ emissions as an environmental objective alongside time, cost, and quality. However, no data exist for the case studies where their model was implemented, preventing further investigation and even case study replication.

2.8.2 Multi-mode construction scheduling

In traditional project scheduling, the duration for each project task is determined by selecting a time/cost/resource combination for each (Mohamed 2018). However, a trade-off exists between task duration, assigned resources, and the direct cost to complete the task; the less expensive the resources, the larger duration they take to complete a task (Hu et al. 2025a). Early scheduling models considered, for a construction task, time-cost functions are mainly linear or discrete, though discrete formulations are the most represented versions in literature (Mohamed 2018). In discrete

models, each task can be executed using alternate construction methods that range from cheap and slow to expensive and fast. In recent years, modeling alternative activity execution options multi-mode discrete function-based analysis has been extensively studied, mainly in the context of the planning stage. Recent research has extensively studied modeling these alternative execution options, particularly at the planning stage. This evolution has expanded the scope of multi-mode models beyond time and cost to incorporate quality, environmental impacts, and risk. Comprehensive literature surveys of these developments can be found in Ghasemi et al. (2023), García-Nieves et al. (2018), Shrivastava and Singh (2025), Hegazy and Kamarah (2022) and Cao et al. (2025).

Recent advances have addressed the computational complexity of multi-mode repetitive scheduling, expanding the scope and applicability of optimization frameworks in construction planning. For example, Cao et al. (2025) introduced a constraint programming framework that integrates multimode execution, multiskilled crews, crew transfers, and soft logic sequencing. This model enables planners to balance multiple objectives, such as minimizing project duration and cost while managing crew utilization and interruptions. Similarly, Hu et al. (2025a) proposed a relax-and-solve algorithm that combines rolling horizon methods with constraint programming to deliver high-quality solutions for large-scale repetitive projects.

Beyond these contributions, García-Nieves et al. (2018) developed a multimode RCSP specifically tailored for repetitive construction activities. Their model considers multiple activities, each comprising identical repetitive sub-activities executed across different modes, such as varying crew sizes. The formulation is particularly applicable to repetitive scenarios like residential buildings, where structural, mechanical, and architectural tasks must be repeated floor by floor. In a related effort, Sroka et al. (2021) presented a profit optimization model for multi-unit construction projects. Recognizing that such projects often involve repetitive elements, their

model incorporates activity durations, costs, alternative execution modes, and contractual restrictions such as unit-specific deadlines.

Meanwhile, Hegazy and Kamarah (2022) addressed the unique challenges of SRPs by proposing an optimization framework that combines scheduling, cost optimization, and interactive progress tracking. Their work highlighted opportunities to improve resource utilization and project delivery by incorporating soft relations (allowing partial overlaps among activities) and advanced optimization techniques such as constraint programming. Complementing these advances, Xie et al. (2025) proposed a multi-mode construction scheduling model designed for prefabricated projects. Their approach enriched the set of scheduling constraints to capture the distinctive characteristics of off-site production and on-site assembly processes. Compared to traditional CPM-based methods, their model demonstrated substantial reductions in project duration and improvements in resource utilization. However, it did not consider the repetitive nature of tasks across multiple similar units, which limits its applicability to large-scale repetitive projects. Furthermore, Ghasemi et al. (2023) introduced a multi-mode project scheduling model that integrates cost, time, and quality trade-offs under uncertainty. Their mixed-integer linear formulation incorporates activity durations, costs, and resource limits. The study also proposed a novel bi-directional projection measure and customized solution method to address multi-objective optimization in uncertain environments.

Together, these contributions illustrate the growing maturity and versatility of modern scheduling models. They demonstrate that multi-mode frameworks are increasingly capable of capturing not only time and cost objectives but also broader considerations, such as quality, resource continuity, production constraints, and in some cases, environmental and contractual factors. Nevertheless, many of these models still focus predominantly on economic dimensions and do not fully integrate environmental sustainability into their formulation.

2.9 Geographic Information Systems (GIS) and ARCGIS

In another direction, Geographic Information Systems (GIS) technology has emerged as a promising solution for addressing the spatial challenges of SRPs and their adoption in the construction-related research is expanding rapidly (Akindele et al. 2023). GIS-based tools have been widely utilized in the construction industry for project planning, route optimization, and logistics management. Han et al. (2022) developed an integrated GIS-BIM model to perform real-time and full-process quality evaluation on asphalt pavement construction. Their model was applied in the Phnom Penh-west Halluk highway construction project, in which the GIS early located and marked the sections with poor construction quality, and the BIM models acquired comprehensive information on the road sections. In another effort, Irizarry et al. (2013) presented an integrated GIS-BIM model to keep track of the supply chain status and provide warning signals to ensure the delivery of materials to construction sites. First, BIM was implemented to accurately provide a detailed takeoff in an early phase of the procurement process. Then, GIS was used to support the wide range of spatial information used in the logistics perspective (warehousing and transportation). Regarding construction project scheduling, Tomar and Bansal (2022) developed an interactive tool for project scheduling in a GIS environment for both repetitive and non-repetitive units. However, the way to quantify and consider the effects of surroundings on the schedule was unclear.

The current study has conducted an extensive review of the available GIS-based tools with promising capabilities to handle the various constraints of scheduling SRPs. ARCGIS's Vehicle Routing Problem (VRP) analysis layer was chosen as a prominent tool that is gaining increasing attention in the operational research field. VRP is still a relatively new tool, so there is not much published material regarding its application in the field of scheduling construction projects. However, VRP has been applied across different disciplines that already share similar constraints

and characteristics as SRPs scheduling process. VRP has been applied to address solid waste collection challenges (Herrera-Granda et al. 2024); optimize truck routing for mixed concrete deliveries to construction sites (Pushpakumara 2021); improve school bus routing efficiency (Eldrandaly and Abdallah 2012); enhance vehicle route optimization for residential recyclables collection (Kûs et al. 2016); streamline food supply chain logistics (Abousaeidi et al. 2016); and maintain the roads serviceability during the snow season (Nguyen and Tran 2024). Furthermore, Das et al. (2024) has used ArcGIS to plan waste collection routes from construction sites to recycling and disposal facilities. Thus, this research selected the VRP tool for further investigation to assess its applicability to plan and manage the scheduling of SRPs.

2.10 Agent-based Simulation Technology

To handle the dynamic nature of the construction projects, efficient modelling and simulation become crucial. Literature shows that System Dynamic (SD), Discrete Event Simulation (DES), and Agent-Based Simulation (ABS) are the main current prominent simulation approaches in almost all fields and industries (Xiang et al. 2022). The construction industry is one of these fields where those approaches have great potential to be utilized due to their ability to solve real problems with various scenarios and actions (Mei et al. 2022). Taking a deeper look into those approaches, the literature reveals that DES is an appropriate approach for modeling complex systems with cyclic features, such as material distribution process (Alvanchi et al. 2021). On the other hand, SD is preferably adopted to describe the causes and effects of system behaviors in a holistic perspective using positive and negative feedback loops, such as the construction workers' safety behaviours (Jiang et al. 2014). In contrast, at the detailed crew level, Agent-Based Modeling and Simulation (ABSM) is among the most powerful techniques that can be used to examine the impact of workers' allocation and behaviours on task productivity, as well as its ability to provide a flexible

platform to explore what-if scheduling scenarios (Khodabandelu and Park 2021). Thus, ABSM shows great potential to be applied in schedule optimization for repetitive projects.

With the recent increase in computer processing power, ABSM has been applied to almost every industry, including all stages of the construction industry, such as preconstruction, construction, operation, and maintenance (Khodabandelu and Park 2021). The literature shows that the application of ABSM in the construction domain has a rich history that is too vast to fully enumerate. Therefore, this research refers interested readers to extensive literature studies such as Khodabandelu & Park (2021) and Xiang et al. (2022) for more detailed information. However, with regard to resource management and scheduling, only a limited number of studies adopted the ABSM approach. Jabri & Zayed (2017) introduced an impressive Java-based ABSM model including smart and adaptive agents (crews). Although their model included multiple crews (e.g., Bulldozers, Loaders, Haulers), it is only applicable to earthmoving activities. Similarly, Mei et al. (2022) focused on modelling the concrete formwork reuse across several sites, while Khodabandelu et al. (2020) introduced an ABSM model of crane operations in construction sites. In another effort, Senouci et al. (2019) applied ABSM to develop resource-constrained schedules while allowing for activity interruptions. However, their model has limited applicability within single units (e.g., one building) with the assumption that all activities use the same resource (crew). Relatedly, Taghaddos et al. (2012) optimized the allocation of resources under constraints in the module assembly yard of modular projects. Kedir et al. (2022) provided a hybrid ABSM-reinforced learning model to optimize resource-constrained schedules of multi-crew handling various activities. Despite the advantages of their model, it still cannot handle construction projects with scattered sites. Hsieh (2016) utilized ABSM to seek the most efficient scheduling for the construction supply chain under resource limitations. However, it does not consider the allocation of resources at the crew level.

Furthermore, with multiple crews moving across dispersed units (or sites), it becomes crucial to incorporate accurate spatial information of the units and utilize real-life data to calculate travel times effectively. Recent studies employ the GIS structure in the AnyLogic© software to build the simulation environment so that the agents endowed with their location and the connected routes are recognized.

2.11 Summary of Research Gaps

Based on the above literature, research gaps can be grouped into four categories: (1) schedule optimization techniques for repetitive projects and their inefficient constraints representation, (2) the complexity of handling large-scale schedule optimization problems for both LRPs and SRPs; (3) sustainability and environmental impacts effects on the scheduling process that have been overlooked; and (4) lack of efficient schedule visualization and simulation for repetitive projects.

Firstly, despite the extensive literature efforts on repetitive scheduling over the past two decades, a limited number of studies investigated the use of varying unit orders in the schedule optimization of these projects. Additionally, existing efforts address some aspects related to determining the optimum crew routing, but still no comprehensive model exists for optimizing the routing of multiple crews considering detailed spatial and productivity-related conditions at the project units. Meantime, TSP algorithms showed great potential to support flexible and practical scheduling techniques, however, the few research efforts that applied TSP in the repetitive scheduling have simplified assumptions and limitations and, thus, have not fully benefited from the power of the TSP algorithms.

Secondly, a key complex component in large-scale repetitive projects occurs when multiple crews are used to fast-track projects with non-identical units, which are practical conditions. In this case, schedules require not only crew-work continuity to be maintained, but also each crew to work on adjacent units, to reduce travel time and maintain linearity in case of LRPs. The latter

requirement is not easy to achieve. Scheduling models that assign crews consecutively to units and schedule tasks one after the other like Tetris (e.g., Hegazy et al. 2021) end up with long and less-optimum schedules that have time gaps. Optimization models, on the other hand, schedule only identical tasks together and force crews to work in adjacent units by adding constraints between the finish of a predecessor unit and the start of a successor unit.

Thirdly, the sustainability of construction project scheduling has received considerable attention, with a particular focus on the environmental aspects. Market demands and government regulations have placed significant importance on minimizing the environmental impacts of construction activities. Despite this heightened interest, a noticeable gap exists in comprehensive research on practical tools for accurately capturing and assessing environmental impacts. This knowledge gap may stem from a lack of guidance and practical information on applying these tools in construction projects.

Lastly, although benefits exist for adopting GIS and simulation technologies across various industries, only few studies have considered their actual implementation in the construction industry and less for scheduling repetitive projects. The use of GIS and simulation technologies is currently only adopted for small projects with few activities since their use can be costly and time- and effort-consuming.

Chapter 3

Review of Commercial Repetitive Scheduling Software

3.1 Introduction

At the commercial level, few repetitive scheduling software tools exist. While their capabilities keep improving, a need exists to compare their features (through hands-on experimentation), identify their persistent challenges, and suggest improvements to entice construction practitioners to increase their adoption for practical use. Reviewing these tools not only helps situate this research within the current industry landscape but also highlights existing gaps and challenges that this research aims to address. The four popular software systems examined in this chapter are: Spider Project, Chainlink, TILOS, and TimeChainage. The first three are mainly for LRPs, while the fourth is applicable to both LRPs and SRPs. Additionally, ARCGIS's VRP tool has been selected as one of the prominent tools for crew routing across scattered units. Although it is not designed to directly schedule repetitive projects, it has the potential to be adopted as a scheduling tool. The hands-on experimentation involves replicating theoretical small but challenging cases of LRPs and SRPs examples.

3.2 Sample Project and Software Analysis

This chapter uses a theoretical project of four sequential activities (A, B, C, D) repeated along 10 units. Each of the units is 20 feet long, except units 5 and 6, which are 10 feet (i.e., smaller) and 40 feet (larger), respectively. The activities' standard durations for a 20-ft unit are A: 3 days; B: 2 days; C: 3 days; and D: 4 days. The durations of the activities in the smaller unit 5 and the larger unit 6 can be proportionally calculated. The project has a deadline of 40 days, and each of the linear and scattered cases has some constraints that represent challenging practical conditions. These constraints will be introduced in the following sub-sections.

3.2.1 Linear repetitive example

In the linear repetitive case, the 10 project units are consecutive sections of a pipeline project. This sub-section examines if any software system can easily generate an efficient schedule by entering the high-level project data described in subsection 3.2 (activities, relationships, number of units, durations, deadline, and constraints) and accordingly compute and legibly present the resulting schedule. For added practical applications, three additional constraints have been added: (1) in Activity A, the use of crews from both sides of the pipeline (e.g., two crews going from sections 1 to 6, and one crew from sections 10 to 7); (2) in Activity B, it has a maximum of 3 crews; (3) in Activity C, using only two crews and the activity runs only from unit 7 to 6, 5, 4, then 3; and (4) each activity requires two labourers per day, while the available labourers for the project are six per day.

Figure 3.1 shows a schedule for the linear example at hand, automatically generated based on the concepts discussed in Hegazy and Kamarah (2022) and Hegazy et al. (2020), given high-level project data. The schedule was calculated to require the following number of crews for the following activities: Activity A: 3 crews; Activity B: 3 crews; Activity C: 2 crews; and Activity D: 3 crews. The resulting schedule meets all the required constraints of Activities A and C. It shows all crews colour-coded, and each crew has been effectively assigned to a number of adjacent units. For example, Crew1 of Activity A works in units 1, 2, then 3, while Crew 2 works in units 10-9-8-7. In terms of legibility, the resulting schedule also shows all durations, crew assignments, and the flowlines (totalling 11, for a total of 11 crews). The vertical axis was also scaled to represent unit size. The schedule also satisfies the constraint of 6 labourers per day, with project duration being 42 days, which is the optimal schedule that meets the resource limit. Excluding the resource constraint, the resulting schedule met all constraints including the project deadline.

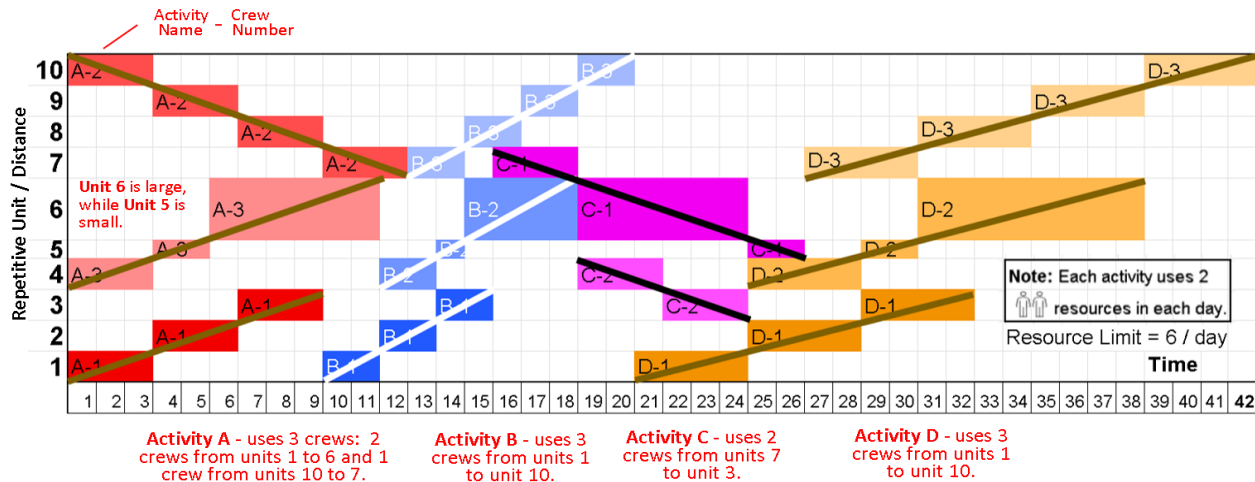


Figure 3.1 Linear schedule for 4 sequential tasks along 10 repetitive unit

The first experiment with the various software systems involved examining if the software systems would accept the high-level project data discussed subsection 3.2.1 as sufficient to compute and automatically present a schedule like that in Figure 3.1. It was found that none of the software systems calculate the number of necessary crews needed considering the given deadline, nor do they automatically assign crews to units, let alone minimize project cost. The second experiment, therefore, involved examining how easy it might be to replicate the schedule of Figure 3.1 with the various software systems. In this regard, all software systems were found to easily define a single crew that works in consecutive units. As such, the four project activities had to be split into 11 crew flowlines (see Figure 3.2) to simulate the schedule in Figure 3.1.

The schedules in Figure 3.2 show that each software presents the same schedule differently depending on the orientation of the axes. Overall, however, the number of activity flowlines (crews) is determined by the user, not automatically calculated based on a deadline. The scheduling process in existing tools, therefore, is a trial-and-error process, with little decision support on the number of crews and their assignment to units. Rather than using optimization to arrive at the best combination of crews, construction methods, and crew assignments, the manual approach starts with a single crew per activity and then tries to reduce project duration either by increasing the

size of some crews or splitting activities (to allow multiple crews) using a trial-and-error process.

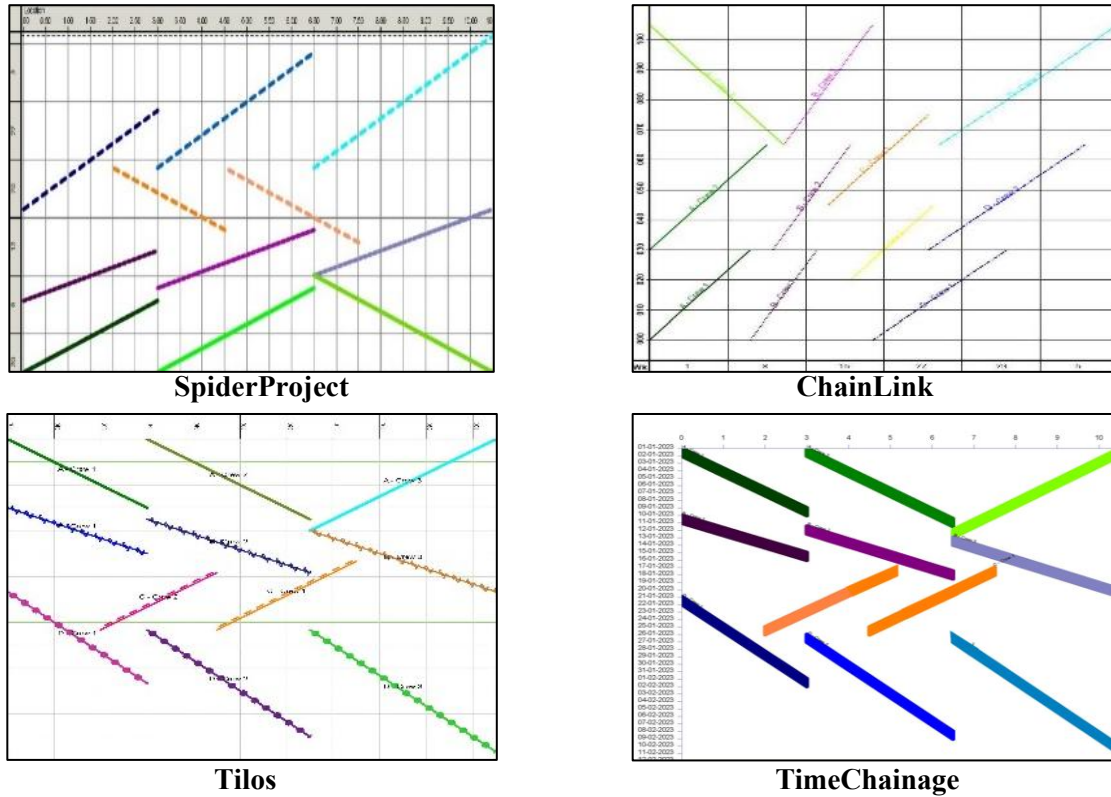


Figure 3.2 Comparable linear schedules of experimented software systems

Also, the process of handling resource limits was not an easy task for the research, thus this constraint was removed from the following experimentation. All the resulting schedules, however, are reasonably legible and all software systems have good features for changing the orientation of axes, colours, and the flowline visuals of the generated schedules.

3.2.2 Scattered repetitive example

In the scattered repetitive case, the activities and the units are the same as in the linear case, except that each activity crew can follow any sequence among units, not necessarily consecutive ones, simulating the case when units are scattered in different geographical locations. In this case, the

planner has the flexibility to specify any priority order (sequence) for executing the units, where the priority can be different for each activity. As such, having each activity using a variable sequence among units is the generic case, with consecutive units being a special case. For the sample project at hand, the constraints (other than the deadline) are: (1) Activity A uses 4 crews, two going from units 1 to 6, and two from units 10 to 7); (2) Activities B and C have the same constraints as the linear case; and (3) Activity D has a maximum of 4 crews. Using concepts discussed in Hegazy and Kamarah (2022) and Hegazy et al. (2020), a basic schedule was generated as shown in Figure 3.3, based on the given high-level project data. The resulting schedule satisfies all conditions and meets the deadline. The schedule shows each crew has its own sequence of units. For example, Crew1 of activity A works along units 1-3-5, while Crew 2 works along units 2-4-6, etc. The schedule in Figure 3.3 was then communicated to the software systems' technical support personnel to get their help on replicating this schedule.

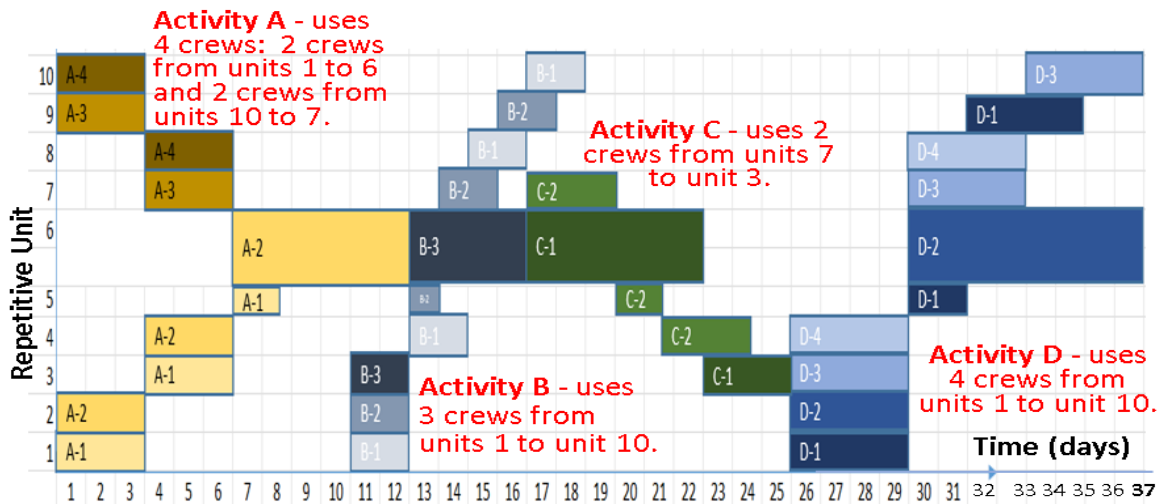


Figure 3.3 Schedule for the repetitive scattered example

Based on input from technical support, to replicate the schedule in Figure 3.3, the four activities had to be split into 35 smaller activities that represent one unit each [A (10 units) + B

(10 units) + C (5 units) + D (10 units) = 35], in addition to entering many relationships from each unit to its successor unit. As such, it takes considerable effort for end-users to replicate the schedule on existing software. This is because they do not offer an easy way (e.g., fewer steps) to define a desired sequence or have tools to assign crews to units, added to the fact that most of the systems have been primarily designed to handle linear projects only.

It is thus concluded that simplified and more flexible project definition is needed for repetitive scheduling tools to allow richer definition of project data and avoid working at the very low level of each activity unit, which is time consuming and error prone. The result of the extensive process of replicating the schedule of Figure 3.3 is shown in Figure 3.4. After entering the data of the schedule's 35 activities, the highest flexibility in existing systems is in their schedule presentation, despite the differences in their default orientations. However, the differences in the visuals indicate a general need for more innovative, or at least standardized, visuals that are more legible and easier to interpreted by all project managers and decision-makers.

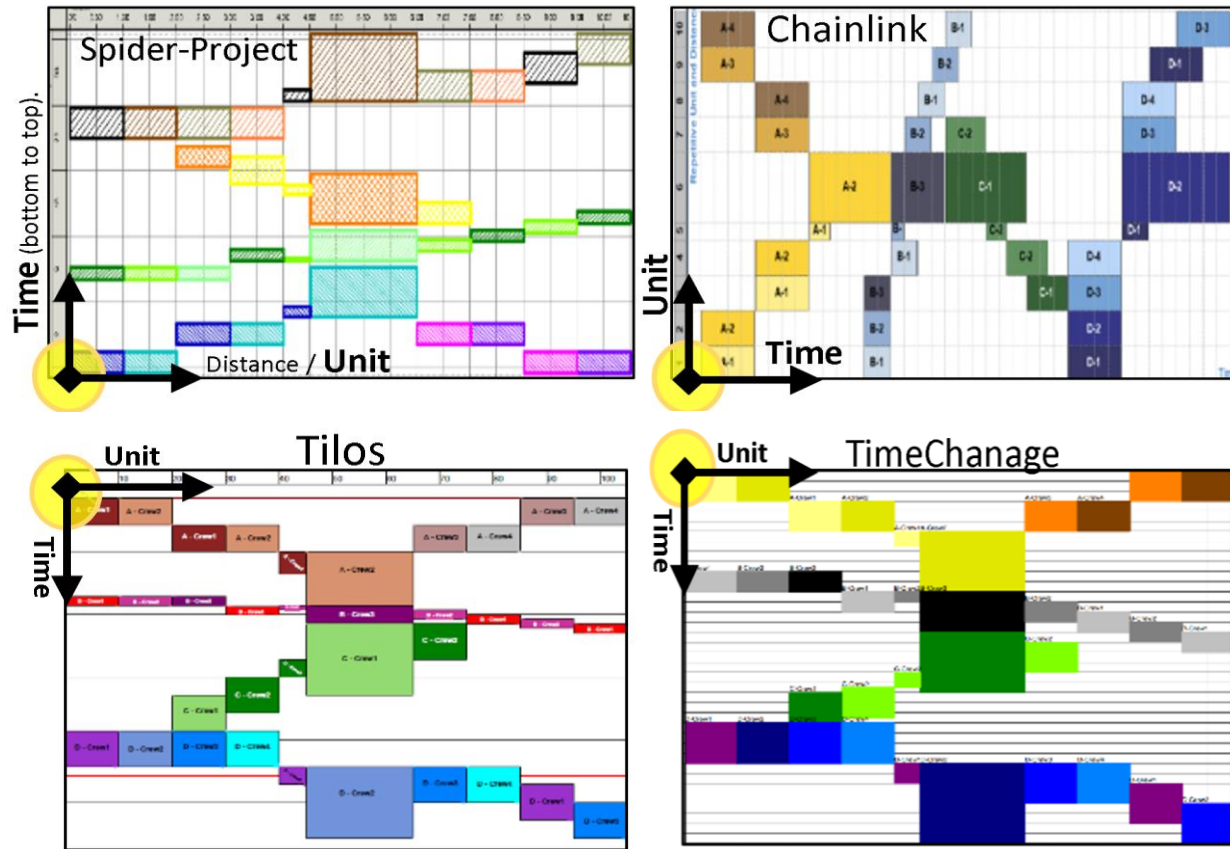


Figure 3.4 Applying the selected software systems to the scattered project example

3.2.3 Features and improvement suggestions

Based on the above hands-on experimentation with four software systems and responses from technical-support personnel of these systems on a feature survey, common threads among software system features emerge. Despite their sophistication in terms of interesting features such as mapping, collaboration, and progress follow-up, etc., several improvement suggestions apply to them all related to their need for: (1) easier project definition; (2) better decision Support; and (3) better visualization. Easier project definition is needed to allow for simpler, more practical, and high-level definition of projects. Generating a basic repetitive schedule should be as simple and convenient as entering the activities of a single unit, durations, relationships, and number of repetitive units. This minimum data entry assumes that all units are identical (i.e., same durations),

each task follows a sequential order (i.e., from units 1, 2, 3..., to unit N), and each task uses a single crew. All the examined software systems can define this simple project case with ease.

Practical projects, however, require a more comprehensive yet user-friendly project definition of all practical conditions, including complex relations, non-identical units, deadline, resource limits, and multiple crews among units. To specify non-identical units, all experimented software systems allow users to enter information about non-standard sizes of any special unit, specifying different unit sizes, distances, durations, and costs. Also, it is possible to introduce a logical and simplified high-level representation of sequence requirements.

In an ideal repetitive scheduling software, deadline and resource limits would have the most impact on the resulting project schedule and, in addition, the number of necessary crews should be calculated as a function of these parameters, as done in many research studies such as (Hegazy et al. 2021). A decision support mechanism would also be necessary in ideal repetitive scheduling software to account for project constraints, determine the necessary number of crews, and the efficient work assignments for each crew. In addition, because repetitive schedules require a well-trained eye to interpret the information, visual reports would benefit from further improvements resulting in new innovative visual reports that clearly communicate essential information to all stakeholders.

3.3 Scattered Repetitive Example Using ARCGIS

ARCGIS's Vehicle Routing Problem (VRP) analysis tool was chosen for hands-on experimentation in this research because it is a prominent tool that is receiving increasing attention in the operations research field. ARCGIS's VRP tool was developed mainly to solve the well-known VRP, where the solver tries to find the best routes for a fleet of vehicles to service many orders. It enables planners to model optimal routing paths between work units, taking into account factors such as travel distances, traffic conditions, and location-specific constraints (Nguyen and

Tran 2024). The process of scheduling SRPs has been proven to share many constraints and characteristics with the VRP, where crews travel across different units to complete their tasks. Such similarities could make the VRP tool a great option for the construction industry to adopt. Meanwhile, it provides unique features through enabling real-time data integration, such as live traffic updates, into the scheduling process which inform routing decisions and enhance flexibility. The study uses ARCGIS Pro software (version 3.0.0) under the license of the University of Waterloo, Ontario, Canada.

3.3.1 VRP description and case study data

The case study for experimenting with the ARCGIS's VRP tool has been adapted from Saeed et al. (2024b) encompassing a rehabilitation project of 10 (N) non-identical units that are geographically scattered across different locations (Figure 3.5). The table in Figure 3.5 shows the units' locations, which are used as the key inputs to the model. Also, VRP accepts a user input of the starting points for the two (E) crews involved in the activity (i.e., starting point SP) from which a crew starts its move to the assigned work units, and moves back after completing all these tasks. All crews have to start their work from the same starting point (meeting/mobilization point).

ID	Building	Location
1	Building_1	50 Francine Dr., North York
2	Building_2	400 Scarborough Rd., Toronto
3	Building_3	2621 Midland Ave., Scarborough
4	Building_4	29 Lockie Ave., Scarborough
5	Building_5	112 Goldhawk Trail, Scarborough
6	Building_6	1550 Sandhurst Cir, Toronto
7	Building_7	45 Lynmont Rd., Etobicoke
8	Building_8	108 Gladstone Ave., Toronto
9	Building_9	70 Fawcett Trail, Toronto
10	Building_10	1570 Dundas ST. E, Mississauga
SP	Crew Depot	65 Kirkham Dr, Markham
RS	Refill Station	65 Kirkham Dr, Markham

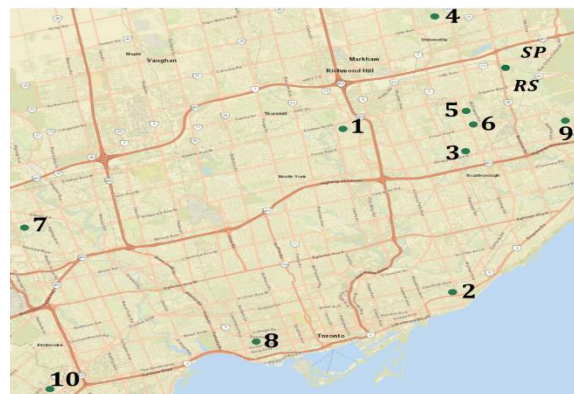


Figure 3.5 Locations of ten buildings (units), and the crews' starting points

The various columns in Figure 3.6 show the data inputs required for the activity units. Column F shows the time needed to complete the activity (task) in each unit representing the

general case of non-identical units. Column G shows the input for the Start-Not-Before (SNB_i) constraint for each unit i (date and time) to start the task/project. This constraint means that no work is allowed to start in each unit before the given date and time, representing the expected delivery date of a required material, or receiving specific approvals (e.g., Environmental, Cultural, Safety, Traffic, etc.). The SNB_i constraint can be also deployed to represent the logical relationships among activities by assigning the finish time of all predecessor activities for an activity as the SNB_i value for this activity.

	A	B	C	D	E	F	G	H	I	J
	ID	Building	Address	City	Postal Code	Task Duration D_i (days)	Start Not Before SNB_i	Crew Name	Assignment Rule	Sequence
1										
2	1	Building_1	50 Francine Dr.	North York	M2H2G6	5	17/12/2025 8:00 AM		3	
3	2	Building_2	400 Scarborough Rd.	Toronto	M4E3M8	4	20/12/2025 8:00 AM		3	
4	3	Building_3	2621 Midland Ave.	Scarborough	M1S1R6	3	19/12/2025 8:00 AM		3	
5	4	Building_4	29 Lockie Ave.	Scarborough	M1S1N3	5	16/12/2025 8:00 AM		3	
6	5	Building_5	112 Goldhawk Trail	Scarborough	M1V1W5	6	17/12/2025 8:00 AM		3	
7	6	Building_6	1550 Sandhurst Cir.	Toronto	M1V1S6	4	18/12/2025 8:00 AM		3	
8	7	Building_7	45 Lynmont Rd.	Etobicoke	M9V3W9	5	22/12/2025 8:00 AM		3	
9	8	Building_8	108 Gladstone Ave.	Toronto	M6J3L2	3	23/12/2025 8:00 AM		3	
10	9	Building_9	70 Fawcett Trail	Toronto	M1B3A9	5	16/12/2025 8:00 AM	Crew_2	2	2
11	10	Building_10	1570 Dundas ST. E.	Mississauga	L4X1L4	7	21/12/2025 8:00 AM		3	

Figure 3.6 Input data for the ten scattered buildings (units) in a sample repetitive activity

As a unique feature of the VRP model, any unit i may require non-reusable/consumable resources (e.g., soil for backfill, gravel, reinforcing steel, etc.) and reusable resources (e.g., cranes). For consumable resources, VRP can handle up to nine different types of consumable resources to be delivered to the units (e.g., windows), through the Delivery Quantity feature, or to be picked up from the site (e.g., excavated soil), through the Pickup Quantity feature (ESRI 2024). However, these two features only function if the total duration of the project is less than or equal to one day, which is not the case for most construction projects. Additionally, any unit i may require a specific crew (e.g., having certain unique skills) to complete the work. In this case, the mandatory Crew_ID is listed for those units in column H (e.g., building 9 requires Crew 2), and the assignment rule to

be set to 2 (Preserve Route) to enforce the assignment of this crew to the unit (ESRI 2024). Also, a valid sequence (2 as shown in Column J in our case) must also be set even though the sequence may or may not be preserved.

The VRP tool also has the ability to assign work units with special requirements to crews that meet those specific criteria. To specify the set of required crew skills/features at any units, Figure 3.7a specifies the required skills/tools/features, with each requirement for a building being inserted in a separate row. These will be used as constraints so that each unit will be assigned the appropriate crew that match the desired feature/skill. Meanwhile, as the model can deal with multiple crews to perform the required work, Figure 3.7b shows the data inputs for the two crews involved in the sample activity. Each data row represents an available skill for a crew. These skills will be used to match each unit with crews that best meet their requirements, while optimizing the objective function (e.g., minimizing the overall project duration).

(a)

	A	B
	UnitName	SpecialityName
2	Building_1	F1
3	Building_1	F2
4	Building_1	F4
5	Building_1	F5
6	Building_3	F3
7	Building_3	F6
8	Building_4	F1
9	Building_4	F4
10	Building_5	F2
11	Building_5	F5
12	Building_6	F1
13	Building_6	F4
14	Building_7	F3
15	Building_7	F6
16	Building_8	F2
17	Building_8	F5
18	Building_10	F2
19	Building_10	F5

Building_5 requires skill F2

(b)

	A	B
	RouteName	SpecialityName
2	Crew_1	F1
3	Crew_1	F3
4	Crew_1	F4
5	Crew_1	F6
6	Crew_2	F1
7	Crew_2	F2
8	Crew_2	F4
9	Crew_2	F5

Crew_2 has four Skills:
F1, F2, F4, F5

Figure 3.7 Data input of (a) building requirements; and (b) crew characteristics

3.3.2 Implementation and results

The process begins with case study data preparation. All data were inputted into the software as Excel comma-delimited files (CSV). Figure 3.8 includes defining the locations of units (Orders), the starting and ending points for vehicles (Depots), and preparing a network dataset that represents the transportation infrastructure, such as roads, traffic rules, and travel restrictions. Figure 3.8a

displays the user interface of the ARCGIS system with the output routes for the two crews plotted on a map in the middle part, the analysis units (activity time in days, travel distance in kilometers, start date of the project on 8:00 AM, 2025-12-16) in the top part, and the list of the imported datasets representing different input attributes and constraints (as shown in Figure 3.8b-d).

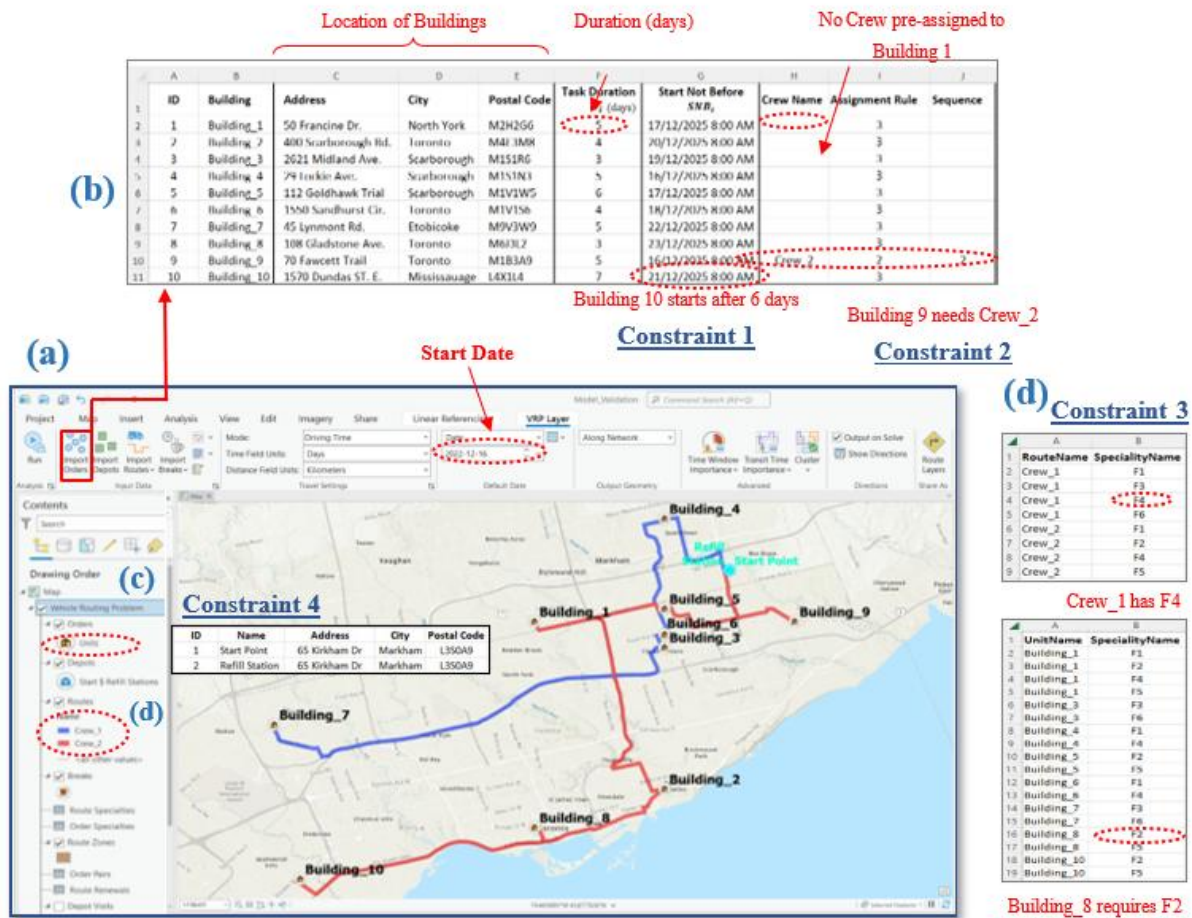


Figure 3.8 An overview of the VRP routing tool

Once all the data and parameters are set, the VRP solver is activated to run. The solver processes the inputs and generates optimized routes for the crews, taking into account all constraints, including travel times, site-specific conditions, and capacity limitations, if given. The results include detailed route plans showing the sequence of stops, assigned crews, schedules, and key metrics like total travel time, and distance.

For the given case study, the VRP solver generated a schedule with a total duration of 30 days + 2 hours, where Crew 1 serves units 4-6-3-7 and Crew 2 serves units 9-5-1-2-8-10. Finally, the efficiency of the routes can be assessed, adjustments to be made, if necessary, and the finalized routes and schedules to be exported. These schedules can be shared as maps, reports, or digital files compatible with navigation systems (ESRI 2024).

3.3.3 Advantages and limitations

The resulting schedule, plotted in the middle of Figure 3.8a, proved the promising use of ARCGIS's VRP tool to optimize the schedule of multiple crews among sites that are scattered across a large geographical area. VRP tool is able to enhance project timelines and reduce the travel time for the crews while considering varying work volumes, crew productivity rates, and live traffic data. Despite these benefits, the VRP tool still needs to undergo several enhancement and adaptation efforts to be capable of optimizing the high complexities involved in scheduling scattered projects. One improvement would target the employed optimization engine. Because the VRP solving engine currently optimizes only one activity at a time, it can be integrated with a CPM/LOB system for repetitive scheduling to support the planning of SRPs. One option is re-designing the repetitive scheduling engine to incorporate all the activities of a project, one at a time, according to the logical relations of the project. In that case, the Start-Not-Before (SNB_i) constraint on each activity will be taken directly from the finish dates of the preceding activities. Alternatively, the model could be used as a powerful routing algorithm for a specific activity within the project.

On the other hand, the VRP tool has other features yet to be discussed and applied to the scheduling problem or other similar disciplines. The VRP tool leverages spatial data to address critical site-specific constraints, such as restricted work hours, unique access conditions, and local

environmental factors, all of which are pivotal for meeting project deadlines and maintaining compliance with project requirements. Table 3.1 provides an overview of the available features in the VRP tool against the key practical constraints identified in the literature for scheduling SRPs.

Table 3.1 Feature explanation of the ARCGIS's VRP tool

Features Already Used in This Study	
Start & Refill Station	Constraint 4 in Figure 3.8a
Multiple Crews	Handles more than one crew working across units
Crew Specialization & Special Units	Constraint 3 in Figure 3.8d
Identical and Nonidentical Units	Takes the task duration in unit(s)
Logistical Constraints	Constraint 1 in Figure 3.8b
Live Traffic Data	Embedded in the solver engine
Crew Work Sequence	Routes exported as maps/digital file to navigation systems
Features Not Applicable to Construction	
Crew Capacities of Consumable Resources	Only for total project duration ≤ 1 day
Curb Approach	Direction a vehicle may arrive at and depart from site
Features to be Utilized in the Future	
Restricted work hours	Tasks only allowed during time windows during the day
Unload/Reload Time	Fixed time across all crews
Crew Idle Time	Crew is not working at a unit or travelling between units
Revenue	Weights relative importance of completing the task across units
Objective Function	Total duration, travel time, travel distance
Features Currently Not Available	
Productivity Rates and Duration Calculation	Only one duration input per unit
Crew Fatigue & Learning Rates	Not Applicable
Multiple Tasks	Limited to only one task at a time

In summary, while few commercial software tools exist for scheduling LRPs, their application to more complex or SRPs remains limited. The hands-on-experimentations conducted in this chapter reveals notable gaps in flexibility and integration of real-world constraints. These limitations underscore the need for more advanced optimization models that can accommodate the unique characteristics of such projects. The next chapter introduces a novel Multi-Travelling Salesman Problem (MTSP)-based model designed specifically to optimize crew routing across scattered construction units, addressing many of the challenges identified in current tools.

Chapter 4

MTSP Scheduling Model for Optimum Crew Routing (Module I)

4.1 Introduction

This chapter proposes a novel approach for optimally scheduling multiple crews among scattered repetitive units while considering several practical constraints. The novelty and practicality of the proposed model stem from its formulation that involves four aspects: (1) considers the units' accurate spatial information and live traffic data to compute accurate travel times; (2) calculates units' durations considering the key factors that affect the productivity of each individual crew, such as work quantity, fatigue rate, and learning rate; (3) considers the loading and unloading time and capacities/skills of crews in handling consumable resource constraints; and (4) incorporates crew routing orders as key scheduling variables for Scattered Repetitive Projects (SRPs) and formulates a multi-travelling-salesman optimization problem (MTSP) to handle multiple crews simultaneously. The schedule optimization model uses evolutionary solvers (GAs engine in Excel Solver) to arrive at the near-optimal schedule. The objective function used to reach that near-optimal schedule is set to minimize total project duration, total travel time of crews, or a combination of both, with relative weights based on the project needs or stakeholders' preferences.

4.2 Proposed MTSP Model and a case study

The proposed model is designed to use project information (units, durations, constraints, and available resources) to formulate schedule optimization that supports determining the optimum number of crews, methods of construction, as well as the crews' execution orders. For practicality, the model addresses the various challenges discussed in the literature, as highlighted in Table 4.1.

The implementation steps of the proposed framework are discussed in the next subsections along with the description of a case study of an example activity in an SRP project.

Table 4.1 Crew routing challenges addressed by the proposed model.

Challenge	Description
Multiple Crews	Each activity can use one or multiple crews.
Productivity Rates	Activity crews have different productivity rates.
Crew Capacity	Each crew can have one or more capacities to load & unload consumable resources.
Fatigue & Learning	Crews have different fatigue rates and learning rates.
Crew Specialization	Some crews can have special tools/skills that better fit some units.
Consumable Resources	Each activity can have reusable and/or consumable resources.
Order of Execution	(Scheduling variable) Each crew follows its order of execution among units.
Special Units	Some units can require a special crew and can have a special productivity factor.
Non-identical Units	The model can accommodate units with varying work quantities.
Stakeholders Preferences	Stakeholders to input their preferences (weights) among the optimization objectives

4.2.1 Case study data: Scattered units and multiple crews

The case study used along with the description of the proposed model has been adapted from Saeed et al. (2024b). It encompasses a rehabilitation project of 10 (N) non-identical units that are geographically scattered in different locations (Figure 4.1). The table in Figure 4.1 shows the units' locations, which are used as the key inputs to the model. Although this case study utilizes only two crews, the model's formulation is scalable and flexible to handle any given number of crews (E). Optionally, the model accepts a user input of the starting points for the two available crews involved in the activity (i.e., starting points SP1 and SP2) from which a crew starts its move to the work unit, and at the end of the workday (8 hours) the crew moves from the last unit to it. The starting points (meeting/mobilization point) for all the crews could be the same or different.

ID	Building	Location
1	Building_1	50 Francine Dr., North York
2	Building_2	400 Scarborough Rd., Toronto
3	Building_3	2621 Midland Ave., Scarborough
4	Building_4	432 Wilfred Murison Ave, Markham
5	Building_5	112 Goldhawk Trail, Scarborough
6	Building_6	1550 Sandhurst Cir, Toronto
7	Building_7	45 Lynmont Rd., Etobicoke
8	Building_8	108 Gladstone Ave., Toronto
9	Building_9	70 Fawcett Trail, Toronto
10	Building_10	1570 Dundas ST. E, Mississauga
SP1	Crew 1 Depot	65 Kirkham Dr, Markham
SP2	Crew 2 Depot	65 Kirkham Dr, Markham
RS	Refill Station	65 Kirkham Dr, Markham

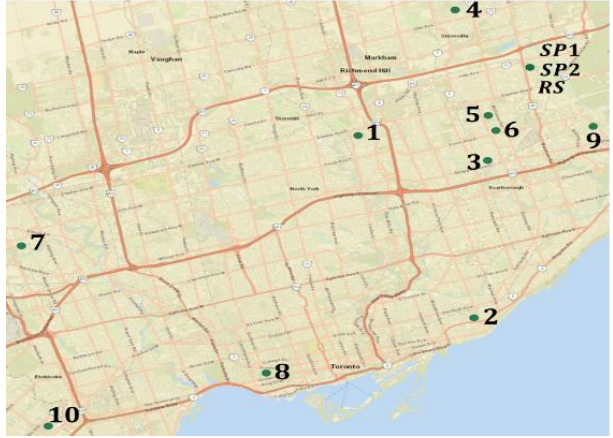


Figure 4.1 Locations of ten buildings (units), and crew starting points

Figure 4.2 shows the data inputs required for the activity units. The second column shows the varying quantity of work (Q_i) to be performed at each unit i (e.g., m³ of soil to be excavated or sq. ft of bridge deck to be repaired), which govern the unit duration, thus representing the general case of non-identical units. The third column shows a Start-Not-Before, SNB_i constraint for each unit i (day number), representing the expected delivery date of a required material, or receiving any specific approvals (e.g., Environmental, Cultural, Safety, Traffic, etc.) to start the task/project. The SNB_i constraint can also be deployed to represent the logical relationships among activities by assigning its value as the finish time of all predecessor activities for each unit i .

ID	Quantity of Work Q_i (m ³)	Start Not Before SNB_i	ConRes* R_{ki}	Mandatory Crew ID	Crew features required for each building.					
					Required Skill/Feature (F1 to F6)					
					F1	F2	F3	F4	F5	F6
1	2,400	2	2,400		1	1		1	1	
2	1,920	5	1,920							
3	1,440	4	1,440				1			1
4	2,400	1	2,400		1			1		
5	2,880	2	2,880			1			1	
6	1,920	3	1,920		1			1		
7	2,400	7	2,400				1			1
8	1,440	8	1,440			1			1	
9	2,400	1	2,400	2						
10	3,360	6	3,360			1			1	

ConRes* = Consumable Resources

Building 9 may start from 1st day

Building 9 requires Crew 2

Figure 4.2 Input data for the ten scattered buildings (units) in a sample repetitive activity

To add more practicality, the model can accommodate scenarios where any unit i requires non-reusable/consumable resources (e.g., soil for backfill, gravel, sand, reinforcing steel, etc.) as well as reusable resources (e.g., cranes). It also supports the general case where both resource types are required. For consumable resources, the fourth column of Figure 4.2 shows the amount (R_{ki}) required of resource k at each unit i . Additionally, any unit i may require a specific crew (e.g., having certain unique skills/features) to complete the work. In this case, the mandatory crew ID is listed for those units in column 5 (e.g., building 9 requires Crew 2). To specify the set of required crew skills/features at any units, the right side of Figure 4.2 specifies up to six ($l = 1 \dots 6$) required skills/tools/features, represented as binary values (1 means a required skill). These will be used as constraints so that each unit will be assigned to the appropriate crew that matches the desired feature/skill (F_l).

Meanwhile, as the model can deal with multiple crews to perform the required work, Figure 4.3 shows the data inputs for the two crews involved in the sample activity. These inputs include the Crew Ideal Production Rate (IP_j), representing the daily production rate of crew j , leading to different unit durations based on the assigned crews. The Fatigue (F_j) and Learning (L_j) rates per

day, are inputs to calculate the Practical Production Rate (PR_{ij}) of a crew j performing a task in unit i . These rates are not calculated as part of the proposed model but can be retrieved from crew performance charts while performing similar projects. On one hand, exposing construction workers to physically demanding tasks for long periods will considerably degrade their performance due to fatigue (Abuwarda et al. 2023), according to the preset crew j fatigue rate (F_j). On the other hand, having the crew work continuously across units improves their learning momentum(L_j) rate, leading to better productivity and reduced durations.

ID	Crew	Ideal Production (m3/day) IP_j	Fatigue Rate (per day) F_j	Learning Rate (per day) L_j	Available Crew Skills / Features (F1 to F6)						Max. Capacity of Consumable Resources (m3)	Reload/Unload Time (mins.)
					F1	F2	F3	F4	F5	F6		
1	Crew_1	480			1		1	1		1	5000	
2	Crew_2	480			1	1		1	1		5000	

Crew 1 has features 1, 3, 4, 6

Figure 4.3 Data input of the activity crews and their characteristics

Furthermore, the middle part of Figure 4.3 shows user input for the availability of six possible features/skills characterizing each crew j . For example, in bridge rehabilitation projects, certain segments may require specialized skills such as certified welding and rigging for structural steel replacement, while others only need surface preparation and painting. Modeling crew skill sets ensures that only qualified crews are assigned to technically demanding tasks. These features will be used to match each unit with crews that best meet their requirements, while optimizing the objective function (e.g., minimizing the total project duration). The next column of Figure 4.3 then specifies the maximum capacity ($Max(C_{kj})$) of crew j to transport consumable resource k (e.g., truck size) before the crew needs to travel for a reload/ unload. To avoid unnecessary delays in the schedule, the proposed model considers the refill time (reload/unload time RT_j , last column of

Figure 4.3) in the optimization, where a crew j is assigned to a set of units resulting in least number of refills.

4.2.2 Pre-processing: Calculation of crew travel times

Travel times and distances are key parameters in optimizing the order of execution among units. To compute travel times, an Excel-based macro that interacts with Google Maps platform has been developed. As shown in Figure 4.4, the model uses the units' spatial locations (addresses or coordinates) to compute a travel time matrix across the units. This approach enables the model to use live data regarding the units' geographic characteristics.

ID	Building	Location	Travel time to building ID TT_{im} (mins.)									
			1	2	3	4	5	6	7	8	9	10
1	Building_1	50 Francine Dr., North York		34	21	20	20	20	34	43	24	13
2	Building_2	400 Scarborough Rd., Toronto	34		31	40	35	34	55	41	35	33
3	Building_3	2621 Midland Ave., Scarborough	21	31		22	14	10	45	50	16	16
4	Building_4	432 Wilfred Murison Ave, Markham	20	40	22		16	18	44	58	22	44
5	Building_5	112 Goldhawk Trail, Scarborough	20	35	14	16		5	35	52	15	12
6	Building_6	1550 Sandhurst Cir, Toronto	20	34	10	18	5		34	48	14	14
7	Building_7	45 Lynmont Rd., Etobicoke	34	55	45	44	35	34		31	44	33
8	Building_8	108 Gladstone Ave., Toronto	43	41	50	58	52	48	31		52	44
9	Building_9	70 Fawcett Trail, Toronto	24	35	16	22	15	14	44	52		22
10	Building_10	1570 Dundas ST. E, Mississauga	13	33	16	44	12	14	33	44	22	
SP1	Crew 1 Depot	65 Kirkham Dr, Markham	26	43	21	16	12	13	42	56	17	14
SP2	Crew 2 Depot	65 Kirkham Dr, Markham	26	43	21	16	12	13	42	56	17	14
RS	Refill Station	65 Kirkham Dr, Markham	26	43	21	16	12	13	42	56	17	14

It takes 44 mins. To go from buildings 9 to 7.
Equation 4.1

Figure 4.4 Unit locations and corresponding travel time matrix.

To calculate the travel time (TT_{im}) and distance (TD_{im}) from unit i , to another unit m , the model employs a Google Map API called "Direction API". A VBA-JSON file was also created to import the results into the excel model. Two functions, *TRAVELTIME* and *TRAVELDISTANCE* (Equation 4.1 Equation 4.2), enable the model to use real traffic data and spatial characteristics of the routes to determine the actual travel times and distances, respectively. Furthermore, to control the model's dependency on external data sources such as APIs and real-time traffic data, the model optionally allows users to manually input the travel time matrix.

$$TT_{im} = TRAVELTIME(Origin, Destination, API_{key}) \quad \text{Equation 4.1}$$

$$TD_{im} = TRAVELDISTANCE(Origin, Destination, API_{key}) \quad \text{Equation 4.2}$$

Where, *Origin* is Unit *i* and *Destination* is Unit *m*

4.2.3 Schedule optimization: Mathematical formulation

The decision variables are the crew assigned to each unit, and the order of units. Depending on the distance between the units and the size of the work required, the number of units assigned to each crew may not be equal. For each unit *i*, the Ideal Duration (ID_i) is calculated using Equation 4.3 as a function of the quantity of work (Q_i) and the ideal production rate of the assigned crew *j* (IP_j).

$$ID_i = \frac{Q_i}{IP_j} \quad \text{Equation 4.3}$$

Where, *i* is the unit range from 1 to *N*
j is the crew range from 1 to *E*

This ideal duration is then adjusted by both the Fatigue (F_j) and Learning (L_j) rates to determine each unit's actual duration. Both F_j and L_j rates have been combined into one Adjustment factor (A_{ij}) which is calculated using Equation 4.4 (adapted from (Jaber et al. 2013)). Unlike traditional models that apply a fixed efficiency factor to account for practical conditions, this model uses a dynamic adjustment factor that evolves with the crew's task sequence. This factor simultaneously captures fatigue (productivity decline) and learning (efficiency gain), allowing task durations to reflect real-time performance changes rather than assuming constant productivity. The Adjustment factor (A_{ij}) reflects the total work done in all the units in which crew *j* was engaged until it reaches unit *i*, as follows:

$$A_{ij} = \left(\frac{\sum_{i=1}^n Q_i}{IP_j} \right)^{L_j - F_j} \quad \text{Equation 4.4}$$

Where, *n* is the number of units completed by crew *j* before arriving to unit *i*
 IP_j is a constant ideal production rate for crew *j* working across all the units

Using this adjustment factor, the crew practical production rate (PR_{ij}) is calculated using Equation 4.5 by adjusting the ideal production rate (IP_j) for crew j as follows:

$$PR_{ij} = IP_j \times A_{ij} \quad \text{Equation 4.5}$$

In this flexible formulation, the actual duration (AD_{ij}) crew j will need to complete the work at unit i becomes a function of all the schedule variables, including work quantities (Q_i), crews' ideal productions (IP_j), learning (L_j) and fatigue (F_j) rates, as well as the sequence of the units followed by for each crew, as follows:

$$AD_{ij} = \frac{Q_i}{PR_{ij}} \quad \text{Equation 4.6}$$

Consumable resources are handled using Equation 4.7 where available amount of resource (k) is checked before unit i is approached by crew j (C_{kji}). This feature models scenarios in bridge rehabilitation activities, such as deck resurfacing and joint sealing, where consumable materials (e.g., hot-mix asphalt, sealants) need to be refilled due to volume limits or material lifespan, making resource capacity a relevant constraint across repetitive units. Thus, Equation 4.7 monitors the crew capacity moving across the units throughout the project duration. If the required amount of resource (k) for unit i (R_{ki}) is less than the remaining crew capacity (C_{kji-1}), then the crew may go directly to unit i and start working. Otherwise, the crew will need to travel to the refill station, bring its capacity to the maximum ($Max(C_{kj})$), and then travel from the refill station to the unit in question to start working.

$$C_{kji} = \begin{cases} C_{kji-1} - R_{ki} & \text{if } C_{kji-1} \geq R_{ki} \\ Max(C_{kj}) - R_{ki} & \text{otherwise} \end{cases} \quad \text{Equation 4.7}$$

Where, C_{kji} is the available amount of resource k with crew j after completing the work at unit $i - 1$ and before proceeding to unit i

Then, the travelling time TT_{im} for a crew to move from unit i to unit m is calculated using Equation 4.8. If the crew has to refill their capacity, then the travelling time TT_{im} will be the summation of the travelling time from unit i to the refill station ($TT_{i \text{ Refill station}}$) and back from the refill station to unit m ($TT_{\text{Refill station } m}$).

$$TT_{im} = \begin{cases} TT_{im} & \text{if } C_{kj \ i-1} \geq R_{ki} \\ TT_{i \text{ Refill station}} + TT_{\text{Refill station } m} & \text{otherwise} \end{cases} \quad \text{Equation 4.8}$$

Then, the scheduled starting date of unit i (SD_{ji}) is calculated as the maximum of its Start-Not-Before time (SNB_i), and the time when crew j completes their assigned work at unit $i - 1$ (prior unit in their order sequence) and travel toward and can reach it (Equation 4.9). The finish date (FD_{ji}) of unit i is the summation of its start date (SD_{ji}) and the duration (AD_{ij}) crew j will take to complete the required work, as shown in Equation 4.10. Thus, the total project duration is the finish date of the last unit, and as the units have no preset order (this is part of the decision variables), the project finish date is the maximum finish date (Max (FD)) of all units.

$$SD_{ji} = \text{Max. of } \begin{cases} FD_{i-1} + TT_{i-1, i} \\ SNB_i \end{cases} \quad \text{Equation 4.9}$$

$$FD_{ji} = SD_{ji} + AD_{ij} \quad \text{Equation 4.10}$$

When crew j is assigned to unit i , it has to travel daily from its starting point (SP_j) to unit i to perform its required tasks and returns to its starting point at the end of day. This daily trip ($TT_{i \ SP_j}$) is repeated throughout the duration of work required (AD_{ij}). Thus, the End-Of-Day travelling time for crew j ($TT_{j \ (EOD)}$) is calculated as shown in Equation 4.11.

$$TT_{j \ (EOD)} = TT_{i \ SP_j} * AD_{ij} \text{ (in days)} * 2 \quad \text{Equation 4.11}$$

For each reusable feature/skill, hereby referred to as feature (F_l), it is assigned two binary values; one that indicates whether this feature is required by unit i (F_{li}) (Figure 4.2) and another one to indicate whether crew j has access to the feature (F_{lj}) (Figure 4.3). As such, ensuring the required features are received can be simply modelled using Equation 4.12.

$$F_{li} \leq F_{lj} \quad \text{Equation 4.12}$$

where $l = 1 \dots 6$, *represents the project related skills/tools/features*

The model can also force a crew to tend to a specific unit based on the stakeholder requirements. To model this scenario, a constraint was set as per Equation 4.13. This equation can also support the case of not having a preset crew requirement (i.e., ID of crew required = 0).

$$\text{Crew Received (ID)} * \text{Crew Required (ID)} = \text{Crew Required (ID)}^2 \quad \text{Equation 4.13}$$

Finally, the total traveling time of each crew j ($TT_{j(total)}$) is calculated, as shown in Equation 4.14, incorporating the travelling time across the units ($TT_{j(im)}$) and their movement from their starting point (SP_j) toward unit i and returning back at the End-Of-Day ($TT_{j(EOB)}$). Also, the total travelling time of crews (TTT) to complete the work at all units in question, Equation 4.15, is the sum of the travel time for all crews.

$$TT_{j(total)} = TT_{j(im)} + TT_{j(EOB)} \quad \text{Equation 4.14}$$

$$TTT = \sum_{j=1}^E TT_{j(total)} \quad \text{Equation 4.15}$$

Where, E is the total number of crews

4.3 Objective Function and User Preferences

Now after having all the activity/crew data inputted in the model, it offers the flexibility to optimize the SRPs by minimizing one of the following criteria: (1) the total project duration (Max (FD)); (2) the total traveling time of crews (TTT); or (3) a weighted combination of both. The objective function can be tailored to the user's preferences, allowing for a combination of both, as shown in Equation 4.16. W represents the decision maker's preferences (user input) whether to minimize the total project duration ($w = 1$); minimize the total traveling time of crews ($w = 0$); or a weighted combination of both ($0 < w < 1$). With this representation, an overview of the model implementation in Excel is shown in Figure 4.5.

$$Obj. Function = w * FD_{max} + (1 - w) * TTT \quad \text{Equation 4.16}$$

Where, w is the relative weight of the total project duration.

4.4 Implementation and Results

A computer prototype of the proposed framework was developed in Excel, shown in Figure 4.5, utilizing the Excel Solver engine to optimize the schedule while satisfying all defined constraints, using project information such as unit quantities, site locations, durations, and resource availability. Figure 4.5a shows the unit's spatial information (addresses, travel time matrix), while Figure 4.5b displays the unit locations plotted on a GIS map. Figure 4.5c shows the unit's data including quantities of work, Start-Not-Before (SNB_i) constraint, consumable resources required, pre-requested crew ID, required skills/tools. Figure 4.5d ensures that the crew/special feature requirements constraints (Equation 4.12) are satisfied. Figure 4.5e displays the crew characteristics (productivity rate, fatigue rate, learning rate, crew skill/tool availability, maximum capacity of consumable resources, and reload/unload time). Figure 4.5f displays the decision variables in yellow columns with their current values representing the solution values (unit sequence and related crew ID), in addition to other calculated columns related to the schedule details.

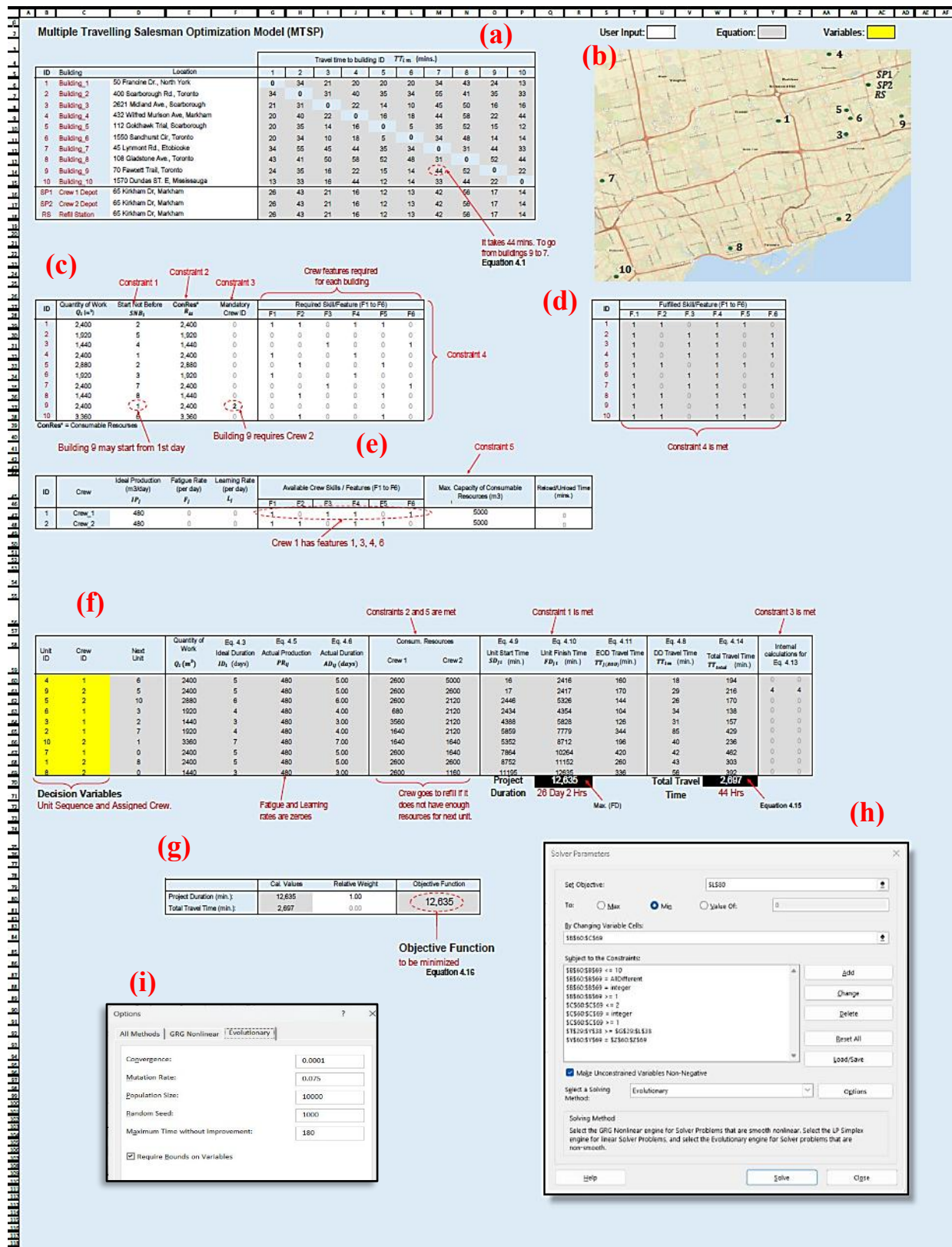


Figure 4.5 An overview of the proposed computer prototype

Figure 4.5g shows the objective function the model is minimizing to optimize the SRP in question. To setup and carry out the optimization, Figure 4.5h displays Excel's solver setup of the ranges that point to the objective function, decision variables, and constraints, in addition to the selected evolutionary engine that is used in the optimization. Lastly, the parameters of the utilized GA solver are shown in Figure 4.5i. These settings were selected to prevent Excel's solver engine getting trapped in local optima. Additionally, repeated runs under the same settings yielded consistent solutions, demonstrating robustness and repeatability.

4.4.1 Outputs and schedule details

Once the model was setup and the evolutionary solver was activated, the model outputs were produced. Each unit is assigned to a crew and the following unit in the order of execution which the crew will move to next. The start and finish time for each unit are calculated in minutes and displayed. Finally, the duration of the optimized repetitive activity is displayed. After the model concludes its calculations, the final solution was sorted by crew as shown in

Figure 4.6.

Unit ID	Assigned Crew	Detailed Sequence	Quantity of Work Q_i (m ³)	Eq. 4.3 Ideal Duration (days) ID_i	Eq. 4.5 Actual Production Pr_{ij}	Eq. 4.6 Actual Duration D_{ij} (min)	Consumable Used (m ³)	Available after refill (m ³)	Eq. 4.9 Unit Start Time (min.) SD_{ji}	Eq. 4.10 Unit Finish Time (min.) FD_{ji}	Eq. 4.11 EOD Travel Time (min.) EOD_{ji}	Eq. 4.8 DD Travel Time (min.) TT_{im}	Eq. 4.14 Total Travel Time (min.) TT_{total}
		SP1 → unit 4						5000				16	16
4	1	unit 4 → unit 6	2400	5	480	2400	2400		16	2416	160	18	178
6	1	unit 6 → Refill	1920	4	480	1920	1920		2434	4354	104	13	117
		Refill → unit 3					Refill	5000				21	21
3	1	unit 3 → unit 2	1440	3	480	1440	1440		4388	5828	126	31	157
2	1	unit 2 → Refill	1920	4	480	1920	1920		5859	7779	344	43	387
		Refill → unit 7					Refill	5000				42	42
7	1	unit 7 → SP1	2400	5	480	2400	2400		7864	10264	420	42	462
		SP2 → unit 9						5000				17	17
9	2	unit 9 → Refill	2400	5	480	2400	2400		17	2417	170	17	187
		Refill → unit 5					Refill	5000				12	12
5	2	unit 5 → Refill	2880	6	480	2880	2880		2446	5326	144	12	156
		Refill → unit 10					Refill	5000				14	14
10	2	unit 10 → Refill	3360	7	480	3360	3360		5352	8712	196	14	210
		Refill → unit 1					Refill	5000				26	26
1	2	unit 1 → unit 8	2400	5	480	2400	2400		8752	11152	260	43	303
8	2	unit 8 → SP2	1440	3	480	1440	1440		11195	12635	336	56	392
Decision Variables Unit Sequence and Assigned Crew. Fatigue & Learning rates are zeroes. Crew goes to refill if it does not have enough resources for next unit. Project Duration (min) = 12,635 26 Day, 2 Hrs. Total Travel Time (min) = 2,697 44 Hrs													

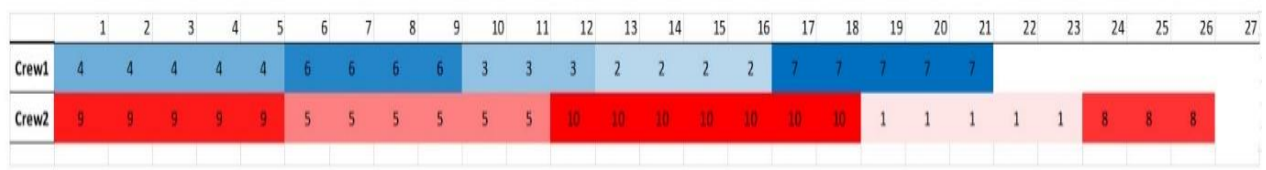
Figure 4.6 Sample model solution, sorted by crews

The first two columns show the values for the decision variables (unit sequence and assigned crew), while the third column shows the detailed work sequence incorporating the start position and the necessary resource refills. For Crew 1, the solution sequence is: SP1 to 4, 4 to 6, 6 to refill, refill to 3, 3 to 2, 2 to refill, refill to 7, then 7 to SP1. Crew 2, on the other hand follows the sequence: SP2 to 9, 9 to refill, refill to 5, 5 to refill, refill to 10, 10 to refill, refill to 1, 1 to 8, then 8 to SP2. Figure 4.7 can also be used to confirm the computations and track the satisfaction of the constraints discussed earlier. It is noted that when experimenting with alternative work sequences, e.g., having Crew1 involved in units 1 to 5 and Crew 2 in units 6 to 10, the optimality of the solution was confirmed.

Based on the optimized variable values, Figure 4.7 a and b show two schedule visualizations produced by the model. Figure 4.7a shows a schedule using a time versus variable-unit chart. Because the vertical axis does not use sequential units, the unit numbers are displayed on the bars. Also, Figure 4.7b shows a multi-crew Gantt chart that legibly shows the assignments allocated to each crew separately along with the start and finish times of each unit.



(a) Duration-Distance Chart



(b) Multi-Crew Gantt Chart

Figure 4.7 The schedule visualization of the proposed model

4.4.2 Model validation

To validate the proposed model, an example activity in an SRP involving nonidentical units with multiple crews is employed. The proposed model and the commercial mapping VRP Analysis software (ARCGIS) are used to determine the order of execution for those units, thus comparing the model's performance to an off-the-shelf commercial counterpart. The software was used to implement the same 10-unit case discussed earlier. First, the Vehicle Routing Problem (VRP), routing feature in ARCGIS, was examined to determine how to model the constraints in the proposed model. The feature comparison is presented in Table 4.2.

Table 4.2 Feature comparison of the proposed model and ARC-GIS software.

Feature	MTSP	ARCGIS	Comments
Start & Refill Station	√	√	
Multiple Crews	√	√	
Productivity Rates and Duration Calculation	√		ARC-GIS uses one duration input.
Crew Capacities of Consumable Resources	√		
Fatigue & Learning Rates	√		
Crew Specialization & Special Units	√	√	
Identical and Nonidentical Units	√	√	
Spatial Constraints and Travel Time Calculation	√	√	
Live Traffic Data	√	√	
Schedule Visualisation	√		
Unload/Reload Time	√		
Multiple Objective Functions	√		ARC-GIS optimizes only total duration.

Hence, the model was validated considering only constraints that can be accommodated in ARC-GIS (i.e., constraints 1, 3, and 4 in Figure 4.5). The case study data was entered into the ARC-GIS system, as shown in Figure 4.8. Figure 4.8a displays the user interface of the ARC-GIS system with the output routes for the two crews plotted on a map in the middle part, the analysis units (activity time in days, travel distance in kilometers, start date of the project on 8:00 AM, 2022-12-16) in the top part, and the list of the imported datasets representing different input attributes and constraints (discussed in more detail in Figure 4.8b-d) in the left side. All data were inputted as Excel comma-delimited files (CSV) to the system.

After completing the analysis in both systems, the proposed model and ARC-GIS tool produced a total duration of 26 days + 1 hour and 30 days + 2 hours, respectively. The order of execution of units produced by the two models was different. For ARC-GIS (Figure 4.9a), Crew 1 served units 4-6-3-7, while Crew 2 served units 9-5-1-2-8-10. For the proposed model (Figure 4.9b), on the other hand, Crew 1 served units 4-6-3-2-7, while Crew 2 served units 9-5-10-1-8.

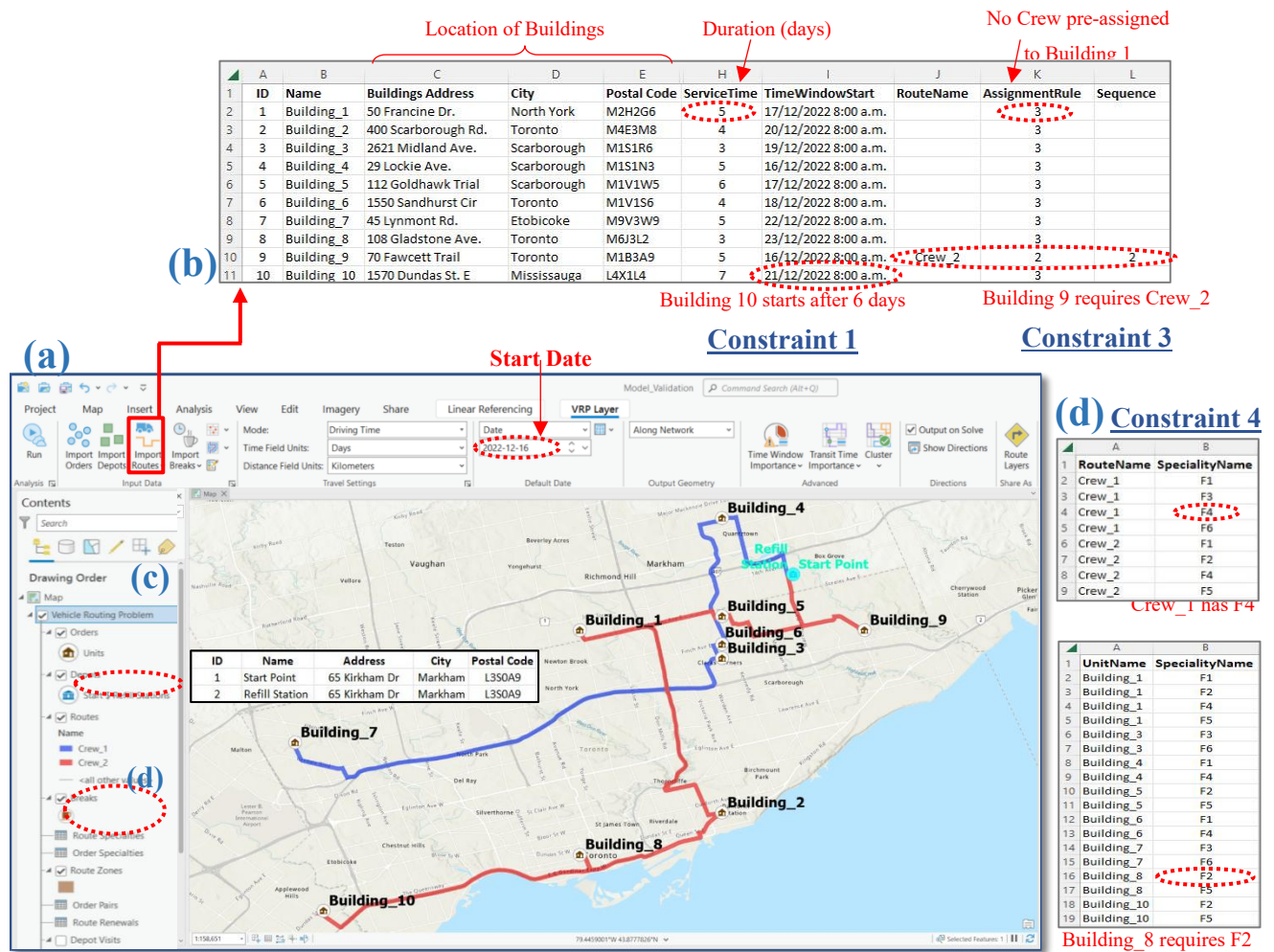
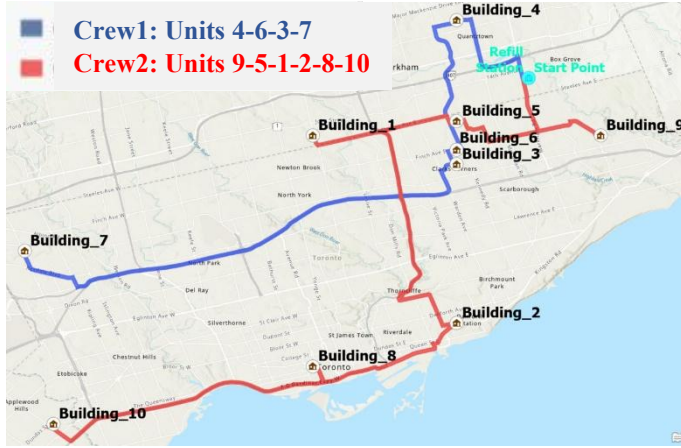
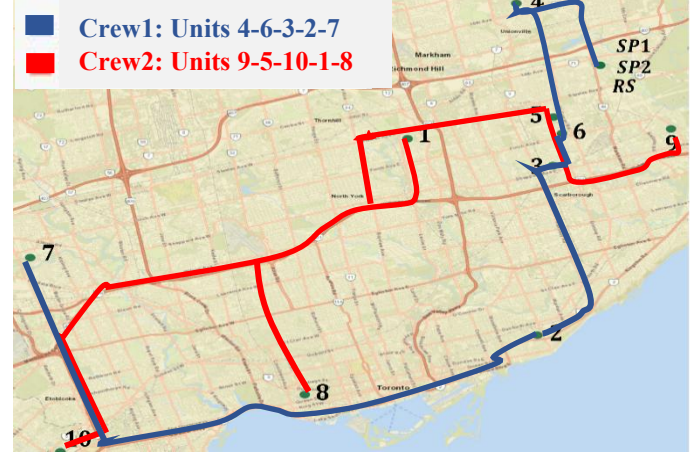


Figure 4.8 An overview of the ARC-GIS routing.



(a) ARC-GIS output



(b) Proposed model output

Figure 4.9 Routing differences between the proposed model and Arc-GIS.

To validate the robustness of the model and its ability to accommodate all practical constraints investigated in this section, the same validation case study was implemented where all constraints (1-5 in Figure 4.5) are in action. The maximum capacity for each crew for consumable resources (C_{kj}) was set to be 5000 m³ while the required consumable resources (R_{ki}) for each unit can be inserted as shown in Figure 4.5d. Because of the additional constraints, the new schedule is one hour longer than the one produced earlier where only constraints 1,3, and 5 were in effect (26 Days + 2 hours compared to 26 days + 1 hour). In the new proposed schedule, Crew 1 serves units 4-6-3-2-7, while Crew 2 serves units 9-5-10-1-8. Furthermore, several experiments were conducted with different variations of the activities and crews' characteristics and the optimization results showed consistent super performance.

To sum up, the proposed model proved the promising use of MTSP formulation to optimize the schedule of multiple crews among project units. Meanwhile, this study, like many others, has proven that changing the execution order can reduce the total transfer time between units for crews, thus shortening the activity duration. Additionally, many studies also point out that changing the execution order can effectively utilize the float time of activity units to reduce the overall project

duration. Even if changing the execution order extends the duration of a particular activity due to increased transfer time for crews, the project duration might still be significantly reduced.

Because this module works with one activity at a time, it is not fully able to handle the high complexities involved in repetitive projects. To overcome this issue, one option could be re-designing the repetitive scheduling engine to utilize the MTSP model in all the activities of a project according to the logical relations of the project. Additionally, given the limited number of variables the GAs engine of Excel Solver can handle and handle large-scale projects, it is important to utilize advanced optimization engines (e.g., Constraint Programming). Alternatively, the module in its current version could be used as a powerful routing algorithm for specific activities within projects.

Chapter 5

Enhanced CP Formulation Using Novel Adjacency Constraints (Module II)

5.1 Introduction

This chapter begins with highlighting the key limitations that restrict the practical application of scheduling models in linear repetitive project environments. To overcome the highlighted limitations, this chapter then introduces an original CP Schedule Optimization Model for repetitive projects that is equally applicable in both linear and scattered projects. The proposed model is validated through several case studies demonstrating not only significant improvements across various optimization objectives (e.g., project duration, crew transition-time, crew idle-time, and various combinations), but also efficient computational performance in terms of less processing time.

5.2 Research Methodology

The key complexity in repetitive projects occurs when multiple crews are used to fast-track projects with non-identical units, which are practical conditions. In this case, linear schedules require, beside other constraints, not only crew-work continuity to be maintained, but also each crew to work on adjacent units, to maintain linearity and reduce travel time. The latter requirement is not easy to achieve because the permutations of assigning each crew to a group of adjacent units (to maintain linearity) are extremely large. Unlike previous research in literature, the proposed model avoids constraining units' start and finish times and instead uses a set of novel adjacency constraints on the work units of each crew. As such, the constraints apply to the unit IDs assigned to each crew, which must follow a sequential order to maintain linearity, for which a CP model can be more easily modeled. Furthermore, the model formulation has been designed to work with large-scale projects, with the following design criteria:

- 1- Accommodates the general case of multiple activity crews across non-identical units.
- 2- Simplifies linear scheduling using adjacency constraints among the units assigned to each crew.
- 3- Models the transition time of crews among the units, mobilization/setup time, and/or rest time.
- 4- Employs a powerful solver engine to optimize large projects in a reasonable processing time.
- 5- Supports multiple optimization objectives: minimum duration, minimum crew transition time, minimum crew idle time or a combination of objectives.
- 6- Provides clear visualization of the overall schedule.

5.3 CP Schedule optimization Model

The proposed model is designed to optimize the schedule of repetitive projects by minimizing the total project duration, crews total idle time, and/or crews total transition times. Meanwhile, the model still maintains the linearity of units assigned to each crew (as illustrated in Figure 2.2). As repetitive units may require mobilization or preparation times, crew transfers between units consume both time and cost. Therefore, the impact of crew transitions on repetitive project scheduling is considered. The model has some assumptions and limitations, including:

1. Each activity has one execution mode, i.e., duration is fixed, although not the same in all units.
2. The number of used activity crews is a variable bound by the maximum availability.
3. Crew cooperation is not allowed; thus, each activity unit uses only one crew.
4. Work interruption is not allowed; therefore, a crew works in a unit until it is completed.
5. The precedence relationships among the activities can be FS, SS, FF, SF, with or without lags.
6. Soft-logic relationships are allowed; thus, any crew can start at any unit and proceed to adjacent units. The number of concurrent units is constrained by available resources.

The CP implementation of the proposed model consists of two main stages: problem specification and problem solving. The CPLEX-CP optimizer defines the scheduling problem by a set of time intervals representing activities to be completed; a set of constraints that apply during

these intervals or between intervals; and an objective function. Once the model is coded using the modeling language of the IBM ILOG tool, the problem is solved by the CPLEXCP solver engine using constructive search and constraint propagation techniques. The following sub-sections explain the details of the CP model.

5.3.1 Notations

Symbols presented in Table 5.1 will be used throughout the chapter, and additional symbols will be introduced where needed in the subsequent sections.

Table 5.1 List of symbols and their explanation

Symbol	Explanation
m	Number of units indexed by $i = 1, \dots, m$.
n	Number of activities indexed by $j = 1, \dots, n$.
C_j	Number of crews available for activity j indexed by $k = 1, \dots, C_j$
d_{ji}	Duration of activity j in unit i .
P_j	Set of predecessors of activity j .
L_{pj}	Lag-time between activity j and its predecessor $p \in P_j$
S_{ji}	Start time of the activity j in unit i .
F_{ji}	Finish time of the activity j in unit i .
PD	Total project duration
TT_{hl}	Crew k transition time from unit h to unit l where h and $l \in m$
TT	Total transition time for all crews
Q_{ji}^k	Number of crew k required to complete activity j at unit i
R_k	Availability of crew type k over the course of project
A_{ji}	Interval variable associated with the task of activity j in unit i .
U_i	Interval variable associated with the i^{th} unit
Cr_{kj}	Interval sequence variable associated with the k^{th} crew of activity j across units

5.3.2 General activity representation

Each activity task j at unit i is denoted by an interval decision variable (A_{ji}), Equation 5.1, that has start time (S_{ji}) and finish time (F_{ji}), and a size or duration (d_{ji}) (IBM Documentation 2024).

Activity durations are restricted to integer values to reflect typical construction practice. Furthermore, the start and finish times can take any value between zero and a defined upper limit (e.g., project deadline).

$$A_{ji} \text{ size } d_{ji}, \quad \forall_i \in \{1, \dots, m\}, \quad \forall_j \in \{1, \dots, n\} \quad \text{Equation 5.1}$$

Where, m is the total number of units, indexed by i , n is the total number of activities, indexed by j , and d_{ji} is the fixed time required to complete activity j .

Additionally, an interval variable (U_i) is defined for each unit i to represent the time span (duration) of all tasks within that unit. This variable (Equation 5.2) serves as a container that encompasses the execution of all tasks within a given unit while considering all task dependencies.

$$U_i = \text{span}(A_{ji}), \quad \forall_i \in \{1, \dots, m\}, \quad \forall_j \in \{1, \dots, n\} \quad \text{Equation 5.2}$$

Furthermore, as a representation of the schedule solution, each crew k is assigned to a list of units to be executed by that crew. To represent the sequencing of the unit allocations, an interval sequence decision variable (Cr_{kj}) is defined (Equation 5.3). Each sequence is associated with a set of interval variables, where each interval relates to a specific task unit. As an example, $Cr_{34} = 7,6,5$, indicating that Crew 3 of task 4 is assigned to execute unit 7, then 6, then 5, in a linear order.

$$Cr_{kj} = \text{sequence}(A_{ji}), \quad \forall_i \in \{1, \dots, m\}, \quad \forall_j \in \{1, \dots, n\} \quad \text{Equation 5.3}$$

Because the sequence variable itself does not impose constraints on the start and end times of these intervals, additional constraints (e.g., no overlap constraints) must be explicitly incorporated into the model.

5.3.3 Precedence Relationships (PRs) among activities

The proposed model accommodates all four standard types of precedence relationships among activities, summarized in Table 5.2, incorporating lead or lag times (L_{pj}).

Table 5.2 Precedence relationships and their CP mathematical representations

Relationship	CP optimizer language	Mathematical Formulation*	Equation
Finish-to-Start (FS)	<i>endBeforeStart</i> (A_{pi}, A_{ji}, L_{pj})	$F_{pi} + L_{pj} \leq S_{ji}$	5.4
Start-to-Start (SS)	<i>startAtStart</i> (A_{pi}, A_{ji}, L_{pj})	$S_{ji} \geq S_{pi} + L_{pj}$	5.5
Finish-to-Finish (FF)	<i>endAtEnd</i> (A_{pi}, A_{ji}, L_{pj})	$F_{ji} \geq F_{pi} + L_{pj}$	5.6
Start-to-Finish (SF)	<i>startBeforeEnd</i> (A_{pi}, A_{ji}, L_{pj})	$F_{ji} \geq S_{pi} + L_{pj}$	5.7

*
 $\forall p \in P_j, \forall j \in \{1, \dots, n\}$
 P_j is set of predecessor activities for activity j
 L_{pj} is lag/lead time required between predecessor p and activity j

5.3.4 Resource-related constraints

This type of constraint ensures that in any time period, the crews in service do not exceed maximum availability (R_k). The CP Optimizer provides a powerful function, *Pulse*(A_{ji}, Q_{ji}^k), to track the usage of resource k throughout the project. This function generates an expression that returns the resource demand (Q_{ji}^k) when the interval variable A_{ji} is active, and zero when the activity is absent. A graphical illustration of the Pulse function is provided in Figure 5.1, using a simple project example composed of 10 units and two activities, A and B that employ 4 crews each ($R_k = 4$). The precedence relation is FS with a two-day lag. As shown in Figure 5.1, the aggregate resource utilization, calculated using Equation 5.8, peaks at 3 and 4 per day for Activity A and B respectively. To prevent exceeding the resource limits, the cumulative usage of resources can be constrained using Equation 5.9.

$$cumuls_k = \sum_{i=1}^m \sum_{j=1}^n Pulse(A_{ji}, Q_{ji}^k), \quad \forall k \in \{1, \dots, K\} \quad \text{Equation 5.8}$$

Where, $cumuls_k$ is the cumulative function tracking the total usage of resource k

$$cumuls_k \leq R_k, \quad \forall_k \in \{1, \dots, K\} \quad \text{Equation 5.9}$$

Where, R_k is the total daily availability of crew/resource k over the project

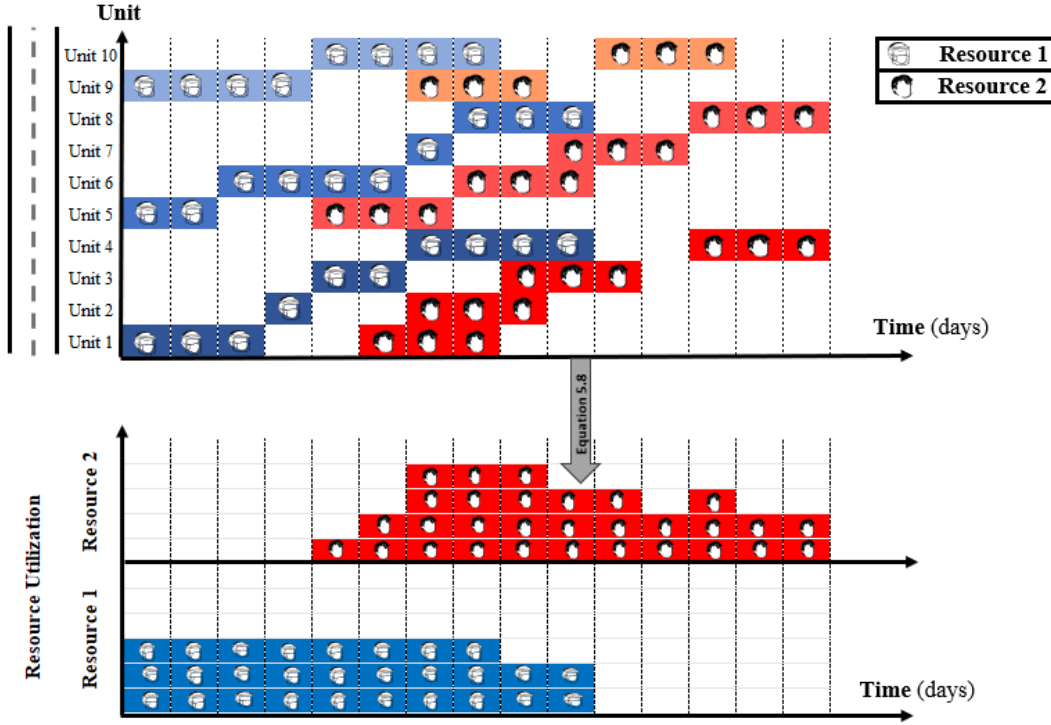


Figure 5.1 An example of a Pulse-Function that accumulates resource use

The resource-related constraint described above ensures that resource availability limits are respected over the project timespan. A second resource allocation constraint is added to ensure that each task-unit receives its required resources, and only the required resources, while allowing for alternative assignments. The CPLEX CP Optimizer offers the alternative function $(a, \{b_1, \dots, b_n\}, c)$, which models the selection of c intervals from the set $\{b_1, \dots, b_n\}$. If interval a (i.e., task-unit) is present, then exactly c intervals (resources) from $\{b_1, \dots, b_n\}$ start and end with a . If a is absent, then all b intervals are absent. This constraint models the assignment of c resources to a task from a pool of alternatives (IBM Documentation 2024) and is modelled as shown in Equation 5.10.

$$\text{alternative } (A_{ji}, Talloc_j, Q_{ji}^k), \quad \forall_i \in \{1, \dots, m\}, \quad \forall_j \in \{1, \dots, n\} \quad \text{Equation 5.10}$$

Where, $Talloc_j$ is an interval variable representing possible crew assignments for task j in unit i , and Q_{ji}^k is number of crew k required to complete activity j at unit i , always 1 in this study.

5.3.5 Transition constraints

In repetitive projects, crews move from one unit to the next, where crew transition time may be needed based on real situations such as mobilization/setup time (for equipment/material preparation) or rest time (for worker fatigue considerations). Therefore, a set of transition constraints is applied to the k^{th} crew assigned to activity j , as formulated in Equation 5.11. These constraints are critical for avoiding scheduling conflicts, optimizing crew utilization, and maintaining feasible and efficient construction timelines. For the k^{th} crew of activity j , TT_{li} is the transition time from unit l to unit i such that:

$$S_{ji}^k \geq F_{jl}^k + TT_{li}, \quad \forall_{i,l} \in \{1, \dots, m\}, \quad i \neq l \quad \text{Equation 5.11}$$

5.3.6 Unit-Start constraints

The proposed model incorporates two constraints related to the start dates of units. The first, referred to as the non-negative constraint, ensures that the start date of any unit i is greater than or equal to zero. This is enforced using the unit-level interval variable (U_i), as shown in Equation 5.12. Optionally, users can impose more specific scheduling requirements by defining unit-specific release dates (e.g., delays due to permit approvals or site access limitations) as represented in Equation 5.13, which prevents units from starting before their designated release dates.

$$StartOf(U_i) \geq 0, \quad \forall_i \in \{1, \dots, m\} \quad \text{Equation 5.12}$$

$$StartOf(U_i) \geq S_i, \quad \forall_i \in \{1, \dots, m\} \quad \text{Equation 5.13}$$

Where, S_i is the start date for unit i that it cannot start before

5.3.7 Adjacency constraints

As a key innovation in the proposed model, it incorporates adjacency constraints that ensure linearity among the units assigned to each crew, as illustrated in Figure 2.2. Generally, the model assumes Soft logic relationships among activity units, and as such, different units can be executed in parallel by different crews. For instance, a single activity within ten units and two crews, the schedule may involve Crew 1 working in units 5-4-3-2-1, while Crew working in units 6-7-8-9-10. To generically formalize this requirement, a novel Global Difference Constraint is introduced. This constraint penalizes non-sequential (non-adjacent) assignment of crews across units and any gaps in the assigned units. This constraint is deployed by observing for each crew k , the previously assigned unit, current unit (e.g., unit 2), and next assigned unit (e.g., unit 4). The difference (Δ) between consecutive unit assignments is computed (e.g., $\Delta = \text{unit } 4 - \text{unit } 2 = 2$), and a penalty is applied whenever non-sequential jumps are detected as described in Equation 5.14, otherwise zero. Global Differences constraint is set to Zero ensuring crews follow a rigid sequential path across the assigned units. In this simplified modelling approach, the model has a better chance of arriving at optimum solution since no complex constraints between the unit-finish and unit-start are necessary.

$$globalDifferences = \sum_{k=1}^K \sum_{i=1}^m \Delta_{l,i} = l - i \quad \forall_{l,i} \in \{1, \dots, m\}, \quad i \neq l \quad \text{Equation 5.14}$$

5.3.8 Objective functions

To accommodate the diverse scheduling requirements of repetitive projects, the proposed model is designed to optimize multiple objective functions depending on the decision maker's preference. Table 5.3 summarizes the various objective functions supported by the proposed model, with their mathematical formulations and brief comments on their rationale. One of the primary objectives is the minimization of total project duration (PD), calculated using Equation 5.15, as the finish time of the last unit of the last activity. Additionally, the proposed model is able to minimize the total crew transition time (TT), as formulated in Equation 5.16. Here, $TT_{h,l}$ represents the transition time of crews across the units and $x_{k,h,l}$ is a binary variable equal to 1 if crew k moves from unit h to unit l , 0 otherwise. To enhance schedule efficiency, the proposed model introduces an additional objective minimizing crew idle time (IT), Equation 5.17. Idle time is quantified as the cumulative time between consecutive units assigned to the same crew, excluding the accounted transition times. Equation 5.18, on the other hand, meets the main objective function suited for linear projects as it minimizes crew unit jumps.

Table 5.3 Objective functions and their mathematical formulation

No.	Objective Function	Mathematical Formulation	Equation	Comments
1	Project Duration	$\min(PD) = \max_{i,j}(F_{ji})$	5.15	Faster project delivery
2	Crew Transition Time	$\min(TT) = \sum_{k=1}^{C_j} \sum_{h,l}^m TT_{h,l} * x_{k,h,l}$	5.16	Least transition time
3	Crew Idle Time	$\min(IT) = \sum_{k=1}^{C_j} \sum_{h,l}^m S_{li} - F_{hi} - TT_{h,l}$	5.17	Least idle time
4	Units Sequential Order	$\min(globalDifferences)$	5.18	Avoid violation to linear constraints
5	Weighted multi-objectives	$\min(Z) = w_1 * PD + w_2 * TT$	5.19	Any number of objectives together
6	Dual objective	$\min staticLex (Obj.1, Obj.2, \dots n)$	5.20	Built-in CP function for any two objectives

While Equations 5.15 to 5.18 represent single-objective functions, the model is designed with flexibility to address real-life situations where multiple objectives need to be optimized simultaneously (e.g., total project duration and crew transition times). As such, the model supports two distinct approaches for handling multi-objective scenarios. One approach uses Equation 5.19 to assign weights to any number of individual objectives, thereby enabling the model to trade-offs among multiple objectives. The second approach uses a built-in CP function, `staticLex(Objective1, Objective 2, ... n)` as shown in Equation 5.20. This method enables the simultaneous optimization of two, or more, objectives functions by prioritizing Objective 1 over Objective 2. Unlike the weighted approach, the user does not have to assign specific weights, making it particularly useful when the objectives differ in scale (e.g., duration and cost) and to avoid complicated calculations. Note that although the model is primarily developed to optimize the scheduling of linear repetitive projects, it is equally applicable to scattered projects that do not follow linear geometry, by simply omitting the adjacency constraints from the model.

5.3.9 Model implementation in CPLEX CP

The core code of the proposed CP model consists of three parts, namely decision variables and expressions, objective function(s), and constraints. The model was coded in the CPLEX CP Optimizer and ILOG OPL language. For more details about interval variables and CP functions, the readers are referred to IBM Documentation (2024).

5.4 Application Cases

This section demonstrates the application of the proposed model on two types of repetitive construction projects, linear and scattered, using four different project cases. The obtained results are compared to those of recent models. In addition, a comparative analysis is conducted to validate the performance and practicability of the proposed model by benchmarking it against previously

published approaches. The model was executed on a personal laptop equipped with an Intel Core i7-12700H CPU, 16 GB RAM, and running Windows 11 (64-bit) operating system. All computational experiments are conducted using IBM ILOG CPLEX Optimization Studio (version 22.1.1), with a time limit of five minutes.

5.4.1 Linear project example

To demonstrate the computational ability of the proposed model in generating near-optimum solutions for linear repetitive projects, it was applied to a 10-segment highway project. This project was originally introduced by Dolabi et al. (2014), then reused by Hegazy et al. (2021), and most recently adopted in Hu et al. (2025b). The project represents a linear infrastructure project compromised of 24 activities across 10 identical segments. The project data (Table 5.4) were input into the model and all constraints outlined in Section 5.3, including the adjacency constraints, were enforced except for the construction start date for units (Equation 5.13) to replicate the original conditions.

Table 5.4 Project data (retrieved from Dolabi et al. (2014))

Task ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Duration (days)	6	4	12	9	13	10	2	4	9	5	8	7	9	8	20	7	9	7	6	8	1	3	5	4
No. of Crews	3	2	5	4	5	4	1	2	4	2	3	3	4	3	8	3	4	3	3	3	1	2	2	2

In the first experiment, the objective function was set to minimize the total project duration, Equation 5.15, and the model generated a 231-day schedule using a total of 76 crews. Figure 5.2a presents the tabular CP work sequence results for the three crews of Task 1, which was exported as (.CSV) format and the related Gantt chart schedule plotted as shown on Figure 5.2b.

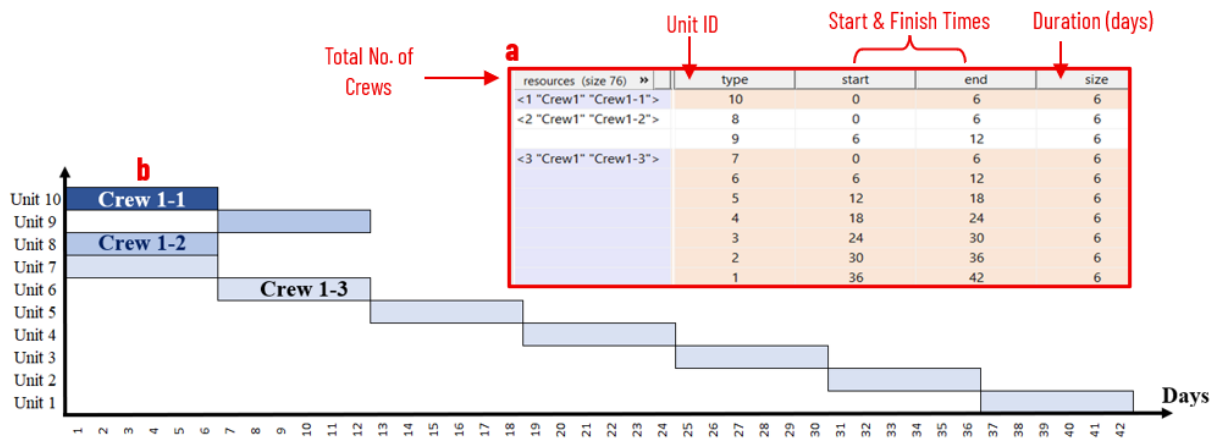


Figure 5.2 Details on crews work sequence across units for Task 1

The complete schedule of all tasks and crew assignments is summarized in Figure 5.3, where each crew maintains a sequential work order across the units. For instance, Crew 1-3 (Activity 1 - Crew3) works across units in descending order ($7 \rightarrow 6 \rightarrow 5 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 1$). While the sequential linear order is preserved, crews are allowed to move in either direction (descending or ascending among adjacent units). The direction of movement for each crew is visualized with colored arrows.

	No. of Crews	Unit									
		1	2	3	4	5	6	7	8	9	10
Task 1	3	Crew1-3							Crew1-2		Crew1-1
Task 2	2	Crew2-2								Crew2-1	
Task 3	5	Crew3-1			Crew3-4		Crew3-2			Crew3-5	Crew3-3
Task 4	4	Crew4-3			Crew4-4		Crew4-2			Crew4-1	
Task 5	5	Crew5-2			Crew5-3		Crew5-5			Crew5-1	Crew5-4
Task 6	4	Crew6-4					Crew6-2		Crew6-1	Crew6-3	
Task 7	1	Crew7-1									
Task 8	2	Crew8-2					Crew8-1				
Task 9	4	Crew9-4			Crew9-1				Crew9-2	Crew9-3	
Task 10	2	Crew10-1			Crew10-2						
Task 11	3	Crew11-1			Crew11-3			Crew11-2			
Task 12	3	Crew12-2			Crew12-3			Crew12-1			
Task 13	4	Crew13-1	Crew13-2		Crew13-3			Crew13-4			
Task 14	3	Crew14-3			Crew14-2			Crew14-1			
Task 15	8	Crew15-4	Crew15-6	Crew15-8	Crew15-5	Crew15-3	Crew15-1	Crew15-7		Crew15-2	
Task 16	3	Crew16-3			Crew16-1			Crew16-2			
Task 17	4	Crew17-2			Crew17-3			Crew17-1			Crew17-4
Task 18	3	Crew18-1			Crew18-3			Crew18-2			
Task 19	3	Crew19-2			Crew19-3			Crew19-1			
Task 20	3	Crew20-3			Crew20-1			Crew20-2			
Task 21	1	Crew21-1									
Task 22	2	Crew22-1			Crew22-2						
Task 23	2	Crew23-2			Crew23-1						
Task 24	2	Crew24-1			Crew24-2						

Figure 5.3 Optimized schedule and crew assignments with Minimum-Duration objective

Using Equation 5.8, the crew utilization can be tracked throughout the project timeline. Although the schedule is constrained by the maximum available crews for each task, the model does not use all available crews and provides an efficient resource utilization. For example, although five crews were available for Task 3, the optimization used only four (Figure 5.4).

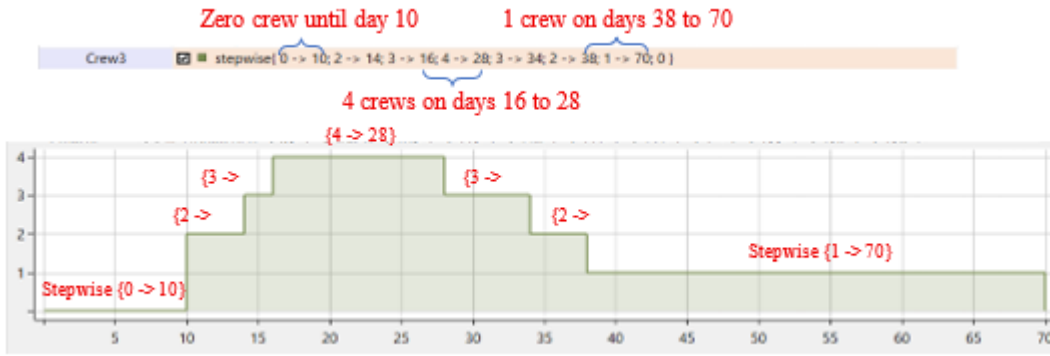


Figure 5.4 Task 3 crew utilization profile

In the second experiment, the objective function was set to minimize both total duration and total idle time, using Equation 5.20. Under this formulation, the optimized schedule resulted in a project duration of 236 days and a total idle time of 215 days. This represents an improvement over the first experiment, which yielded a shorter duration of 231 days but a significantly higher idle time of 299 days.

In a series of experiments, Equation 5.19 was adopted as the objective function, assigning equal relative weights to both project duration (w_1) and idle time (w_2). Figure 5.5 presents the Pareto frontier obtained from the weighted-sum approach for balancing Project Duration (PD) and Idle Time (IT). Each solution corresponds to a different set of weights (w_1, w_2), where w_1 prioritizes PD and w_2 prioritizes IT. The frontier confirms the expected trade-off: minimizing PD alone ($w_1 = 1, w_2 = 0$) yields the shortest schedule (231 days) but results in excessive idle time (383 units), whereas minimizing IT alone ($w_1 = 0, w_2 = 1$) achieves the most efficient crew utilization (only 71 days of idle) but extends the project to 300 days.

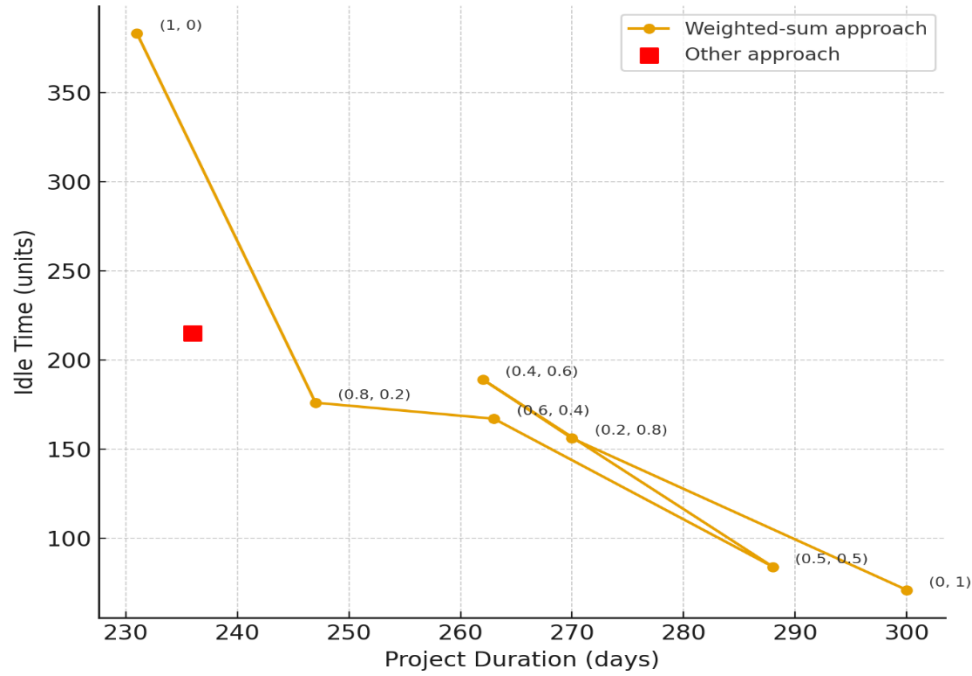


Figure 5.5 Pareto Frontier: Project Duration vs Idle Time

All solutions generated are non-dominated and thus belong to the Pareto set. The shape of the curve highlights the non-linear trade-off: relatively small gains in project duration often come at the cost of disproportionately higher idle times. For example, reducing PD from 247 to 231 days (a 6.5% improvement) requires accepting an increase in IT from 176 to 383 units (a 117% increase). This demonstrates that idle time is far more sensitive than duration to changes in the weight distribution once PD is heavily emphasized.

A particularly important solution is the knee point, located at ($PD = 247, IT = 176$) with weights ($w_1 = 0.8, w_2 = 0.2$). This point represents a practical compromise: PD is only ~7% longer than the absolute minimum, but idle time is cut by more than 50% relative to the shortest-duration solution. From a managerial perspective, this is a highly attractive option, since modest concessions in schedule acceleration led to disproportionately large gains in crew efficiency.

For comparison, the alternative optimization approach, using Equation 5.20, produced a solution of ($PD = 236, IT = 215$), marked in Figure 5.5 by the red square. This solution is also

non-dominated and lies close to the knee region of the frontier. Relative to the extreme PD-focused solution, it achieves a comparable duration with significantly less idle time. Compared to intermediate weighted-sum solutions such as (247,176), it provides a shorter schedule but at the expense of moderately higher idle time. Its location in the mid-range of the frontier indicates that it is less sensitive to small changes in weight values, reinforcing its robustness as a compromise solution.

5.4.2 Comparison with other models: Non-sequential example

For the purpose of comparing with other studies in the literature that do not have adjacency constraints to enforce linearity, the adjacency constraint was deactivated, and the objective function was set to minimize the total project duration (TD). Three scenarios were conducted using the proposed model, with each employing a distinct crew availability profile to replicate conditions from previous studies. The results of comparison against previous studies are shown in Table 5.5.

Table 5.5 Comparison of results with previous studies

Comparison Criteria	Dolabi et al. (2014)	Hegazy et al. (2021)		Hu et al. (2025b)	Proposed Model		
	Best Result	CPM/LOB + ASAP	ASAP+ geometric improvements	Metaheuristic Algorithm	Scenario 1	Scenario 2	Scenario 3
Crew Availability limit	76	76	85	95	76	81	94
Optimum Project Duration	226	226	215	196	200	200	196

Compared to the results of Hegazy et al. (2021) and Dolabi et al. (2014), the proposed model outperformed their best model by achieving a shorter project duration of 200 days under Scenario 1, compared to their 215 days that even used more total crews. Also, compared to the model of

Hu et al. (2025), the proposed model matched their best-known result of 196 days, while requiring slightly less resources (94 crews vs their 95 crews).

5.4.3 Scattered project examples

Although the proposed model is primarily targeted to optimize linear projects, it is equally applicable to scattered projects as well. To demonstrate this, two scattered projects from literature were adopted, with the adjacency constraint deactivated to reflect the non-linear nature of scattered units. The first case study, originally presented by Hegazy et al. (2021), involves six tasks to be completed across 15 units. All activities follow finish-to-start relationships with zero lags. Most activity units have identical durations, except for tasks A and B, as specified in Figure 5.6.

The project data were input into the proposed model, with the objective function set to minimize the project total duration (TD) while assuming zero crew transition time across units. The model generated a schedule with a total duration of 26 days, matching the results reported by Hegazy et al. (2021). However, as shown in Table 5.6, several units were completed earlier than the reference schedule, indicating a more efficient allocation of tasks.

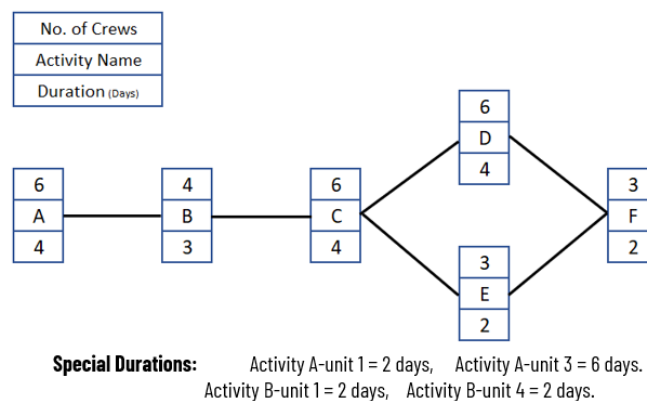


Figure 5.6 Scattered project data (derived from Hegazy et al. (2021))

Table 5.6 Schedule comparison for a scattered project case

Unit ID	Finish Time (days)		Saved Time
	Hegazy et al. (2021)	Proposed model	
1	15	14	1
2	17	17	
3	19	19	
4	18	16	2
5	19	17	2
6	20	18	2
7	21	20	1
8	21	21	
9	22	21	1
10	23	22	1
11	23	23	
12	24	24	
13	25	24	1
14	25	25	
15	26	26	

The second case study is based on a housing project originally introduced by Fan et al. (2012) and reused by Zou & Zhang (2020). The project involves the construction of five buildings; each consists of six sequential activities. Table 5.7 summarizes the activity durations for each building, along with the maximum crew availability for the respective activities. This case was selected to evaluate the effectiveness of the crew transition time function, which was configured to apply a one-day transition between any two units.

Table 5.7 Durations and crew availabilities of scattered case 2 (adapted from Zou & Zhang (2020))

Activity (j)	Description	No. of Crews	Duration in days (d_{ji})				
			Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
A	Dismantling and cleaning	2	10	8	8	8	7
B	Excavation	2	20	25	10	18	35
C	Set forms	2	9	12	5	7	15
D	Rebar tie-up	3	10	15	5	8	20
E	Piping location arrangement	2	10	15	5	8	20
F	Concrete pouring	2	10	15	5	8	20

The project data in Table 5.7 were input into the developed model and the objective function was set to minimize the total duration of the project where the adjacency constraint were deactivated. Zou & Zhang (2020) reported a project schedule with a total duration of 139 days, whereas the proposed model generated a more efficient schedule with a reduced duration of 117 days. A colour-coded Gantt Chart illustrating the optimized schedule produced by the developed model is presented in Figure 5.7.

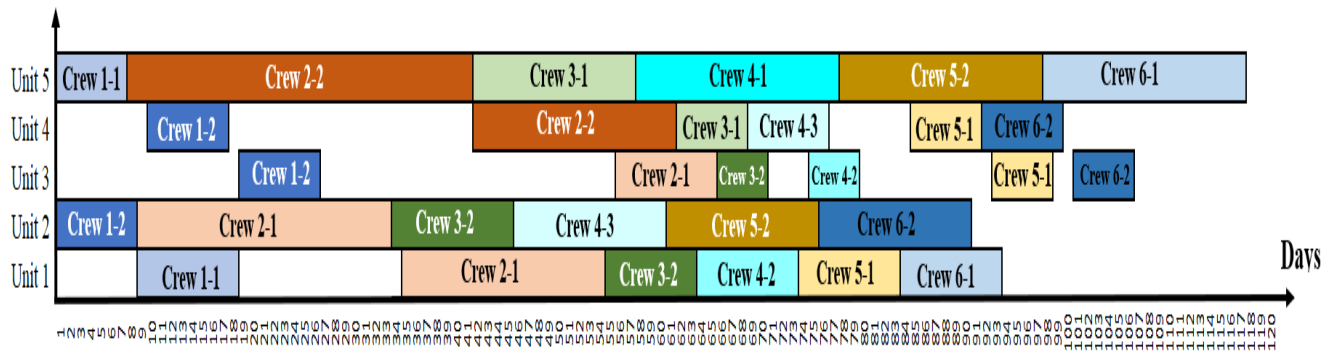


Figure 5.7 Optimized schedule using the proposed model

Another experiment was then conducted to examine the effect of adjacency constraints on this case. Figure 5.8 visualizes the crew assignments to different units through a multi-crew Gantt chart. As illustrated in Figure 5.8, the generated schedule has a longer duration of 125 days, where crew assignments maintained both linearity and continuity. For instance, Crew1-1 works in units 5 – 4 – 3 with zero idle time. The gaps between the consecutive units represent the transition time between the assigned units (one day each). This visual represents an informative multi-crew chart that shows for each crew their assigned units. Figure 5.7Figure 5.8, therefore, represent different legible visuals for the resulting schedules.

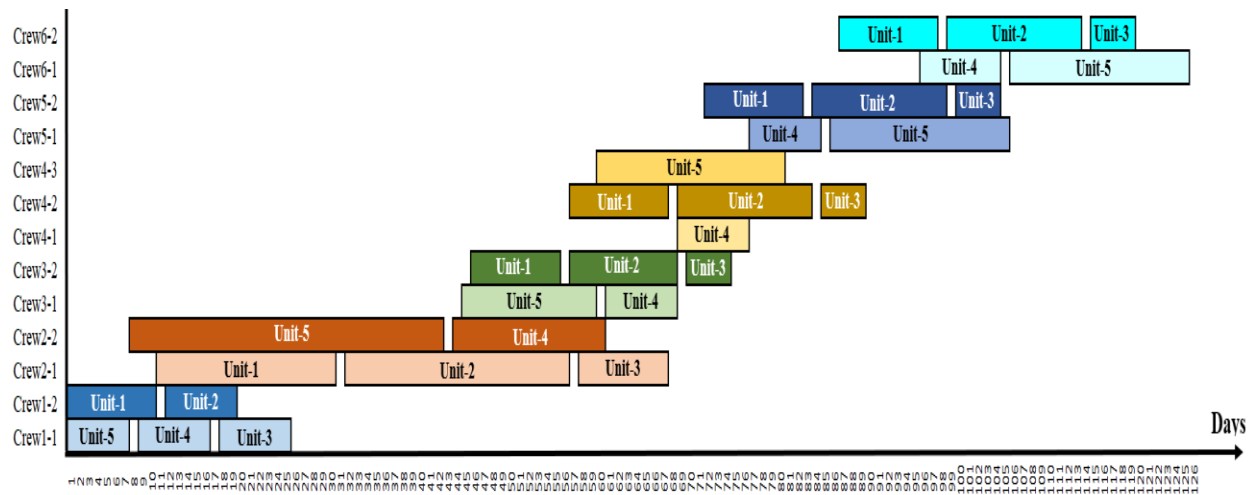


Figure 5.8 Multi-crew Gantt chart sechedule enforcing linearity and continuity constraints

To sum up, the key innovation of the proposed model (Module II) lies in its capability to maintain both work continuity and linearity while optimizing multi-objective functions. By integrating multiple objective functions, sequential and non-sequential crew assignment logic, and transition time considerations, the model enables nuanced trade-offs between project duration, crew idle time, and resource utilization. This flexibility allows the model to accommodate various construction strategies, offering practitioners a powerful tool for minimizing project duration and improving crew productivity. The proposed model has been proven to have sufficient flexibility to generate optimized schedules for both linear and scattered repetitive projects. Moreover, its adoption of CP techniques ensures computational efficiency, even when dealing with large and complex projects. The validation of the model through case studies confirmed its effectiveness in achieving shorter project durations and better resource utilization compared to existing methods, including heuristic and metaheuristic approaches.

While the model's performance is noteworthy, certain areas require further development. One key limitation is the assumption that each task can be executed only through one construction option. Additionally, the model does not incorporate either monetary (e.g., cost) or environmental

(e.g., co2 emissions) considerations into the optimization process. Thus, the next chapter introduces a multi-mode construction schedule optimization algorithm that allows each task to be executed using alternative construction methods and materials while accounting for their effects on time, cost, and environmental sustainability.

Chapter 6

Environmental Assessment and Sustainability Scheduling (Module III)

6.1 Introduction

This section introduces Module III which aims to quantify, monetize and incorporate the environmental impacts into the optimization process, accounting for variations in construction methods and materials and their effects on time, cost, and sustainability. The environmental impacts of the construction activities may vary depending on the construction method, equipment utilization, crews travelling across project units, and materials (e.g., using reclaimed vs. raw materials). These factors also affect the cost and duration of the construction projects. The proposed model consists of two components. Part I quantifies and monetizes the environmental impact during the construction phase. Part II formulates a multi-mode construction scheduling algorithm where each task can be executed using optimal alternative methods and materials affecting time, cost and environmental considerations. Part I interacts with Part II to consider the impact of changing the construction methods and materials on construction time, cost, and environmental impacts.

6.2 Part I: Environmental Impacts and Cost Assessment

A Decision Support System (DSS) was developed to quantify and monetize the environmental impacts from different construction methods (cast in place vs. precast concrete element), material choices (reinforced concrete vs. mass timber), or resource strategies (recycled vs. raw materials). As a proof of concept, the developed DSS was tested for its ability to manage construction waste generated during end-of-life (EOL) activities for building projects. The DSS framework provides the following functions: (1) monetizing potential environmental savings from different recovery

options (e.g., reuse, recycle); (2) applying multi-objective optimization to determine the optimal quantity of material to undergo each material recovery scenario; and (3) using parametric weights to consider stakeholders' preferences, and their "appreciation" of environmental benefits compared to costs.

The proposed DSS framework consists of five main steps: (1) Creating a Building Information Model (BIM) for the case study; (2) Performing consequential Life Cycle Assessment (LCA) for the material reuse scenarios; (3) Carrying out a cost-benefit analysis; (4) Monetizing the achieved environmental savings; and (5) Optimizing the decision-making process through the multi-objectives model. A case study of a renovation project of the Martin Luther University College (MLUC) building in Waterloo, Ontario is used to demonstrate how the proposed DSS framework can divert concrete and glass waste from the landfill.

6.2.1 BIM model and inventory data

The first step in the proposed DSS framework relies on obtaining an accurate and up-to-date BIM model. The case study was recreated with the original technical input data, provided by the architectural firm, to develop a precise renovation as-built model. This BIM model has an overall average Level Of Details (LOD) of 350, which contains precise information about the elements and outlines the elements' relations and connections with other components (Alferieff and Bomba 2019). Such LOD was vital not only for conducting a quantity take-off of materials but also for identifying the potential for disassembly over selective demolition for extraction of components. Using One-Click LCA®'s Add-in designed for Revit software; the inventory data was generated with other LCA results. The produced data includes a long list of waste materials (e.g., Asbestos, Cement Plaster, Floor ceiling, etc.). Still, following this study's scope, only glass and concrete data are included. For the current MLUC case study, the demolition process will produce 3.0525 tons

of glass waste and 151.75 tons of concrete waste (ignoring the weight of steel reinforcing bars), representing 1.25% and 62.19% of the total waste generated in our case study, respectively.

6.2.2 LCA: goal, boundaries, and environmental impacts

LCA is the most common way to measure the environmental impacts associated with products or services, leading to more opportunities for environmental savings and better decisions throughout the life cycle of projects. Since this study focuses on typical EOL activities, our LCA has modified boundaries (i.e., not a comprehensive cradle-to-grave LCA). A consequential LCA approach is used to quantify the environmental impacts per material type. The building's operational phase is dismissed from the LCA system boundaries since this study focuses on quantifying embodied carbon. The impact factors depend on the subject and intended use of the study. The environmental impacts to be quantified in this study are Global Warming Potential (GWP) in kg CO₂eq, Primary Energy Demand (PED) in Mega Joules, and Water Consumption (WC) in m³ of water. The functional unit for waste is one ton.

Our principal reason for these modified boundaries comes from the fact that most of the Construction and Demolition Wastes (CDW) come from EOL activities (i.e., demolition), which can be upwards of 95% of all CDW (US EPA 2018). LCA was performed using One-Click LCA® software, where three scenarios are introduced for dealing with different types of waste generated from building projects. The first scenario, the least preferred, assumes that all generated waste is sent directly to landfills without any recycling or reuse. This scenario represents the linear economy approach, providing a baseline for comparing circular strategies. The two other scenarios are recycling and reuse of materials.

The LCA results are studied and compared to identify the potential benefits in reducing environmental impacts by reusing or recycling materials. In this study, any reduction of the environmental impacts between the proposed scenarios is enumerated as environmental savings.

Environmental savings can result from changing the EOL for those materials, using fewer raw materials, and/or improvements in those components' production process.

6.2.3 Cost-Benefit analysis for material scenarios

The cost of reusing materials varies from project to project and depends on the technology used and building characteristics (e.g., the materials within a building, the quantity of those materials, and the difficulty of removing and reusing them). Cost assessment is performed based on recent literature, RS-Means® (2021) database and this researcher assumptions based on professional judgement, as specified in each corresponding section, and were determined according to the most common current industry practices.

The estimates used in this study reflect the local market values for the case study at hand where possible. Table 6.1 contains the cost breakdown for the different scenarios of reprocessing glass and concrete waste generated from the case study. The transportation distance is set to 8 km which is the distance from the building site to the nearest landfill.

Table 6.1 Cost breakdown for reprocessing glass and concrete waste scenarios.

Cost	Cost for Glass Waste <i>Cad per ton</i>			Cost for Concrete Waste <i>Cad per ton</i>		
	Landfill	Recycling*	Reusing*	Landfill	Recycling	Reusing
<i>Cost of demolition</i>	---	---	---	---	---	---
<i>Cost of dismantling</i>	---	284	420	---	---	---
<i>Cost of stocking</i>	15	15	15	---	---	---
<i>Cost of transportation from construction site</i>	16	16	16	16	---	---
<i>Cost of landfill</i>	88	---	---	88	---	---
<i>Cost of crushing /treating</i>	---	50: 75	26	---	35	---
<i>Cost of transportation to recycling facility</i>	---	26	---	---	16	---
TOTAL COST	119	401	477	104	51	---

**These estimates are derived from a study done by the UK Glass Technology Services ("Glass Testing Laboratory | Glass Technology Services | Glass Technology Services" 2021; The Delphi Group 2021) and considering the increase of minimum wage per hour for labours and other factors.*

6.2.4 Environmental savings monetization

Based on the LCA results, the environmental savings gained from each scenario are calculated as summarized in Table 6.2 and compared to landfill disposal, which has zero environmental gain. PED values were monetized based on the distribution of energy use per source (CEEDC 2021) and the average fuel price rates. The monetization of the GWP and WC was estimated according to the available literature on the topic. For instance, the cost of air pollution and climate change gases, and water usage have been investigated comprehensively in several studies (Sanchez et al. 2019; Yeung et al. 2017). Accordingly, a conservative cost for carbon emissions and water consumption in North America for 2017 was 112 Cad per ton of CO₂ and 2.15 Cad per m³ of water, respectively.

Table 6.2 Environmental savings per ton of waste

Material Type	EOL Scenario	Env. Impact	Env. Savings	Monetization Env. Savings
Glass waste	Recycling	PED	15774.31 MJ	233.918 Cad
		GWP	1893.94 kg CO _{2eq}	212.121 Cad
		WC	2.59 m ³	5.57 Cad
	Reusing	PED	51823.86 MJ	768.50 Cad
		GWP	2201.21 kg CO _{2eq}	246.512 Cad
		WC	7.24 m ³	15.57 Cad
Concrete waste	Recycling	PED	222.18 MJ	3.29 Cad
		GWP	35.72 kg CO _{2eq}	4.00 Cad
		WC	---	---

6.2.5 Materials optimization

The amount of waste generated for each material was obtained from the building's BIM model. Costs and revenues for each scenario can be obtained from the building's LCA and/or market data. Based on this data, an optimization model was created to guide the decision-makers as to the optimal amount of material to undergo each recycle/reuse scenario. A multi-objective formulation was used since the optimization model deals with two conflicting objectives: minimizing costs and maximizing environmental savings. For each material under investigation, the model shall determine the amount of material to undergo each recycle/reuse scenario such that the optimization

model's objective function is optimized (gained environmental benefits minus the costs; $Z_1 - Z_2$). The objective function can be modified based on the preference of the project stakeholders and their “appreciation” of the gained environmental benefits compared to the costs incurred. This is represented by adding a custom weight (W) in the objective function. W can only take values between 0 and 1, where a high W represents a higher preference to be environmentally friendly. In comparison, a low W represents a higher preference to minimize costs regardless of the environmental impact of the process. The mathematical formulation for the optimization problem is as follows (Equation 6.1- Equation 6.5), with Figure 6.1 showing the optimization solver input data.

Decision Variables:

$$T_{ij} = \text{Amount of material (i)(Tons) undergoing recyc/reuse scenario (j)} \quad \text{Equation 6.1}$$

(1 = landfill, 2 = recycle, 3 = reuse)

Objective Function:

$$Z_1 = \sum_{i=1}^M \sum_{j=1}^3 T_{ij} * \text{Unit Envr. Benefit of Scenario (j) for material (i)} \quad \text{Equation 6.2}$$

$$Z_2 = \sum_{i=1}^M \sum_{j=1}^3 T_{ij} * \text{Unit Cost of Scenario (j) for material (i)} \quad \text{Equation 6.3}$$

M = the total number of Materials under investigation

$$\text{Max } Z_{\text{total}} = W * Z_1 - (1 - W) * Z_2 \quad 0 \leq W \leq 1 \quad \text{Equation 6.4}$$

W =user-inputted parameter indicating the user's interest in achieving environmental savings compared to cutting costs

Constraints:

$$\sum_{j=1}^3 T_{ij} = T_{i\text{-total}} \quad \text{for every material (i)} \quad \text{Equation 6.5}$$

$T_{i\text{-total}}$ = the total amount of material i available for disposal

Cost	Material 1			Material 2			Material X		
	Cost <i>Cost per ton</i>			Cost <i>Cost per ton</i>			Cost <i>Cost per ton</i>		
	Landfill	Recycling	Reusing	Landfill	Recycling	Reusing	Landfill	Recycling	Reusing
Cost of demolition	---	---	---	---	---	---	---	---	---
Cost of dismantling	---	---	---	Material Type	EOL Scenario	Env. Impact	Env. Savings	Monetization Env. Savings	
Cost of stocking	---	---	---		Material 1	Recycling	PED	---	---
Cost of transportation from construction site	---	---	---				GWP	---	---
Cost of landfill	---	---	---				WC	---	---
Cost of crushing /treating	---	---	---		Material 1	Reusing	PED	---	---
Cost of transportation to recycling facility	---	---	---				GWP	---	---
	---	---	---				WC	---	---
Total	---	---	---		Material 2	Recycling	PED	---	---
							GWP	---	---
							WC	---	---
					Material 2	Reusing	PED	---	---
							GWP	---	---
							WC	---	---
					Material X	Recycling	PED	---	---
							GWP	---	---
							WC	---	---
					Material X	Reusing	PED	---	---
							GWP	---	---
							WC	---	---

Figure 6.1 Setup of the optimization solver input data

6.2.6 Recycling/Reusing results

Table 6.1 and Table 6.2 were used as inputs to the developed DSS to guide the decision makers as to the optimal amount of material to undergo each recycle/reuse scenario. First, the possible combinations of the different EOL scenarios were investigated. Because there are no constraints on the quantities to undergo any given disposal scenario, the solutions provided by the developed DSS commit all available amounts from any given material to only one disposal scenario (landfill, recycle, or reuse). The costs and rewards accompanying each possible scenario are presented on the chart in Figure 6.2. Given that the optimization objective is to minimize costs and maximize savings, the points closer to the top left-hand corner of the chart are preferred. Hence, the solutions obtained by sending the concrete to landfills (SL, RL, and LL) are seen to be “dominated” by their concrete-recycling counterparts (SR, RR, and LR). Accordingly, the boundary representing the set of non-dominated optimal solutions (i.e., Pareto frontier) is represented as a black line (Figure 6.2).

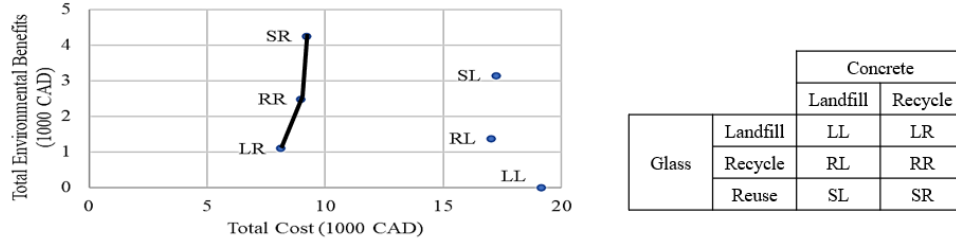


Figure 6.2 Pareto frontier generated by comparing different EOL scenarios

Second, the weighting method was used to examine the options displayed on the Pareto frontier and to determine when one solution becomes preferable compared to others. Figure 6.3 shows how different values of W impact the overall objective function.

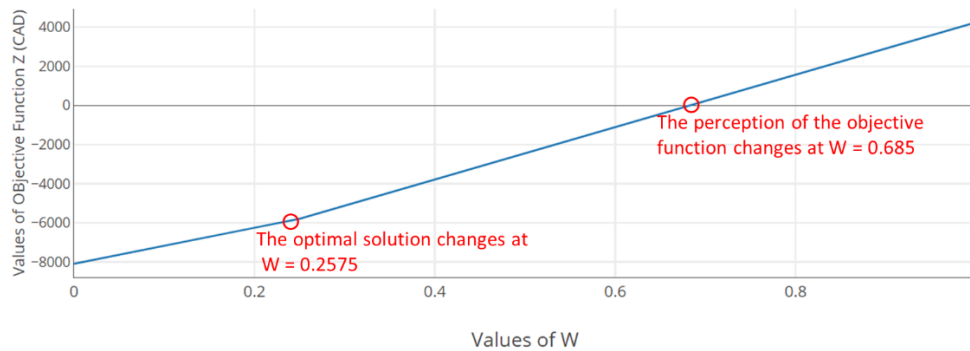


Figure 6.3 Relationship between values of w and corresponding objective function value

Two crucial observations from Figure 6.3 are to be noted. First, it was found that most of the time, the solution that maximizes environmental savings results only when the decision makers desires to aggressively minimize costs ($W < 0.2575$). This indicates that the gained environmental savings rewards outweigh the extra costs incurred in selecting the greener material reuse options. Second, the objective function starts taking negative values if W is less than or equal to 0.685. While this has no impact on the real monetary values of the options, it impacts how the stakeholders perceive them. For example, at high values of W (i.e., heightened environmental awareness), the project personnel perceive their assets' end-of-life activities and disposal activities

as value-generating activities. At low values of W (i.e., high interest in profitability), the project personnel perceive the end-of-life activities as “money pits” that provide no value, and their objective is to minimize the incurred losses. Finally, the fact that the objective function value at $W = 0.5$ (equal valuation of monetary costs and environmental benefits) is less than zero implies that end-of-life activities in the current construction and asset management ecosystem are not profitable.

6.3 Part II: Multi-Mode Schedule Optimization for Sustainability

While the proposed framework in Part I mainly focused on reuse and recycling options at the EOL phase of projects, it establishes a clear pathway for capturing and monetizing various environmental impacts. These impacts will be incorporated into the schedule optimization process for repetitive projects through a novel multi-mode resource constraint scheduling optimization model (Module III). Module III builds upon the foundations established in Module II, with any modifications and enhancements are described in the following sub-sections.

6.3.1 Module III description

To efficiently incorporate sustainability into the schedule optimization for repetitive projects, an enhanced multi-mode schedule optimization model (Module III) is presented in this chapter as an extension to the capabilities of the earlier single-mode version (Module II). The extended model basically allows two types of extensions: (a) each activity to be executed using one of several alternative modes, each characterized by distinct durations, costs, and environmental impacts; and (b) an additional dimension (variable) in the optimization formulation to determine which mode to use for each activity so that the environmental impact is minimal. Unlike the single-mode formulation, which assumed a fixed method and duration for every task across all units, the multi-mode approach provides greater modeling flexibility and better reflects real-world construction practices, where contractors can choose among different technologies or work methods to balance

schedule, cost, and sustainability objectives. In this extended formulation, for each activity in each unit, the model handles a set of optional interval variables representing all feasible execution modes and applies exclusive alternative constraints to ensure that exactly one mode is selected. This enables the optimizer to dynamically determine the most appropriate combination of modes across all repetitive units, while simultaneously respecting crew continuity, precedence relationships, and unit-specific start and due dates. Moreover, the model retains key features of Module II, including interval-based crew assignment, crew travel time constraints, and the ability to optimize multiple objectives such as minimizing total project duration, or idle time. Notably, the multi-mode formulation introduces two additional objective functions that were not available in Module II, enabling direct optimization of the total project cost and the total environmental impact in terms of estimated carbon emissions associated with the selected execution modes.

6.3.2 Multi-Mode execution activity representation

Instead of restricting each activity to a single execution mode, this new representation incorporates a number of alternative construction modes (m_c), where each mode provides a distinct combination of duration, cost, and environmental impact. Accordingly, each activity j at unit i , executed using mode O , is denoted by an interval decision variable (A_{jio}) (Equation 6.6), which defines the start time (S_{jio}) and finish time (F_{jio}), and the mode-based duration (d_{jio}) (IBM Documentation 2024).

$$A_{jio} \text{ size } d_{jio}, \quad \forall i \in \{1, \dots, m\}, \quad \forall j \in \{1, \dots, n\}, \quad \forall o \in \{1, \dots, m_c\} \quad \text{Equation 6.6}$$

Where, m represents the total number of units, indexed by i , n represents the total number of activities, indexed by j , m_c represents the number of construction modes, indexed by o , and d_{jio} represents the mode-based time required to complete activity j .

6.3.3 New exclusive constraints

The resource-related constraints introduced in Subsection 5.3.4 are maintained in this module without modification to their underlying logic. While certain aspects of the mathematical formulation have been updated to accommodate the new feature of multi-mode construction, the same fundamental concepts and principles still apply. These adjustments primarily address the need to represent multiple alternative execution modes for each activity while ensuring that only one mode is selected in the final solution, without altering the original approach to modeling resource allocation, crew continuity, and precedence relationships.

However, to ensure that each activity j is executed in exactly one mode, an additional constraint is incorporated. Specifically, a resource allocation constraint is introduced using the alternative function, $\text{alternative}(a, \{b_1, \dots, b_n\}, c)$, which restricts the selection of construction modes for each task to exactly one option from the available pool of alternatives (IBM Documentation 2024). This formulation guarantees mutual exclusivity among modes while maintaining compatibility with all other constraints described in Module II, including crew allocation, precedence relationships, and resource availability limits. The new constraint is formulated as shown in Equation 6.7.

$$\text{alternative}(A_{jio}, Tmod_o, 1), \forall_i \in \{1, \dots, m\}, \forall_j \in \{1, \dots, n\}, \forall_o \in \{1, \dots, m_c\} \quad \text{Equation 6.7}$$

Where, $Tmod_o$ represents an interval variable representing possible modes for task j in unit i .

6.3.4 New objective functions

In addition to the objective functions presented in Table 5.3, Module III is designed to optimize two more practical objective functions: project total cost (PTC) and total environmental impacts (TEnv). The total cost calculations (Equation 6.8) incorporate all key aspects of cost including the total direct cost (TDC), project indirect cost (PIC), lateness completion penalties (LCP), and crew

travelling cost (CTC). Additionally, Module III models the scenario where the owner provides an early completion incentive (ECI) to the contractor if the project is completed before the deadline.

$$PTC = TDC + PIC + LCP + CTC - ECI \quad \text{Equation 6.8}$$

Where, PTC represents the project total cost, TDC represents the total direct cost, PIC represents the project indirect cost, LCP represents the total lateness penalties, CTC represents the crew travel cost, and ECI represents the early completion incentive.

As each activity has more than one possible construction mode and each mode results in different costs, the project total direct cost (TDC) is calculated (Equation 6.9) as the summation of direct cost of all tasks based on the mode selected in the optimized schedule. The direct cost for each activity is the product of its direct cost per day (DC_{jio}) and the activity duration (d_{jio}) based on the selected mode. On the other hand, the project indirect cost (PIC) is calculated (Equation 6.10) by multiplying the project duration (PD) and the daily indirect cost of the project (η).

$$PDC = \sum_i^m \sum_j^n \sum_o^{mc} (DC_{jio} * d_{jio}) \quad \text{Equation 6.9}$$

Where, DC_{jio} represents the direct cost (per day) to complete activity j ($\forall j \in \{1, \dots, n\}$) at unit i ($\forall i \in \{1, \dots, m\}$) through construction mode o ($\forall o \in \{1, \dots, m_c\}$), and d_{jio} represents the time needed to complete activity j

$$PIC = PD * \eta \quad \text{Equation 6.10}$$

Where, PD represents the project duration and η represents project indirect cost per day

If the project is delayed beyond its deadline (PD^-) (i.e., $PD \geq PD^-$), the contractor must pay a financial penalty to the owner. This penalty is calculated by multiplying the daily liquidated damages (γ) by the differences between the scheduled project duration and the contractual deadline ($PD - PD^-$), as shown in Equation 6.11. Similarly, some projects have deadlines not only for project completion, but also for rigid completion dates for some of their units (e.g., rehabilitation

of bridge segment that passes over a railroad). In these cases, the contractor must pay a late penalty charge to the owner to compensate them for the late completion. This penalty is calculated by multiplying the daily late penalty ($\mathcal{E}_i$) for unit i by the difference between the scheduled finish time of the unit and the planned finish time ($F_i - F_{jio}$). The late completion penalty (LCP) combines these two penalties as shown in Equation 6.11.

$$\text{LCP} = (\text{PD} - \text{PD}^-) * \gamma + \sum_i^n [(F_i - F_{jio}) * \mathcal{E}_i] \quad \text{Equation 6.11}$$

Where, PD represents the scheduled project duration, PD⁻ represents the project deadline, F_i represents the planned finish time for unit I, F_{jio} represents the scheduled finish time of the same unit, and γ and $\mathcal{E}_i$ represent the daily liquidation damage

Additionally, repetitive projects scheduling involves multiple crews moving across the project units, and their movements consume both time and cost. Crew travelling time is calculated as described earlier in Equation 5.11. To model real-life practices, crew travel cost (CTC) is calculated (as shown in Equation 6.12) as the product of the total crew travelling time (TT) and the travel cost per time unit ($\mathcal{T}$, e.g. day or hr.). It worth to noting that crew transition time may be needed to model other real-life situations such as mobilization/setup time (for equipment/material preparation) or rest time (for worker fatigue considerations).

$$\text{CTC} = \mathcal{T} * \text{TT} \quad \text{Equation 6.12}$$

Where, TT represents the total travelling time for all crews and $\mathcal{T}$ represents the travelling cost per time unit

Lastly, if the project is completed before the contractual deadline (PD^-) (i.e., $\text{PD}^- \geq \text{PD}$), the contractor is entitled to receive a financial incentive from the owner. This incentive is calculated by multiplying the daily early completion reward (β) by the difference between the deadline and the actual project duration ($\text{PD}^- - \text{PD}$), as shown in Equation 6.13. This formulation

ensures that any reduction in project duration relative to the contractual deadline results in a proportional incentive payment to the contractor.

$$ECI = (PD^- - PD) * \beta \quad \text{Equation 6.13}$$

Where, PD is the scheduled project duration, PD^- is the project deadline, and β is the incentive per day

To incorporate environmental sustainability into the scheduling problem, this proposed model (Module III) introduces the total environmental impacts (TE_{Env}) as a novel optimization objective. TE_{Env} represents total carbon emissions (in kg CO₂eq) resulting from two primary sources (Equation 6.14): (1) crew travel across units; and (2) variations in construction methods and materials quantified through the LCA presented in Part I. The environmental impacts associated with crew travel are calculated as the product of total crew travelling time (TT) and the carbon emission rate per travelling unit ($\acute{c}$, e.g., per hr). Although an alternative approach could calculate emissions based on travel distances, the time-based method was adopted to simplify data requirements and reduce the burden on users. The distance-based formulation would additionally require users to input a distance matrix between units in parallel with the travel time matrix already used for scheduling optimization. The second component of the environmental impact calculations reflects the emissions attributable to the completion of each task j completed at unit i using construction mode o , where each mode represents a construction method (cast in place vs. precast concrete element), material choices (reinforced concrete vs. mass timber), or resource strategies (recycled vs. raw materials).

$$TE_{Env} = TT * \acute{c} + \sum_i^m \sum_j^n \sum_o^{mc} Env_{jio} \quad \text{Equation 6.14}$$

Where, TT represents the total travelling time for all crews, $\acute{c}$ represents the carbon emissions per travelling unit, and Env_{jio} represents the carbon emissions for executing activity j at unit i using mode o

6.3.5 Model implementation and validation

Similar to Module II, Module III was coded in the CPLEX CP Optimizer and ILOG OPL language. It was executed on a personal laptop equipped with an Intel Core i7-12700H CPU, 16 GB RAM, and running Windows 11 (64-bit) operating system. All computational experiments were conducted using IBM ILOG CPLEX Optimization Studio (version 22.1.1), with a time limit of five minutes. The following sub-sections aim to demonstrate the capability of the proposed model (Module III) to optimize the scheduling of repetitive projects in different construction scenarios through two case studies.

Time-Cost Trade off Case Study

The first case study assessing the Module III was originally introduced by Hegazy and Kamarah (2022), then reused by Cao et al. (2025) to renovate seven classrooms at seven different schools. The project consists of 10 activities, each with three optional execution modes, as shown in Table 6.3. The sizes of the renovated rooms vary from one school (unit) to another. Table 6.4 indicates that typical units consumed 100% of the activity cost (per day) and duration (in days), whereas non-identical units had a percentage (less or more than 100%) for their costs and durations. Using data provided in Table 6.3 and Table 6.4, activity durations and costs at project units are calculated where durations are rounded up to have only integer values. Additionally, the project has a total of 30 crews, with a maximum of three assigned to each activity.

Table 6.3 Case study activities and methods of construction (retrieved from Cao et al. (2025))

Activity	Prede- cessors	Description	Mode 1		Mode 2		Mode 3		No. of crews
			Cost ¹	Dur. ² (day)	Cost	Dur. (day)	Cost	Dur. (day)	
A	—	Demolition	3,750	4	5,667	3	10,000	2	3
B	A	Metal stud	3,000	5	4,500	4	7,667	3	3
C	B	Mechanical roughing	4,286	7	5,833	6	8,400	5	3
D	B	Electrical roughing	4,000	5	5,750	4	9,000	3	3
E	C, D	Boarding and taping	3,571	7	5,600	6	7,000	5	3
F	E	Flooring	3,000	5	4,500	4	7,667	3	3
G	F	Millwork	12,500	3	18,333	2	31,000	2	3
H	G	Mechanical finishes	21,429	7	26,667	6	35,000	5	3
I	G	Electrical finishes	16,667	6	22,999	5	32,500	4	3
J	H, I	Painting	3,750	4	6,000	3	11,000	2	3

¹ Cost per day² Durations in days

Table 6.4 Site size factors for the case study (retrieved from Hegazy and Kamarah (2022))

Activity	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7
A. Demolition	1.00	0.75	1.25	1.00	0.50	0.85	0.75
B. Metal stud	1.00	1.25	1.50	1.00	0.75	1.10	0.50
C. Mechanical roughing	1.00	0.75	1.25	1.00	0.80	0.70	1.25
D. Electrical roughing	1.00	0.75	1.20	1.00	1.00	0.50	1.00
E. Boarding and taping	1.00	1.25	1.50	1.00	0.75	1.10	0.50
F. Flooring	1.00	1.00	1.25	1.00	0.00	1.25	1.00
G. Millwork	1.00	0.50	1.00	1.00	0.75	0.50	1.25
H. Mechanical finishes	1.00	0.75	0.75	1.00	0.80	0.70	1.25
I. Electrical finishes	1.00	0.75	0.75	1.00	1.00	0.50	1.00
J. Painting	1.00	0.75	0.50	1.00	0.85	1.25	0.50

Because the seven schools are situated in different locations, it is important to account for the time and cost associated with moving crews between units. However, as the referenced papers did not report a detailed traveling time matrix, this experiment assumes a uniform travel time of one day between any two units, with an associated cost of \$1,000 per crew transfer. The estimated indirect cost for this project is \$5,000 per day, with liquidated damages of \$10,000 per day. Additionally, an incentive of \$2,000 per day for early completion is also included. The contractual deadline for the project is 75 days. The construction scenario was originally multimode, multicrew, and single-skilled, and considered soft logic.

With the objective of minimizing the project total cost (PTC), Hegazy and Kamarah (2022) reported an optimized project duration of 74 days, slightly below the 75-day project deadline, and a total cost of \$3,799,306. More recently, Cao et al. (2025) applied their framework to the same case study and achieved a reduced project duration of 57 days with a total cost of \$3,168,663.20. In comparison, the proposed model (Module III) produced an optimized schedule with the same accelerated duration of 57 days while further lowering the total cost to \$3,016,300. This result represents an approximate 5% cost reduction relative to Cao et al.'s (2025) results and nearly 21% savings compared to Hegazy and Kamarah (2022), alongside a 23% shorter schedule relative to the earlier study. The optimized schedule produced by the proposed model (Module III) under the original construction scenario is shown in Figure 6.4.

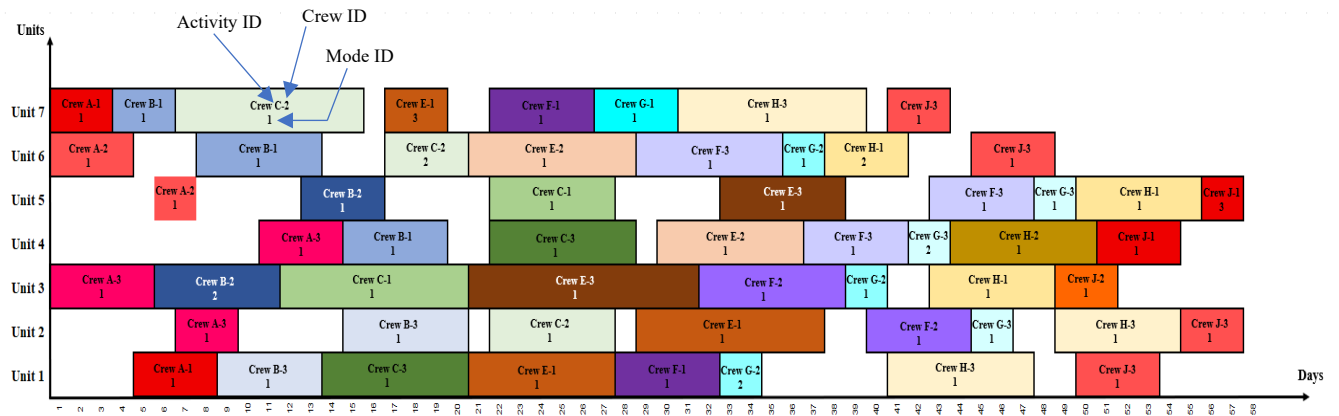


Figure 6.4 The proposed model's optimized schedule

In another experiment, the objective function was set to minimize the project duration (PD). The resulting schedule showed a reduced duration of 38-days project duration compared to 57 in the baseline scenario. As expected, this acceleration was associated with a higher total cost, with the new project cost increasing to \$3,659,880 compared to \$3,016,300 previously.

Next, the objective function was set to optimize the project total cost (PTC) and the project duration (PD) simultaneously using Equation 5.20 (minimize staticLex (PTC, PD)). Initially, under a 5-minute processing time constraint, the resulting schedule was similar to the baseline schedule generated in Module III's first experiment. However, after extending the processing time to 15 minutes, the model produced a schedule with a total duration of 55 days and a slightly reduced cost of \$3,009,000.

Time-Cost-Environmental Trade off Case Study

Due to the lack of previous studies that incorporate environmental impacts into the multi-mode resource constraints scheduling models, a hypothetical case study is used as a second case study, based on the seven schools case introduced by Hegazy and Kamarah (2022). The project data shown in Table 6.3 and Table 6.4 were used as the basis for the analysis. To estimate the carbon emissions associated with each activity across the different units (schools), the data were processed using an AI generative tool (ChatGPT), which generated approximate carbon emissions values informed by published LCA references. The resulting estimates are summarized in Table 6.5. These carbon emissions, along with the other project parameters, were then input into Module III to demonstrate and evaluate the proposed model's multi-objective optimization capabilities, including minimizing both project cost and environmental impacts. Additionally, the carbon emission rate per travelling unit ($\dot{c}$) is assumed 35 kg CO₂eq per day.

Table 6.5 Second case study activities, durations, costs, and environmental impacts for three methods of construction

Activity	Mode 1			Mode 2			Mode 3		
	Cost	Dur. (day)	Emissions	Cost	Dur. (day)	Emissions	Cost	Dur. (day)	Emissions
A. Demolition	3,750	4	1,600	5,667	3	1,200	10,000	2	800
B. Metal stud	3,000	5	1,500	4,500	4	1,200	7,667	3	900
C. Mechanical roughing	4,286	7	3,500	5,833	6	3,000	8,400	5	2,500
D. Electrical roughing	4,000	5	2,000	5,750	4	1,600	9,000	3	1,200
E. Boarding and taping	3,571	7	1,750	5,600	6	1,500	7,000	5	1,250
F. Flooring	3,000	5	1,000	4,500	4	800	7,667	3	600
G. Millwork	12,500	3	1,050	18,333	2	700	31,000	2	700
H. Mechanical finishes	21,429	7	3,500	26,667	6	3,000	35,000	5	2,500
I. Electrical finishes	16,667	6	2,400	22,999	5	2,000	32,500	4	1,600
J. Painting	3,750	4	600	6,000	3	450	11,000	2	300

In a series of experiments, different objective functions were optimized to evaluate and compare the resulting project schedules in terms of duration, cost, and environmental impacts.

Table 6.6 summarizes the main results of these experiments.

Table 6.6 Optimization results under different objective functions

Objective Function	Project Duration	Total Cost	Envir. Impacts
Project total cost (PTC)	52	3,222,700	1.934×10^5
Project duration (PD)	39	3,802,600	92,252
Total environmental impacts (TEnv)	53	4,169,000	81,116
PTC and TEnv	52	3,222,700	1.1977×10^5
PD and TEnv	39	3,974,700	81,116

These results highlight important trade-offs among the objectives. When the model prioritized minimizing total cost (PTC), the project achieved a relatively moderate duration of 52 days and the highest environmental emissions. Conversely, optimizing for project duration (PD) alone led to a significantly shorter 39-day schedule, but at a markedly increased total cost of approximately \$3.8 million. Interestingly, when the optimization targeted total environmental impacts (TEnv), the project duration increased to 53 days, the longest among all scenarios, while

the emissions were reduced to their lowest level of 81,116 kg CO₂eq. Combining objectives, such as optimizing both PTC and TEnv, resulted in a balanced solution: the duration remained similar to the cost-minimization scenario (52 days), the cost was controlled at \$3.22 million, and emissions were reduced compared to optimizing cost alone. Finally, the dual-objective optimization of PD and TEnv yielded the same low emissions but maintained the fastest schedule of 39 days, though at the highest cost of nearly \$4 million.

Additionally, it is essential to highlight the processing time and CPU usage for the model in these cases. The model was solved using IBM ILOG CP Optimizer with a 300 s time limit. As shown in Figure 6.5, within this limit, the solver explored ~31.4 million branches (~104,600 branches/sec), identifying 21 feasible solutions. The best solution achieved an objective of 39; 81,116 with an optimality gap of 12.82%. Memory usage was modest (~112 MB), and nearly all runtime was spent in the search engine (299.95 s vs 0.08 s extraction). This indicates that the formulation is computationally efficient in terms of memory but requires significant branching effort to approach optimality, which is expected given the combinatorial complexity of repetitive scheduling.

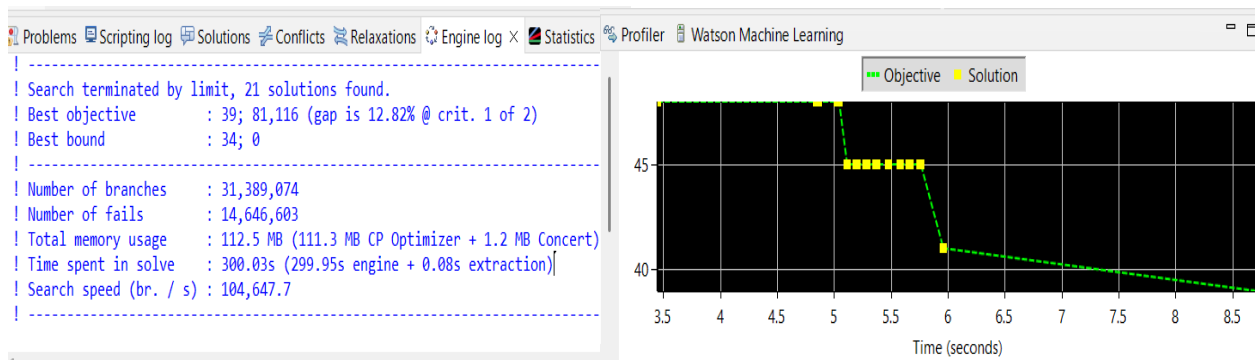


Figure 6.5 The proposed model's processing time and CPU usage

Overall, these experiments illustrate the capability of the proposed model to flexibly balance economic and environmental objectives. They also underscore that prioritizing shorter project durations often increases both costs and emissions, while targeting environmental

sustainability alone can extend project timelines. Such insights can inform decision-makers in selecting the most appropriate scheduling strategy based on project priorities and stakeholder preferences.

This chapter introduced an integrated framework that combines environmental impact assessment, life cycle analysis, and multi-mode repetitive scheduling optimization into a cohesive decision-support tool for construction projects. By extending the previous single-mode scheduling model (Module II), the proposed formulation in Module III enables each activity to be executed with alternative methods and materials that carry distinct time, cost, and carbon emission profiles. Through two case studies, the proposed model (Module III) demonstrated its ability to generate optimized schedules that balance project duration, cost, and environmental performance. The results show that, compared to prior studies that relied on long computational times (e.g., up to 60 minutes) or large solution populations, the proposed model achieved comparable or superior solutions in a fraction of the time (as little as 5 minutes). Additionally, the incorporation of carbon emissions as an explicit objective offers a novel contribution to the field of construction scheduling, which may assist in bringing environmental sustainability to the construction sector.

Chapter 7

Schedule Simulation and Visualization

7.1 Introduction

To support efficient allocation of crews to repetitive projects and particularly SRPs, this chapter introduces an Agent Based Simulation Model (ABSM) using the AnyLogic software to simulate multi-crew allocation to scattered units, incorporating crews' travel times among the units using impeded GIS feature. This chapter discusses the model and its implementation on a case study of scattered linear projects where the activities in each location are sequential. The proposed ABSM was validated against a powerful schedule optimization model, proving its flexibility and applicability.

7.2 Agent-Based Simulation Model

The proposed model has been developed using AnyLogic Software, a Java-based platform, where agent-based models can be created and analyzed through full simulations. AnyLogic has powerful features including a built-in GIS system to enable spatial characteristics to be included in the model. As such, it has great potential for modeling high level of complexity in scheduling and resource allocation for repetitive projects.

Within this proposed ABSM model, two distinct agent types, Unit agents and Crew agents, interact within the GIS environment. Unit agents emulate project units dispersed across various geographical sites, while Crew agents replicate mobile crews traversing these sites to fulfill designated tasks at each unit. Developing the ABSM model involved four main processes: (1) identifying repetitive unit data and accordingly creating agents at their dispersed locations. These Unit agents encapsulate essential attributes such as addresses, assigned tasks, and duration for the crews to complete each task; (2) soliciting detailed information about the working resources

(crews, represented by agents) such as: dispatch location (start point, e.g., head office), available number of crews for each task and the travel speed limitation (if any) for each one; (3) using AnyLogic's computational and visual simulation to schedule the movement of crew agents among the location agents, following all the constraints described in the previous first and second processes; and (4) calculating the actual total duration for the whole project, allowing the user to verify if the current scenario satisfies the project objectives (e.g., project deadline, budget, crews' performance, etc.), and carrying out additional what-if scenarios. These processes are explained further in the following sub-section, followed by the implementation and validation on a case study.

7.2.1 Model description

In ABSM models, diagrams, referred to as state charts, are often used to describe the different stages (states) that agents go through while performing their roles. Furthermore, state charts are used to construct agents and govern their roles as well as their communication mechanisms. The overall behavior of ABSM is generated from the interaction of its agents' state charts. The state chart of the repetitive units, presented in Figure 7.1a, outlines the unit's states and interactions with other agents (crews) and the environment (spatial surroundings). Each unit undergoes one of three states for each task (e.g., activity): (1) Idle state: the unit remains in this state, awaiting the designated crew's arrival and the commencement of work; (2) Build state: upon the arrival of the available crew, the unit changes from Idle to Build state; and (3) Finished state: after the crew completes their assigned task for a set period of time (activity duration), it leaves the current unit and proceeds to the next unit on their list. After the completion of each task, the unit sends a message to the next crew (next activity on schedule) indicating that it is ready for the next crew to begin work, thereby maintaining precedence relationships among various tasks in each unit. Each

unit's data is displayed as shown in Figure 7.1b while Figure 7.1c displays exactly which crew is currently working in each unit at any time of the schedule.

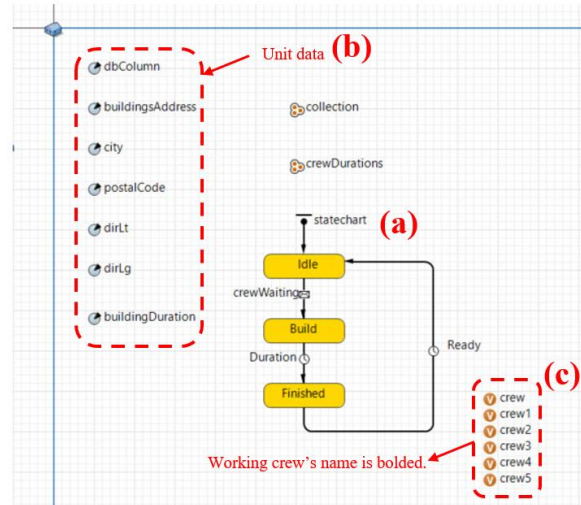


Figure 7.1 Unit agent's state chart

Figure 7.2a depicts the state chart of the crew agents which governs the crew agent's behavior, beginning with the crew at the start point, ready to commence work. The crew then checks their Request Queue for any outstanding work requests (tasks, e.g., activities). If a request is found, the crew proceeds to the first unit on their list to fulfill the request, with the First-Come-First-Served scheduling technique proposed by Hegazy et al., (2021; 2022). Upon arrival at a unit, the crew sends a message to the building agent indicating the start time of the planned work. Following the completion of the assigned work package, the crew checks their request queue for the next destination (building unit). However, if there are no further work requests, the crew returns to the starting point, where they remain idle until additional requests are received. The population parameter, displayed in Figure 7.2b, denotes the number of available crews of this particular agent type (e.g., 2 painting crews). Additionally, the "building unit" variable, as shown in Figure 7.2c, is employed to indicate the specific building where the crew is currently working at any given point during the construction process. This feature enables planners to track any deficiencies in the

proposed schedule, ultimately leading to the development of an optimal schedule. Finally, Figure 7.2d displays the parameters that the model uses to track, store, and later display the simulated-actual endeavors of each crew through the project lifespan.

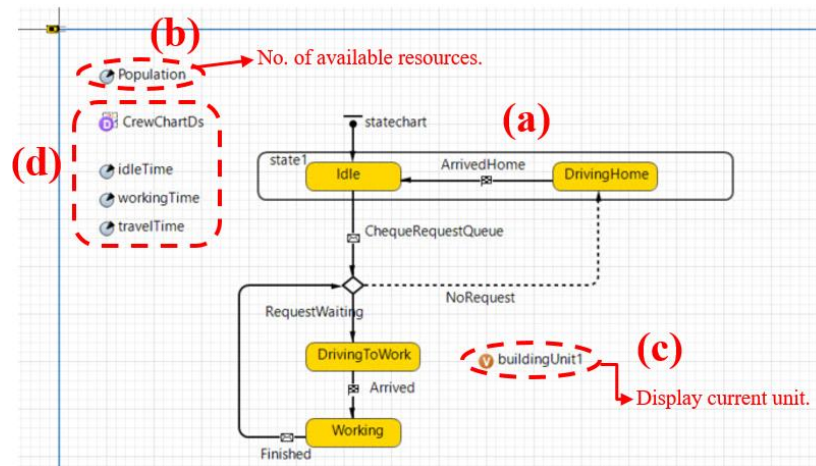


Figure 7.2 Crew agent's state chart

Then, as shown in Figure 7.3, the environment where the unit and crew agents are going to interact with each other is set up using the built-in GIS system. This feature provides a near-live simulation of the surroundings of the units and their spatial and temporal characteristics.

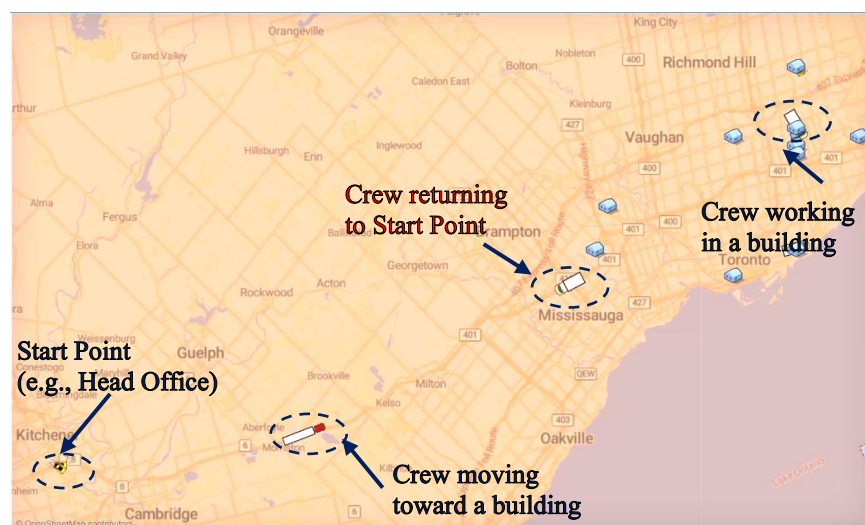


Figure 7.3 GIS map with crew agents moving across the units

The proposed model produces three types of outputs to give the stakeholders an in-depth understanding of the schedules and their attributes (e.g., Idle-time, Travel-time). Firstly, a simulation of the movement of crews across the units is displayed on the GIS map. Secondly, a detailed schedule visualization is produced showing the assignments allocated to each crew separately along with the start and finish times of each unit. The developed visualization displays any periods of idle or travelling time for crews over the project duration. Lastly, the model generates a stack-chart (bar chart) to display the time a crew has been Idle, working or travelling across the units, resulting in more in-depth insights into the crew's productivity and working efficiency based on the simulated scenario.

7.2.2 Model implementation

The proposed ABSM takes the outputs from any one of the previous proposed scheduling optimization models (e.g., Module III) and uses them as inputs to the simulation model. An Excel comma-delimited file (.CSV) is used to store the project's data and then be automatically input into the ABSM from the linked file. To demonstrate the flexibility and applicability of the proposed ABSM, it was applied to a theoretical rehabilitation project of scattered schools employing multiple crews. The case study is comprised of 10 nonidentical units that are geographically dispersed across different locations, as presented in Table 7.1 (Saeed et al. 2024b). The project involves six activities (A1- 6) that require different types of crews. These activities include: (A1) Condition Assessment; (A2) Structural Repairs; (A3) Electrical Systems Upgrade; (A4) Plumbing System Repair/Replace; (A5) Interior Refurbishments (e.g., walls painting); and (A6) Energy Efficiency Enhancements (e.g., installing energy-efficient windows and doors). The time required for a crew to complete each task is given in days as shown in Table 7.1. The number and type of available crews are critical variables that play a pivotal role in scheduling SRPs. In the validation

example, one crew is assigned to each task (activity) except for A1 and A3, which have two crews each. All crews start from the predefined starting point (SP) which can be changed, if needed.

Table 7.1 Data of the ten scattered schools of the rehabilitation project (Saeed et al. 2024b)

Units (Buildings)					Activities (Duration, days)					
ID	Address	Postal Code	Lat.	Long.	A1	A2	A3	A4	A5	A6
1	50 Francine Dr., North York	M2H2G6	43.81	-79.4	2	3	0	3	2	3
2	400 Scarborough Rd., Toronto	M4E3M8	43.68	-79.3	3	4	3	4	3	4
3	2621 Midland Ave., Scarborough	M1S1R6	43.79	-79.3	4	5	4	5	4	5
4	29 Lockie Ave., Scarborough	M1S1N3	43.89	-79.3	2	3	2	3	2	3
5	112 Goldhawk Trail, Scarborough	M1V1W5	43.82	-79.3	3	4	3	4	3	4
6	1550 Sandhurst Cir, Toronto	M1V1S6	43.8	-79.3	4	5	4	5	4	5
7	45 Lynmont Rd., Etobicoke	M9V3W9	43.73	-79.6	2	3	2	3	2	3
8	108 Gladstone Ave., Toronto	M6J3L2	43.65	-79.4	3	4	3	4	3	4
9	70 Fawcett Trail, Toronto	M1B3A9	43.81	-79.2	4	5	4	5	4	5
10	6301 Silver Dart Dr, Mississauga	L5P1B2	43.68	-79.62	5	5	5	5	5	5
SP	65 Kirkham Dr, Markham (Starting point for all crews)	L3S 0A9	43.85	-79.25						

As a first step, the ABSM model retrieves the data of the schools, as in Table 7.1, from the CSV file that was linked to the model's database. Then, the information about the working resources such as dispatch location (start point, e.g., head office), available number of crews for each task and the travel speed limitation (if any) for each one are inputted by the user to impose project constraints. All crew agents start from the given starting point (SP) and return back to the same location after they complete their tasks. Figure 7.4 shows AnyLogic's computational and visual simulation of a schedule scenario where the crew agents move among the location agents. Figure 7.4a displays the GIS map with the dynamic visualization of the crews moving across the scattered units and returning back to the starting point after finishing their assigned work packages. Figure 7.4b shows a multi-crew Gantt chart that shows the assignments allocated to each crew separately along with the start and finish times of each unit. Light blue, red and dark blue colours

are used to represent the working, travel, and idle time for each crew respectively. Furthermore, to give more insights into the efficiency of each crew, Figure 7.4c shows the composition of different crew states (Working, Travel, Idle) over the project duration. Values are shown in two formats: relative (in percentage) and absolute (in days). It is important to note that the ABSM model only considers the Idle time a crew may encounter during their work sequence across the units, not the time a crew will wait until the project is finished. Lastly, after the project is finished, the ABSM model displays the total duration of the project in days (66.46 days in this case study).

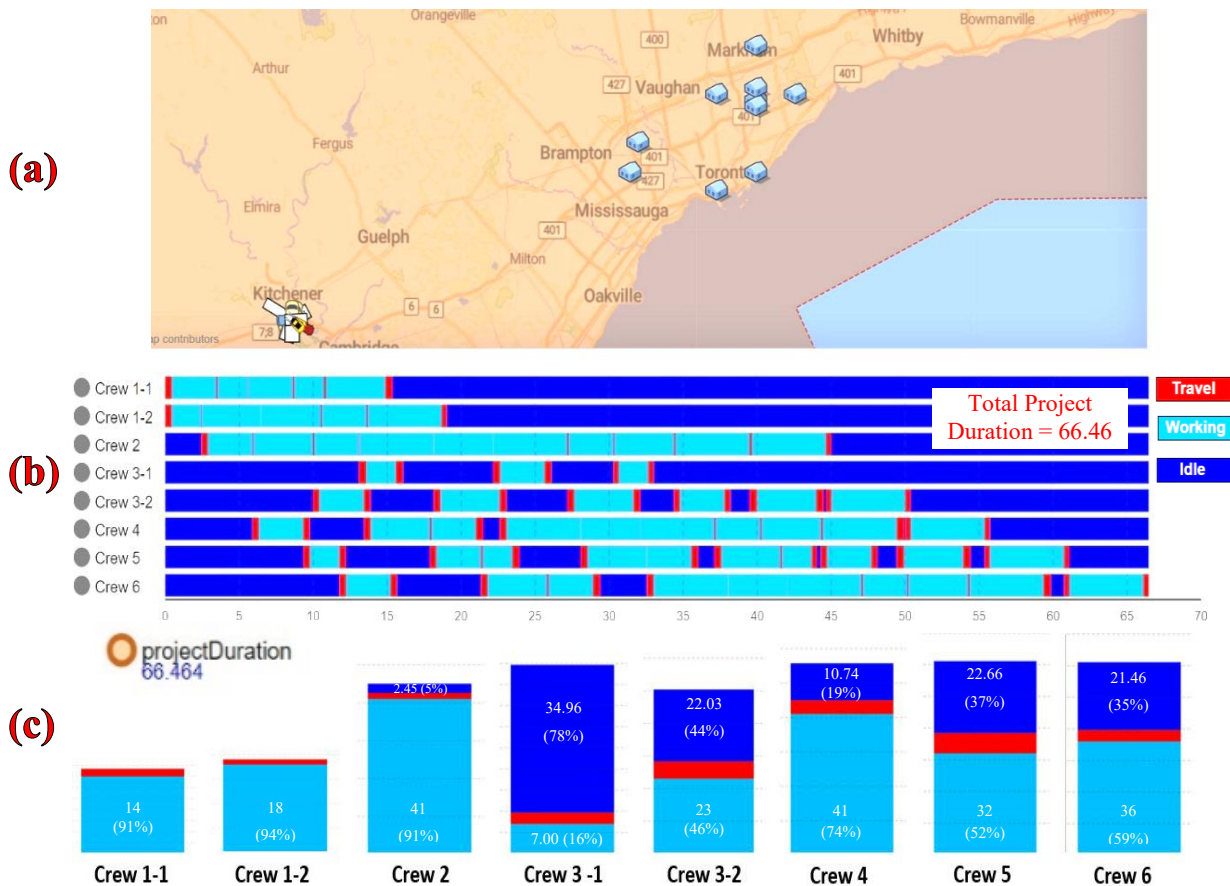


Figure 7.4 The outputs of the proposed ABSM model

7.2.3 Model validation

The schedule produced by the proposed ABSM model was compared against the comprehensive schedule optimization model developed for linear and scattered projects by Ojulari, (2022). To do

the comparison, the data in Table 7.1 was input to Ojulari's model and the resulting schedule is shown in Figure 7.5, with a total duration of 65 days, as compared to the 66.46 days of the AnyLogic model. While the schedule logic is identical, the difference in duration occurs because Ojulari's model does not incorporate crew travel times into its calculations.

Figure 7.5 The outputs of Ojulari, (2022)'s model

Chapter 8

Conclusions and Future Research

8.1 Introduction

This research comes at a critical time for the construction industry, which is facing growing environmental pressures, persistent inefficiencies in project delivery, and an urgent need for innovation in how infrastructure projects are planned and built. Long-standing challenges such as project delays, cost overruns, inefficient resource utilization, and the environmental footprint of large-scale projects have often been accepted as inherent constraints of the industry. However, this work challenges that assumption. It demonstrates that through the integration of advanced optimization models, particularly those tailored to the repetitive and multimodal nature of modern construction, it is possible to address these issues. By coupling efficient scheduling techniques with environmental impact assessment, this research paves the way for a new class of decision-support tools that are not only technically robust but also environmentally responsive. It affirms that change is not only needed but also possible, and that data-driven, sustainability-conscious scheduling can become a viable cornerstone of construction practice. In doing so, this thesis responds directly to the call for rethinking how construction projects are managed in the face of global climate imperatives and industry-wide inefficiencies.

8.2 Research Summary

The diverse and often interchanging objectives inherent in the construction industry require optimization approaches that are both flexible and responsive to project characteristics and the stakeholders' preferences. Civil infrastructure projects are typically large and complex involving construction activities that are repetitive across multiple units. Generally, three types of repetitive projects exist in construction projects: (1) linear projects such as pipelines and highways; (2)

scattered projects such as multiple school or multiple-bridge rehabilitation projects; and (3) vertical projects such as high-rise buildings. While each type has its unique characteristics, linear and scattered projects represent most of civil infrastructure projects, and as such, they have been the focus of this research. These repetitive projects require multiple construction crews to repeat the same activities in their assigned units, ideally with each crew scheduled to work continuously across units with minimum interruption. Maintaining work continuity realizes a large benefit by establishing good work momentum (i.e., learning) and ultimately saving time and cost. In addition to crew-work continuity, an ideal repetitive schedule exhibits other key characteristics such as having proper crew assignments in all tasks; meeting deadlines; having all consecutive tasks progress with minimal gaps; optimal resource use and providing clear schedule visuals showing all crew assignment details. Additionally, sustainable practices need to be promoted through integrating the environmental impacts into the optimization process. With these conflicting objectives, arriving at an optimal and feasible schedule is extremely difficult for large scale projects.

To overcome these challenges, this research first systematically analyzed the unique scheduling requirements of repetitive construction and proposed constraints representation enhancements and an integrated resource management framework. Central to this work is a novel Multi-Travelling Salesman Problem (MTSP)-based optimization model (Module I) that formulates crew routing and sequencing as key decision variables. The scattered scheduling problem, in its core, is focusing on developing a scheduling model for SRPs where unit order is key to an optimized schedule. The proposed model takes this problem and integrates it with the different practical considerations related to the construction industry such as crew specialties (can be thought of as construction trades and/or having access to special equipment) and whether these specialties are required by a particular unit, crew fatigue and learning curve effects due to

undertaking these jobs in succession, varying work volumes and productivity rates, and live traffic data. Furthermore, Module I proved the promising use of MTSP formulation to optimize the schedule of multiple crews among project units. However, because this module works with one activity at a time, it is not fully able to optimize the high complexities involved in the construction industry. To overcome this issue, it was important to utilize advanced optimization engines (e.g., Constraint Programming). Alternatively, Module I, in its current version, could be used as a powerful routing algorithm for specific activities within the project.

Additionally, this research developed a constraint programming (CP) schedule optimization model (Module II) to preserve computational efficiency while maintaining both work continuity and linearity and optimizing multi-objective functions. By integrating multiple objective functions, sequential and non-sequential crew assignment logic, and transition time considerations, the model enables nuanced trade-offs between project duration, crew idle time, and resource utilization. This flexibility allows the model to accommodate various construction strategies, offering practitioners a powerful tool for minimizing project duration and improving crew productivity. Module II has been proven to have sufficient flexibility to generate optimized schedules for both linear and scattered repetitive projects. Moreover, its adoption of CP technique ensures computational efficiency, even when dealing with large and complex projects. The validation of the model through case studies confirmed its effectiveness in achieving shorter project durations and better resource utilization compared to existing methods, including heuristic and metaheuristic approaches. While the model's performance is noteworthy, certain areas required further development. One key limitation was the assumption that each task can be executed only through one construction option. Additionally, the model did not incorporate either monetary (e.g., cost) or environmental considerations (e.g., CO₂ emissions) into the optimization process.

Therefore, this research developed an integrated framework that combines environmental impact assessment, life cycle analysis, and multi-mode repetitive scheduling optimization into a cohesive decision-support tool for construction projects. By extending previous single-mode scheduling model (Module II), the proposed formulation (Module III) enables each activity to be executed with alternative methods and materials that carry distinct time, cost, and emissions profiles. The extended model basically allows two types of extensions: (a) each activity to be executed using one of several alternative modes, each characterized by distinct durations, costs, and environmental impacts; and (b) an additional dimension (variable) in the optimization formulation to determine which mode to use for each activity so that the environmental impact is minimum. Two case studies demonstrated the model's ability to balance complex trade-offs between economic and environmental objectives.

Lastly, this research developed an agent-based simulation model (ABSM) using AnyLogic software to analyze the dynamic processes involved in the repetitive projects and the interactions between multiple crews across several sites. The proposed ABSM is employed to model the individual behaviors of crews and buildings, through their agents, and their interactions with the surroundings, by using the built-in GIS system of Anylogic software. The developed model was able to simulate the main features of repetitive projects including multiple crews, non-identical units, resources and spatial constraints. As well as it was able to generate legible schedule visualizations in multiple formats to easily track the project's progress and improve the resources' efficiency throughout the project. Also, the implementation of the ABSM model on a case study has proven that its ability to provide a flexible and efficient platform for experimenting with various scheduling scenarios.

Overall, this research integrates soft logic, multi-skilled crews, multimode execution, and detailed crew routing in a scalable, adaptable optimization tool capable of generating clear

schedule visualizations, Gantt charts, and GIS-based maps. This research makes three key contributions: (1) designing a flexible repetitive construction scheduling framework that addresses the operational realities of linear and scattered projects; (2) presenting practical methodologies for deploying CP and ABSM in scheduling optimization; and (3) demonstrating significant improvements in project timelines, resource utilization, cost efficiency, and environmental sustainability. By bridging gaps in existing practices, this research provides a robust decision-support platform to enhance the planning and execution of infrastructure projects, ultimately supporting a more efficient, sustainable, and resilient construction industry.

8.3 Expected Contributions

This research advances the schedule optimization research by introducing a MTSP formulation to improve the scheduling of large-scale infrastructure projects. The main contributions of this research can be encapsulated as follows:

- **New Understanding of Repetitive Project Challenges:** Through in-depth literature review, this study identifies critical operational difficulties, including synchronization of crews with varying productivity, inefficiencies of current scheduling systems, which inform recommendations for improved project delivery practices.
- **Improved Representation of Repetitive Project Constraints:** The proposed scheduling modules capture the complexities of repetitive construction projects more accurately, accommodating both linear and scattered project types, non-sequential unit sequences, and varying work quantities across units.
- **Handling of Complex Activity Networks:** The proposed scheduling framework robustly models complex precedence relationships, including all activity relation types and accounts

for activities with multiple predecessors and successors, reflecting real-world construction interdependencies.

- **Adoption of Constraint Programming (CP) Optimization Engine:** The CP-based modules demonstrated faster and more optimal solutions compared to literature case studies. Its fully automated feature represents a step forward in making advanced optimization options more accessible for integration into commercial scheduling systems.
- **Efficient Integration of Environmental Considerations:** By embedding environmental impact quantification and monetization into the optimization framework, this research supports more sustainable construction scheduling decisions that balance cost, duration, and environmental impacts. This introduces new options into the construction with significant benefits for both the construction industry and environment.
- **Bridging Theory and Practice:** Beyond its optimization capabilities during the planning phase, the developed model demonstrates clear applicability during the execution phase of construction. Completed tasks can be set aside and the model can re-optimize the remaining schedule under updated constraints, enabling adaptive responses to real-time conditions.
- **Enhanced Scheduling of Repetitive Projects:** This research improves scheduling accuracy by simultaneously optimizing the execution order of several units using multiple crews while incorporating practical considerations such as crew-specific productivity factors, fatigue rates, learning effects, and travel time between sites.
- **Effective Tools for Public Organizations:** The model provides large public-sector decision-makers, such as municipalities and school boards, with a powerful scheduling tool to improve the delivery of their construction and rehabilitation programs.

Collectively, these contributions advance both theoretical knowledge and practical capabilities in repetitive construction scheduling, enabling more efficient, cost-effective, and sustainable infrastructure project delivery.

8.4 Future Research

Despite the features and benefits this research presents, some limitations and potential improvements also need to be addressed as follows:

- The proposed research framework neglects the effects of uncertainties during project execution on the planned schedule, which may lead to considerable schedule disruptions. Future work can address the uncertainties associated with weather, site conditions, and other factors through probabilistic scheduling optimization.
- Future work could extend the developed model to evaluate and compare circular economy (CE) strategies in construction. The framework can be adapted to test scenarios such as design-for-deconstruction and modular construction, while capturing their effects on project time, cost, and environmental impacts.
- The applicability of the proposed repetitive scheduling algorithms needs to be assessed with real-world megaprojects.
- One key limitation of this research is its static crew assignment approach, which does not account for dynamic adjustments based on changing project conditions.
- Lastly, further research is needed targeting the integration with other engineering software such as BIM for automated calculation of Bill-Of-Quantities and accordingly durations, costs, and environmental impacts of project activities.

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