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PROACTIVE TACTICAL PLANNING APPROACH

for large scale engineering and construction projects

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• ABSTRACT •

Large-scale engineering and construction projects are subject to a great level of uncertainty which lead planners to use time buffers and add contingencies to the estimated budget. However, the size of the buffers and the contingency amounts are usually arbitrarily established and projects still encounter severe time and cost overruns. In this paper, a robust planning approach for tactical planning of large-scale engineering and construction projects is proposed. The approach relies on a simple resource buffering strategy applied to the aggregate periods. An extensive simulation-based experiment was conducted to test the robustness and performance of the proposed approach. Results show that the proposed buffering strategy can considerably reduce project cost variations and can provide comparable performance results with those obtained using a disaggregated approach, especially on instances characterized by a large number of resource groups.

1. INTRODUCTION

Large-scale engineering and construction (LSEC) projects are highly complex (An & Shuai, 2011; Russell, 2013) and are subject to a great level of uncertainty especially during the early phases as detailed engineering is not completed yet. LSEC projects also last for a long duration. For instance, Miller and Lessard (2000) have studied 60 large-scale engineering projects and the average duration was six and a half years, with a construction period of four years.

Planning is thus a key factor to the success or failure of large projects (Gibson Jr et al., 2006; Serrador, 2013). In practice, most LSEC projects are planned hierarchically in order to deal with their planning complexity. Unlike the monolithic planning approach that consists in scheduling the project at a unique detailed level, hierarchical planning consists of breaking down planning into more manageable parts by subdividing it to sub-problems at different aggregation levels consistent with the degree of project definition and the intended schedule usage (AACE International, 2010a, 2010b; De Boer, 1998). High-level decision schedules, based on limited information, are developed during the first phases of the project where only preliminary and basic engineering have been performed, while more detailed schedules are developed as engineering progresses and more specific information and accurate estimates become available. As the level of detail increases, the planning horizon decreases and the use of the schedule migrates from management planning to performance-level and control (de Leon, 2011).

In the literature, the tactical planning level refers to project planning during the bidding and order acceptance phase of a project (De Boer, 1998). In the context of engineering and construction projects, this phase corresponds to the final stage of the pre-execution where the final investment decision is taken (Cherkaoui et al., 2013). The main objective of tactical planning is thus to make budgetary and due date commitments. In this paper, the tactical planning level is extended to the execution main phase while the detailed engineering is still in progress. Indeed, the tactical plan developed at the end of the pre-execution phase needs to be updated in order to consider the new available information and make the adequate commitments with the corresponding stakeholders of the project.

The tactical planning level includes rough-cut capacity planning (RCCP) decisions about due dates and milestones of projects, overtime work levels, subcontracting, etc., that are usually updated every six months or so, depending on expected project durations (De Boer, 1998). Based on customer specifications, the RCCP problem consists in generating a network of work packages (WPs) with rough estimates of resource requirements and minimum durations under global resource availability constraints over aggregate periods. Work packages are clusters of yet undefined related activities that extend over a long duration, i.e. several weeks or months. Resource allocation to WPs are considered flexible over periods, which allows the durations of the WPs to be adapted according to time and cost-related considerations (Baydoun et al., 2016).

Over the years, several exact and heuristic methods, based on RCCP, have been proposed for the tactical planning of LSEC projects (Leachman and Boysen (1985); Speranza and Vercellis, 1993; De Boer (1998); Hans (2001); Neumann et al. (2003); Wullink et al. (2004); Gademann and Schutten (2005); Masmoudi (2011); Alfieri et al. (2011), Alfieri et al. (2012); Haït and Baydoun (2012); Cherkaoui et al. (2015); Baydoun et al. (2016); Carvalho et al. (2016)). In general, these methods do not take into account uncertainty which however arises very frequently in practice at the tactical level. In fact, most of these methods are deterministic, since the input data is assumed to be precisely known and set to some nominal value (Carvalho et al., 2016). Furthermore, the deterministic models for the tactical capacity planning have been developed under the assumption that uncertainties are implicitly dealt with by choosing a proper level of aggregation (Wullink, 2005). However, explicitly incorporating uncertainty in tactical capacity planning models can lead to a significant advantage in terms of plan effectiveness when compared to a deterministic approach (Alfieri et al., 2012; Carvalho et al., 2016; Wullink, 2005). To the best of our knowledge, none of the RCCP-based methods proposed to date explicitly incorporate the disaggregation uncertainty. In project planning, disaggregation uncertainty is related to all forms of disaggregation, including the disaggregation of aggregate resource capacities into precise capacity estimates on short periods and the disaggregation of WPs into detailed activities.

In this paper, the impact of the disaggregation uncertainty on the robustness of the baseline schedule produced at the tactical level is studied and a buffering strategy is proposed to improve the robustness. More precisely, we are interested in maximizing the quality robustness of the tactical baseline schedule, not its solution robustness. Quality robustness refers to the insensitivity of the plan in terms of target performance, i.e., the objective function value, to the occurrence of uncertain events. Solution robustness or stability addresses insensitivity of the schedule in terms of activity start times (Alfieri et al., 2012). Since the aim of scheduling at the tactical planning level is to quote a tight and reliable cost and duration of the project, the exactitude of the start times of the WPs is not our priority at this level.

In practice, common scheduling methods used for tactical planning ignore uncertainty when building the schedule. In order to overcome this problem, practitioners incorporate some slack in the schedule to protect the important project milestones (Russell, 2013; Yeo & Ning, 2006) and add contingencies to the estimated budget (Touran, 2003) to cover uncertainties. However, the size of the slacks and the contingency amounts are usually arbitrarily established. This is problematic as it does not guarantee objective and rigorous estimations which can impact the quality of the plans. These limitations in considering uncertainty in tactical planning together with the importance of having a tight and reliable schedule at the tactical level as a base for the long term budget and due date commitments led us to propose, in this paper, a proactive planning approach based on a simple and efficient capacity buffering strategy to be applied to a RCCP model. As highlighted by Van de Vonder (2006), a proactive approach focuses at incorporating safety in the baseline schedule to absorb future disruptions, i.e., aiming at robustness. At the opposite, reactive approaches provide a proper strategy to revise or re-optimize a schedule when an unexpected event occurs (Van de Vonder et al., 2007). Two sources of uncertainties are considered in this paper: the disaggregation uncertainty of rough resource capacity estimates into more detailed ones and the uncertainty in the estimation of the work contents of WPs. The robustness and performance of the proposed proactive approach is evaluated through an extensive simulation-based analysis.

The remainder of the paper is organized as follows. Section 2 describes the problem under study: the RCCP problem under uncertainty intended for the tactical planning level of LSEC projects. Section 3 presents the methodological approach including the description of the proactive planning approach proposed to resolve the RCCP problem under uncertainty and the experimental set-up. Computational results are presented in Section 4 and concluding remarks in Section 5.

2. PROBLEM DESCRIPTION

The problem under study is a RCCP problem under uncertainty intended for the tactical planning level of LSEC projects. The uncertainties considered are the uncertainty in work package work contents and the uncertainty in the capacities of resources over periods. The uncertainty in the forecasted resource capacities can result from two possible sources: the uncertainty in the magnitude (i.e., amount) and the uncertainty in the temporal distribution over the forecast period. In this paper, only the second source of uncertainty is considered: the temporal distribution, i.e., the disaggregation uncertainty.

In the literature, the majority of the tactical capacity planning models consider the resource capacities flexible by allowing the use of non-regular capacity (e.g., hiring additional personal, overtime, subcontracting, or outsourcing). These models are generally time-driven with an imposed project deadline. This capacity flexibility is often present in the tactical level unlike the operational level where critical resources (e.g., requiring long-lead times or a certain level of expertise) are difficult or even impossible to expand in the short term. Another relevant attribute for the context of LSEC projects is the variability of the period lengths. Considering varying period durations through the horizon allows to consider different aggregation levels. However, all tactical capacity planning models proposed in the literature consider the same aggregation level through the project horizon.

In this paper, we propose a proactive approach based on a time-driven RCCP model with variable period lengths where the first periods are considered more detailed than the further ones. The model aims at maximizing the robustness cost function under uncertain data.

The problem can be described as follows. Consider a planning horizon H that is discretized into time buckets of not necessarily equal length. These buckets are referred to as periods. Let P be the set of periods (index p) where each period has a duration D_p. Without loss of generality, the time unit is assumed to be one day and the horizon and the durations D_p are expressed in weeks. Let I be the set of work packages (index i) where each WP requires a subset of R independent resource groups (index r). The work packages have generic precedence relations (i.e., network structures) of finish-to-start zero-lag type. The set $Pred_i$ consists of all predecessors of WP i. Each WP has a required stochastic work content to be completed. A WP's work content is defined as the sum of its required workloads Q_{ri} on each resource group r. Q_{ri} is defined as the total amount of resource group r required by the WP i. For instance, a required workload of twenty man-days could be realized in different ways. Twenty men can work during one day, or two men during ten days, or even a flexible profile of five men for two days, and ten men for one day. A WP may require several resource groups simultaneously. The parameter Q_i^{max} is the maximum workload that can be assigned to i during one week due to technical or spatial constraints. A WP has a release date RD_i before which it cannot start. These dates are usually specified by external factors as local permissions, certificate requirements or weather conditions. Each resource group r has a regular capacity of K_{rp} (e.g., 30 man-days) available in period p. The temporal disaggregation of the capacity over a period into subperiods is uncertain. The number of subperiods should reflect the level of detail required for the next planning level in the hierarchy, the operational level, where the resource capacities are considered certain. Without loss of generality, each subperiod is assumed to have a length of one week. The disaggregated capacities over the subperiods should aggregate up to the estimated cumulated sum. Dividing the period p into n subperiods, K_{rp} is disaggregated as:

$$K_{rp}=\sum\nolimits^{n}_{j=1} k_{rpj} \quad p \in P, r \in R$$

where k_{rpj} is the disaggregated capacity of the jth subperiod of period p (**FIGURE 1**). The subperiods are grouped from all periods in one global set of detailed periods.

$$L = \{\, l=1, ..., H \,\}$$

The objective is to build a robust feasible schedule in respect of all constraints (precedence relations, maximum allowable workloads, release dates and global resource constraints over periods) by minimizing the robustness cost function $E(cost\%)$, which measures the expected percentage deviation of $cost_r$, the project cost of the realized schedule, from the optimal project cost of the baseline schedule $cost_{bas}$*. The baseline schedule represents the schedule obtained by applying an exact procedure on the estimated data at the tactical planning stage. The realized schedule is the schedule obtained after project execution. In this paper, since data of a real project is not available, the project execution will be simulated with a reactive procedure as described in Section 3.

In this paper, the project cost refers to the cost of non-regular capacities used over all resource groups and periods. Therefore,

$$cost_{bas}* = \sum\nolimits_{r\in R} \sum\nolimits_{p\in P} yext*_{rp}$$

where $yext*_{rp}$ represents the external load of resource r in period p in the baseline schedule and

$$cost_r = \sum\nolimits_{r\in R} \sum\nolimits_{l\in L} yext_{rl}$$

where $yext_{rl}$ represents the actual external load of resource r in the detailed period l in the realized schedule.

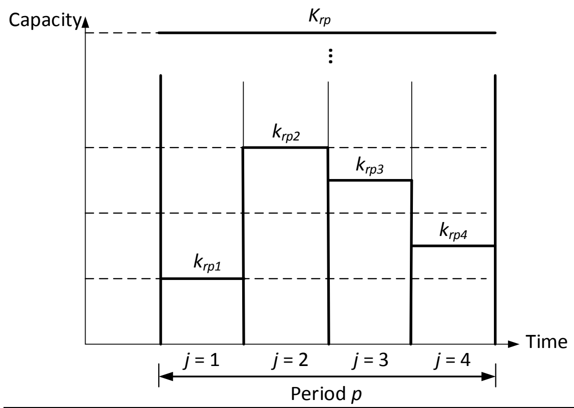

FIGURE 01. Illustration of disaggregating resource capacities

Unfortunately, the robustness cost functions are very hard to evaluate and optimize, even for problems without resource constraints, due to the stochastic nature of the uncertain parameters (Hagstrom, 1988). Therefore, in order to produce a robust schedule that optimizes the robustness objective function, the majority of the proactive scheduling methods proposed in literature (intended for the resource constrained project scheduling problem at the operational level) are heuristics and metaheuristics that aim at producing a sound baseline schedule by adding some safety in it and then use simulation to evaluate the robustness objective function.

In this sense, a proactive methodology is proposed in the next section to solve the RCCP problem under uncertainty based on a resource buffering strategy and then evaluate the robustness cost function using a multi-stage simulation-based reactive approach.

3. METHODOLOGICAL APPROACH

3.1 Description of the proactive approach and the experimental set-up

FIGURE 2 presents a flowchart of the methodological approach adopted in this paper. The first block presents the proposed proactive approach to generate a quality robust baseline RCCP schedule, while the second block presents the multi-stage simulation-based reactive approach used for experimental analysis.

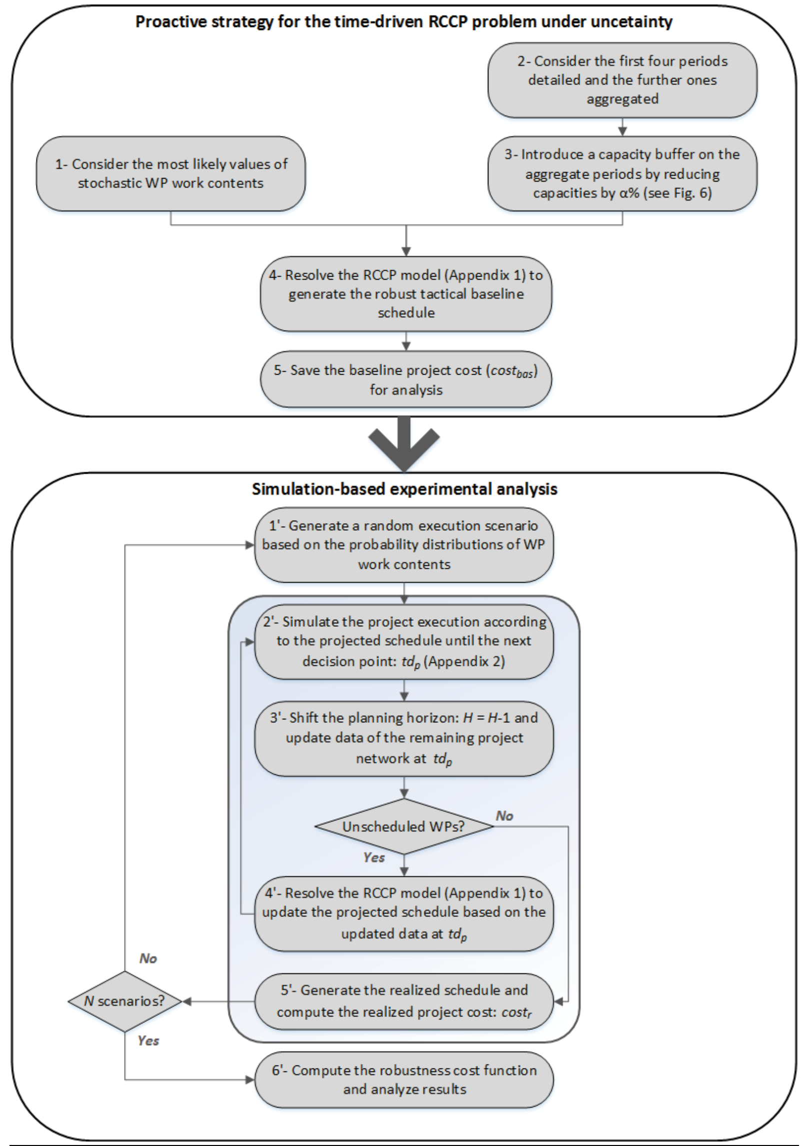

FIGURE 02. Flowchart of the global methodological approach

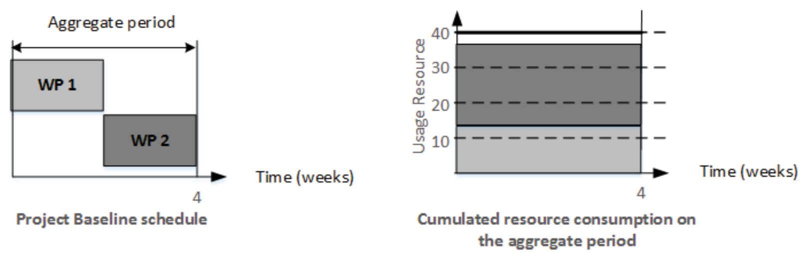

FIGURE 03. Project planned with a null cost at an aggregate level

The uncertainty in the WP work contents is taken into account by considering the most probable values from their stochastic distributions (step 1 in **FIGURE 2**). The disaggregation uncertainty of resource capacities is taken into account by reducing the capacities on aggregate periods by a certain percentage α%, or in other words by introducing a capacity buffer (step 3 in Figure 2). The strategy followed to find the value of parameter α is described in detail in Section 3.2. By introducing capacity buffers, the higher flexibility of resource constraints on aggregate periods compared to detailed periods is reduced. This high flexibility can yield to an underestimation of the project cost as illustrated in the following example. Suppose that a project is composed of two WPs using one resource r. The first WP requires 14 units from this resource to complete and the second one requires 24 units. The project is supposed to be planned at first on a unique aggregate period with an estimated capacity of 40 units from the resource r. The project was therefore planned with an optimal null cost as illustrated in **FIGURE 3**. The assumption is made that once more information becomes available, the real disaggregated capacities on the four detailed periods composing the aggregate period are respectively 5, 15, 10 and 10 units. By adopting the schedule of **FIGURE 3**, the project cost increases by 6 units as shown in **FIGURE 4.**

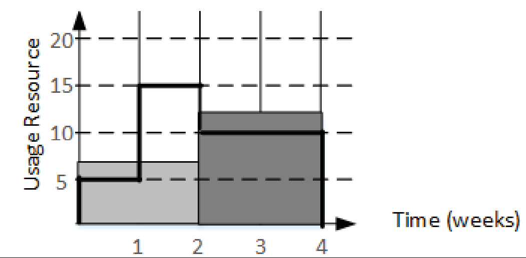

FIGURE 04. Cost increase in the detailed level

The RCCP model resolved as part of the proposed proactive strategy (step 4 in **FIGURE 2**) generalizes the MILP (Mixed Integer Linear Programming) RCCP model proposed by Haït and Baydoun (2012) by considering different aggregation levels of periods and therefore resource capacities. The RCCP model is presented in **APPENDIX 1**. The resolution of the RCCP model (step 4 in **FIGURE 2**) is performed using the solver CPLEX Optimization Studio 12.6.1.0 with the time limit set to 1000 seconds. The proactive approach is tested on 450 test project instances based on the commonly used RCCP instances of De Boer (1998). The base instances of De Boer (1998) have been modified to adopt the variable period lengths characteristic of the problem studied. Therefore, the first four periods of the horizon were kept with a duration of one week as in the base instances, while the further periods were grouped by clusters of four to form aggregate periods with a duration of four weeks each. Capacities have been aggregated in consequence by summing the capacities on the clustered periods of the base instances. Note that since the project horizon is not necessarily a multiple of four, the duration of the fifth period in this case corresponds to the rest of the Euclidean division of the time horizon by four.

The instances are characterized by two parameters, namely the number of WPs N and the number of resource groups K. Three levels are defined for the parameter N (10, 20 and 50 WPs) and the parameter K (3, 10 and 20 resource groups), which provides nine instance classes. 50 instances are generated for each of these classes.

Once the baseline schedule is generated for all the test project instances, we move to the experimental analysis as shown in the second block of **FIGURE 2**. For each instance, 100 random execution scenarios are generated based on the triangular probability distributions of WPs. The most probable value of the triangular distribution corresponds to the baseline WP work content, the minimum and maximum values are respectively set to 0.9 and 1.1 times the baseline value. For each generated scenario, a multi-stage reactive approach is applied. This approach updates the schedule at each new decision point (td_p) and simulates the project execution between each of two consecutive decision points. Decision points are situated at the end of each detailed one-week period. The updated schedule at a given decision point is called the projected schedule. The simulation algorithm between two consecutive decision points (step 2' in **FIGURE 2**) is detailed in **APPENDIX 2**. To describe it briefly, it follows the resource allocation decisions of the projected schedule but updates if necessary the durations of the WPs on the simulated period according to the up-to-date information about their work contents. At the end of the simulated period, the horizon is reduced by one week and the data of the instance is updated (step 3' in **FIGURE 2**) as follows: WPs already completed are omitted from the network, WPs not yet started are kept with their estimated work content as in the baseline schedule and WPs in progress are considered with the real reminder of their work content as illustrated in **FIGURE 5**. The hatched (parts of) WPs are the ones omitted at the decision point td_1. The same aggregation procedure used to generate the initial instances is used for the updated instances. This way, the four periods following the decision point are considered detailed and the rest of the periods are aggregated as shown in **FIGURE 5**. Also, the same capacity buffers are applied to the new aggregate periods.

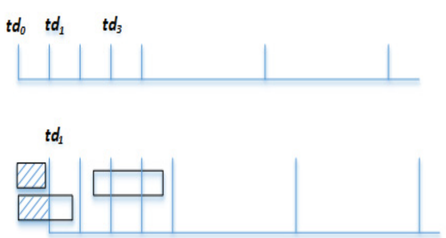

FIGURE 05. Updating data at the decision point td_i

For each scenario, once all the WPs have been scheduled, the reactive approach ends and the realized schedule is generated. The project cost of the realized schedule $cost_r$ is then compared with the optimal project cost of the baseline schedule $cost_{bas}$*. Once all scenarios are simulated, the robustness cost function of the studied project instance is evaluated as follows:

$$E\ (cost\%) = avg\ [(cost_r - cost^*_{bas})/cost^*_{bas}]$$

where *avg* is used as an acronym for the average measure.

This multi-stage simulation-based reactive approach was implemented in Matlab R2013a interfaced with CPLEX Optimization Studio 12.6.1.0 by using the CPLEX class API in Matlab. The time limit for the CPLEX resolution at each decision point was set to 1000 seconds.

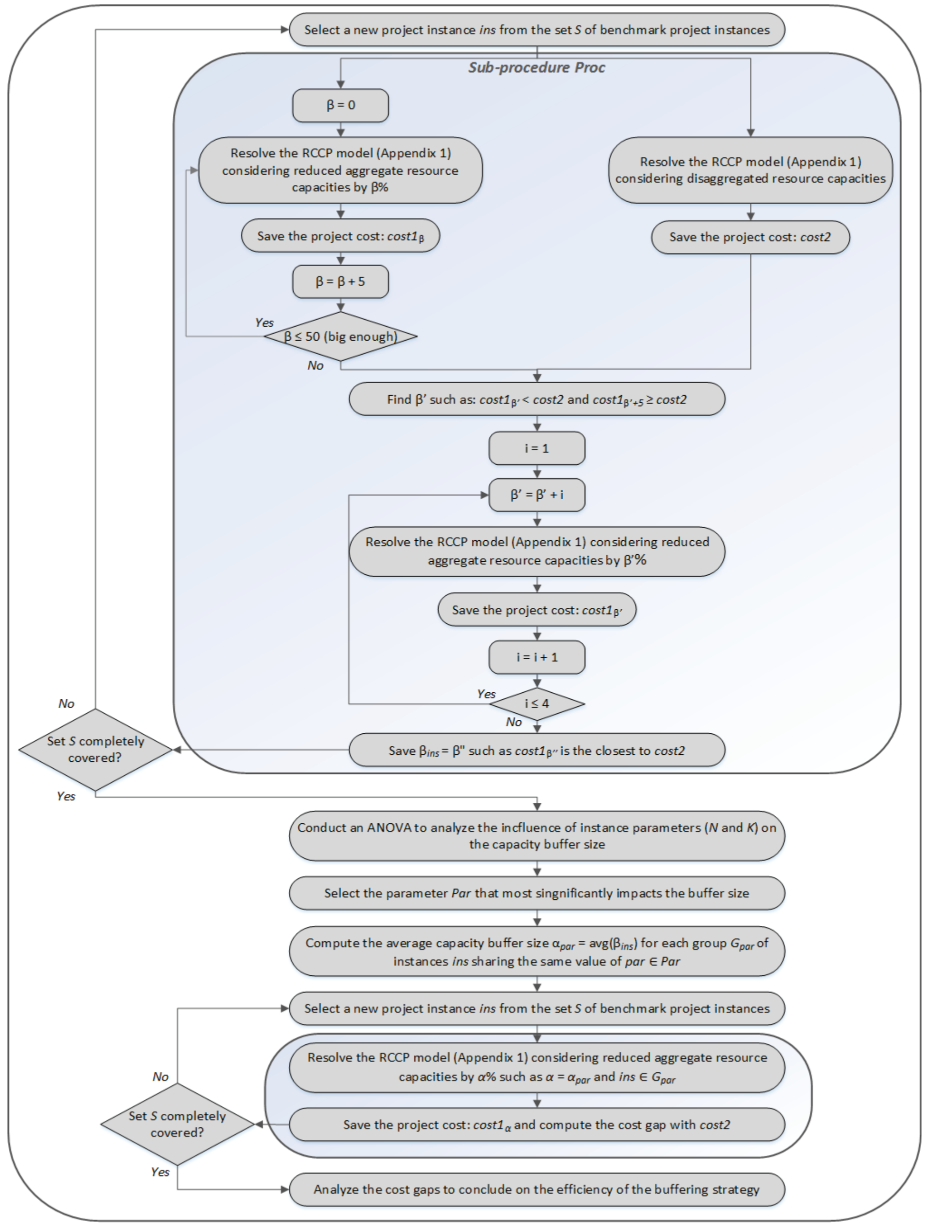

FIGURE 06. Flowchart of the strategy defining the capacity buffer

--- 3.2 Strategy defining the capacity buffer size ---

FIGURE 6 presents the strategy used to define the right capacity buffer sizes. The principle of the strategy is to predict the buffer size based only on relevant project parameters. To reach this objective, the sub-procedure *Proc* (see **FIGURE 6**) is first applied to each project instance. The aim of this sub-procedure is to find for each instance the optimal buffer size β_{ins}% (β_{ins} being a natural number) that once applied, allows to find the closest project cost to the one that would have been found if all the periods were detailed and the disaggregated capacities were known with certainty. The base instances of De Boer (1998) are used to represent these detailed disaggregated data. Once this procedure is applied to all instances, a two-way analysis of variance (ANOVA) is performed to analyze the impact of the parameters *K* and *N* on the buffer sizes. Then, the most significantly influencing parameter *Par* is selected and the instances are grouped according to this parameter value levels. For each of these groups, the average of the optimal capacity buffers found with the procedure *Proc* is computed. Then, the RCCP model (**APPENDIX 1**) is solved for all project instances applying these average capacity buffers: α_{par}% (see **FIGURE 6**). For each instance, the obtained project cost is compared to the cost of the corresponding disaggregated instance of De Boer (1998). If the cost gaps obtained are small enough, one can conclude on the efficiency of the capacity buffer strategy based only on the selected project parameter *Par* in compensating the underestimation of cost estimations caused by the aggregation.

4. COMPUTATIONAL RESULTS

All computational results have been obtained on the computational grid consisting of 26 PCs with two 3.07 GHz Intel(R) Xeon(R) X5675 processors using Linux. The results of applying the strategy defining the capacity buffer size (**FIGURE 6**) are presented in the next section. This will be followed by the computational results of the simulation-based experimental analysis.

--- 4.1 Capacity buffer size ---

When applying the strategy defining the capacity buffers, each time the RCCP model (**APPENDIX 1**) is solved, the model is run on the solver IBM ILOG CPLEX Optimization Studio 12.6.1.0 and the search is terminated after 50000 seconds. **TABLE 1** compares the project cost $cost1_0$ of the aggregate schedule before introducing the capacity buffers with the project cost $cost2$ of the disaggregated schedule:

$$cost\ gap = (cost1_0 - cost2)/cost2$$

As predicted, the costs of the unbuffered aggregate schedule are underestimated in comparison to those of the disaggregated schedule. Notice that the cost gaps decrease as the number of resource groups *K* increases and the number of WPs *N* decreases. However, the effect of *N* tends to decrease with the increase of *K*. A smaller dispersion of results is also noted when *K* increases.

TABLE 2 presents the cost gaps between the buffered aggregate schedules using the resulting optimal capacity buffers from the procedure *Proc* and the disaggregated schedules. Capacity buffers are expressed in percentage of the initial capacities. The table shows that parameter *K* has a clear influence on the capacity buffer sizes. In order to validate this observation, ANOVA was conducted on *Statistica* Software to analyze the effects of both parameters *N* and *K*. The analysis shows that both parameters have a significant impact on the buffer sizes with a greater impact of the parameter *K* (p-value of parameter *K* = 3,54E-14 versus a p-value of 1,58E-03 for parameter *N*). **FIGURE 7** and **FIGURE 8** report the mean values and the 95% confidence interval of the resource buffer sizes according to the values of the parameters *N* and *K*. We notice the clear and easily interpretable effect of parameter *K* in comparison to parameter *N*. Indeed, the buffer sizes increase with the increase of *K*. *K* is therefore the selected parameter *Par* (see **FIGURE 6**). We also notice a decrease in the slope of the curve as the parameter *K* increases, which suggests that the curve will tend to flatten with higher values of parameter *K*.

	Average (*Avg*) cost gap	Standard deviation (*SD*) of cost gap
***K* = 3**	**-56,6%**	**32,6%**
N = 10	-43,7%	30,2%
N = 20	-53,1%	32,1%
N = 50	-73,0%	28,6%
***K* = 10**	**-33,8%**	**15,2%**
N = 10	-22,5%	9,5%
N = 20	-31,7%	9,3%
N = 50	-47,2%	14,5%
***K* = 20**	**-20,1%**	**8,7%**
N = 10	-12,1%	4,2%
N = 20	-18,5%	3,6%
N = 50	-29,7%	6,2%

TABLE 01. Cost gaps between the unbuffered aggregate schedule and the disaggregated schedule

	Avg capacity buffers	*SD* of capacity buffers	*Avg* cost gap	*SD* of cost gap
K = 3	**14,9%**	**7,4%**	**-0,6%**	**3,7%**
N = 10	15,3%	9,0%	0,2%	1,4%
N = 20	15,9%	8,1%	-0,4%	1,6%
N = 50	13,5%	4,4%	-1,5%	6,0%
K = 10	**18,9%**	**4,7%**	**0,0%**	**0,7%**
N = 10	19,4%	5,2%	-0,1%	0,4%
N = 20	19,9%	4,9%	-0,1%	0,5%
N = 50	17,5%	3,6%	0,1%	1,0%
K = 20	**20,0%**	**4,7%**	**0,1%**	**0,4%**
N = 10	19,7%	6,5%	0,0%	0,2%
N = 20	21,2%	4,2%	0,0%	0,3%
N = 50	19,0%	2,4%	0,2%	0,5%

TABLE 02. Results of applying the optimal capacity buffers found with procedure Proc on the cost gap between the aggregate and detailed schedules

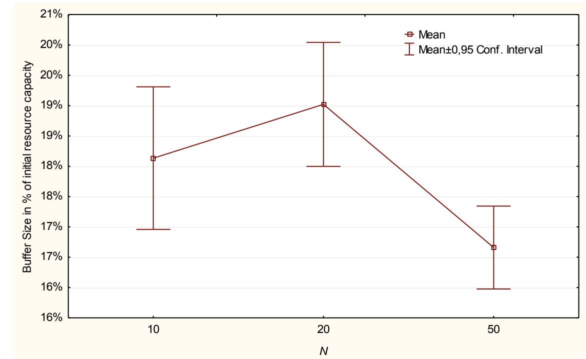

FIGURE 07. Mean Plot of the Capacity Buffer Size grouped by number of WPs *N*

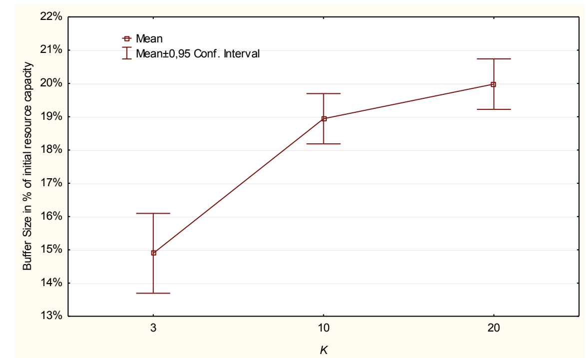

FIGURE 08. Mean Plot of the Capacity Buffer Size grouped by number of resource groups *K*

As depicted in **Fig. 6**, for each group of instances characterized by the same number of resource groups *K*, the resulting average buffer size is applied from the procedure *Proc*. As shown in **TABLE 2**, the buffer sizes are as follows: 14.9% for the group of instances G_3, 18.9% for the group G_{10} and 20.0% for the group G_{20}. The results of applying these average capacity buffers and resolving the RCCP model (**APPENDIX 1**) are reported in **TABLE 3**. Observe that the buffering strategy greatly reduces the gap between the cost estimates of the aggregate and disaggregate schedules, especially when the number of resource groups is important. However, an important dispersion of results is observed when the number of resource groups is very small: *K* = 3. Since we are interested in LSEC projects usually characterized by a large number of resource groups, this group of instances is not very relevant to the study.

In order to measure the effect of the imprecision in the estimation of capacity buffer sizes on the cost estimates, for each instance, the

	Average cost gap	Standard deviation of cost gap
K = 3	**16,3%**	**71,0%**
N = 10	4,8%	38,1%
N = 20	-0,3%	55,5%
N = 50	44,5%	97,8%
K = 10	**0,5%**	**9,0%**
N = 10	-0,6%	7,0%
N = 20	-1,4%	8,7%
N = 50	4,7%	10,6%
K = 20	**0,0%**	**4,2%**
N = 10	0,5%	4,3%
N = 20	-0,9%	3,9%
N = 50	0,8%	4,4%

TABLE 03. Cost gaps between the buffered aggregate schedules and the disaggregate schedules

	Avg evolution of the cost gap	*SD* of the evolution of the cost gap
K = 3	8,8%	10,0%
K = 10	2,2%	1,1%
K = 20	1,1%	0,6%

TABLE 04. The effect of an additional 1% capacity reduction on the cost gap between the aggregate and disaggregate schedules

effect of an additional 1% capacity reduction on the cost gap with the disaggregated schedule is measured. To illustrate the approach, let us suppose that the optimal capacity buffer size of an instance is 19% of the initial capacity. All the following buffer sizes were tested: 19%-5%, 19%-4% … 19%+5% and each time the cost gap with the disaggregated schedule was calculated. Then, the average evolution of this gap is calculated when the buffer size is increased by 1% of the initial capacity. Average results are reported in **TABLE 4**. Observe that a small inaccuracy in the estimation of capacity buffer sizes does not have a significant impact on the cost estimates for instances characterized by a large number of resource groups *K*. Based on this finding, together with the observation of the decrease in the slope of the curve in **FIGURE 8**, we suggest using the same buffer sizes for all project instances characterized by a number of resource groups greater than 20. However, it is better to validate this suggestion with additional tests.

To conclude this section, the strategy presented seeks to define the adequate capacity buffer sizes to apply to the aggregate periods in the proactive approach. These buffers are solely based on the number of resource groups. These capacity buffers aim at counteracting the underestimation of project costs in aggregate planning levels caused by the disaggregation uncertainty of resource capacities. The proposed strategy suggests that the buffer sizes are more reliable for the instances characterized by a large number of resource groups.

The next section presents the computational results of the simulation-based experimental analysis that will evaluate the robustness and performance of the baseline schedules generated with the proposed proactive approach to confirm its effectiveness in an uncertain context.

--- 4.2 Simulation-based experimental analysis ---

In the simulation-based experimentations, the group of instances G_3 (K = 3) was eliminated and the two groups of instances G_{10} (K = 10) and G_{20} (K = 20) were kept since the study concerns large projects. The robustness and performance of the robust buffered aggregate schedules (referred to as *B-Ag)* generated with the proposed proactive approach are compared to those of the unbuffered aggregate schedules (referred to as *U-Ag*) to test the efficiency of the capacity buffering strategy. The reactive approach was also performed on the disaggregated schedules (referred to as *Det*) obtained by resolving the RCCP model (**APPENDIX 1**) on the detailed base instances of De Boer (1998) with the most probable values of WP work contents in order to distinguish between the effect of the uncertainty in WP work contents and the effect of the disaggregation uncertainty of capacities. When applying the reactive approach to the disaggregated schedules, the remaining horizon at the decision points is always decomposed into equal one-week periods. As for the unbuffered aggregate schedules, no buffering is applied throughout the reactive approach.

TABLE 5 reports the average results of the robustness cost function evaluation. Between the buffered (*B-Ag*) and unbuffered (*U-Ag*) aggregate schedules, notice the great influence of the capacity buffering strategy. Indeed, the cost variations have been considerably reduced. In the detailed schedules (*Det*), the disaggregation uncertainty is absent, only the uncertainty in WP work contents influences the robustness cost function. Therefore, by comparing the robustness of the unbuffered aggregate schedules (*U-Ag*) with the robustness of the detailed schedules (*Det*), one can see that the disaggregation uncertainty is the uncertainty that most influences the robustness cost function. The work contents uncertainty has a minimal impact in comparison. The proposed proactive strategy allows to obtain comparable cost variations with the detailed schedules (*B-Ag* vs. *Det*), especially for instances characterized by a large number of resource groups (K = 20).

Table 6 compares the costs of the realized schedules obtained after applying the reactive approach on the buffered aggregate schedules, $cost_r$ (*B-Ag*), on the unbuffered aggregate schedules, $cost_r$ (*U-Ag*), and on the detailed schedules, $cost_r$ (*Det*). Thus, the following variables are introduced: Var_1 = ($cost_r$(*U-Ag*) - $cost_r$(*B-Ag*) / $cost_r$(*B-Ag*) and Var_2 = ($cost_r$(*Det*) - $cost_r$(*B-Ag*) / $cost_r$(*B-Ag*). Observe that the same costs are practically obtained in the realized schedule whether the buffering strategy is applied or not. In other terms, more realistic cost estimations are generated in the planning phase with the proactive strategy (*B-Ag*) and approximately the same final cost are obtained after the realization of the project. However, when the disaggregation uncertainty is absent (schedules *Det*) the costs of the realized schedules are smaller, which again emphasis on the influence of the disaggregation uncertainty.

--- 4.3 Influence of the level of uncertainty in WP work contents ---

In this sub-section, we study the impact of the level of uncertainty in WP work contents on the robustness and performance of the baseline schedules. Work contents uncertainty is set to three possible values. For each level of uncertainty, the simulated WP work contents are drawn from a triangular distribution with the most probable values being equal to the baseline WP work contents and the minimum and maximum values being set to 1-α and 1+α times the baseline values. The value of the parameter α depends on the level of uncertainty as shown in **TABLE 7**. The test set contains the 50 largest project instances from the class of instances (K = 20 and N = 50) as we are interested in LSEC projects. 100 simulation runs are conducted for each method (*B-Ag, U-Ag, Det*), instance and level of WP work content uncertainty totalling 45000 simulation runs.

TABLE 8 reports the average results of the robustness cost function evaluation. Observe that whatever the method used to generate the baseline schedules, the level of uncertainty in WP work contents does not have a significant impact on the robustness cost function. For instance, for the unbuffered aggregate schedules (*U-Ag*), even without any variability in WP work contents, cost variations are obtained with an order of magnitude of 50% as for the ± 50% uncertainty level in WP work contents. This finding consolidate the earlier observations from **TABLE 5** that the disaggregation uncertainty of resource capacities is the main cause of cost variations. Concerning the baseline schedules obtained with the proposed proactive approach, we obtain average cost variations less than 4.3% and an acceptable dispersion of results for all uncertainty levels under ±25%. For the ± 50% uncertainty level, we observe a slight increase in average cost variations. However, this level of uncertainty is rarely reached in practice. Note the non-zero average cost variation of the disaggregated approach *Det* for the ± 0% uncertainty level. This is a result of some instances that do not reach optimality in the CPLEX optimisations.

	B-Ag		*U-Ag*		*Det*	
	Average $E(cost\%)$	Standard deviation of $E(cost\%)$	Average $E(cost\%)$	Standard deviation of $E(cost\%)$	Average $E(cost\%)$	Standard deviation of $E(cost\%)$
K = 10	**7,0%**	**11,1%**	**74,2%**	**77,3%**	**-1,5%**	**7,3%**
N = 10	4,7%	8,7%	35,0%	21,6%	0,3%	0,5%
N = 20	8,5%	11,5%	58,4%	37,8%	0,6%	1,0%
N = 50	7,8%	12,7%	129,1%	106,6%	-5,3%	11,8%
K = 20	**3,2%**	**4,4%**	**31,1%**	**17,4%**	**-0,8%**	**3,1%**
N = 10	2,0%	4,2%	16,7%	6,6%	0,2%	0,3%
N = 20	3,8%	3,5%	26,1%	5,5%	0,1%	0,5%
N = 50	3,8%	5,0%	50,4%	15,0%	-2,6%	4,8%

TABLE 05. Average results of the robustness cost function evaluation

	U-Ag vs. *B-Ag*		*Det* vs. *B-Ag*	
	Avg realized cost variation (Var_1)	*SD* of realized cost variation	*Avg* realized cost variation (Var_2)	*SD* of realized cost variation
K = 10	**-0,2%**	**3,2%**	**-6,3%**	**4,5%**
N = 10	0,0%	1,9%	-3,3%	2,4%
N = 20	-0,1%	2,9%	-5,6%	3,4%
N = 50	-0,5%	4,3%	-9,9%	4,7%
K = 20	**-0,1%**	**1,2%**	**-3,1%**	**2,1%**
N = 10	-0,1%	0,9%	-1,8%	1,5%
N = 20	-0,1%	0,8%	-2,8%	1,6%
N = 50	-0,2%	1,8%	-4,7%	2,0%

TABLE 06. Comparison of the costs of the realized schedule

Level of WP work content uncertainty	High	Medium	Low
Value of parameter α	0,5	0,25	0,1

TABLE 07. Experimental parameter settings

As in **TABLE 6**, **TABLE 9** compares the costs of the realized schedules obtained with the different approaches (*B-Ag, U-Ag, Det*) but this time for all levels of uncertainty in WP work contents and only for the subset of largest instances (K = 20 and N = 50). Again, we observe that the uncertainty in WP work contents does not have a significant impact on the performance of the realized schedules. For all uncertainty levels, the realized project costs by the buffered aggregate approach are very similar to the unbuffered approach and comparable to the disaggregated approach with an average variation of less than 5.1%. These results prove that the proposed proactive approach has a good performance, regardless of the level of uncertainty in WP work contents.

5. CONCLUSION

In this paper, a robust planning approach for tactical planning of large scale engineering and construction (LSEC) projects is proposed. At this planning level, planners tend to use aggregate planning techniques in order to provide high-level schedules to the client. The proposed approach relies on a simple strategy of keeping a resource buffer on the aggregate periods by lowering the capacity levels by an adequate amount. As the project advances, periods and capacities over periods are gradually disaggregated as more accurate estimates become available. We found that the adequate resource buffer size is 20% of the original estimated capacity on the aggregate periods for instances with a large number of resource groups. However, this result has only been validated for a disaggregation factor of four. More tests should be conducted to study the influence of the disaggregation factor on the resource buffer size.

Work content uncertainty	*B-Ag*		*U-Ag*		*Det*	
	Average $E(cost\%)$	Standard deviation of $E(cost\%)$	Average $E(cost\%)$	Standard deviation of $E(cost\%)$	Average $E(cost\%)$	Standard deviation of $E(cost\%)$
± 0%	4,2%	5,1%	51,3%	15,8%	-2,6%	5,8%
± 10%	3,8%	5,0%	50,4%	15,0%	-2,6%	4,8%
± 25%	4,3%	4,8%	50,9%	15,5%	-1,8%	5,4%
± 50%	6,6%	4,9%	53,6%	16,9%	0,8%	4.0%

TABLE 08. Influence of the level of uncertainty in WP work contents on the robustness cost function

	U-Ag vs. *B-Ag*		*Det* vs. *B-Ag*	
	Avg realized cost variation (Var_1)	*SD* of realized cost variation	*Avg* realized cost variation (Var_2)	*SD* of realized cost variation
+- 0%	0,1%	2,2%	-5,1%	2,3%
+- 10%	-0,2%	1,8%	-4,7%	2,0%
+- 25%	-0,3%	1,6%	-4,3%	1,8%
+- 50%	-0,7%	1,4%	-4,0%	1,6%

TABLE 09. Influence of the level of uncertainty in WP work contents on the performance of the realized schedules

An extensive simulation-based experiment on a large RCCP benchmark set of project instances proved that the proposed approach is very effective in dealing with the disaggregation uncertainty of resource capacities characterizing the tactical planning level. It considerably improves the robustness of the generated aggregate schedules. Indeed, the study reveals a robustness improvement by an approximate factor of 10 in comparison to the unbuffered aggregate approach. The robustness and performance of the proposed aggregate approach is also comparable with a disaggregated detailed approach (a disaggregation factor of four) especially for instances characterized by a large number of resource groups. The proposed approach also proves to be effective whatever the level of uncertainty in WP work contents which do not have a significant impact in comparison to the disaggregation uncertainty of resource capacities. Although a small increase in cost variations was observed for the highest level of uncertainty in WP work contents, this uncertainty level is rarely reached in practice.

We therefore conclude on the significance of the proposed robust planning approach in dealing with the uncertainties characterizing the tactical level of LSEC projects, while keeping the planning effort to a minimum. The approach can provide tight and reliable project cost estimates at project phases where the lack of information and uncertainty level are still high especially for the work planned for further periods. Future research avenues would be to test the influence of the disaggregation factor on the resource buffer sizes, and to test the relevance of the proposed approach for other types of disaggregation, especially the disaggregation of WPs into smaller activities. However, we should note that the consideration of uncertainty in WP work contents in the proposed reactive simulation approach is an indirect way to consider the disaggregation uncertainty of WPs. It would also be interesting to test the proposed approach on real projects. ◆

• APPENDIX •

The notations of sets, parameters, and variables are presented in Table 10

Sets	
P	Set of time periods ($p \in P$)
I	Set of work packages ($i \in I$)
R	Set of resource groups ($r \in R$)
$Pred_i$	Set of predecessors of WP i
Parameters	
D_p	Duration of period p (in weeks)
H	Time horizon: $H = \sum_{p \in P} D_p$
RD_i	Release date of WP i
Q_i^{max}	Maximum workload that can be assigned to i during one week
Q_{ri}	Required workload of WP i on resource group r
K_{rp}	Available capacity of resource group r during period p
Variables	
ts_i , tf_i	Start time and finish time of WP i
zs_{ip}	Binary variable that equals 1 if ts_i is in period p or before
zf_{ip}	Binary variable that equals 1 if tf_i is in period p or before
d_{ip}	Duration of WP i within the period p ($0 \le d_{ip} \le D_p$)
x_{ip}	Intensity (fraction performed) of WP i in period p ($0 \le x_{ip} \le 1$)
$yint_{rp}$	Internal load of resource r in period p
$yext_{rp}$	External load of resource r in period p

TABLE 10. Nomenclature: sets, parameters, and variables

• APPENDIX •

APPENDIX 1

$$\text{Minimize} \sum_{r\in R}\sum_{p\in P} yext_{rp} \tag{1}$$

$$ts_i \geq \sum_{k=1}^{p} D_k * \left(1 - zs_{ip}\right) \qquad \forall i \in I, p \in P \tag{2}$$

$$ts_i \leq \sum_{k=1}^{p} D_k + \left(H - \sum_{k=1}^{p} D_k\right) * \left(1 - zs_{ip}\right) \qquad \forall i \in I, p \in P \tag{3}$$

$$zs_{ip} \geq zs_{ip-1} \qquad \forall i \in I, p \in P \tag{4}$$

$$d_{ip} \leq D_p * \left(zs_{ip} - zf_{ip-1}\right) \qquad \forall i \in I, p \in P \tag{5}$$

$$d_{ip} \geq D_p * \left(zs_{ip-1} - zf_{ip}\right) \qquad \forall i \in I, p \in P \tag{6}$$

$$d_{ip} \geq tf_i - \sum_{k=1}^{p} D_k + D_p * zs_{ip-1} - H * \left(1 - zf_{ip}\right) \qquad \forall i \in I, p \in P \tag{7}$$

$$d_{ip} \geq \sum_{k=1}^{p} D_k * \left(1 - zs_{ip-1}\right) - ts_i - D_p * zf_{ip} \qquad \forall i \in I, p \in P \tag{8}$$

$$\sum_{p\in P} d_{ip} = tf_i - ts_i \qquad \forall i \in I \tag{9}$$

$$ts_i \geq RD_i \qquad \forall i \in I \tag{10}$$

$$ts_i \geq tf_j \qquad \forall i \in I, j \in Pred_i \tag{11}$$

$$x_{ip} * \sum_{r\in R} Q_{ri} \leq Q_i^{max} * d_{ip} \qquad \forall i \in I, p \in P \tag{12}$$

$$\sum_{p\in P} x_{ip} = 1 \qquad \forall i \in I \tag{13}$$

$$yint_{rp} + yext_{rp} = \sum_{i\in I} x_{ip} * Q_{ri} \qquad \forall r \in R, p \in P \tag{14}$$

$$yint_{rp} \leq K_{rp} \qquad \forall r \in R, p \in P \tag{15}$$

$$zs_{ip}, zf_{ip} \in \{0,1\} \qquad \forall i \in I, p \in P \tag{16}$$

$$\text{all variables} \geq 0 \tag{17}$$

The objective of the model (1) is to minimize the project cost. Constraints (2) to (4) position WP start times with regards to periods based on binary variables zs_{ip}. Equivalent constraints are used to situate WP end times tf_i using binary variables zf_{ip}. Constraints (5) to (9) define WP durations over periods d_{ip} based on the binary variables and WP start and end times. Constraints (10) ensure the respect of WPs release dates and constraints (11) the respect of precedence constraints. Constraints (12) ensure the respect of the maximum allowed workload per WP. Constraints (13) ensure the realization of the total required workload per WP. For each resource group and period, constraints (14) ensure that the sum of the internal and external loads corresponds to the total assigned workload to all WPs. The external load corresponds to the fraction of workload over the regular capacity limit. Constraints (15) ensure the respect of the capacities by the internal loads.

APPENDIX 2

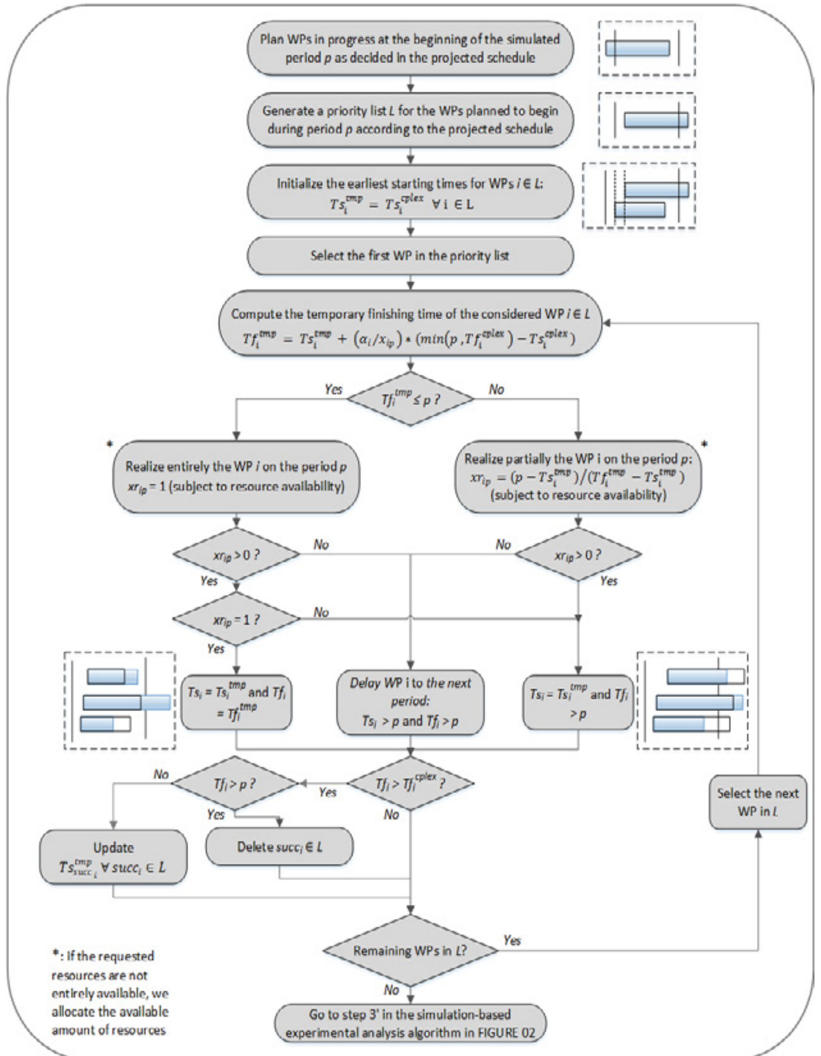

FIGURE 09. Simulation algorithm on period p between the decision points td_{p-1} and td_p

Variables and parameters	Description
Ts_i^{cplex}, Tf_i^{cplex}	Start time and finish time of WP *i according to the projected schedule*
Ts_i^{tmp}, Tf_i^{tmp}	Temporary start time and finish time of WP *i*
Ts_i, Tf_i	Start time and finish time of WP *i* in the realized schedule
Q'_{ri}	Real required workload of WP *i* on resource *r*
α_i	Modification factor of the work content of WP *i* ($Q'_{ri} = \alpha_i * Q_{ri} \ \forall\ r \in R$)
xr_{ip}	Real intensity of WP *i* in period *p*
$succ_i$	Successor of WP *i*

TABLE 11. Nomenclature of the variables and parameters introduced in the simulation algorithm

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