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NEW MODEL TO MINIMIZE COST AND TIME OF REWORK DUE TO PREFABRICATED CONSTRUCTION ERRORS

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ABSTRACT

The problem of minimizing the cost and time of rework due to fabrication and assembly errors in prefabricated construction considering the spatial relationship between elements was revisited. The time required to remedy the element's error was used as the basis to find optimal crew sizing and scheduling to minimize rework. Using the modeled time, two formulations, namely, a mixed integer linear programming (MILP) and mixed integer quadratically constrained programming (MIQCP) were derived. The latter formulation captured the impact of crew occupied space on the available space for adjacent crews. Furthermore, the impact of uncertainty in the estimated time demand for each zone was incorporated through robust optimization. Finally, a new objective function term was included to balance work demand in each zone to approach takt time scheduling. The formulations were applied on a typical building construction project to correct the locations of reinforced concrete columns with assembly errors. While the formulations provide direct crew sizing and scheduling results, the methodology can benefit from: (i) incorporating flow continuity within zones; (ii) including multiple objectives to capture aspects, such as sustainability; and (iii) estimating the terms of the time demand model from real data.

KEYWORDS

Lean construction, mixed integer programming, crew sizing and scheduling, quality control, location-based scheduling.

INTRODUCTION

Rework on construction projects occurs when the same activities are either redone more than once or changed due to factors, such as quality defects and deviations from project specifications. Cost of rework due to construction defects alone can span 2.75-5% of the contracted cost (Forcada et al., 2017). Each team member is projected to spend an average of 9.6% of their work time on rework (PlanGrids & FMI, 2018). The expenditure can grow even further in projects with higher field rework index (FRI) scores (Rogge et al., 2001). In the US, reports by the construction industry institute (CII) revealed that failure to adhere to quality standards resulted in over \$15 billion in rework expenses per annum (Matthews & Burati, 1989). In 2022, this cost was projected at roughly \$68 billion (Autodesk and FMI, 2022).

One category of rework expenses pertains to the added resources required to remedy poor quality associated with fabrication and installation errors in prefabricated construction (Park & Ock, 2016). The erroneous construction of prefabricated modules–depending on the module's function–can negatively impact various construction related performance indicators, such as

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safety, cost and time (Hyun et al., 2020). In the case of prefabricated concrete bridges, for example, errors during construction have been reported to contribute to 6-17% of collapses (Galvão et al., 2022). Moreover, the quality defects, when left unnoticed–e.g., due to, say, omission errors (Love et al., 2009)–will hinder the fitting of prospective modules/elements, exponentially increasing the overall resources required to remedy the defect.

A typical strategy to mitigate the risk of construction defects involves the adoption of best practices in lean construction, total quality management and quality performance management system (QPMS) to frequently monitor construction progress, detect the discrepancies between design and construction early, and progressively remedy defects through a continual improvement cycle. In line with such efforts, the utilization of digital technologies, such as laser scanners, to frequently collect temporal field data, enables the early detection of discrepancies between the actual and the planned (Golparvar-Fard et al., 2015; R. Maalek et al., 2019). Once a discrepancy is identified, it is imperative to take corrective action so that the negative consequences of rework on the overall project productivity, schedule and cost are minimized.

An example of how laser scanner point clouds can be utilized to estimate and detect construction errors in rectilinear reinforced concrete construction is presented in Figure 1. Figure 1a shows the digital model of the site, acquired through the building information modelling (BIM) process, superimposed onto the planar surfaces of the acquired point cloud. Each colour represents the set of points belonging to the same planar surface. For each BIM element in the model, the corresponding planar point clouds can be automatically assigned through best practices in scan vs. BIM (Bosché, 2010). The resulting assignment can then be used to automatically estimate the construction error by determining the rigid body transformation required to fit the local planar point clouds onto the planar surfaces of the BIM element. This estimated construction error for each BIM element can be visualized through a colourmap to provide further descriptive analytics. Figure 1b shows the result of the automatic comparison of the designed/planned and actual with colours representing the estimated construction errors. Here, the BIM elements, exhibiting errors larger than the acceptable tolerances, say through industry quality standards (Ballast, 2006), must be corrected.

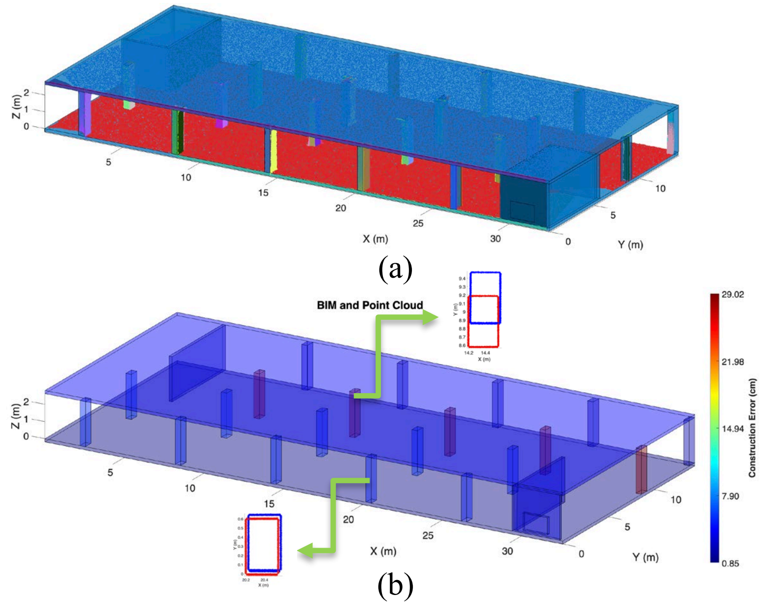

Figure 1: Automatic estimation of construction errors in reinforced concrete construction: (a) planar segments of point cloud registered with the planned 4D model, acquired from BIM; and (b) construction errors colour-coded based on plan vs. actual errors.

The effort and resources required to remedy the construction error for elements with larger estimated errors will be likely higher. In other words, the larger the estimated error, the higher will be the potential rework's cost and time. As such, the results obtained from automatic estimation of construction errors (Figure 1b) can be utilized to predict the time demand and cost associated with remediation work. Other than the associated construction errors, elements may differ in terms of project specific aspects, such as their relative importance, size, and available space to work. For instance, a particular set of columns might have been designed to carry more load compared to another set of columns. Higher accuracy (and likely effort) is, therefore, necessary to correct the construction errors in the more critical set of columns. Other factors, such as size and the space available to work may further impact the amount of rework. As such, the amount of rework (time demand and cost) for each element can be estimated through a set of predictor variables, such as construction error, importance, size, and available working space. Using the estimated scope of rework, an action-plan can be devised to coordinate the sequence of rework activities along with the allocated resources to remedy each element's defects. To this end, this study focused on finding the optimal crew sizing and scheduling to minimize the cost and time of rework due to onsite errors in prefabricated construction.

REVIEW OF CONSTRUCTION SCHEDULING METHODS

Construction scheduling is a crucial phase in project planning, aiming to coordinate and time activities to meet project objectives and satisfy key performance indicators. Several scheduling methods exist, mainly differing in aspects including method to sequence activities, ability to incorporate risks and uncertainties, and strategy to incorporate constraints (e.g., resource limitations, flow continuity, and available workspace). As one of the most established scheduling methods, the critical path method (CPM) is considered the default scheduling technique since the 1950s (Galloway, 2006). This method relies on the creation of a detailed work breakdown structure (WBS) to determine the activities, followed by activity sequencing to establish precedence. Given the activity durations, a graph network is developed through which the project duration as well as the critical activities are determined. In this method, critical activities are those whose total float equals zeros (i.e., activities where a delay or increase in duration directly influences the project's duration). The CPM in its original form does not, however, account for the variation (e.g., to account for risk and uncertainty) in the duration of activities. To achieve this, the program evaluation and review technique (PERT)–based on the principles of the central limit theorem–was introduced to account for the stochastic variability in the project's duration. PERT, however, requires many activities with generally independent and identically distributed (iid) random durations. Furthermore, PERT does not account for the possible changes in the critical path for activities with larger standard deviations. To address these shortcomings, CPM using Monte-Carlo simulation was proposed (van Slyke, 1963). Using this approach, activities will achieve a criticality index (CI), which defines the percentage of times (i.e., simulations) an activity falls on the critical path (Hulett & Nosbisch, 2012). Activities with higher CI values must be given special attention during planning and execution as they are more likely to influence the total project duration.

The CPM-based methods do not directly account for the project-specific resource limitations/constraints. As such, a resource optimization strategy must be employed separately. Examples of these strategies include resource levelling (Wiest, 1964), crashing (Kelley, 1961), and line of balance (LoB) (Al Sarraj, 1990). The goal of resource levelling is to rearrange activities (ideally those with free floats), such that the project-specific resource constraints are met with minimum impact on the project's duration. Crashing involves the reduction of the duration of critical activities–by expending resources, such as adding crews–to reduce the overall project's duration and overhead cost. The early development of the cost-time trade-off formulation in crashing, solved through linear programming, was referred to as the critical-path planning and scheduling (CPPS) technique (Kelley, 1961). LoB focuses on the rearrangement of repetitive activities such that continuity of flow is preserved. LoB was also shown advantageous to support collaboration for projects in progress (Pereira et al., 2022). With some adjustment, the LoB becomes synonymous to the flowline method used for linear scheduling in 1-dimensional (1D) sequential construction such as civil infrastructure projects.

Another set of solutions, consistent with the theory of bottlenecks and theory of constraints (ToC), aim to formulate the scheduling problem as constraints (Pacheco et al., 2021) and strategic buffers (Büchmann-Slorup, 2014). In lean construction literature, common methods include the location-based scheduling (LBS)–space and flow constrained (Kenley & Seppänen, 2009), takt time planning (TTP)–work zone demand constrained (Tommelein & Emdanat, 2022), and tri-constraint method (TCM)–precedence, resource and space constrained (M. Fischer et al., 2018). LBS extends the idea of linear scheduling to incorporate spatial dependencies between activities by subdividing the project into physical zones. Unlike conventional CPM, which primarily models time and logical dependencies, LBS preserves continuity of flow and minimizes trade interruptions through the definition of these zones.

The TTP method extends the LBS by defining criticality in terms of the work demand in each zone. Following the ToC, the progress of construction is constrained by the zone with the highest demand. Optimality is achieved if the work demand in all zones is balanced through the appropriate work supply–e.g., by adjusting the crew size (Seppänen, 2014). One method to help balance the work demand within the zones is the work density method (WDM) (A. Fischer et al., 2024). Using the WDM, it becomes possible to find the optimal zoning that minimizes variation in work density, supporting TTP (Jabbari et al., 2020). TTP was shown to be particularly advantageous in projects where the critical path was dependent on the zones with the highest work demand (Seppänen, 2014); however, if the exact same zones between TTP and LBS are used, the solution might impose gaps in the flow continuity in zones (Seppänen, 2014). Additional constrains can be imposed such that continuity gaps are minimized.

The TCM proposes to model the construction scheduling problem as the solution to a globally constrained iterative event simulation strategy (Hall et al., 2022). The method proposes to consider only three constraints: (i) activity precedence from physics (e.g., stress diagrams) as well as context; (ii) project specific resource limitations (e.g., worker, tool or equipment); and (iii) temporal space availability predicting clashes and preventing the simultaneous task execution. The event simulator generates many possible solutions to satisfy these constraints. These solutions can then be refined within a population-based metaheuristic method, such as Genetic Algorithm, to find the best solution iteratively (Waugh & Froese, 1990).

In the case of the present study, the problem of crew sizing and scheduling to minimize cost and time of rehabilitation work was considered. While event simulation and metaheuristic optimization can be employed, the aim here was to formulate the problem as a globally constrained integer optimization problem, which can be solved deterministically using available integer programming libraries. Further refinements are also proposed to extend the method to balance work demand by incorporating TTP within work zones. Finally, a strategy based on the first order propagation of uncertainty was proposed to incorporate the impact of uncertainty in the estimated duration of each rehabilitation work using robust optimization.

METHODOLOGY

In this section, first, the method of estimating the time demand for rework due to construction error using a set of predictor variables was formulated. This time demand formulation was then utilized to develop the mathematical bases to solve the crew sizing and scheduling for rework. In this study, the time demand, t_j, for rehabilitation work on prefabricated element, j, was considered as a log-linear model of (i) construction error (E_j), estimated through automated laser scanner processing (Figure 1); (ii) importance of element (P_j) and size (s_j), measured on the digital model, obtained from BIM; (iii) available space (A_j), from actual or planned digital site layout model; and (iv) crew size, n_{c_j}, the main decision variable. These predictor variables were used within a power function (i.e., log-linear) to adjust a standard time, t_0, constituting the expected value for a base rehabilitation work through the following formulation:

$$\begin{cases} t_j = \frac{\Gamma_j}{n_{c_j}} t_0 \\ \Gamma_j = \frac{E_j^{\alpha} . P_j^{\gamma} . s_j^{\beta}}{A_j^{\omega}} \end{cases} \tag{1}$$

where Γ_j represents the power relationship between the considered predictor variables (representing a log-linear relationship). The formulation suggests that as the size of the element, amount of error, and importance (e.g., higher precision required for correction) increases, and the available space decreases, the time demand for rehabilitation work increases. It is to mention that the main formulations (derived in the following sections) are independent of the mathematical composition of Γ_j. As such, by incorporating real data, it would be possible–through recent advancements in symbolic regression (Cranmer et al., 2020)–to find the best formula for Γ_j. Furthermore, without loss of generality, t_0 can be set as the standard time quantile (e.g., days/weeks) for the prospective formulations. This is since any standard quantile such as days or weeks can be related to t_0 by incorporating the appropriate coefficient into Γ_j.

In the remaining sections, based on the time demand equation above, first, the mathematical bases for the crew sizing and scheduling problem to minimize the cost and time of rework in the basic form was derived as the solution to a mixed integer linear programming (MILP) formulation. The spatial relationship between different work zones was then included as a quadratic equality constraint, leading to a mixed integer quadratically constraint programming (MIQCP) solution to the problem. Furthermore, a TTP formulation was proposed by adding a linear objective function term to help balance average work demand between zones at each time quantile. Finally, the impact of the uncertainties associated with the formulation of the time demand function was integrated by adopting a typical relaxation strategy in robust optimization.

MILP FOR CREW SIZING AND SCHEDULING

The goal is to find the number of crews required for each element/zone, n_{c_j} ($j = 1 \dots n$), for each time quantile, t_0, to satisfy the time demand requirement, Γ_j, to minimize total cost. The total cost consists of the cost of crews and the cost of overhead. As such, reduction in the number of crew members as well as the overall rehabilitation time will reduce the overall project's cost. The required number of time quantiles, k, depends on the time demand and crew size. The number of quantiles must satisfy $k \le k_{max} = \sum_{j=1}^{n} \lceil \Gamma_j \rceil$, which represents the worst case (i.e., completion time in sequence using only one crew). While this defines an upper bound for the maximum number of quantiles, it is also possible to restrict k by defining a target completion (maximum) date. The latter is particularly beneficial to limit the number of decision variables in the MILP formulation. To account for resource constraints, the number of crews per time quantile can be restricted (i.e., M_{c_i} for $i = 1 \dots k$). Using these assumptions, the problem of crew sizing and scheduling is formulated as follows:

$$\min C_c \sum_{i=1}^{k} \sum_{j=1}^{n} X_{ij} + C_o \sum_{i=1}^{k} Z_i \tag{2}$$

$$s.t.: \left| \begin{array}{lll} (1) & Z_i \le \sum_{j=1}^{n} b_{ij}\,, & \forall i = 1 \dots k \\ (2) & \sum_{j=1}^{n} X_{ij} \le M_{c_i} . Z_i, & \forall i = 1 \dots k \\ (3) & b_{ij} \le X_{ij}, & \forall i = 1 \dots k; \forall j = 1 \dots n \\ (4) & X_{ij} \le M_{c_i} b_{ij}, & \forall i = 1 \dots k; \forall j = 1 \dots n \\ (5) & \lceil \Gamma_j \rceil \le \sum_{i=1}^{k} X_{ij} . \sum_{i=1}^{k} b_{ij} & \forall j = 1 \dots n \end{array} \right.$$

where $i = 1 \dots k$ represents the time quantile indices, $j = 1 \dots n$ represents the element indices, X_{ij} is a $k \times n$ integer matrix with each matrix element representing the number of crews assigned in quantile i to the rehabilitation zone/element j, b_{ij} is the $k \times n$ binary matrix of matrix X_{ij}, Z_i is a vector of size k of binary variables representing the number of occupied time quantiles by any crew on any zone, C_c represents the cost per crew, and C_o represents the overhead cost per time quantile. It is to mention that C_c and C_o could also be defined as variable to account for different types of crews or variation in resources within time quantiles.

Constraints (1) and (2) are designed to restrict the value of Z_i based on the assigned crews in time quantile i. The big-M relaxation of constraint (2) also serves to guarantee that the number of crews assigned to time quantile, i, are less than the resource constraint M_{c_i}. Constraints (3) and (4) are linear relaxations designed to guarantee that b_{ij} equals 1 if $X_{ij} \geq 1$ and zeros everywhere else. The last constraint is presented to satisfy the time demand of each rehabilitation element/zone based on equation (1).

Constraint 5, however, is non-linear and requires either specialized non-linear integer programming software or AI-based metaheuristic optimization strategies. Given the goal of this work was to provide a formulation that can be solved deterministically using existing numerical solvers, such as Gurobi, the following linear relaxation on constraint (5) was imposed:

$$\left|\begin{array}{lll} \text{Define} & Y_{il_j} = X_{ij}.b_{lj}^T, & \forall i,l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.1) & Y_{il_j} \leq X_{ij}, & \forall i,l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.2) & Y_{il_j} \leq M_j.b_{lj}, & \forall i,l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.3) & b_{lj} \leq Y_{il_j}, & \forall i,l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.4) & X_{ij} - M_j.(1 - b_{lj}) \leq Y_{il_j} & \forall i,l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.5) & \lceil \Gamma_j \rceil \leq \sum_{i=1}^{k} \sum_{l=1}^{k} Y_{il_j} & \forall j = 1 \dots n \end{array}\right. \qquad (3)$$

It is to mention that the relaxation of equation (3) will add $n \times k^2$ new integer decision variables. As such, restricting k through a target/desired completion time (instead of k_{max}) will considerably improve the computational speed of the numerical solver.

ADDING SPATIAL CONSTRAINTS

A binary adjacency matrix, $Q_{n\times n}$, is introduced to restrict the spatial proximity of zones for every time quantile, i. The diagonal elements of $Q_{n\times n}$ are all zeros. Q_{jv} is equal to 1 if element j and v $(j, v = 1 \dots n)$ can be occupied at the same time. This can be accomplished by introducing a distance matrix and setting the matrix entries of elements whose distances is smaller than a minimum distance to zero. Using this matrix, the following quadratic constraint was formulated to guarantee only elements/zones whose off-diagonal $Q_{n\times n}$ matrix entries are equal to 1 are selected:

$$\left| (6) \quad \sum_{j=1}^{n} \sum_{v=1}^{n} b_{ij}.(Q_{jv} - 1).b_{iv} + \sum_{j=1}^{n} b_{ij} = 0, \quad \forall i = 1 \dots k \right. \qquad (4)$$

TTP FORMULATION

Takt can be accomplished by enforcing to finish all elements at the same time. The hard constraint is, however, generally challenging to guarantee when other factors such as spatial constraints and resource constraints must be met. As such, TTP is formulated by incentivizing solutions that minimize discrepancies between each element/zone distribution of crews, b_{ij}, and the number of occupied time quantiles, Z_i. To this end, a penalty can be imposed for any element/zone whose crews were not working/assigned when at least one other zone/element was occupied. This penalty was introduced in the objective function as follows:

$$\min C_c \sum_{i=1}^{k} \sum_{j=1}^{n} X_{ij} + C_o \sum_{i=1}^{k} Z_i + C_t\left(\sum_{i=1}^{k} \sum_{j=1}^{n} b_{ij} - n \sum_{i=1}^{k} Z_i\right) \qquad (5)$$

ACCOUNTING FOR UNCERTAINTY

The first order propagation of uncertainty for Γ_j was derived below based on the standard deviation of the measured quantities:

$$\sigma_{\Gamma_j}^2 = \left(\frac{\alpha}{E_j}\Gamma_j\right)^2 \sigma_{E_j}^2 + \left(\frac{\gamma}{P_j}\Gamma_j\right)^2 \sigma_{P_j}^2 + \left(\frac{\beta}{s_j}\Gamma_j\right)^2 \sigma_{s_j}^2 + \left(\frac{\omega}{A_j}\Gamma_j\right)^2 \sigma_{A_j}^2 \qquad (6)$$

where $\sigma_{x_j}^2$ represents the variance of the measured quantity x at element/zone j. Assuming a normal distribution, the constraint (5.5) in equation (3) can be adjusted using the hypograph reformulation (Dontchev & Tyrrell Rockafellar, 2009) of the linear constraint and simplified by including an acceptable worst-case estimate for Γ_j (maximum acceptable) using the estimated variances from equation (6):

$$\left|(5.5) \quad \left\lceil \Gamma_j + \psi . \sigma_{\Gamma_j} \right\rceil \leq \sum_{i=1}^{k} \sum_{l=1}^{k} Y_{il_j}, \quad \forall j = 1 \dots n \right. \qquad (7)$$

where ψ represents the desired confidence interval for normal distribution. Here, $\psi = 1.96$ is used to represent 97.5% confidence, allowing 2.5% significance for violation of the constraint.

SOLUTION AND IMPLEMENTATION

The summary of all mathematical formulations is provided in equation (8) below.

$$\min C_c \sum_{i=1}^{k} \sum_{j=1}^{n} X_{ij} + C_o \sum_{i=1}^{k} Z_i + C_t\left(\sum_{i=1}^{k} \sum_{j=1}^{n} b_{ij} - n \sum_{i=1}^{k} Z_i\right) \qquad (8)$$

$$s.t.: \left| \begin{array}{lll} (1) & Z_i \leq \sum_{j=1}^{n} b_{ij}, & \forall i = 1 \dots k \\ (2) & \sum_{j=1}^{n} X_{ij} \leq M_{c_i}.Z_i, & \forall i = 1 \dots k \\ (3) & b_{ij} \leq X_{ij}, & \forall i = 1 \dots k; \forall j = 1 \dots n \\ (4) & X_{ij} \leq M_{c_i} b_{ij}, & \forall i = 1 \dots k; \forall j = 1 \dots n \\ (5.1) & Y_{il_j} \leq X_{ij}, & \forall i, l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.2) & Y_{il_j} \leq M_j . b_{lj}, & \forall i, l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.3) & b_{lj} \leq Y_{il_j}, & \forall i, l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.4) & X_{ij} - M_j.(1 - b_{lj}) \leq Y_{il_j} & \forall i, l = 1 \dots k;\ \forall j = 1 \dots n \\ (5.5) & \left\lceil \Gamma_j + \psi . \sigma_{\Gamma_j} \right\rceil \leq \sum_{i=1}^{k} \sum_{l=1}^{k} Y_{il_j} & \forall j = 1 \dots n \\ (6) & \begin{array}{l} \sum_{j=1}^{n} \sum_{v=1}^{n} b_{ij}.(Q_{jv} - 1).b_{iv} \\ + \sum_{j=1}^{n} b_{ij} = 0 \end{array}, & \forall i = 1 \dots k \end{array} \right.$$

This equation demonstrated four new formulations by (i) deriving the foundational MILP for the crew sizing and scheduling problem; (ii) incorporating the spatial constraints between zones through a new quadratic constraint (constraint #6 shown in green below), converting the problem into a MIQCP; (iii) accounting for the uncertainty in the modeled time demand through hypograph relaxation in robust optimization (constraint #5.5 bellow represented by the addition of the blue term); and (iv) including a linear penalty term to balance work demand within zones to approach TTP (new linear term added to the objective function below shown in red). Both MILP and MIQCP were implemented in MATLAB® and solved using the Gurobi integer programming software (v. 12.0.0) with and without the inclusion of the TTP term in the objective function. The code and data used in this study was made publicly available through the author's GitHub repository (Reza Maalek, 2025). The results for the site shown in Figure 1a, considering the element's automatically estimated construction errors (Figure 1b), available workspace/area, and size were generated and reported.

PRELIMINARY EXPERIMENT RESULTS

Figure 2 shows the results of the zoning and time demand–based on equation (1)–for the elements from Figure 1b. In Figure 2, the red elements are those requiring correction (e.g., errors beyond the acceptable tolerances), and the colours of the zones around the elements represent the time demand. The problem was solved using the four methods derived above: (i) without spatial constraints and without TTP; (ii) with spatial constraints and without TTP; (iii) without spatial constraints and with TTP; and (iv) with spatial constraints and with TTP.

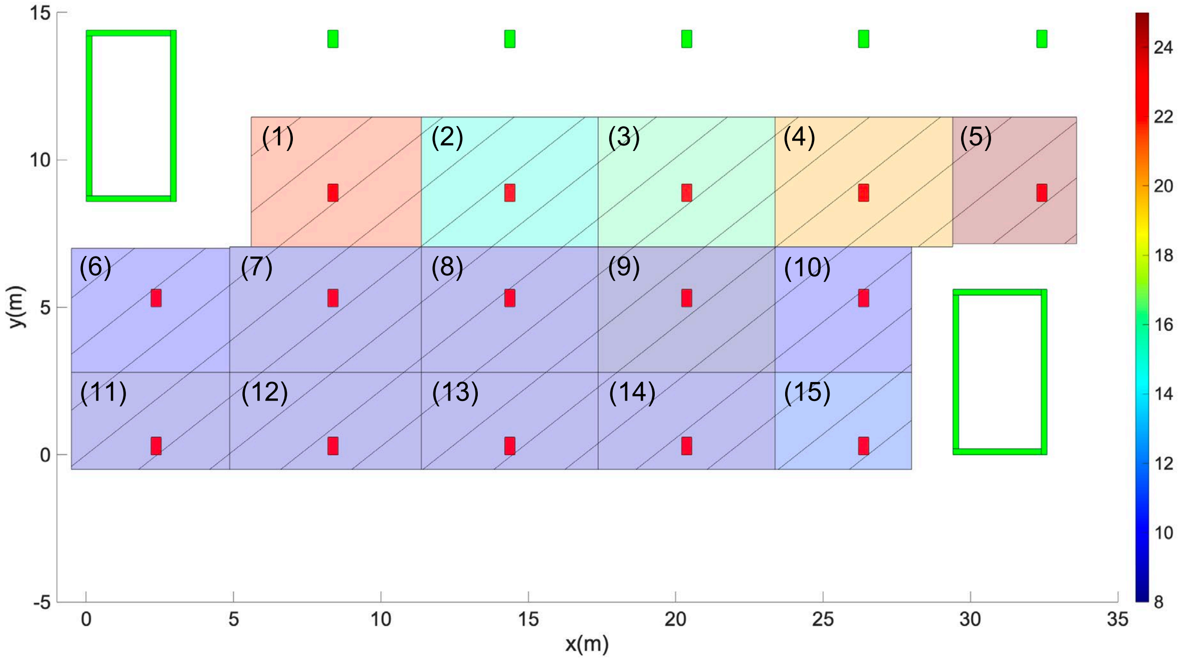

Figure 2: Results of the automatic zoning and time demand estimation using equation (1) for the elements requiring rehabilitation work (e.g., errors above desired tolerances).

In this problem, given that only one type of element was considered for rehabilitation, the cost per crew member, C_c, as well as the maximum allowable crew per time quantile, M_c, were set as constants in each run. The tuning parameters, C_c, C_o, C_t, and k were set to 10, 100, 5, and 10, respectively. The results were reported for all four methods using three different values of M_c equal to 20, 30, and 40 crews (e.g., crew members). The results of the crew sizing and scheduling for a total of 12 combinations were presented in Figure 3. In Figure 3, the colours represent the density of crews for each element/zone corresponding to the respective colourmap. The numbering of the zones was ordered from the top-left to bottom-right elements in Figure 2 to correspond to the ordered matrix columns from left to right in Figure 3.

It was observed that as the allowable number of crews per day, M_c, increased, the duration of the project as well as the overall cost decreased. This pattern was observed for all four formulations. The difference between the four formulations arose in the distribution of crews (e.g., number of crew members) for a given element at a given time quantile. Overall, the TTP formulation without spatial constraints provided the most balanced work density. This was since this formulation–as visually demonstrated–achieved considerably fewer empty zones at different time quantiles of different elements compared to other methods. Despite the utility of the penalty TTP term, when the spatial constraint matrix was considered, the work balance was only slightly improved compared to the methods without TTP. This was expected given the TTP term was included as a penalty within the object function while the spatial constraint was considered as a hard constraint.

Continuity of flow was, however, neither guaranteed nor considered in the proposed methods. In practice, continuity of flow suggests that activities in the same zones proceed uninterrupted between consecutive time quantiles. Maintaining continuous workflow supports: (i) progressive improvement in work efficiency by following the learning curve principle (Hegazy et al., 2025); and (ii) reducing the time lost on setup and transitions, contributing to fewer mobilizations and demobilizations (Olivieri et al., 2018). Given the significance of the continuous workflow, its inclusion within the crew sizing and scheduling solution is beneficial. Future studies must, hence, focus on either incorporating a constraint or a penalty term within equation (8) to reduce violations from continuity of workflow within zones.

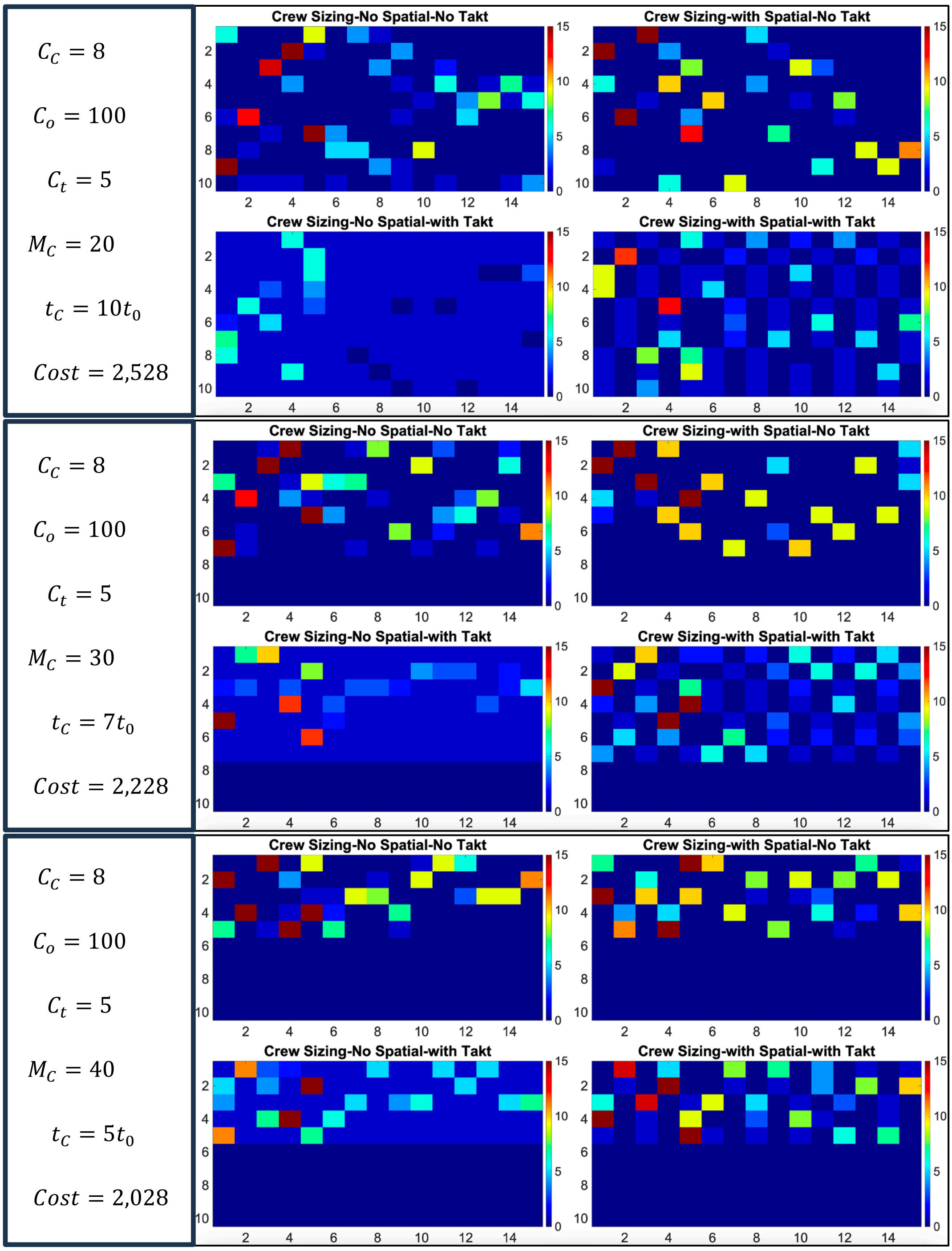

Figure 3: Results of the distribution of crews depending on different allowable number of crews per time quantile.

CONCLUSIONS

This study considered the problem of crew sizing and scheduling to minimize cost and time of rehabilitation work, estimated by comparing the actual to the planned status of projects using point clouds. To this end, four formulations were provided to incorporate spatial constraints and work demand balancing by adopting TTP. The formulations also considered the impact of random measurement errors through the application of hypograph relaxation, used in robust optimization strategies. The solutions considering the spatial constraints were formulated as MIQCP, while others were reduced to MILP. The TTP work balancing was formulated by adding a linear penalty term for violation of average work balance between different elements/zones. The results of all methods were presented for a sample rectilinear concrete structure with visible construction errors.

These four new formulations provide the opportunity to determine crew sizing and scheduling for each rehabilitation work zone to minimize the adverse consequences of rework due to construction errors. While the methods were applied to rehabilitation work on erroneously installed concrete columns, the same formulations can be used to include any type of element as long as the standardized time quantile formulation in equation (1)–without loss of generality-is supposed. Furthermore, the formulae provide flexibility to set different values for the number of crew and cost coefficients. The latter property enables Monte Carlo-based simulations to account for uncertainties and provide stochastic solutions to the crew sizing and scheduling problem. Finally, by adjusting the estimated time demand, the same formulations can be applied to calculate the optimal crew sizing and scheduling for total work.

While the results show potential for future implementation in practice, the following possibilities for further development were identified:

- Flow continuity within zones was not considered. As such, a new formulation, either as a constraint or penalty, must be formulated to balance the results toward flow continuity.
- Other aspects, such as sustainability, were not considered within the objective function. As such, multi-objective optimization can be a possible future development.
- The time demand was modelled as a log-linear function of a set of variables, including, construction error, element priority, element size and available work area. It would be advantageous to incorporate real data in the estimation of the time demand using advanced regression methods, such as symbolic regression.

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