Employing Ant Colony for the Optimal Reduction of Project Risk Severity

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Abstract -

Efforts undertaken in identifying, analyzing and assessing project risks are only made good use of when proper risk treatment strategies are decided upon and pursued. Based on the criteria established by senior management, the risk management plan goes about defining how each risk is to be handled. There are options to that end, including acceptance, avoidance, transfer and mitigation. Whilst these strategies are known to all in the industry, the decision-making process is far from easy. A research was undertaken to optimize risk treatment in construction projects, where both costs and benefits are balanced out at the project level. The paper particularly introduces Ant Colony Optimization (ACO) as a capable algorithm for the balanced selection of risk treatment strategies; that is to reduce the overall risk severity in a project at the minimum cost possible. ACO resembles the real life behavior of ants in their intelligent and guided search for food. The research is being applied in the pipeline construction sector and made use of professional knowledge and project records from a big construction company in the Middle East. The paper further presents an example project to demonstrate how ACO explores the risk treatment alternatives in a project and chooses the optimal set of strategies in such context.

Keywords -

Risk management; Risk treatment; Risk mapping; Optimization; Ant Colony

1 Introduction

Project risk management (PRM) is crucial and indispensable to the success of projects. Indeed, risks in the complex projects of nowadays have magnified in terms of number and global impact. Projects are more than ever exposed and averse to risks, and stakeholders are asking for more risk management to cover themselves against financial or legal consequences [1].

Efforts have been undertaken over the years to help us better identify and analyze risky events in projects. Yet, little has been done to address the decision-making component during the risk handling/treatment stage [2, 3]. A review of the literature revealed that research on risk handling/treatment is mostly opinion- or case-based and, as such, it offers scant guidelines for making the decision [2].

Only recently have researchers realized the need to address risk treatment in more depth. Chapman and Ward [4] recommended balancing the cost of treatment actions with the consequences of the associated risks. Quantitative approaches were then adopted to optimize and/or simulate the risk treatment strategies in light of the set project objectives [1, 2, 3].

2 Challenge and Research Approach

The aforementioned researches are difficult to apply in construction projects, as they depend on numerical variables difficult to estimate in real world practice. Furthermore, the poor and inefficient record keeping, which is not uncommon in some construction companies, will complicate the matter further. Accordingly, the authors developed a model that employs indices for the risk treatment decision-making [5, 6].

2.1 Optimizing the Risk Treatment Actions

Optimizing the risk treatment in a project involves identifying the actions with the highest benefit-cost (B/C) balance to that project. A risk treatment index, I_{RT}, is devised to measure the B/C balance, as follows:

$$I_{RT} = ((RM_b – RM_a) / C_{RT}) * RM_b \quad (1a)$$
$$I_{RT} = (P_bI_b * (P_bI_b – P_aI_a)) / C_{RT} \quad (1b)$$

where RM_b is the risk magnitude prior to the risk treatment action, RM_a is the risk magnitude after the risk treatment action, P_b is the probability of risk occurrence prior to applying the risk treatment action, I_b is the risk impact prior to applying the risk treatment action, P_a is the probability of risk occurrence after applying the risk treatment action, I_a is the risk impact after applying the risk treatment action, and C_{RT} is the cost associated with the risk treatment action.

As noted, the B/C ratio is multiplied by the term RM_b so as to factor in the relative significance of the project risks, which is a fundamental aspect in the succeeding optimization process. The authors' approach allows using either qualitative or quantitative data sources [6]. Utilizing the model in case of qualitative data is made possible via the use of numerical rating scales that correspond to the qualitative terms.

2.2 Why Ant Colony?

The optimal reduction of project risk severity requires comparing potential actions for treating individual risks. The literature has noted the difficulties associated with using mathematical optimization on large-scale problems [7]. This has contributed to the development of alternative optimizers, such as genetic algorithms, ant colony, particle swarm, etc. The study by El-Beltagi *et al.* [7] compared these alternative optimizers in an attempt to identify the ones with the better performance. Study noted ant colony to perform superiorly in discrete optimization problems besides being the least demanding in regards to the computer processing time. As a result Ant Colony Optimization (ACO) was the evolutionary algorithm of choice in this study. The paper focuses on this element of the research.

3 Ant Colony Optimization

ACO was developed by Dorigo *et al.* [8] based on the fact that ants are able to find the shortest route between their nest and a source of food. This is done using pheromone trails, which ants deposit whenever they travel as a form of indirect communication, figure 1. When ants leave their nest to search for a food source, they randomly rotate around an obstacle, and initially the pheromone deposits will be the same for the right and left directions. When the ants in the shorter direction find a food source, they carry the food and start returning back following their pheromone trails and still depositing more pheromone. New ants at the nest will choose the shortest path with the more concentrated pheromone. Over time, this positive feedback (autocatalytic) process prompts all ants to choose the shorter path [9].

Implementing ACO for a certain problem requires a representation of S variables for each ant, with each variable i having a set of n_i options with values l_{ij} and associated pheromone concentrations τ_{ij}; where i = 1, 2, ..., S, and j = 1, 2, ..., n_i. As such, an ant is consisted of S values that describe the path chosen by the ant, figure 2 [10].

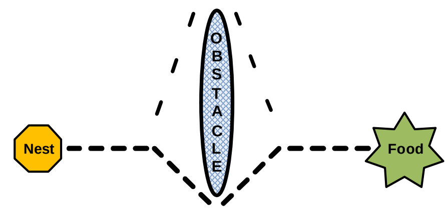

Figure 1. Schematic of the ant colony search for food

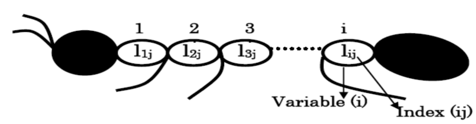

Figure 2. Ant representation

Many researchers use a variation of this general algorithm, incorporating a local search to improve the solution [11]. In the ACO, the process starts by generating m random ants (solutions). An ant k (where k = 1, 2, ..., m) represents a solution string, with a selected value for each variable. Each ant is then evaluated according to an objective function τ. Accordingly, pheromone concentration associated with each possible route (variable value) is changed in a way to reinforce good solutions, as per equation 2 [8]:

$$\tau_{ij}(t) = \rho\ \tau_{ij}(t\text{-}1) + \Delta\tau_{ij}\ ;\ t = 1, 2, \ldots, T \qquad (2)$$

where T is the number of iterations (generation cycles); τ_{ij}(t) is the revised concentration of pheromone associated with option l_{ij} at iteration t, τ_{ij}(t-1) is the concentration of pheromone at the previous iteration (t-1); $\Delta\tau_{ij}$ is the change in pheromone concentration; and ρ is the pheromone evaporation rate (0–1).

In equation 2, the change in pheromone concentration $\Delta\tau_{ij}$ is calculated as [8]:

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \begin{cases} R / fitness_k\ ; & \text{if } l_{ij} \text{ is chosen by } k \\ 0 & ;\ otherwise \end{cases} \qquad (3)$$

where R is a constant called the pheromone reward factor; and $fitness_k$ is the value of the objective function (solution performance) calculated for ant k. It is noted that the amount of pheromone gets higher as the solution improves. Therefore, for minimization problems, equation 3 shows the pheromone change as proportional to the inverse of the fitness. In maximization problems, on the other hand, the fitness value itself can be directly used.

Once the pheromone is updated after an iteration, the next iteration starts by changing the ants' paths (i.e. associated variable values) in a manner that respects pheromone concentration and also some heuristic preference. As such, an ant k at iteration t will change the value for each variable according to the following probability [8]:

$$p_{ij}(k, t) = \frac{[\,\tau_{ij}(t)]^{\alpha} * [\,\eta_{ij}(t)]^{\beta}}{\Sigma_{l_{ij}}\,[\,\tau_{ij}(t)]^{\alpha} * [\,\eta_{ij}(t)]^{\beta}} \qquad (4)$$

where p_{ij}(k, t) is the probability that option l_{ij} is chosen by ant k for variable i at iteration t; $\tau_{ij}(t)$ is the pheromone concentration associated with option l_{ij} at iteration t; η_{ij} is a heuristic factor for preferring among available options and is an indicator of how good it is for ant k to select option l_{ij} (this heuristic factor is generated as per the problem characteristics and its value is fixed for each option l_{ij}); and α and β are exponent parameters that control the relative importance of pheromone concentration versus the heuristic factor [10]. Both α and β can take values greater than zero and can be determined by trial and error.

Based on the previous discussion, the main parameters involved in ACO are: number of ants m; number of iterations t; exponents α and β; pheromone evaporation rate ρ; and pheromone reward factor R.

4 Proposed ACO Model

The index I_{RT} can be employed to quantify the suitability of potential risk treatment strategies in a project. However, deciding upon the optimum risk treatment strategy for a project can be more challenging than it appears. Any project would have a number of risk treatment options constituting the decision points. Each of these risk treatment options can possibly associate with and positively influence multiple risk factors. Another dimension is the inter-dependency of risk factors. Development of a given risk can give rise to other risks. As such, risk mapping is indispensable to modeling such inter-dependency. The authors, in an earlier research [5], have addressed the development of risk maps in construction projects. The pipeline construction sector was used to exemplify the risk mapping process, where 9 risk groups were identified. Each group had a set of potential risks relevant to that group and denoted by GxRy. In this context, x refers to the group number and y refers to the risk code.

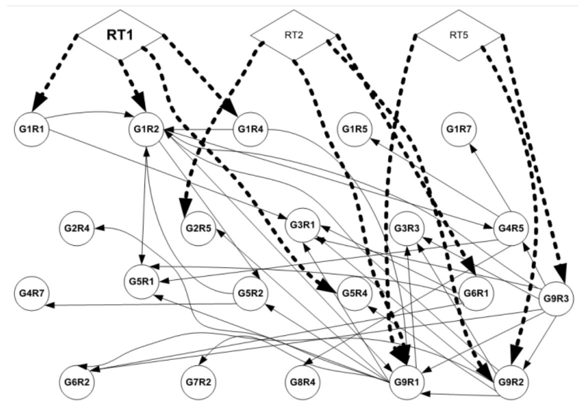

Figure 3. Sample dynamic risk treatment pattern (DRTP)

Obviously, each risk treatment action has a cost associated with it, and when enacted will affect the risks in concern in a certain way. Let us now assume the treatment strategy for the project, i.e., the set of treatments for reducing the project's risk severity, is represented by an ant. Each treatment i has a total of n_i options. Finding the optimum set of treatment actions then follows as per figure 4.

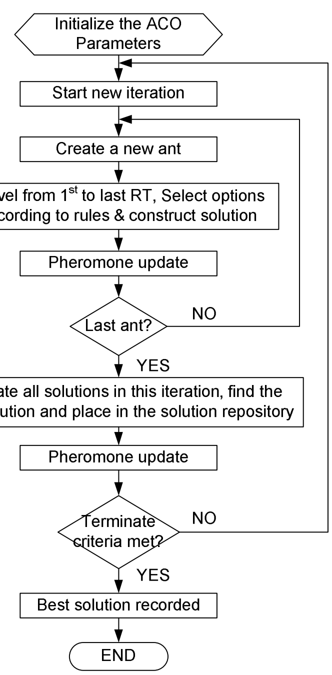

Figure 4. ACO process for risk treatment optimization

In a given iteration, the process starts with initializing potential treatments based on the options available for each. Such scenario would correspond to a certain pheromone concentration τ_0. An artificial ant is launched for the 1st treatment strategy and proceeds, i.e., pseudo-randomly walks, till the last treatment as shown in figure 5.

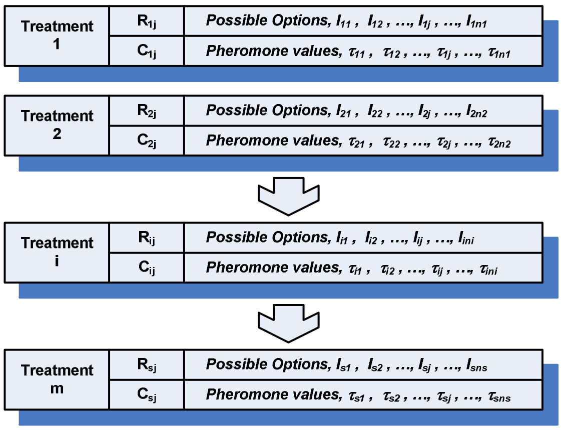

Figure 5. Solution progression using ACO

Each ant k would generate a solution. Having completed a cycle, the pheromone value of the selected options τ_{ij} as generated by the ant is updated according to the pheromone updating rules. After all ants finish their travels, their fitness values are evaluated as per equations 1a and 1b and the best ant solutions then selected.

The approach adopted in this study allows the pheromone updating to be performed according to both the local and global updating rules. The local updating rule implies that the updating is performed after each solution is completed, i.e., when an ant has traveled from 1st to last treatment. On the other hand, the global updating rule involves updating the pheromone after an entire iteration is over, that is to say, after all ants have completed their travels. When the iteration is completed, the pheromone values associated with options belonging to the best solution in that iteration (i.e., inter-best solution) are updated.

As for the stopping/termination criteria, a maximum number of iterations is used in the proposed model due to its convenience and popularity [12]. The algorithm loops back for another iteration until the maximum number of iterations is reached.

5 Illustrative Application in Pipeline Construction Example Project

Substantial research was carried out by the authors to identify, assess and find means to treat the risks that have potential to influence pipeline construction delivery.

Identification and assessment of risks benefited from: (1) the literature, (2) unstructured interviews with selected experts in the field, and (3) a questionnaire survey to a large pool of qualified experts in the Middle East region, where some of the authors work. Full details can be found in an earlier publication by the authors [5].

Survey highlighted 47 risks to exist in the pipeline construction context, tables 1a and 1b. It further revealed the prior probabilities and impacts of these risks. A DRM was then developed to model the interdependencies amongst the risks in reference. Part of such DRM was presented earlier in figure 3.

In a similar effort, risk treatment actions for pipeline construction projects were identified and associated with the risks from the previous research step. Fifty two treatment actions resulted, as illustrated in tables 2a and 2b. Full details can be found in another publication by the authors [6].

A computerized ACO engine was developed using Visual Studio 8 to perform the required optimization process. An example project was used to demonstrate the functioning of ACO. Given the magnitudes of all risks, a total sum of 167 was recorded as indicator of the project's risk severity. When risk treatments are adopted, the project's risk severity is reduced. Obviously the dilemma is to find the most effective risk treatment pattern while accounting for the costs associated with each. The latter are represented via cost indices, table 2b.

Assume that four risk treatments RT1, RT2, RT3 and RT4 were available to pursue with a target of reducing the project's risk severity by 10%. The objective of the optimization process is to maximize the reduction of the risk severity at the least cost possible.

One can think of different patterns comprising the four treatments RT1, RT2, etc. To find the *optimum* risk treatment pattern, the process starts with initializing the ACO parameters and proceeding with the steps depicted in figure 4. A number of ants (solutions) are created, each of which represents a scenario of using available risk treatment option(s). The evaluation and pheromone updating continue till the termination condition is met.

To exemplify let us consider 16 patterns for risk treatment. Four patterns concern the adoption of only one of the risk treatments RT1, RT2, RT3 and RT4 while the rest comprises combinations of two risk treatments, e.g., RT1 and RT2.

As per table 3, results show the pattern leading to the optimum reduction of project's risk severity to be pattern 16. This risk treatment pattern consists of RT4 and RT3. It provides the greatest reduction in risk severity compared to the costs invested. Also it satisfies the original target of 10% reduction in risk severity. Any further reductions will require other risk treatment patterns that will apparently incur additional costs.

Table 1a Risks in pipeline construction

Code	Description
G1R1	Inability of the owner to finance the project
G1R2	Delay in progress payments
G1R3	Inefficient decision making by the owner
G1R4	Owner's refusal or questioning of the compensations
G1R5	Changes in owner expectations
G1R6	Delay or inability of owner to give full possession of site
G1R7	Delay or inability of owner to proceed with final acceptance
G1R8	Owner's high expectations for quality beyond standards
G2R1	Subcontractors low credibility
G2R2	Subcontractors lack of required technical skills
G2R3	Subcontractors lack of managerial skills
G2R4	Subcontractors lack of productivity
G2R5	Poor quality of subcontractor works
G3R1	Scope creep/shrinkage
G3R2	Scope vagueness
G3R3	Drawing change
G3R4	Actual quantities of work
G3R5	Complex design
G3R6	Delay of work shop drawings
G3R7	Incomplete design & information
G4R1	Poor communication between all parties
G4R2	Poor qualification of consultant's supervision staff
G4R3	Delay in approval of contractor submittals
G4R4	Delay in performing testing and inspection
G4R5	Suspension of work
G4R6	Lack of experience
G4R7	Change in key staffing throughout the project
G5R1	Bad Quality of work
G5R2	Low productivity of labor
G5R3	Surveying mistakes
G5R4	Delay in the start of the project
G5R5	Deficient and/or insufficient safety rules
G5R6	Shortage of labor
G5R7	Site accidents
G6R1	Material price fluctuation
G6R2	Material shortage
G6R3	Delays in material delivery
G7R1	Maintenance cost of equipment
G7R2	Low productivity and efficiency of equipment
G7R3	Equipment frequently out of order or damaged
G8R1	Corruption risks
G8R2	Failure to obtain approvals and permits
G8R3	Import/export restrictions
G8R4	Potential of delay by others
G9R1	Cash shortage
G9R2	Inflation and interest rates risks
G9R3	Economic crisis

Table 1b Risks in pipeline construction

Code	Magnitude*	Related Risks**	Related Treatments
G1R1	2.61	2	5
G1R2	4.57	4	4
G1R3	3.85	4	3
G1R4	4.12	2	14
…	…	…	…
G9R3	2.48	7	3

** Based on surveyed probabilities and impacts.*
*** Relations defined via the DRM, whether directly or indirectly.*

Table 2a Risk treatments in pipeline construction (*samples*)

Code	Description
RT1	The contractors should study the owner's financial position, and his ability to finance the project for its entire duration
RT2	Contractors should study & analyze the effect of inflation and devaluation on the project's costs and consider them in its cost estimate
RT3	The contractors should obtain a large advance payment, as possible
RT4	The contractors should ensure receipt of advance payment
…	…
RT52	Cultural and commercial awareness training for management and key personnel who may have to deal with corrupt officials

Table 2b Risk treatments in pipeline construction

Code	Cost Index*	Related Risks**
RT1	2.33	4
RT2	2.80	4
RT3	2.17	6
RT4	1.70	6
…	…	…
RT52	6.47	9

** Based on surveyed costs.*
*** Relations defined via the DRTP.*

6 Conclusion

Decisions made about risk treatment actions are sometimes too subjective. The primary contribution of the research at hand is to devise means that can facilitate making *informed* decisions about risk treatment in projects. With a sound decision-making process, one can justify why a given set of actions are adopted rather than others.

The paper attempted to develop an optimization algorithm that utilizes ant colony for the balanced selection of a project's risk treatment strategy. In this context, the benefits and costs associated with the project's risk treatment strategy are balanced out. Due to the complexity of projects and the inter-dependency of risks, the algorithm made use of Dynamic Risk Maps (DRMs) which were introduced by the authors in an earlier publication. The novelty of this algorithm lies in its multilevel evaluation process, which accounts for not only the direct impacts but the indirect ones as well.

Table 3 ACO solution

Pattern	Ant's Path	Risk Severity (before)	Risk Severity (after)	Change in Risk Severity	Cost Index
1	RT1	167.00	163.00	2.40%	2.33
2	RT2	167.00	159.00	4.80%	2.80
3	RT3	167.00	156.00	6.50%	2.17
4	RT4	167.00	155.40	6.90%	1.70
5	RT1-RT2	167.00	160.00	4.19%	5.13
6	RT2-RT1	167.00	156.00	6.58%	5.13
7	RT1-RT3	167.00	152.00	8.98%	4.50
8	RT3-RT1	167.00	154.00	7.78%	4.50
9	RT2-RT3	167.00	151.00	9.58%	4.97
10	RT3-RT2	167.00	155.00	7.18%	4.97
11	RT1-RT4	167.00	154.00	7.78%	4.03
12	RT4-RT1	167.00	152.00	8.98%	4.03
13	RT2-RT4	167.00	150.00	10.17%	4.50
14	RT4-RT2	167.00	150.80	9.70%	4.50
15	RT3-RT4	167.00	156.00	9.58%	3.87
16	RT4-RT3	167.00	147.32	11.78%	3.87

The study showed ACO to work fairly well. It is understandable that other optimization engines could be used for such step, however, earlier studies proved ACO to be superior in this particular context. Despite that, further research on parameter selection may be conducted to further improve the robustness of the ACO model.

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