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Construction Management

# Dynamic Optimization for Analyzing Effects of Multiple Resource Failures on Project Schedule Robustness

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**ABSTRACT**

This study develops hybrid modeling and algorithmic frameworks for analyzing the mutual effects of multiple sources of uncertainty on the quality and the robustness of construction schedules. To cope with multiple sources of disruptions, i.e., random resource failures and severe weather conditions, this paper develops a simulation-optimization model that aims to generate delay resistant project schedules. The Variable Neighborhood Search (VNS) is hybridized with an event-driven simulation framework to generate efficient and robust solutions for computationally expensive resource-constrained project scheduling problems (RCPSP). The simulation experiments have been carried out by a flexible modeling framework that can be adopted by project experts to design construction schedules subject to the uncertainty associated with the multiple resource failure. The problem is mathematically formulated as a bi-objective optimization model aiming to minimize the project makespan and maximize a novel surrogate robustness function simultaneously. The computational results of the proposed VNS method have been compared with those obtained from the commercial optimization solvers. The simulation-optimization model's application is demonstrated through a case study of the hydropower plant construction project with multiple renewable and non-renewable resources. Based on an extensive statistical analysis of real-life scenarios, this study contributes to a trade-off analysis of project makespan and robustness in construction projects. The t-test statistical analysis results indicate the significance of the project's average delay reduction by implementing the robust project schedule. The outcomes confirm that the designed framework can generate a more efficient project schedule with a higher rate of protection compared with the existing robust approaches.

## 1. Introduction

Today, one of the most critical sectors of economic growth and development is the construction industry. Reducing the delay in finishing contracts is one of the major contracting companies' key goals to improve customer satisfaction (Memarpour et al., 2019). Recent research trends have focused on designing and implementing advanced technologies, i.e., building information model (BIM), and intelligent solution methods for construction scheduling, assuming incomplete information (Shafieezadeh et al., 2019). However, due to computational complexity and modeling challenges, the assumption of the simultaneous occurrence of several disturbance factors during construction operations is often overlooked by researchers. However, disruption management in the construction industry has become increasingly important due to the need for reinvestment. Based on the dynamic characteristics of the construction industry, project management faces various uncertainties in the planning phase and the implementation phase (Birjandi and Mousavi, 2019). Various sources of uncertainty, e.g., adverse weather conditions, can lead to minor and significant deviation in the project activities' initially planned start time (Ballesteros-Pérez et al., 2018). During the execution phase, an execution plan may be subject to substantial uncertainty, leading to numerous schedule disruptions (Hassannayebi et al., 2016). For example, project tasks can last longer than what is primarily expected, the project may face a budget deficit, resource usage and availability may vary, new precedence relationship or new activities may have to be included,

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etc. (Song et al., 2018).

This research investigates solution methods and algorithmic frameworks for project scheduling problems in situations where different uncertainties coincide. To this aim, robust solution methods for construction scheduling is targeted. The resource-constrained project scheduling problem (RCPSP) is a well-known NP-hard problem with a rich classified literature. RCPSP can be categorized based on the number of activity execution mode (e.g., single-mode vs. multi-mode), the task resuming possibility (e.g., non-preemptive vs. pre-emptive resources), type of resources (e.g., renewable vs. non-renewable resources), etc. Conventionally, RCPSP has been modeled and solved in a deterministic way to minimize the project completion time (Cheng and Tran, 2016).

Nevertheless, various uncertain factors such as unpredictable weather conditions, supplier delays, and resource failure occur, and in these cases, the traditional methods may be ineffective (Zhang and Zhong, 2018). To deal with random uncertainty, Goldratt (1997) suggested Critical Chain Project Management (CC/PM) discipline. CC/PM follows the concepts and framework of the constraint (TOC) theory to mitigate with project delay assuming the resource-activity interrelationships. Despite the practical application of CC/PM, in recent studies, the topic of integrated robust and reactive construction scheduling has appeared as a motivating problem for both researchers and project experts (Ansari et al., 2018). In general, the proactive scheduling approach aims to provide a delay resistance or robust schedule, taking into account the uncertainty's statistical knowledge (Birjandi and Mousavi, 2019). Various robustness measures were proposed that provide appropriate estimates of the schedule robustness. A robust schedule usually attempts to improve the solution stability or robustness metric, i.e., how much the planned start time of project activities are sensitive to schedule disturbances, and quality robustness, i.e., the degree of schedule stability as against the schedule disturbances.

A wide range of definitions for schedule robustness was suggested over the last decades (Zahid et al., 2019). In the basic description, a robust plan refers to the solution that can absorb unexpected events to some extent without rescheduling" (Herroelen and Leus, 2004). Daniels and Kouvelis (1995) defined a robust schedule as a plan with stable performance against the possible random realization of task duration compared with an optimal initial schedule. Zhu et al. (2004) introduced different types of disruptions in projects, including 1) the project network, 2) activities, and 3) resources. This study addressed the impact of the disruptions associated with resource shortage, resource consumption, and activity duration on the project's completion time. The slack time or buffer allocation is the most popular method for improving schedule robustness (Russell et al., 2013). The theory of float maximization has also gained growing attention in robust project scheduling. Recently, Zahid et al. (2019) suggested alternative surrogate criteria based on activity float (e.g., such as the average ratio of float to task duration) for project scheduling under uncertainty.

The most popular approach to robust scheduling is to utilize contingency buffer times (Poshdar et al., 2018). In such an approach, a trade-off between solution quality and quality robustness is needed, i.e. (Liang et al., 2019), since it is unavoidably associated with an expense of a delay (Russell et al., 2013). An alternative approach suggests surrogate functions that provide an approximation for the schedule robustness (Basirati et al., 2019). The robust surrogate functions enable the generation and evaluation of the alternative construction schedules, having the same makespan (Ning et al., 2017). Some well-known robust functions are the average total float proposed by Jorge Leon et al. (1994), and free float suggested by Kim (2003). Ma et al. (2019) proposed a novel weighted robustness index for project schedules. Nevertheless, the robustness metrics' effectiveness is verified using different techniques on different test sets and with different schemes of disruption.

The contribution of this research to fill the research gaps is threefold. First, hybrid modeling and algorithmic frameworks are proposed for analyzing the mutual effects of multiple disruptions on the quality and the robustness of the construction schedules. To cope with multiple sources of uncertainty, i.e., random activity duration, unpredicted unavailability of the resources, random loss of capacity, and severe weather conditions, this paper develops an efficient simulation-optimization method using Variable Neighborhood Search (VNS) meta-heuristic that aims to generate delay resistant project schedules.

Second, a new slack-based surrogate robustness metric is introduced to generate efficient and robust solutions for computationally expensive RCPSP. This study is the first to propose a simulation-optimization method to solve the stochastic RCPSP problem with multiple resources and activity disruptions to the best of our knowledge. The proposed surrogate robustness metric is shown to be adequate for a case study of a hydropower plant construction project as well as standard test instances of PSBLIB library.

Third, the validity of the solution method is verified through comparison with the state-of-the-art OptQuest solver. The impact of the different uncertain environments on the efficiency of the surrogate robustness metric is quantified in terms of delay time and the number of disturbing activities. The performance of the proposed simulation-optimization method is examined through extensive simulation experiments and statistical hypothesis tests.

## 2. Literature Review

The literature of project scheduling under uncertainty includes a variety of techniques and modeling frameworks (Gan and Xu, 2015). In this section, the most relevant papers are reviewed, attempting to identify the concepts of surrogate robustness and discrete-event simulation (DES) approaches to design stable construction schedules. Table 1 reports a taxonomy of the simulation methodologies for construction scheduling. To examine the articles more thoroughly, previous researches have been compared based on their methodology and their robust scheduling

**Table 1.** A Taxonomy of the Simulation Methodologies for Construction Scheduling

| References | Simulation method | Framework and criteria | Approach | Source of disturbances | | |
|---|---|---|---|---|---|---|
| | | | | Activity duration | Cost | Resource availability |
| Zhang and Li (2004) | DES | Project duration | Heuristic algorithm | √ | × | × |
| Lee et al. (2010) | DES | Productivity and performance | Heuristic algorithm | √ | × | × |
| Li et al. (2012) | DES | Average project duration | Heuristic algorithm | √ | × | × |
| Lee et al. (2012) | DES | Project duration | CPM | √ | × | × |
| Said and Haouari, 2015 | Monte-carlo simulation | Project cost | Golden section search procedure | √ | × | × |
| Alzraiee et al., 2015 | Hybrid simulation framework (DES and SD) | Productivity | CPM | √ | × | × |
| Li et al., 2019 | DES | A trade-off between change duration and cost | Genetic algorithm (GA) | √ | × | × |
| Salimi et al., 2018 | DES | time-cost trade-off | GA | √ | √ | × |
| Senouci et al., 2019 | Agent-based simulation | Project duration | - | × | × | × |
| Current study | DES + optimization | Makespan and Robustness | VNS | √ | × | √ |

approach.

## 2.1 Surrogate Measures of Robustness

Current robust scheduling methods mostly use either direct measures that calculate the deviation of the realized start time of the activities from the targeted time or approximation approaches that employ heuristic surrogate metrics (Bruni et al., 2017). Even if perfect information is presumed, the definition of the robustness of a given schedule is challenging. Due to the extensive computational effort needed to evaluate the accurate robustness metrics, a practical approach is to increase the computational efficiency by using a surrogate metric and develop an algorithm optimizing the robustness function (Boroun et al., 2020). Most of the existing research articles suggested the float-based surrogate measures that assess schedule robustness (Fu et al., 2015). Typically, nominal activity durations are used to determine the activity slacks. For example, Al-Fawzan and Haouari (2005) addressed the robust project scheduling problem with float-based robust criteria. They assumed that the total free float times could measure the robustness of a project schedule. Kobylański and Kuchta (2007) criticized the total free float's validity and suggested a revised metric. They pointed out that the total free float could be misleading, and they defined the schedule robustness as, e.g., the minimum of all free float times and a ratio of the minimum of free float over activity duration. Lambrechts et al. (2008) introduced a general form of the activity free float function to generate robust schedules via a Tabu search (TS) algorithm. A similar study was conducted by Chtourou and Haouari (2008). They proposed twelve surrogate metrics and applied a simulation-based framework to solve RCPSP for the minimum project completion time and maximum quality robustness. The advantages of the proposed robustness measures are validated through simulation experiments on the project scheduling problem library known as PSBLIB (available at http://www.om-db.wi.tum.de) benchmark problems. Schatteman et al. (2008) developed a methodology for planning a construction project that integrates risk management concepts and project scheduling methods. The proposed computer-aided framework accounts for the critical risk factors and their effect on the project tasks' duration. Ash and Pittman (2008) developed a heuristic approach to RCPSP enhanced with the Program Evaluation and Review Technique (PERT) method for the project buffer sizing while Hazır et al. (2010) studied the time/cost trade-off problem under uncertain conditions. The problem is formulated as a robust multi-mode project scheduling program. They introduced surrogate measures aimed at providing a precise approximation of the schedule robustness. Khemakhem and Chtourou (2013) studied the single-mode RCPSP and aimed to develop alternative robustness criteria. Likewise, Qi et al. (2014) addressed the multi-mode RCPSP with modified particle swarm optimization to find the solutions that minimize the resource availability cost required to complete all project activities within a project deadline. Chen et al. (2016) presented robust execution action plans for the multi-mode RCPSP under generalized precedence relationships. To solve large-size instances of the problem, an intelligent Bee Colony algorithm was used. The proposed robustness measure is related to the slack of each activity in the associated execution modes. The model was solved by solution-robustness; however, until the difference between the expected and observed start times of the estimated schedule was calculated. Chakrabortty et al. (2016) addressed a multi-mode RCPSP in the case of resource disruptions. Alternative time-index formulations were proposed to cope with resource disruption scenarios in a real-time setting. Given the disruption's imperfect information, a project re-scheduling algorithm was implemented to recover the baseline schedule. To deal with lack of perfect information, Bruni et al. (2017) developed a robust optimization approach to solve large-size instances of the RCPSP under uncertain activity durations. As an alternative approach, Pang et al. (2018) proposed a distributed buffer allocation method for robust project scheduling based on the weighting method. To measure the robustness of the generated schedules, the model takes into account the deviation between the planned starting time and the realized starting time of all the activities. Chand et al. (2019) proposed genetic programming methods to generate robust solutions in the case of resource disruptions. The solution method was based on priority rules and can cope with dynamic resource availability. Burgelman and Vanhoucke (2020) proposed mathematical models and algorithmic frameworks for optimizing the number of execution modes under different disruption scenarios.

To sum up, most of the existing research has focused on robust project schedule design while the multiple disruptions have not taken into account. As reviewed above, few articles addressed the resource disruption in the context of RCPSP. Among these studies, most of the existing research ignored the mutual uncertainty associated with activity duration and resource availability.

### 2.2 Simulation Approaches for Construction Scheduling

As reviewed until now, most of the relevant studies were focused on test instances of the available libraries. This is mainly because of the mathematical models' inefficiency, exact solution methods, and heuristic approaches to deal with real-world projects. In this situation, the simulation-optimization models may give good results and may be very useful in practice (Hassannayebi et al., 2014). Different simulation modeling techniques have also been used in the literature (Gholizad et al., 2017; Hassannayebi et al., 2019). In the following parts, the most significant contributions in simulation models for project scheduling are introduced. Zhang et al. (2002) studied the application of discrete-event simulation (DES) to project scheduling. They proposed an integrated approach to project planning based on the critical path method (CPM). The quality of the generated solutions was improved by utilizing float time and activity scanning capabilities. There exist few research in the area of simulation-optimization for construction scheduling. Zhang and Li (2004) proposed a simulation-optimization approach to resource allocation problems. Lee (2005) proposed a stochastic simulation framework for project scheduling problems. Likewise, Lee et al. (2010) introduced an integrated simulation system for the construction operation and project schedule to analyze the productivity of construction operations and a project schedule's performance. Li et al. (2012) proposed a hybrid heuristic and DES approach to solve the real-world instances of the stochastic RCPSP aimed at minimizing the average project duration. To cope with random uncertainties in construction scheduling, Lee et al. (2012) introduced an advanced stochastic schedule simulation system. It integrated CPM and historical activity duration to compute the best-fit probability distribution functions of historical activity durations. However, despite the practical aspects, the effects of resource constraints have been neglected. Furthermore, a similar approach was used by Lee et al. (2013) in which a risk quantification method is introduced that determines the best-fit probability distribution function of project completion times. The algorithm was coded in MATLAB, and a set of simulation outputs were generated by changing the probability distribution functions. Without considering the effects of multiple disruptions, they analyzed the impact of various distributions of activity durations on the project completion times' distribution. Bruni et al. (2015) provided a summary of models and methods for the resource-constrained project scheduling under uncertainty. They investigated the joint probabilistic constraints within the framework of a stochastic scheduling problem. In the point of view of human resource scheduling, Hu et al. (2018) implemented a DES method for dynamic resource allocation and workforce planning in construction projects. The model considered a time-based approach that outperforms the traditional CPM-based solution method. Andalib et al. (2018) designed a decision model for stochastic analysis of cash flow to estimate the delays in vendors' payments. The estimation model was based on historical data of previous projects. Shi et al. (2020) studied robust project scheduling problem with priority rules and the tabu search algorithm. The proposed resource flow network model to enhance the performance of the robust scheduling method. In the above studies, the modeling framework mainly focuses on simulation experiments. However, hybrid simulation-optimization algorithms are rarely studied. Based on the review of the literature, the following research gaps are found: Simulation-based optimization is an effective method of optimizing robustness in the context of resource disruptions. Moreover, the existing robustness measures usually ignored the effect of the resource capacity and requirement disturbances. The current study aims at contributing by adopting a quantitative discrete-event simulation platform that addresses the stochastic disturbances of both resources and activities.

## 3. Problem Definition and Formulation

This study addresses the stochastic RCPSP under uncertainty conditions. Resource unavailability is one of the most common types of disruption in construction projects that may cause the initial plan's infeasibility. Suppose a set of project tasks of stochastic duration ($d_i$) with known distribution are required to be scheduled, subject to both precedence relationship and resource constraints. It is assumed that the project network is given by a directed graph $G(N, V)$. The set of nodes characterize the activities, and the arcs $(i,j) \in N$ represent the generalized precedence relations between activities with a non-zero time lag. It should be noted that all the precedence relationships can be transformed into a start-to-start (SS) type. In this study, without loss of generality, it is assumed that all the precedence relationships have non-zero lag time $\gamma$. It must be noted that all the SS relationships can be changed into a standardized version. It can be easily shown that the formula of the precedence relationship transformation is summarized as follows (Bianco and Caramia, 2010):

$$\begin{aligned}
&\textit{Finish - to - Start}: FS_{ij}(\gamma) \rightarrow lag_{ij} = d_i + \gamma \\
&\textit{Finish - to - Finish}: FF_{ij}(\gamma) \rightarrow lag_{ij} = d_i - d_j + \gamma \\
&\textit{Start - to - Finish}: SF_{ij}(\gamma) \rightarrow lag_{ij} = \gamma + d_j
\end{aligned}$$

where $lag_{ij}$ denotes the time lag between activity $i$ and $j$.

In this study, a schedule is identified by the set of start times of activities. A solution to stochastic resource-constrained project scheduling problems (SRCPSP) can be defined as an execution plan or scheduling policy that decides on the sequence of project activities. In this study, the optimization model of SRCPSP is formulated as follows:

$$Minimise\ Z_1 = \mathbb{E}[Cmax]\,, \quad (1)$$

$$Minimise\ Z_2 = RM\,, \quad (2)$$

s.t.

$$\sum_{t=ES_i}^{LS_i} \le (t+lag_{ij})x_{it} \le \sum_{t=ES_j}^{LS_j} x_{it}\times t \qquad ;\forall j, \forall i\in P_j\,, \quad (3)$$

$$\sum_{t=ES_i}^{LS_i} x_{it} = 1, \qquad \forall i\,, \quad (4)$$

$$\sum_{t=ES_{n+1}}^{LS_{n+1}} x_{n+1,t}(t+d_{n+1}) \le C_{max}\,, \quad (5)$$

$$\sum_{i\in N}\sum_{t'=max\{t-d_i,ES_i\}}^{min\{t-1,LS_i\}} r_{ikt}x_{it'} \le a_{kt}, \ \forall k, \forall t\,, \quad (6)$$

$$x\in\{0,1\},\ \ i\in N,\ \ t = ES_i,\ldots,LS_i\,. \quad (7)$$

In the above optimization model, Eq. (1) represents the minimization of the expected makespan of schedule *S*, Eq. (2) specifies the maximization of the robustness measure (RM). Eq. (3) define the precedence relationships between activities, that is, the activity *i* cannot be started until all of its predecessors are completed. Eq. (4) ensure that each activity starts exactly at an specific time slot within the earliest and latest start time. Eq. (5) define the makespan of the project. The resource constraint expressed in Eq. (6) indicates that the total amount of the resources allocated at any time slot cannot exceed the maximum resource availability. The domain of the variables is defined in Eq. (7).

In this paper, the quality robustness is of the significant concern that refers to the completion time of the project as the performance measure. Here, a hybrid robustness measure (RM) is proposed that takes into account some information on the resource constraints and the total slack time of the non-critical chains; see Eq. (2). RM is defined based on the resistance of the schedule against resource shortage during the disruption. Since the effect of disruption on the critical chain has already been considered in the makespan objective, the focus of the robust scheduling method is on the possible delay caused by non-critical chains. The objective is to measure the possibility of the delay for each non-critical chain based on the total float and resource criticality index. First, the effect of the resource criticality index on the non-critical chains is described using a weighted factor ($w_c$):

$$w_c = \frac{\max\limits_{t\in T,i\in\{NC_c\},k\in K}\left\{\dfrac{r_{ikt}}{a_{kt}}\right\}}{\sum_{c'\in NC}\max\limits_{t\in T,i\in\{NC_{c'}\},k\in K}\left\{\dfrac{r_{ikt}}{a_{kt}}\right\}},\quad c\in NC\,. \quad (8)$$

The weight factor is a normalized term and thus the equation $0 < w_c \le 1$ holds. In the equation above, *NC* represents the set of non-critical chains. RM is based on the idea that the degree of criticality for each non-critical chain can be measured by the tightness of the resource usage and the total slack (or float). $TS_c$ and $TD_c$ denote total slack and the duration of activities that belong to the of the $c^{th}$ non-critical chain. With this definition, the robustness measure is calculated as follows:

$$RM = \max_{c\in NC}\left\{\frac{1}{w_c}\times\frac{TS_c}{TD_c}\right\}, \quad (9)$$

where $0 \le RM \le 1$. As already mentioned, the definition above of the robustness refers to the quality robustness. To better reflect the combinatorial complexity of the problem, the model size of the optimization problem along with the number of continuous/discrete variables and constraints are counted. Model contains $|N|\times|T|$ number of binary variables, and $|N|^2+|N|+|K|\times|T|$ number of constraints.

## 4. Research Methodology and Framework

The proposed simulation-based optimization method improves the scheduling procedure's robustness, considering the uncertainties associated with the duration of activities, resource requirements, and resource breakdowns. In this study, the simulation platform is designed in ARENA, because of its capability for modeling complex and dynamic processes (Altiok and Melamed, 2010). This software was used in different practical problems, and its successful applications were reported (Vieira, 2004; Cosgrove, 2008; Eskandari et al., 2013). The simulation-based optimization method integrates a DES model and a meta-heuristic algorithm to further improve the obtained solutions' robustness.

In this section, the conceptual model is presented, and the stages of the simulation-based optimization approach are discussed. The scope of this research is limited to proactive robustness, yet the reactive policies are not included. Fig. 1 illustrates the main stages of the proposed simulation-optimization approach from VNS to the robust project scheduling problem. At the first stage, a nominal near-optimal schedule will be generated via optimization methods. In other words, at this stage, the objective is to produce the best schedule through observing the task precedence and resource constraints, while satisfying the minimum project completion time. Accordingly, the objective here is to minimize the completion time of the schedule. The baseline schedule with the minimum completion time is named $B_1$. The minimum completion time of the project will be regarded as the threshold value ($C_{min}$). At the $2^{nd}$ stage, the baseline schedule produced will be evaluated, using the simulation model. The performance measures are defined as the probability of the timely project completion and the criticality of the non-critical chains. At the $2^{nd}$ stage, $B_1$ will be evaluated to measure its robustness against different types of disruptions. In this study, three types of disturbances are simultaneously investigated, including disruptions in resource capacity (e.g., human, machinery, tools, and materials), resource requirements, and activity duration. At the next stage, $B_1$

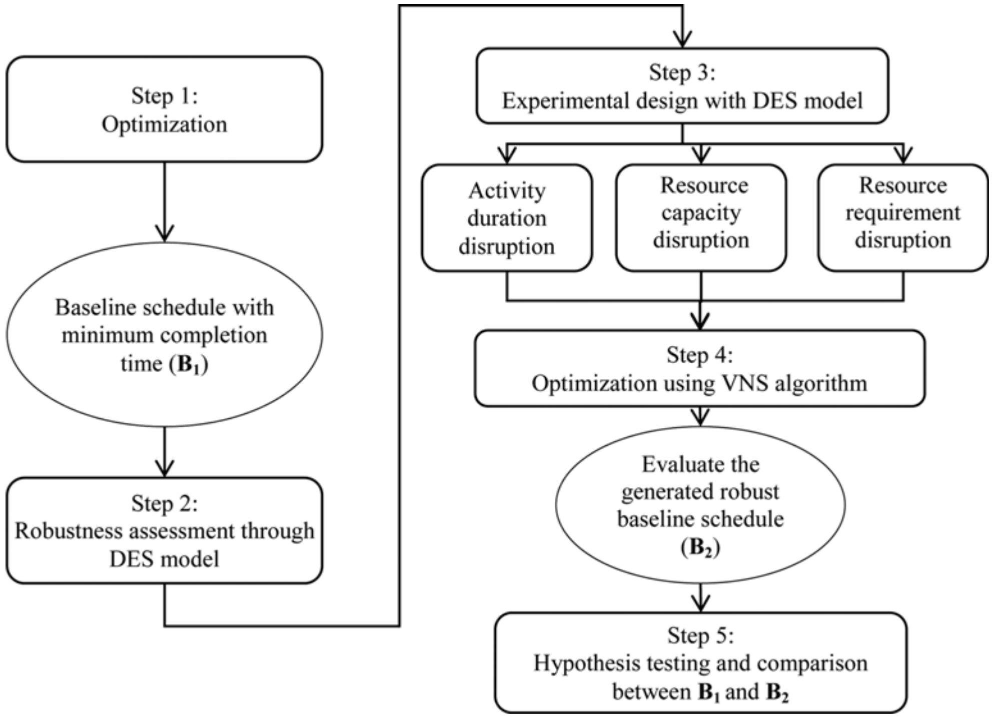



**Fig. 1.** The Conceptual Framework of the Proposed Simulation-Based Robust Project Scheduling

will be reproduced via the simulation-based optimization to improve its robustness. At this stage, the objective function is defined to capture the future uncertainties of resource and project activities. $B_2$ refers to the newly produced robust baseline schedule (output of stage 4). At the 5$^{th}$ stage, the final comparison between the $B_1$ and $B_2$ is made, based on the project completion time's stability. Finally, a sensitivity analysis is made to measure the potential improvement in the schedule robustness by increasing the baseline project ($B_2$).

## 4.1 Variable Neighborhood Search Method for SRCPSP

In this section, the proposed variable neighborhood search algorithm to solve stochastic RCPSP is explained. This is precisely presented to deal with random disturbances and the resource capacity shortage that asks for sophisticated optimization approaches. A neighborhood search (NS) algorithm performs a sequence of local moves in the neighborhood space, e.g., $N(x)$ of an initial solution to improve the expected fitness value until a local optimum ($x'$) is found. The basic functionality of the NS is to avoid trapping in the local optima by altering the neighborhood structure. In this regard, the Variable Neighborhood Search (VNS) is one of the most practical extensions of the NS. The VNS was proposed initially by Mladenović and Hansen (1997), and after that, it has received growing attention regarding theoretical and practical extensions. In method VNS, the systematic change in the neighborhood structure is performed to escape from the local optimum. The notations and their descriptions are defined as follows:

$F(x)$ = The fitness function value
$iter$ = The index of algorithm iteration
$Iter_{max}$ = The maximum algorithm iterations
$l$ = The counter of the neighborhood structures ($l = 1, 2, ..., l_{max}$)
$l_{max}$ = The total number of neighborhood structures
$N_l(x)$ = The set of solutions in the $l^{th}$ neighborhood structures
$x$ = The candidate solution for local search
$x_{best}$ = The best incumbent solution
$x_o$ = The initial solution
$Replication$= The number of simulation replications to evaluate the objective function

## 4.2 Solution Encoding

A solution encoding must be computationally fast in the alteration among solutions. Furthermore, for each potential point in the original solution space, there is a unique solution in the encrypted space, and each encrypted solution corresponds to a single feasible solution in the original solution space. The activity-list representation (ALR) encoding scheme has been recognized as the most widely used solution representation method based on the existing literature. The literature of RCPSP suggested that ALR has performed better than the other solution encoding methods (Debels et al., 2006). Henceforth, in this study, the ALR encoding scheme is used in the proposed VNS. In the ALR encoding scheme, a precedence feasible activity list is supposed, in which each activity is positioned in an array after all of its predecessors. The position of activity in an activity-list defines its priority compared with the other activities.

## 4.3 Neighborhood Structures

In this section, the Neighborhood structures and moves are

**Table 2.** The Pseudo-code of the Proposed Simulation-Based VNS Method for SRCPSP

```
Input (l_max, x_o, Iter_max, Replication)
x := x_o; iter :=1; l := 1;
While iter ≤ Iter_max do /* do while the maximum number of iterations is reached*/
  While l <= l_max do /* do while the maximum number of neighborhood structures not reached*/
   x' := VNS (x , l); /* Search for improved solution using variable neighborhood search */
   F(x') := Evaluate (Replication, x'); /* evaluate the new found solution and estimate the corresponding average fitness value*/
   iter : = iter +1;
   If F(x') < F(x) then
       x_best := x' ; l := 1 ;
     Else
       l := l + 1;
  EndWhile
       l := 1;
EndWhile
Return (x_best) ;
End.
```

explained. As stated previously, a point in the solution space is represented by the valid activity-list, and the neighborhood of this valid list is specified as the set of valid lists that result from moving one activity to a new position. We assume only direct predecessors/successors are taken into account. Thus, a shift move in the neighborhood can be defined such that an activity, e.g., $i$ with position $pos_i$ maybe moved to a new position $pos_i'$ regarding precedence relations. For the problem being dealt with, we define the $N_k$ neighborhood of an order list, e.g., $A$ as the set of ALRs that can be generated starting from $A$ by making $l$ permissible shift moves of $l$ distinctive activities. Consequently, randomly generating an activity-list from neighborhood $N_l$ is performed by a series of $l$ random permitted shift moves of $l$ randomly nominated activities. The pseudo-code of the proposed variable neighborhood search is provided in Table 2. The algorithm starts with a random solution, and then it iteratively changes the properties of an incumbent solution. The process of a move from a fundamental solution to a possibly better one is guided by the evaluation of the fitness function value using simulation experiments.

### 4.4 Benchmark Optimizer

In this article, OptQuest (designed by OptTek System Inc.) commercial package is applied because of its success in intelligent search methods and its capability for finding near-optimal solutions to complex optimization problems containing the elements of uncertainty. It uses a black-box approach to evaluate the results of the simulation. The OptQuest optimization package utilizes intelligent search meta-heuristics, e.g., Scatter Search, Tabu Search, Genetic Algorithm, and Neural Networks to provide a new potential solution, to be later sent to Arena. OptQuest has been far and wide approved in the literature as a state-of-the-art and general-purpose simulation-optimization platform. OptQuest repeats the search process by running multiple simulation experiments. An optimization model in OptQuest for Arena has four primary elements, i.e., control variables, response variables, constraints, and an objective function. Here, the control variables are referred to as the sequence of executing the project tasks. Response variables are defined as deviations, delays, and project completion time. The model constraints include the activity precedence relationships, resource capacity, and project completion deadline. Variables or resource units in the Arena models are called control or decision variables. In our procedure, the operation sequence of project tasks is defined as control variables. Response variables are simulation outcomes, i.e., time performance, resource utilization, and delays. Constraints refer to the relationships among variables of controls and/or responses. In the project scheduling model proposed, the resource constraint ensures that the number of resources allocated to various tasks cannot exceed a specified maximum amount within the study period. In the robustness improvement phase, a constraint will be added to the model. This constraint refers to the project completion deadline. The objective function is an expression consisted of a set of control and response variables for representing the model's objective.

## 5. Computational Results and Discussion

This section provides the simulation experiments and optimization procedure to validate the proposed method of robust project scheduling. As already noted, the robustness improvement is achieved in an optimization framework where the completion time of the project is still constrained. In the next step, the discrete-event simulation method is utilized in the risk analysis of scheduling problems. Likewise, it is used to estimate the actual duration of the project and to analyze the robustness schedule.

### 5.1 Case Study of Hydropower Plant Project

This section provides the stages gone through to implement the proposed framework in this paper. For this purpose, a practical case concerning a mega-project of hydropower plant construction is provided. The project includes 26 major work packages and 12 resource types. The project is defined as an Engineering Procurement Construction (EPC) that comprises three main parts, including consultant service and design, engineering, and civil works. The project area has been located in Iran's Khuzestan Province with installed electricity generating the capability of about 500 MW. According to preliminary estimates, the cost of the project was 128 million £ financed by public investment sources, private bank loans, bonds, and foreign sources. The damage resulting from the project delay includes the excess cost of project completion and loss of profit due to delays in the sale of electricity.

The precedence relationship diagram between project activities is illustrated in Fig. 2. According to the information obtained, the execution of the project started in 2003. The project is scheduled to become operational in early 2016. However, due to disruptions,

**Table 3.** Resource Types in the Real Case Study

| Resource type | Types | Resource code | Maximum availability (units) |
|---|---|---|---|
| Human resources | Workers | R1 | 50 |
| | Technicians | R2 | 25 |
| | Supervisors | R3 | 15 |
| | Engineers | R4 | 20 |
| Machines and tools | Vehicles | R5 | 5 |
| | Concrete pump | R6 | 3 |
| | Truck mixer | R7 | 5 |
| | Compressor | R8 | 2 |
| | Loader (for excavation and embankment) | R9 | 8 |
| | Digger machine | R10 | 2 |
| Materials | Concrete | R11 | 150 |
| | Metal | R12 | 200 |

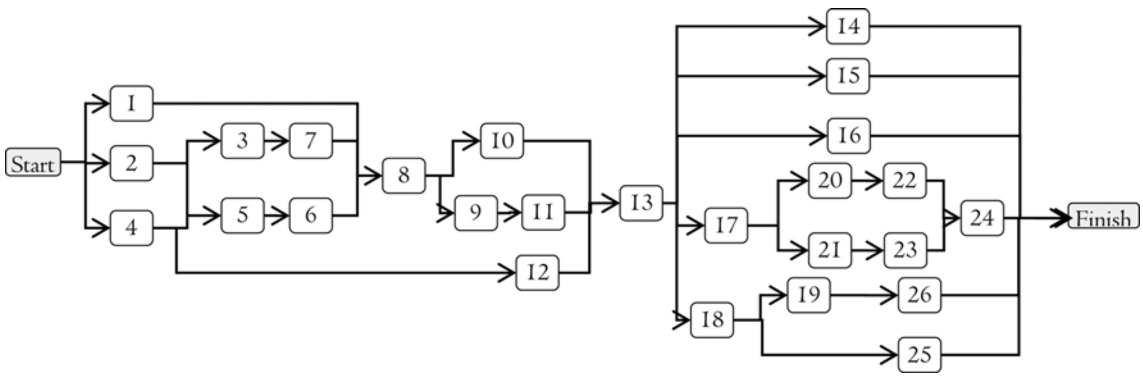



**Fig. 2.** The CPM Graph of the Main Project Activities

the project was delayed. In this project, the main causes of disruption have been identified as the financing problems and the disruptions related to the unforeseen technical changes. The delay in the financing procedure at some point in the project progress of the construction has created a long delay in project completion time. Also, the change in the type of dam from Roller-compacted concrete (RCC) to gravel dam with a clay core, which is the main problem during execution, caused an extra delay. The data associated with disturbances and delays are only qualitative and not appropriate for a thorough comparison. The occurrence time and the effect of disruption on the project performance were not available. It is impossible to compare the actual output with the simulation results in an appropriate setting in this long period. However, the proposed robust scheduling approach is validated by comparing the model results with the baseline schedule's performance under different scenarios of single and multiple disturbances. It should be noted that the case underlying in this study faces different sources of uncertainties, e.g., the adverse effects of climate change, resource absence, and malfunction of the machines and tools. Therefore, the robust baseline schedule has potential advantages; the current study also applied the simulation-based optimization method to produce a stable plan.

Resource availability varies during the planning horizon. These variations are taken into account through the schedule module in ARENA. The availability profiles for human resources ($R_1$, $R_2$, $R_3$, and $R_4$), machines, tools, and materials are depicted in Fig. 3. The renewable resource profile graphs show the daily number of resource units available over time. Likewise, the non-renewable resource profile diagrams illustrate the monthly number of resource units available over time.

It should be noted that the availability profiles presented for human and machine resources are considered repeatedly for 24 hours. Besides, the resources $R_8$ and $R_{10}$ have a fixed capacity during the planning interval.

### 5.1.1 Disruption in Resource Capacity

The resource disruptions usually occur due to a variety of reasons such as instrument failure, machine breakdown, and human resource shortage. As to the current implementation method, the resource disruption occurs when the resource $k$ becomes unavailable for an uncertain duration. When the capacity of a resource is reduced, it cannot be guaranteed that the baseline schedule remains feasible. In this case, the optimization process is required to yield a new workable robust baseline plan. In reality, resource failures could repeatedly happen at different intervals. Hence, the resource breakdowns are introduced using the failure module in ARENA. The probability distributions present the down (mean time to repair) and up times (mean time between failures) for resources. The disruption scenarios regarding

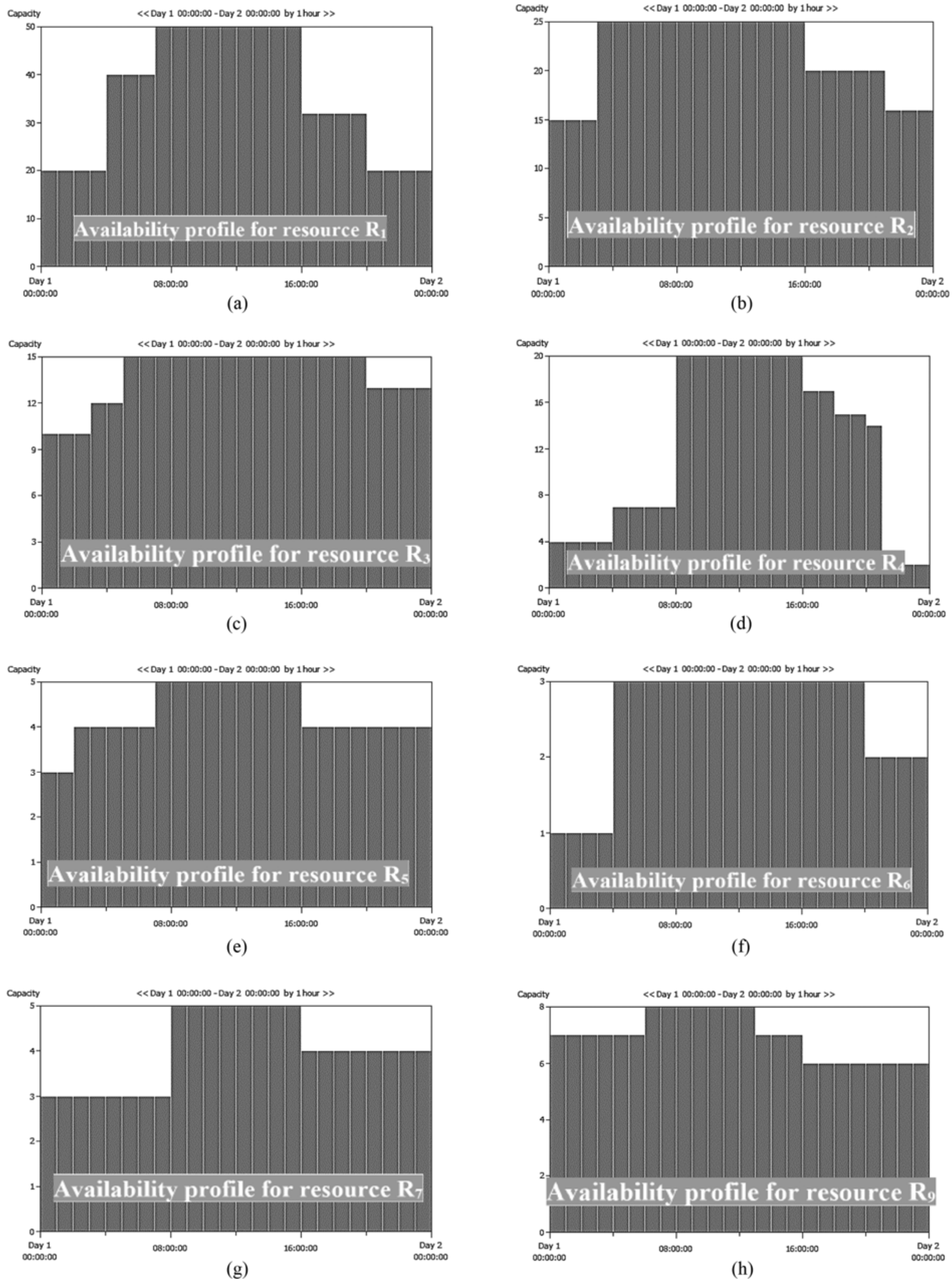
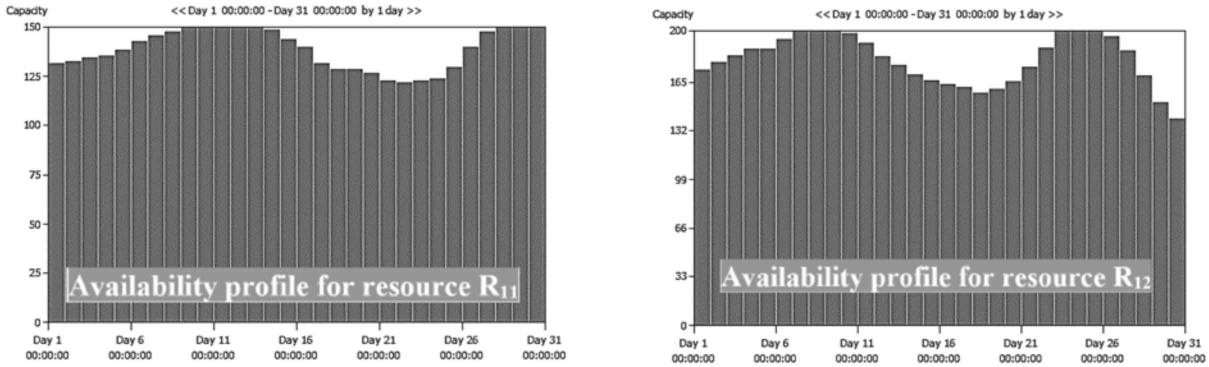



**Fig. 3.** Availability Profiles for Project Resource Units Daily (*a* to *h*) or during One Month (*i* and *j*): (a) Subtitle: Availability profile for resource $R_1$, (b) Subtitle: Availability profile for resource $R_2$, (c) Subtitle: Availability profile for resource $R_3$, (d) Subtitle: Availability profile for resource $R_4$, (e) Subtitle: Availability profile for resource $R_5$, (f) Subtitle: Availability profile for resource $R_6$, (g) Subtitle: Availability profile for resource $R_7$, (h) Subtitle: Availability profile for resource $R_9$




(i) (j)

**Fig. 3.** (continued): (i) Subtitle: Availability profile for resource $R_{11}$, (j) Subtitle: Availability profile for resource $R_{12}$

**Table 4.** The Scenarios of Resource Failure

| Resource code | Uptime (days) | Downtime (days) |
|---|---|---|
| R1 | Normal(45,7) | Normal(2,1) |
| R2 | Normal(90,7) | Normal(3,1) |
| R3 | Normal(90,7) | Normal(3,1) |
| R4 | Normal(30,7) | Normal(2,1) |
| R5 | Exponential(180) | Exponential(7) |
| R6 | Exponential(120) | Exponential(10) |
| R7 | Exponential(150) | Exponential(10) |
| R8 | Exponential(90) | Exponential(3) |
| R9 | Exponential(300) | Exponential(20) |
| R10 | Exponential(150) | Exponential(5) |
| R11 | Uniform(180,360) | Normal(7,1) |
| R12 | Uniform(90,180) | Normal(5,1) |

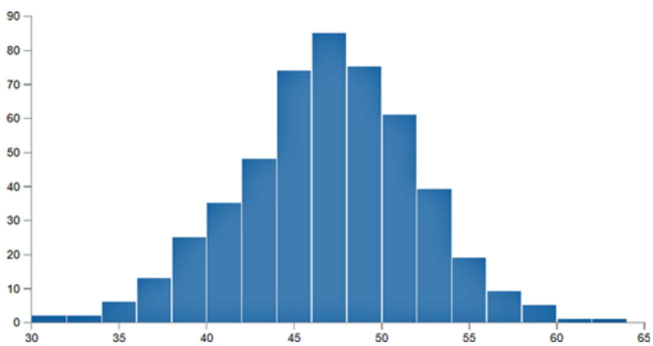


**Fig. 4.** The Histogram of the Resource Up Time ($R_1$)

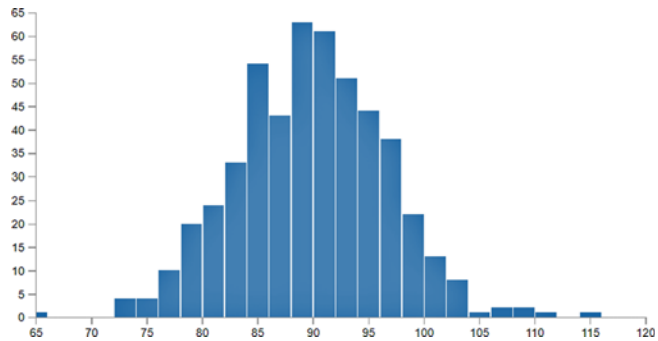


**Fig. 5.** The Histogram of the Resource Up Time ($R_2$)

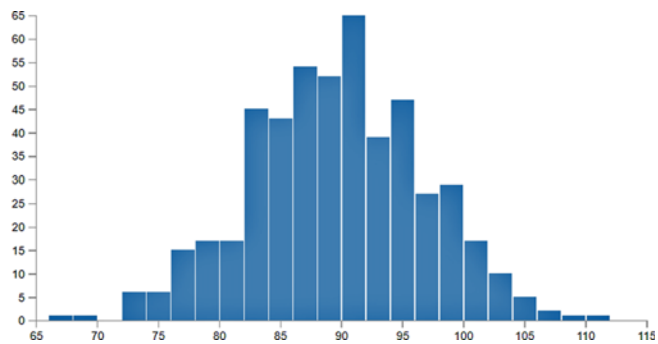


**Fig. 6.** The Histogram of the Resource Up Time ($R_3$)

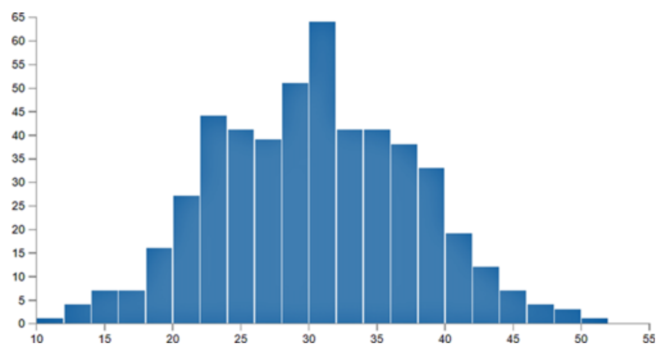


**Fig. 7.** The Histogram of the Resource Up Time ($R_4$)

the capacity of the resources are given in Table 4. In studies by Lambrechts et al. (2008), it was noticed that the inter failure times follow an exponential probability distribution. Thus, our assumption of exponentially distributed inter failure times for machines and tools ($R_5$, $R_6$,…, $R_{10}$) is valid. The probability distributions and their associated parameters have been fitted using historical data of the previous similar projects. For example, the histograms of the uptime for human resources are shown in Figs. 4 to 7. The statistical distribution parameters of the availability of human resources are based on the records of previous projects (including about 500 samples) and obtained with the use of easyfit software. Also, the histogram of the resource usage up time for concrete and metal are illustrated in Figs. 8 and 9,

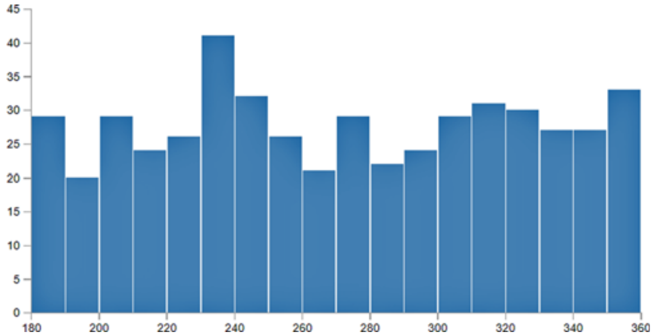


Fig. 8. The Histogram of the Resource Usage Up Time ($R_{11}$)

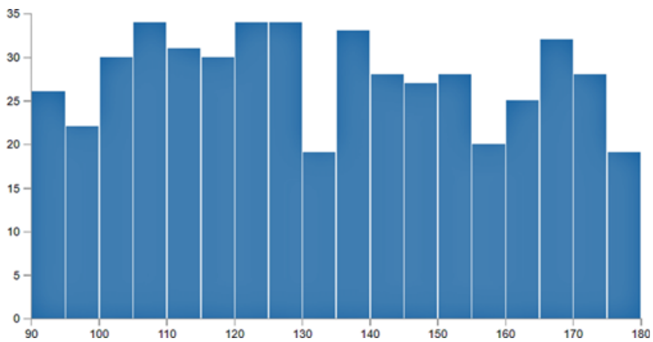


Fig. 9. The Histogram of the Resource Usage Up Time ($R_{12}$)

respectively. The availability of the material resources varies randomly due to the unpredictable delays in the supply process.

### 5.1.2 Disruption in Resource Requirements

Disruption in resource requirements happens when e.g., activity $i$ uses $\beta_{ik}$ units of resource $k$ during its execution more than planned. In the proposed resource allocation framework, the uniform distribution is utilized to model uncertainties associated with resource requirements. The disruption scenarios of resource requirements ($\beta_{ik}$) of the project tasks are presented in Table 5. In all disruption scenarios, it is assumed that the increase in the resource requirement is less than the maximum available resource capacity.

Table 6. Simulation Results under the Activity Duration Disturbances

| C (%) | Average (days) | Standard deviation (days) | The minimum value (days) | The maximum value (days) |
|---|---|---|---|---|
| 1 | 2,293.08 | 137.19 | 2,216.1 | 2,571.4 |
| 5 | 2,314.35 | 136.17 | 2,220.9 | 2,726.4 |
| 10 | 2,354.14 | 130.78 | 2,240 | 2,754.9 |
| 20 | 2,506.85 | 142.02 | 2,329.6 | 2,839.3 |

### 5.1.3 Activity Duration Disturbance

In the simulation model proposed, the uncertainty in task duration is represented by a stochastic variable that follows a normal probability distribution. The standard deviation for activity $i$ ($\sigma_i$) is defined as a percentage ($C\%$) of the expected activity duration. Therefore, $C$ is referred to as the inverse of a statistical measure known as the coefficient of variation. Table 6 illustrates the results of the simulation experiments conducted to analyze the effects of the activity duration disturbances on the completion time of the project.

## 5.2 Robustness Improvement via VNS

The baseline schedule ($B_1$) can be improved by maximizing the robustness measure. For this purpose, the simulation-based

Table 5. Disruption Scenario of Resource Requirements ($\beta_{ik}$) of the Project Tasks

| Task ID | R1 | R2 | R3 | R4 | R5 | R7 | R9 | R11 | R12 |
|---|---|---|---|---|---|---|---|---|---|
| 6 | - | - | UNIF(0,1) | UNIF(0,1) | - | - | - | - | - |
| 15 | UNIF(0,4) | UNIF(0,2) | UNIF(0,3) | UNIF(0,3) | - | - | - | - | - |
| 19 | UNIF(0,5) | UNIF(0,5) | UNIF(0,1) | UNIF(0,1) | UNIF(0,1) | UNIF(0,1) | UNIF(0,1) | UNIF(0,20) | UNIF(0,50) |

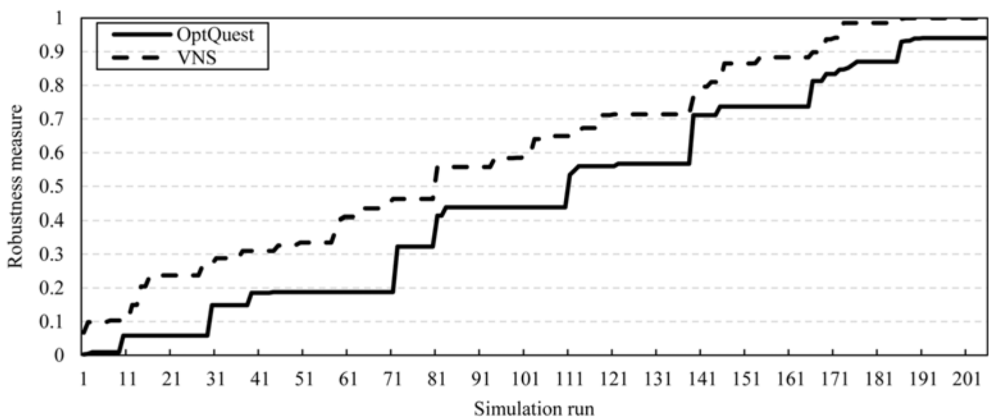



Fig. 10. Optimization of the Robustness Function via OptQuest in ARENA and VNS

optimization method is utilized. Each of the simulation-based optimization iterations is comprised of two main stages. The first stage is the calculating of the response function (robustness measure), and the second one is the selection of new values for the decision variables. The convergence graphs of the robustness optimization using OptQuest and VNS are presented in Fig. 10. As it is noticed, the robustness measure improves during the search more effectively by VNS as compared with OptQuest.

The performance of the VNS result is compared with those obtained by the OptQuest solver for several disruption scenarios considered using real data. The termination condition for both algorithms is defined at the point when no significant improvement in the fitness value is achieved in 100 successive iterations. The number of simulation replications ($n$) is set to guarantee a sufficiently small half-width for a confidence interval of the average fitness value. Kelton et al. (2004) suggested an approximation for deciding the number of replication as follows:

$$n \approx n_0 \left(\frac{h}{h_0}\right)^2. \tag{10}$$

Here, $n_0$ refers to the preliminary number of simulation replications, and $h_0$ corresponds to the half-width of confidence interval obtained after $n_0$ replications. The process continues by adjusting the $n$ replications by changing the size of the half-width from $h_0$ to the desired value, e.g., $h$. In this study, based on preliminary experiments, a sufficiently small confidence interval (in the range of ±5% of the mean value) was gained by adopting the number of replications to $n$ = 60. Numerical outputs for disruption scenarios using OptQuest solver and VNS are shown in Table 7. In most of the disruption scenarios, except for scenarios No. 2 and 8, VNS outperforms OptQuest solver in terms of solution time or average project delay. The computational result indicates that the percentage of improvement in solution quality for VNS as against the OptQuest changes from 5% to about 15%. Also, the mean CPU time of OptQuest is reported to be about 176.29 minutes, which is considerably longer than that of VNS (81.49 minutes on average). This is mainly due to the fast convergence speed of VNS to the global optimum solution. In total, the proposed simulation-based optimization approach is shown to outperform the state-of-the-art OptQuest solver in most of the problem instances in terms of both CPU time and the solution quality.

## 5.3 Result of Simulation Experiments

In the previous section, the examples of a single disruption were presented. In this section, we consider a case with multiple disruptions. To test the proposed VNS, we have created disruption scenarios by randomly generating multiple disruptions. The results of the simulation-based comparison of the robust and non-robust baseline schedules are presented in Table 8. It shows the comparative result of the simulation outputs in the presence of robust and non-robust baseline schedules. It worth noting that the variability of the cost has been analyzed by reporting the standard deviation of the project completion time and the number of activities affected by technical changes due to the project delay.

The first row of Table 8 illustrates the results of the simulation experiments conducted to analyze the effects of the resource capacity disruption on the completion time of the project. With disruptions associated with resource capacity, the average and standard deviations of the completion time are 2,402.20 and 64.23 days, respectively. The number of replication is 20. The simulation results show that the increase in the completion time is 189.45 days, on average, as against the minimum completion time.

In the case of multiple disruptions, the generated robust project schedule ($B_2$) reduces the expected delay by about 8%. Also, the standard deviation of the project completion time could be decreased by 42%, showing the improved robustness of the schedule. As a concluding remark, the results obtained show that the robust baseline schedule ($B_2$) outperforms the non-robust schedule ($B_1$) in terms of both the average and variance of the

**Table 7.** Numerical Results in Disruption Scenarios for OptQuest Solver and VNS Algorithm

| Scenario no. | OptQuest | | | VNS | | | |
|---|---|---|---|---|---|---|---|
| | Best makespan | CPU Time (min) | Average delay (days) | Best makespan | CPU Time (min) | Average delay (days) | Improvement (%) |
| 1 | 2,387.52 | 105.5 | 174.77 | 2,238.83 | 67.22 | 26.08 | 6.23% |
| 2 | 2,293.28 | 227.3 | 80.53 | 2,294.71 | 29.55 | 81.96 | -0.06% |
| 3 | 2,311.66 | 197.3 | 98.91 | 2,219.22 | 169.43 | 6.47 | 4.00% |
| 4 | 2,343.92 | 75.2 | 131.17 | 2,216.54 | 31.10 | 3.79 | 5.43% |
| 5 | 2,416.47 | 214.9 | 203.72 | 2,217.23 | 62.96 | 4.48 | 8.25% |
| 6 | 2,359.46 | 29.8 | 146.71 | 2,246.36 | 57.71 | 33.61 | 4.79% |
| 7 | 2,599.47 | 207.7 | 386.72 | 2,218.19 | 123.25 | 5.44 | 14.67% |
| 8 | 2,217.79 | 259.6 | 5.04 | 2,287.80 | 141.44 | 75.05 | -3.16% |
| 9 | 2,365.80 | 198.0 | 153.05 | 2,219.01 | 38.33 | 6.26 | 6.20% |
| 10 | 2,361.77 | 247.8 | 149.02 | 2,223.58 | 93.91 | 10.83 | 5.85% |
| Average | 2,365.71 | 176.29 | 152.96 | 2,238.15 | 81.49 | 25.40 | 5.22% |

**Table 8.** The Simulation-Based Comparison of the Robust and Non-robust Baseline Schedules

| Source of uncertainty | Project schedules | Average completion time (days) | Average delay (days) | Std of the completion time (days) | Num. of activities affected by technical changes | Minimum completion time (days) | Maximum completion time (days) |
|---|---|---|---|---|---|---|---|
| Resource capacity disruptions | Non-robust schedule (B1) | 2,402.20 | 189.45 | 64.23 | 12 | 2,227.80 | 2,477.40 |
| | Robust schedule (B2) | 2,258.56 | 45.81 | 40.89 | 9 | 2,225.10 | 2,311.80 |
| Resource requirement disruptions | Non-robust schedule (B1) | 2,344.36 | 131.61 | 171.67 | 10 | 2,212.70 | 2,617.30 |
| | Robust schedule (B2) | 2,241.05 | 28.3 | 85.11 | 6 | 2,212.70 | 2,408.70 |
| Activity duration disruptions | Non-robust schedule (B1) | 2,354.14 | 141.39 | 130.78 | 15 | 2,240.00 | 2,754.90 |
| | Robust schedule (B2) | 2,232.74 | 19.99 | 98.68 | 4 | 2,221.00 | 2,417.30 |
| Multiple disruptions | Non-robust schedule (B1) | 2,514.87 | 302.12 | 148.74 | 18 | 2,354.55 | 2,917.68 |
| | Robust schedule (B2) | 2,315.27 | 102.52 | 86.14 | 5 | 2,311.02 | 2,888.25 |

project completion time. The improvement rates are 5.98%, 4.41%, and 5.16%, respectively, for the cases where resource capacity, requirements, and activity disruptions occur. The average reduction in the standard deviation of the project completion time is 37%, being indicative of the robustness of the solution provided by the simulation-based optimization method. The results of the simulation experiments show that different sources of disruptions lead to varying effects on project overruns. As to the case investigated, the effects of the resource capacity disruption were significant, being regarded as the most critical disturbance factor. The robustness measures proposed could produce another baseline schedule that is demonstrated to be a robust plan. Therefore, the maximizing of the robustness measure under the constrained deadline of the project duration can lead to a robust baseline schedule with a higher rate of protection against unpredictable disturbances. Finally, the benefits of the simulation-based optimization of the robustness are illustrated and statistically established for the current real case study. Since it is difficult to compare the actual case study data with simulation results, a study on the standard durations/productivity of activities with disruptions with the actual data is provided to understand the extent of the delay. Also, the number of operations affected by technical changes is reported in Table 8 to compare the simulation results of robust and baseline schedules. To test the statistical significance of the robust and non-robust baseline schedules with standard productivity under disruption, a t-test is used. If the average project delays in the initial (non-robust) schedule and the robust schedule are denoted by $\Delta_{B_1}$ and $\Delta_{B_2}$ respectively, then the statistical hypothesis is defined as follows:

$$\begin{cases} H_0: & \Delta_{B_1} = \Delta_{B_2} \\ H_1: & \Delta_{B_1} \neq \Delta_{B_2} \end{cases}. \tag{11}$$

Here, the $H_0$ assumption is that the use of the proposed robust approach does not have a significant effect on the average project delays. In the test for comparing the means of the two statistical indicators, two independent samples ($n_1$, $\bar{x}_1$ , $s_1$) and ($n_2$, $\bar{x}_2$ , $s_2$) are selected from the first and second populations, respectively. Given the size of the samples $n_1$ and $n_2$, the test statistic is considered as follows:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\left(\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}\right)\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}. \tag{12}$$

The results of the t-test for the significance of the project's average delay in the baseline and robust schedules are presented in Table 9. These results include average, standard deviation (StDev), standard error, and 95% confidence interval (Significance Level = 0.05). Based on the results obtained for the first disruption scenario, the critical value is 1.98. The calculated t exceeds the critical value (12.7563 > 1.98), so the means are significantly different. In the second disruption scenario, the critical value is also 1.98. The calculated t exceeds the critical value (3.7855 >

**Table 9.** The Result of t-Test under Different Disruption Scenarios

| Indicator | Resource capacity disruptions | | Resource requirement disruptions | | Activity duration disruptions | | Multiple disruptions | |
|---|---|---|---|---|---|---|---|---|
| | Group 1 | Group 2 | Group 1 | Group 2 | Group 1 | Group 2 | Group 1 | Group 2 |
| Mean | 186.2189 | 100.8865 | 134.9777 | 106.8921 | 147.4775 | 96.4726 | 301.1861 | 181.405 |
| Variance | 432.0711 | 2,610.8268 | 414.8219 | 3,328.1903 | 335.9069 | 3,844.8788 | 422.7738 | 3,512.4478 |
| Stand. Dev. | 20.7863 | 51.0963 | 20.3672 | 57.6905 | 18.3278 | 62.0071 | 20.5615 | 59.2659 |
| t | 12.7563 | | 3.7855 | | 6.5049 | | 15.7455 | |
| Degrees of freedom | 134 | | 134 | | 134 | | 134 | |
| Critical value | 1.98 | | 1.98 | | 1.98 | | 1.98 | |

1.98), so the responses are significantly different. The calculated t-values exceed the critical values (6.5049 > 1.98 and 15.7455 > 1.98) for third and fourth scenarios, respectively. Thus, the means are significantly different. The results of experiments confirm the rejection of $H_0$ assumptions in various resource disruption scenarios. As a result, it can be argued that the proposed approach to robust project scheduling is efficient.

## 5.4 Experimental Results

To avoid the risk of having biased results from a simulation-based study, an experimental design is provided. In this section, the proposed robustness measure is compared with two existing robust surrogate objective functions. The first benchmark stability measure is to maximize the sum of free floats presented by Al-Fawzan and Haouari (2005):

$$RM_1 = \sum_{i \in A} f_i, \tag{13}$$

where $f_i$ denotes the free slack time of $i^{th}$ activity. Based on this equation, the robustness of a schedule is associated with its capability to be preserved even in the case of disruptive events affecting the realization of the project activities. The second surrogate robustness measure is proposed by Kobylański and Kuchta (2007). They defined the robustness of a schedule by the minimum of the ratios free float/duration for all the project activities.

$$RM_2 = \min_{i \in A} \left\{ \frac{f_i}{d_i} \right\} \tag{14}$$

The results of comparing the measure of robustness with these two surrogate stability functions are presented in Table 10. The test instances are adopted from the PSBLIB library (available at http://www.om-db.wi.tum.de/psplib/newinstances.html). All test problems include 30 activities and four types of renewable resources. The existing schedule robustness indicators are compared with the results obtained by the benchmark robustness measures and through running the VNS algorithm. The results also indicate that the presented robustness measure gives a better performance as against the total float and ratio of float/duration in terms of the deviation and delay costs of disturbances.

It should be remarked that seven out of ten test instances could reach a robust schedule with lower average solution robustness as against Al-Fawzan and Haouari (2005). In the seven out of ten test instances, the proposed robust scheduling method yields better outcomes as against the robustness measure proposed by Kobylański and Kuchta (2007). The schedule designed based on our robustness measure reduced the costs of the project by 5.97% and 21.89% on average compared with Al-Fawzan and Haouari (2005) and Kobylański and Kuchta (2007), respectively. The outcome demonstrates the appropriateness of the suggested surrogate robustness measure that includes the resource consumption of activities.

# 6. Conclusions

Given the stochastic nature of the events in large-scale construction projects, scheduling decisions are severely affected by the task precedence relationships and resource availability during the planning horizon. Project plans are usually affected by a variety of risk factors, such as lack of resources, climate change, and equipment failure, which can delay project execution. Resource breakdown and activity delay are encountered regularly in the context of construction planning. During the construction step, the unpredicted unavailability of the resource units may cause irreparable delays. That is why some recent research efforts have focused on the design and implementation of robust project baseline schedules. The construction industry has faced a growing need to quantify the risk of resource failure effectively and to be prepared for unpredictable disruptions. Here, motivated fundamentally by long delays in the Iranian construction project, this study focused on designing a flexible framework that aims to generate robust schedules in case of the stochastic disturbances. In this study, to cope with the uncertainty associated with resource availability and the random variability during project execution, a simulation-based optimization approach was proposed to produce

**Table 10.** Comparative Analysis of Alternative Robustness Measures

| Problem instances | Due date | Average instability cost | | | Improvement in robustness | |
|---|---|---|---|---|---|---|
| | | *RM* proposed in this study | $RM_2$ | $RM_2$ | $RM_1$ | $RM_2$ |
| j30t6_48_1 | 63 | 0.423 | 0.239 | 0.746 | 77.47% | -68.00% |
| j30t6_48_2 | 54 | 0.462 | 0.283 | 0.318 | 63.28% | -10.91% |
| j30t6_48_3 | 50 | 0.356 | 0.587 | 0.371 | -39.40% | 58.49% |
| j30t6_48_4 | 57 | 0.391 | 0.886 | 0.675 | -55.89% | 31.32% |
| j30t6_48_5 | 58 | 0.497 | 0.294 | 0.799 | 68.96% | -63.21% |
| j30t6_48_6 | 58 | 0.218 | 0.121 | 0.999 | 80.36% | -87.90% |
| j30t6_48_7 | 55 | 0.910 | 0.622 | 0.325 | 46.22% | 91.46% |
| j30t6_48_8 | 44 | 0.261 | 0.137 | 0.036 | 90.32% | 282.45% |
| j30t6_48_9 | 59 | 0.834 | 0.380 | 0.123 | 119.70% | 207.63% |
| j30t6_48_10 | 54 | 0.770 | 0.366 | 0.241 | 110.03% | 51.97% |
| Average | | 0.512 | 0.392 | 0.463 | 56.10% | 49.33% |

stable construction schedules. This solution method attempts to maximize a surrogate robustness metric for project schedules under multiple uncertainties. The optimization was realized through OptQuest and ARENA as a discrete-event simulation platform. In this article, several contributions to various aspects of the research topic have been made. Firstly, a simulation-based optimization method via VNS was adopted for robust project scheduling. An innovative slack-based robustness measure was presented that takes into account the information about the critical chains, project network, and the resources tightness index. The proposed robustness indicator was utilized to handle multiple disruptions that occur due to the resource capacity loss, resource breakdown, random variation of the resource requirement, and stochastic activity duration. Moreover, the flexibility of the simulation framework proposed for dealing with different single and multiple failure scenarios was highlighted. Secondly, new robustness measures are proposed and evaluated for a real case study of dam and hydropower plant construction projects, where the impacts of the multiple stochastic disruptions are analyzed. Also, the efficiency of the proposed robustness measure is assessed by a set of numerical examples from the PSBLIB standard library. The computational results demonstrate the effectiveness and computational practicality of the proposed method compared with the existing project scheduling methods. The baseline project was tested under different types of disruptions, and a robust schedule was produced to absorb the delays as much as possible. The results of the simulation experiments indicate the benefits of employing the robustness measure proposed in the creation of stable project schedules against different types of disruptions.

Because this study was limited to the uncertain activity duration and resource disruption, it would be motivating to conduct extra research work to study the mutual influence of another source of disruptions (e.g., activity insertion or priority changes) on project performance. Future research must address improving the performance of the model by combining proactive and reactive strategies for schedule recovery and by exploiting other constraints and activity attributes. The developed simulation-based optimization model was also limited to a single-objective search method, and for future research, it can utilize multi-objective search methods, e.g., MOPSO and NSGA, to find Pareto optimal solutions. Moreover, since this study was limited to the single-mode RCPSP, it would be beneficial to extend the modeling framework to improve the recoverability of the project schedule using the mode change capability. Another area of further research can be related to the application of the resource-leveling approach to the robust schedule generation. In this regard, an appropriate resource-leveling method is required to provide efficient and stable schedules in real-world cases.

## Nomenclature

In this study, the notations to represent the SRCPSP are described as follows:

### Notation of the Sets

$A$ = Set of immediate precedence relationships
$B_t$ = Set of activities in progress during period $t$
$K$ = The set of renewable resources
$N$ = The set of activity nodes
$NC$ = The set of non-critical chains
$NK$ = The set of non-renewable resources
$P_i$ = The set of the immediate predecessor of activity
$T$ = The set of periods

### Notation of the Parameters

$a_{kt}$ = Dynamic availability of resource type $k$ for activity $i$ at period $t$
$C_{max}$ = Latest finish time of the activity
$d_i$ = The duration of activity $i$ which follows a known probability distribution function
$d_i^{min}, d_i^{max}$ = Minimum and maximum duration of activity $i$
$EF_i$, $LF_i$ = Earliest and latest finish times of activity
$ES_i$, $LS_i$ = Earliest and latest start times of activity $i$
$lag_{ij}$ = The time lag between activity $i$ and $j$
$r_{ikt}$ = The requirement of resource type $k$ for activity $i$ at period $t$
$\sigma_i$ = Excess time for activity $i$ due to disruptions, i.e., resource breakdowns and repair times

### Notations of the Decision Variables

$x_{it}$ = 1 if activity $i$ starts at time $t$, and 0 otherwise

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## Appendix

**Table 11.** Resource Requirements Data in Hydropower Plant Project

| Task ID | Resource requirements (types) | Resource usage (units) |
|---|---|---|
| 1 | R4 | 12 |
| 2 | R4 | 10 |
| 3 | R4 | 15 |
| 4 | R4 | 8 |
| 5 | R4 | 10 |
| 6 | R3,R4 | 2,5 |
| 7 | R3,R4 | 5,5 |
| 8 | R4 | 10 |
| 9 | R3,R4 | 4,6 |
| 10 | R3,R4 | 4,6 |
| 11 | R2, R3, R4 | 5, 10, 20 |
| 12 | R4 | 15 |
| 13 | R1, R2, R3, R4, R5, R6, R7, R8, R9, R10, R11, R12 | 35,18,15,18,4,3,4,2,5,2, 100,180 |
| 14 | R1, R2, R3, R4 | 10,5,3,4 |
| 15 | R1, R2, R3, R4 | 12,5,5,4 |
| 16 | R1, R2, R3, R4 | 12,5,2,5 |
| 17 | R1, R2, R3, R4 | 15,7,5,6 |
| 18 | R2, R3, R4, R5, R8, R12 | 10,10,17,2,2,120 |
| 19 | R1, R2, R3, R4, R5, R7, R9, R11, R12 | 25,10,14,18,2,4,6,100,50 |
| 20 | R2, R3, R5, R12 | 18,10,2,80 |
| 21 | R2, R3, R5, R12 | 7,5,3,70 |
| 22 | R1, R2, R3, R5 | 20,10,5,2 |
| 23 | R1, R2, R3, R5 | 30,8,5,1 |
| 24 | R1, R2, R3, R5, R12 | 25,10,8,1,50 |
| 25 | R1, R2, R3, R5, R12 | 15,10,6,1,75 |
| 26 | R1, R3, R5, R12 | 35,5,3,60 |