南亞技術學院教師專題研究計畫
成果報告

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從專案風險管理觀點進行多組態資源限制專案的排程追蹤與成功度預測

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預測專案干擾所產生之威脅-應用於 MRCPSP/max 之整合排程架構

陳香伶
企管系

摘要

我們的日常生活中隨時都須面對不確定性與進行風險管理，對企業而言，不確定性不僅表示不可預期的意外狀況，更重要的是它往往成為企業是否能夠成功的重要關鍵因素。申請人在科技部補助下所進行的研究，已嘗試針對傳統多組態資源限制專案排程問題（Multi-mode Resource Constrained ProjectScheduling Problem；MRCPSP）的變化型－考慮活動（activities）間的循環（cycle）以及喜好度（preference）權重的最小與最大時滯的多組態資源限制專案排程問題（MRCPSP with minimal andmaximal time lags；MRCPSP/max）進行探討，此變化型問題不僅更加複雜，且亦更能符合具重工（re-engineering）作業環境之實際需求。於此前期研究中，申請人已成功發展出產生穩健底線排程（robust baseline schedule）以及被動排程（reactive schedule）之方式。

過去在追蹤專案排程表現時最常使用的衡量方式應該是屬於財務方面的指標（financialindicator），如淨現值（Net Present Value；NPV），儘管如此，申請人在研究與文獻探討的過程中發現，預測排程成功機率的相關研究卻幾乎是付之闕如。因此本計畫希望達到下面三項目標：1. 決定一可靠的衡量方式來預測一排程是否會成功；2. 定義出績效門檻值，藉以在專案執行期間，準確預測一排程是否仍然可行；3. 希望透過平行運算的方式，發展三個不同的最佳化演算法－差異進化演算法（Differential Evolution；DE）、基因演算法（Genetic Algorithm；GA）、蟻群最佳化（Ant Colony Optimization；ACO），藉以測試所提出的排程方法之穩定性（stability）。

綜而言之，本研究之終極目標在於幫助實務界得以成功的從被動排程的產生轉換到正確追蹤專案的表現，且所定義的門檻值參數將得以讓決策者在問題發生初期即採取適當的措施，減少損失，更可藉此預測當有嚴重的干擾發生時，此專案的不可行性機率。

壹、緒論

Uncertainty and risk management is part of our everyday life and when it comes to business, not only is it not an exception but it becomes decisive in success. Every year, countless man hours and budgets are used in devising and planning projects that can save companies from bankruptcy, or that can make them the sole leaders of an industry. The importance of this topic makes it ever-relevant for research, especially in an economic environment that changes quickly and often dramatically; and yet, despite mounds of research available many projects are still being considered as failure. So, what makes a project successful? Is it possible to predict a project’s success? Even more, is it possible to develop parameters that accurately track and predict if a project is still feasible early enough to raise flags so that it can be reset back on track or so that it can just be declared infeasible while

significantly cutting the losses?

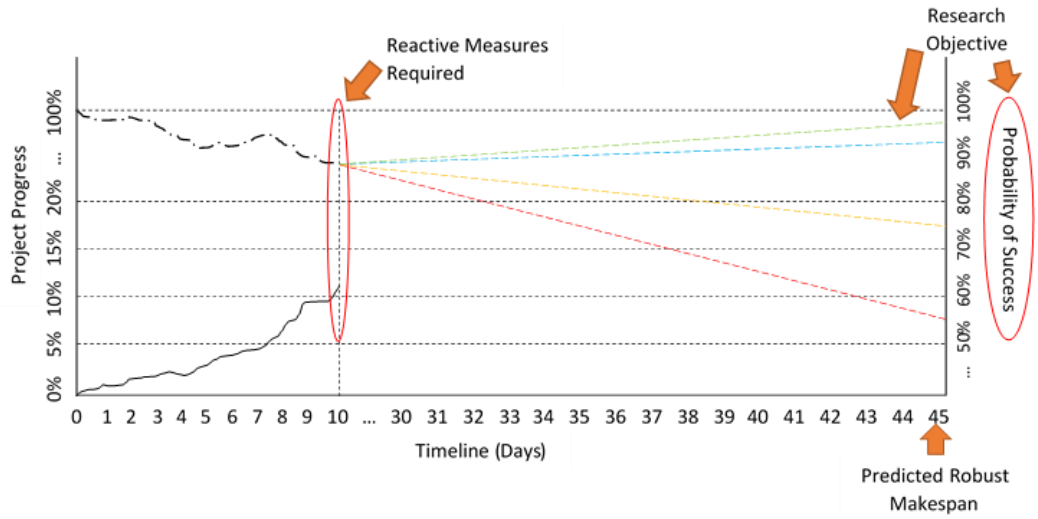

Figure 1. Illustration of the Research Objective

Figure 1 for an illustration of the objective of this research study. Suppose a 45 days makespan project is being developed. In previous published studies we have presented a methodology for the Multi-mode Resource Constrained Problem (MRCPSP) (Chen et al., 2014) and the MRCPSP with minimal and maximal time lags (MRCPSPS/max) (Chen et al., 2016), that can generate robust schedules capable of absorbing small variations caused by uncertainty. If all remains the same as the day of the planning then the probability of success for this project should be 100% once the execution begins. However, a disruption surfaces on day 10 and therefore reactive measures are required. In a yet to be published study, we developed a framework that uses production scheduling environment tools such as stochastic scheduling, Rolling Horizon, Decomposition and Hierarchy, and among others, Sensitivity Analysis to generate predictive and reactive schedules. Nonetheless, in that study we also point out the difficulties regarding the correct application of sensitivity analysis.

Stemming from the disruption there are different probabilities of success for our project, but does it only depend on the reactive measure taken? If so, the challenge now is to determine which reactive measure we should choose in order to maximize the probability of success of the project. But, is it possible that there are other factors affecting our probability of success? Is it possible to define a list of factors and formulate a model in a way such that we are able to accurately predict the probability of success at any given time during the project? Is there a particular factor that weighs more than the others in that prediction? Is there a point in which the projects loses its feasibility, and if so, how can we determine it before the losses are too high? As aforementioned, we already have 2 out of this 3-part scheduling puzzle. And so, inspired on these difficulties and the potential paramount impact that this kind of analysis can have, for our current proposal we want to focus on developing the parameters that can predict the success or failure of a project.

貳、文獻探討

This section highlights current researches in three key aspects: the project scheduling problem, the success criteria, and solution procedures.

2.1 T he Project Scheduling Problem

A more realistic variation of the RCPSP is one in which tasks can be completed in a number of ways or modes. The concept of modes was introduced by Elmaghraby (1977) and in this model, several possible alternatives could lead to different durations, and potentially require different resources or amount of resources. This problem is known as the multi-mode resource-constrained project scheduling problem (MRCPSP) and it has been proven NP-hard as a generalization of the RCPSP (Kolisch, 1995). This model has been thoroughly studied in regards to predictive scheduling but scarcely regarding reactive scheduling and defining parameters that define its success. Recent example of its study can be found in Zhang et al. (2016), Rezaeian et al. (2015), Soliman and Elgendi (2014), Chen et al. (2014), Wang and Fang (2012), Nguyen and Kachitvichyanukul (2012).

A third and more true-to-life variation of the RCPSP is one known as the MRCPSP with minimal and maximal time lags (MRCPSP/max). The characteristics that define this model are: first, unlike in the MRCPCP, here the successor of an activity j can be an activity with a lower index i, this means that activities do not necessarily advance linearly and therefore cycles between activities can appear. Second, there may be a time lag between activities. In real-life situations, practitioners sometimes will sometimes need to delay the beginning of an activity depending on how the activity that is currently ongoing is executed. This is represented by the use of weights on arcs connecting the modes between different activities. Translated to a real-life scenario, these weights can be thought of as “penalties” for particular execution modes imposed by the scheduler probably based on soft constraints. The difficulty of dealing with the constraints of this model has made it one of the less researched variations with very scant studies. Among the studies we find Briand et al. (2002), Heilmann (2003), Barrios et al. (2011), and most recently Chen et al. (2016). For this study we will focus on developing a Schedule Success Predictor and Performance Threshold Parameters, for the MRCPSP and the MRCPSP/max problems and their formulation is detailed later.

2.2 MRCPSP/max

In an early attempt to define different project success criteria Atkinson (1999) introduced what he called the Square Route. In addition to the traditional way to measure a project’s success, the Iron Triangle, (Time, Cost and Quality) Atkinson also includes the company’s information system, Benefits for the organization and Benefits for the stakeholders. His argument is that the Iron Triangle’s criteria, are no more than two best guesses and a phenomenon. He also claims that to focus the success criteria exclusively upon the delivery

criteria to the exclusion of others, may have produced an inaccurate picture of so called failed project management. In Lim and Mohamed (1999) they also try to define a project's success and conclude that it's dependent on the perspectives, two possible viewpoints: micro and macro; and just like in Atkinson's study, they also consider the stakeholders in their definition of success for a project.

Cooke-Davies (2002) identify 12 factors that are, in one way or another, critical to project success based on empirical research from more than 70 large multi-national or national organizations answering three separate questions: "What factors lead to project management success?", "What factors lead to a successful project?" and "What factors lead to consistently successful projects?" Later, on Westerveld (2003), the author defines The Project Excellence Model® where he tried to link project success criteria and success factors. The model consists of six result areas covering project success criteria and six organizational areas covering critical success factors. In Fortune and White (2006), they propose the Formal Systems Model, which they claim can be used as a framing device to deliver the benefits of taking account of 'critical success factors' whilst overcoming most of the problems associated with a checklist approach.

More recently, in Hagen and Park (2013) they solidify that open communication is highly important to both customer perceptions of results and project results that are related to organizational performance, such as project impact organizational strategy and project cost savings. Also, they conclude that ambiguity acceptance, or the ability to work within ambiguous contexts, is very important to a team leaders' ability to guide a complex project through completion with good results and thus we may begin to think of ambiguity acceptance as another, rather important, critical success factor in project management. And finally, Todorović et al. (2015) presents an integrated framework for project success analysis as a new knowledge-based approach in project management. They conducted an empirical research in order to define the contribution of project success analysis framework to knowledge management in project environment.

2.3 Solution Procedures for the Project Scheduling Problem

The complexity combinatorial problems such as the Project Scheduling Problem its variations, and the great advances in personal and scientific computing have pushed the solution procedures to the use of metaheuristic algorithms. However, there have been some competitive exact algorithms for MRCPSP, which mainly derivate from the branch and bound algorithm particularly the ones presented by Hartmann and Drexl (1998), Sprecher and Drexl (1998), Sprecher et al. (1997).

Nonetheless, as aforementioned, the vast majority of solution procedures proposed currently are based on one or a combination of metaheuristic algorithms. Known for their capabilities and accessibility, several metaheuristics such as Taboo Search (TS), Simulated Annealing (SA), and Genetic Algorithm (GA), are some of the early recognized methods.

Among the most recent, beginning from 2010, we find Carazo et al. (2010) who solved project portfolio selection and scheduling problem using TS and Scatter Search (SS). Shi et al. (2010) proposes a hybrid Ant Colony Optimization and Scatter Search (ACOSS) to solve RCPSP in real time. Fang and Wang (2012) uses Estimation of Distribution Algorithm (EDA) to solve MRCPSP with the criterion to minimize makespan. And more recently we find Nguyen and Kachitvichyanukul (2012), which propose an efficient differential evolution (eDE) algorithm is proposed with linear decreasing crossover factor and adaptive penalty cost. Torabi et al. (2013) presents an effective multi-objective particle swarm optimization (MOPSO) algorithm. The use of a discrete Artificial Bee Colony is proposed in Chen et al. (2014). Hao et al. (2014) uses a multi-objective EDA for robust resource constrained project scheduling with uncertain durations. Rezaeian et al. (2015) proposes the use of a sub-population genetic algorithm (SPGA) to find Pareto solutions for a new bi-objective mathematical model. And more among the most recent we find Zhang et al. (2016) which uses a hybrid particle swarm and differential evolution algorithm to solve the MRCPSP.

In this study, we plan to implement and compare three different metaheuristic algorithms to optimize the schedule makespan, namely: the Differential Evolution (DE), Genetic Algorithm (GA), and the Ant Colony Optimization (ACO).

參、問題概要

The following sections detail the formulation of the two models being considered for this proposal as a way to contrast the models and further highlight their differences. Initially, the threshold parameters will be based on the constraints and objectives of the simpler MRCPSP model. In a later stage, the parameters will be adjusted to fit the constraints of the more realistic and complex MRCPSP/max model.

In the MRCPSP with constrained renewable and non-renewable resources, we assume that activity i has an activity number larger than all immediate predecessors (i-1) ∈ Pi. Also, we assume that we have unique dummy activities that represent the project's beginning and end, i = 1 and i = I, and each of these two can only be performed in a single mode with duration zero and zero resource requirements. The mathematical formulation for the MRCPSP is defined by Talbot (1982) as follows:

$$Min\ Z = \sum_{m=1}^{M_I} \sum_{t=EFT_I}^{LFT_I} t * x_{imt}, \qquad (1)$$

Subject to:

$$\sum_{m=1}^{M_i} \sum_{t=EFT_i}^{LFT_i} x_{imt} = 1, \qquad \forall\, i \qquad (2)$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M_i} r_{imk}^{\rho} I_{im}(t) \leq R_k^{\rho}, k = 1, \dots, K^{\rho}; t = EFT_i - d_{im} + 1, \dots, LFT_i \quad (3)$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M_i} r_{imk}^{v} * \sum_{t=EFT_i}^{LFT_i} x_{imt} \leq R_k^{v}, k = 1, \dots, K^{v} \quad (4)$$

$$\sum_{m=1}^{M_i}\sum_{t=EFT_i}^{LFT_i} t x_{imt} \leq T, \qquad \forall\, i \quad (5)$$

$$x_{imt} = \begin{cases} 1 \text{ if activity } i \text{ is executed in mode } m \text{ and finished at time } t \\ 0 \text{ otherwise} \end{cases} \quad (6)$$

$$Y_{im}(t) = \begin{cases} 1 \text{ if activity } i \text{ is executed in mode } m \text{ and in process at time } t \\ 0 \text{ otherwise} \end{cases} \quad (7)$$

Equation (1) establishes that our objective is to minimize the makespan of the project. Given an upper bound of the project's makespan T, the earliest (EFTi), and latest (LFTi) finish times can be determined by the standard forward pass, assigning to each activity its shortest mode and a traditional backward pass after assigning LFTI = T. Equation (2) ensures that each activity must be executed in exactly one of Mi alternative modes and its completion time must be in the range of {EFTi,…,LFTi}. Equation (3) represents renewable resource availability of any type k at any time during project execution while Equation (4) represents the limitation on the total usage of each non-renewable resource type during project execution. Equation (5) specifies the project completion time cannot exceed the deadline T. Equations (6) and (7) define two binary decision variables which identify the completion time and the in-process of activity i, respectively.

In MRCPSP/max, a project consist of a set V = {1,y,n} of activities. The dummy activities 0 and n+1 represent the start and completion of the project, respectively. For each activity j ∈ V a set Mj = {1,y,|Mj|} of modes is available. Each activity j ∈ V has to be performed in exactly one mode μ ∈ Mj. The processing time of activity j executed in mode m is denoted by pjμ ∈ Z≥0. Sj and Cj stand for the start time and the completion time of activity j, respectively. If we define S0 = 0, Sn+1 stands for the project duration. Provided that activity j starts in mode m at time Sj, it is being executed at each point in time t∈ [Sj,Sj+pjμ].

Between the start time Sj of activity j, which is performed in mode μ ∈ Mj, and the start time Sl of activity l (l ≠ j), which is performed in mode λ ∈ Ml, a minimum time lag d_jμlλ^min∈ Z≥0 or a maximum time lag d_jμlλ^max∈ Z≥0 can be given. Note that a time lag between activities j and l depends on mode μ as well as on mode λ. A minimum (maximum) time lag between Sj and Cl, Cj and Sl, and between Cj and Cl can be expressed by a minimum (maximum) time lag between Sj and Sl (Bartusch et al., 1988).

Activities and time lags are represented by an activity-on-node (AoN) network N=<V,E;δ> with node set V, arc set E, and arc weight function δ. Each element of node set V

represents an activity. An arc <j, l> ∈ E indicates that a time lag between Sj and Sl has to be observed.

Arc weight function δ assigns to each arc <j, l>∈ E a |Mj| x |Ml|– matrix (δ_(〖 jμlλ〗 _(μ∈Mj,λ∈Mj))) of arc weights as follows: for a minimum time lag d_jμlλ^min we set δjμlλ = d_jμlλ^min ; and for a maximum time lag d_jμlλ^maxwe set δjμlλ = d_jμlλ^max. The inclusion of maximum time lags lead to cycles in N with more than one node. A cycle structure is a strong component in N with more than one node. N can be divided into cycle structures and single nodes.

Rρ denotes the set of renewable resources and Rv the non-renewable resources in the project. R_k^ρ stands for the amount of renewable resource available per period while R_k^v represent the amount of nonrenewable resources available in total. If activity j, is performed in mode μ, r_jμk^ρ units of renewable resource type k are consumed every time activity j is performed and r_jμk^v are consumed in total. Activities 0 and n+1 have only one mode, last for duration 0 and use no resources at all.

A schedule (M, S) consists of a mode vector M and a start time vector S. A mode vector M = (mj)j∈V assigns to each activity j∈ V exactly one mode μ∈ Mj. Each mode vector M has an associated project, N(M), obtained by choosing the durations, resources and time lags corresponding to the modes of M. A start time vector S= (Sj)j∈V assigns to each activity j ∈ V exactly one point in time t ≥ 0 as start time Sj with S0 = 0.

The objective is to determine a schedule (M, S) such that the time lags (2) are observed, the constraints with respect to the renewable resources (3) and the non-renewable resources (4) are met, and the project duration is minimized (1). Such a schedule is called optimal. A schedule (M, S) obeying constraints (2)–(4) is called feasible. Since MRCPSP/max is a generalization of RCPSP/max, MRCPSP/max is NP-hard (Bartusch et al., 1988). Even the corresponding feasibility problem is NP-complete (Heilmann, 2001).

A mode vector M such that the constraint (4) is observed is called resource feasible. We call a vector of modes M time feasible if the associated project N (M) does not have cycles of positive length. That is, if there exist start times for the activities that fulfil constraint (2). Refer to Barrios et al. (2011) for an example of this model

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肆、研究方法

This study applies two optimization algorithms. First, the Differential Evolution is a powerful evolutionary-type, population-based algorithm created by Storn and Price (1995) to optimize functions over continuous solution spaces. Given its characteristics, simplicity and robustness, it has found its way in numerous applications ranging from registration and treatment of images, optimization of chemical processes, learning of neural networks, and up

through design in aerodynamics, etc. However, its original conception was to handle continuous solution spaces and therefore a discrete DE approach is required in order to be applied when solving combinatorial problems such as the MRCPSP. Because of its popularity, a number of authors have proposed different ways to discretize DE such as in Pan et al. (2008), Peng and Huang (2014), Tasgetiren et al. (2009), and this particular study we will take the approach used in Damak et al. (2009) which is a discrete version of DE. Following is the pseudo-code for DE:

Generate the initial population of individuals

DO

For each individual j in the population

Choose three numbers n_1, n_2, *and* n_3 *that is,* $1 \leq n1, n2, n3 \leq N$ *with* $n1 \neq n2 \neq n3 \neq j$

Generate a random integer $i_{rand} \in (1, N)$

For each parameter i

$$y^{i,g} = x^{n_1,g} + F(x^{n_2,g} - x^{n_3,g})$$

$$z_j^{i,g} = \begin{cases} y_j^{i,g} if\ rand() \leq CR or\ j = j_{rand} \\ x_j^{i,g}\ otherwise \end{cases}$$

End for

Replace $x_j^{i,g}$ *with the child* $z_j^{i,g}$ *if* $z_j^{i,g}$ *is better*

End for

Until the termination condition is achieved

The second algorithm we will use to optimize our schedule's makespan is Genetic Algorithm which is one of the most popularly used optimization metaheuristic algorithms; it was proposed by Holland (1975). In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered. The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. A pseudo-code for a typical GA is presented below:

BEGIN

Initialize *population with random candidate solutions*

Evaluate *fitness for each candidate*

Repeat until termination criteria is satisfied:

Select *parents*

Crossover *pairs of parents*

Mutate *the offsprings*

Evaluate *fitness for each candidate*

Select *individuals for next generation*

End repeat

END

Unlike the EVM proposed by the PMI, we believe that a project's performance and success cannot and should not be based solely on financial indicators. For this reason, the main purpose of this research is to determine which factors should be included in order to predict a schedule's probability of success and which can accurately track its performance once execution is under way.

Ultimately we want to connect predictive and reactive scheduling techniques by never losing sight of a project's performance and therefore be able to raise flag properly and timely before any issues were to be determinant. We plan to do this in one of two ways: one is to define an objective function that can be optimized by the three proposed meta-heuristic algorithm. A second way is to develop a metric which weighs in all the factors in order to accurately to track the progress. These factors however, can be both quantitative and qualitative. For the scope of this study we will focus only on the quantitative.

伍、結果與討論

Because of the complexity and impact of the topic covered the time span considered for this study is two years. Our main target during the first year will be the development and testing of threshold parameters that can accurately track. And they can predict a project's success, first for the MRCPSP and then expand and adjust this knowledge to the MRCPSP/max model. The importance of these threshold parameters resides in that it is costly and time consuming for an organization to set a project back on track so that it can meet a deadline. However, it could be even more expensive to not meet such deadline, achieve the required scope and/or its expected quality. With these parameters we expect to help practitioners raise flags timely when a project is running close to its feasibility limit and facilitate the decision on whether to generate a new schedule, initiate recovery actions or abandon a project which could ultimately result

infeasible.

We used the benchmark sets found in to evaluate our methodology. Suppose a 45 days makespan project is being developed. In previous published studies we have presented a methodology for the Multi-mode Resource Constrained Problem (MRCPSP) (Chen et al., 2014) and the MRCPSP with minimal and maximal time lags (MRCPSPS/max) (Chen et al., 2016), that can generate robust schedules capable of absorbing small variations caused by uncertainty. If all remains the same as the day of the planning then the probability of success for this project should be 100% once the execution begins. However, a disruption surfaces on day 10 and therefore reactive measures are required. In a yet to be published study, we developed a framework that uses production scheduling environment tools such as stochastic scheduling, Rolling Horizon, Decomposition and Hierarchy, and among others, Sensitivity Analysis to generate predictive and reactive schedules. Nonetheless, in that study we also point out the difficulties regarding the correct application of sensitivity analysis. We evaluated our approach using the MRCPSP/max benchmark instances found in http://www.wiwi.tu-clausthal.de/en/chairs/produktion/research/research-areas/project-generator/mrcpspmax/.

At the moment of writing there were 3 benchmark sets divided by number of activities (30, 50, and 100 activities); each set contains 270 instances and every instance uses 3 renewable, 3 non-renewable and 3 doubly constrained resources. Also, every activity can be executed in between 3 and 5 different modes except for the dummy (initial and final) activities which have only one mode with no duration and no resource consumption. The purpose of this study is to develop an approach that basically generates a lower and upper bound for a schedule's makespan and ultimately generates a robust baseline schedule within these boundaries making it capable of absorbing variations caused by its inherent uncertainty. And even though our main objective was not to minimize the makespan, in most of the MRCPSP cases the best know solution was reached as the lower bound.

In Chen et al. (2014) the authors conducted a sensitivity analysis to determine the values of the parameters to be used for the ABC algorithm, and the entropy and robustness functions. In that study the best results were obtained when using higher levels on parameters that increase the search space and using the lowest levels for those parameters that are linked directly to the solution's quality. And given that this is an extension of that methodology from the MRCPSP to the MRCPSP/max we use the same parameters developed and tested in that previous study. Table 4 shows the parameters used in this study.

Table 4. Parameters used for ABC Algorithm

Parameter	Value
Population size	30
Abandonment limit	5
MNC	20
δt (relevant time interval)	1
frac	0.25

With these parameters, we followed our method as described in Section 4: in Stage 1 we used the discrete ABC algorithm to minimize the instances' makespan (MS1); this will serve as the lower bound of the execution time-frame. In Stage 2, we use the entropy equation (1) to determine the upper bound (MS2). Finally, in Stage 3, we compute a third makespan also using the discrete ABC, but in this stage we seek to maximize robustness while keeping the makespan lower than the upper bound, though not necessarily higher than the lower bound.

Table 5 presents summary statistics from evaluating all 270 instances of every benchmark set. Here, the average deviation (Avg. Dev.) is computed as the average of all the deviations when evaluating (Ms – M*) / M*, where M* represents the reference makespan (e.g., the optimal or best-known makespan (BKO) when comparing the results of Stage 1 and Stage 3) and Ms denotes the makespan of the current stage. Furthermore, S1, S2 and BKO represent the makespan of Stage 1, Stage 2 and the Best-Known Optima respectively.

Table 5. Results Summary for Benchmark Instances

	Benchmark Set	**MM30**	**MM50**	**MM100**	**Overall**
	Optima Found	260	123	84	**Average**
Stage 1	*Avg. Dev. vs BKO*	0.18%	4.57%	4.42%	**3.06%**
Stage 2	*Avg. Dev. vs BKO*	9.69%	10.13%	8.50%	**9.44%**
	Avg. Dev. vs S1	6.02%	5.84%	4.27%	**5.38%**
Stage 3	*Avg. Dev. vs BKO*	5.04%	5.39%	4.37%	**4.93%**
	Avg. Dev. vs S1	1.10%	0.79%	-0.12%	**0.59%**
	Avg. Dev. vs S2	-5.36%	-5.48%	-4.62%	**-5.16%**

Decisions about the research problem, research design, data gathering

methodology and data analysis are all affected by the purpose of a research. This research is a descriptive research tending to get information about the cause of a situation. The major concern is accuracy. Rensis Likert scale of 5 points for strongly agree, 4 points for agree, 3 points for not decided, 2 points for disagree and 1 point for strongly disagree will be adopted. Two criticisms of Likert scale in social research is that it is too simple to evolve a strong inference (simplicity) and that it pre-empts respondents by suggesting opinions and asking them to rank the suggested opinions (objectivity). These criticisms were guided against through asking same questions in at least two different ways. For example, “Bad weather” and “Unsuitable weather”, “Procurement method” and “Procurement route” and “Contract value” and “Contract sum”. Deviations of the three were calculated to see if there should be adjustment for others. In the three cases, deviations were less than 5% and considered negligible. The issue of objectivity was solved by leaving spaces in the questionnaires for statement of respondents’ personal opinions on the subject matter. The total point achieved by all the 21 factors is 12739. The average is 606.62. Any factor that is below 606.62 will be considered as weak and discarded.

Table 6. Frequency Table of Respondents on Factors Affecting Duration of Projects

Reasons	**Degree of Importance and Frequency**					
	5 points	4 points	3 points	2 points	1 point	Total points
R1: Poor cash flow	68	69	16	4	0	672
R2: Contractor type (whether professional or non-professional)	58	62	23	9	5	646
R3: Type of design (whether simple or complex, lowrise of highrise)	61	53	19	12	12	610
R4: Type of work either new build or refurbishment	62	57	21	8	9	626
R5: Contract value	59	63	13	6	16	614
R6: Year of project (election year or non-election year)	63	51	39	3	1	643
R7: Date of start of project	60	45	23	12	17	590
R8: Location of project (topography and geology of site)	55	36	25	20	21	555
R9: Procurement route	51	42	28	26	10	569
R10: Poor supply chain management	53	38	26	32	8	567
R11: Method of selection of contractors	38	56	55	5	3	592

R12: Unstable weather	59	53	19	20	6	610
R13: Client type (whether private or public)	64	52	14	15	13	608
R14: Building function (whether residential, commercial, industrial, sport, recreation)	56	41	36	18	6	594
R15: Culture of construction contracts	42	44	12	28	31	509
R16: Disagreement between contractors and clients or clients' representatives	58	53	32	7	7	619
R17: Corruption	71	54	18	11	3	650
R18: Getting approval from government	69	55	15	13	5	641
R19: Poor site communication	48	47	41	16	5	588
R20: Lack of teamwork among participants	49	53	45	9	1	611
R21: Insecurity	58	51	40	3	5	625
Total points						12739

Table 6 is the frequency table of respondents on factors affecting duration of construction projects Reason 1: "Poorcash flow" has the greatest weight with 672 points. This is ranked first followed by Reason 17: "Corruption" with 650 points. Reason 2: "Contractor type (whether professional or non-professional)" has 646 points and was chosen as the third most important reason. Reason 6: "Year of project (election year or non-election year)" has 643 points and takes the fourth position followed by Reason 18: "Getting approval from government" with 641 points. Reason 4: "Type of work either new build or refurbishment" with 626 points followed suit. Reason 21: "Insecurity" has 625 points. Reason 16: "Disagreement between contractors and clients or clients' representatives" has 619 points. Reason 20: "Lack of teamwork among participants" has 611 points followed by Reason 3: "Type of design (whether simple or complex, lowrise of highrise)" followed by Reason 12: "Unstable weather" with 610 points and followed by Reason 13: Client type (private or public) with 608 points each. All other reasons have below 606.62 points and are discarded because they are low.

陸、總結

In this study we proposed an approach to solving a realistic model for what project management practitioners face in their day to day jobs. Given that uncertainty is present in every schedule executed, instead of focusing on minimizing the makespan and remaining vulnerable to unforeseen events we propose a method to determine an execution time-frame based on the characteristics of the project itself, namely the precedence and the durations for the activities. Construction projects duration is predictable but 'poor cash flow, corruption, contractor type (whether professional or

non-professional), year of project (election year or non-election year), getting approval from government, type of work either new build or refurbishment, insecurity, disagreement between contractors and clients or clients' representatives, lack of teamwork among participants, type of design (whether simple or complex, low-rise of high-rise), unstable weather and client type (whether private or public)' are the major factors adduced by respondents (construction participants) as affecting duration of construction projects. The era of giving contract to non-professionals to carry out construction projects should be over if there will be improvement in the duration of construction projects. Knowledge, skill and competence are three major inputs of successful construction projects. The skill dwells in the expatriates, at times, and without stable and conducive construction environment, there will be dearth of expatriates in the construction industry.

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