Scenario selection optimization in system engineering projects under uncertainty: a multi-objective ant colony method based on a learning mechanism

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Scenario Selection Optimization in System Engineering Projects Under Uncertainty: A Multi-Objective Ant Colony Method Based on a Learning Mechanism

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Abstract – **This paper presents a multi-objective Ant Colony Optimization (MOACO) algorithm based on a learning mechanism (named MOACO-L) for the optimization of project scenario selection under uncertainty in a system engineering (SE) process. The objectives to minimize are the total cost of the project, its total duration and the global risk. Risk is considered as an uncertainty about task costs and task durations in the project graph. The learning mechanism aims to improve the MOACO algorithm for the selection of optimal project scenarios in a SE project by considering the uncertainties on the project objectives. The MOACO-L algorithm is then developed by taking into account ants' past experiences. The learning mechanism allows a better exploration of the search space and an improvement of the MOACO algorithm performance. To validate our approach, some experimental results are presented.**

Keywords – **Ant Colony Optimization, learning, multi-objective optimization, Pareto-optimality, risk, uncertainty, system engineering project.**

I. INTRODUCTION

In an increased competitiveness environment, many companies are investing in design projects of new systems to meet customer requirements and the various strategic challenges of the market. The system engineering activities are: definition and design (system development), production, utilization and finally dismantling, recycling and renewing. In project management, the Project Time Management process completes the system engineering process by determining resources that fulfill the project objectives in terms of time, cost, risk, quality, performance, etc. That can be reached through cooperation between designers and project managers to obtain an integrated design process and project planning process by defining some coupling points between both processes **[1] [2]**. Previous works have proposed a hybrid multi-objective optimization approach based on Bayesian networks and evolutionary algorithms for an integrated product design and project design process **[3]**. The work presented in this paper matches this context. The problem we are dealing with is the selection of project scenarios in a resulting oriented graph using Pareto-front solutions (project scenarios). The graph includes the different design and project planning choices of a new system to deliver. The Fig. 1 summarizes the considered problem.
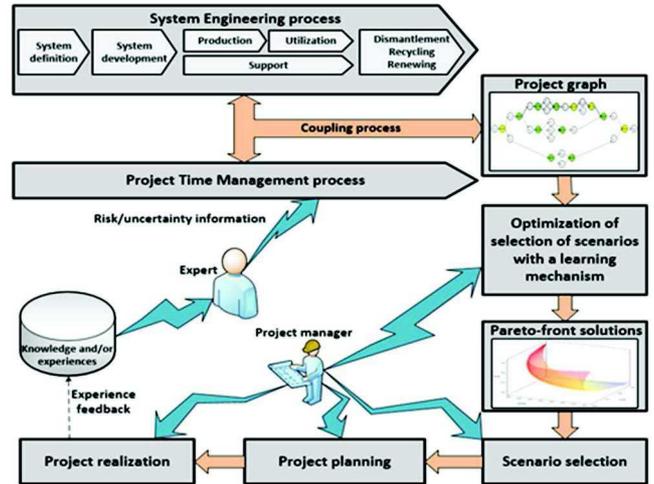

Fig. 1: Graphic representation for the developed problem.

Our **first contribution** consists in the development of a multi-objective ant colony optimization (MOACO) algorithm to select optimal scenarios taking into account their cost and delay, but also their associated risk assessment (risks are considered as uncertainties on costs and delays). The problem is then to optimize the selection of scenarios under uncertainty. The global uncertainty is a third objective to optimize (alongside cost and delay). Indeed, the selected scenario must be optimal regarding the risk associated with the increased duration and cost values of this scenario. The algorithm is based on artificial ants **[4]** which go through a task graph and make random choices to find a path. These choices are biased by the global attractivity of the paths already taken by ants in the previous iterations (experience feedback) and the local attractivity of the next task to reach. We adopt the MOACO metaheuristic **[5]** that allows to select high quality project scenarios of such relevant combinatorial optimization problem in a reasonable amount of time. In some works, the multi-objective optimization problems are handled by aggregating and weighting the multiple objectives depending on their relative importance **[6]**. However, the goal in this article is to offer to decision makers a set of non-dominated Pareto-optimal solutions to select a project to plan for the realization of the designed system. These solutions are optimal in the Pareto sense **[7] [8]**. In **[9],** the authors propose an ant colony optimization (ACO) algorithm in the case of the bi-objective scheduling problem. There are many successful academic and industrial applications of ACO algorithms **[10]**. Some works have proved the power of ACO

algorithms for solving both deterministic and probabilistic CPM/PERT networks by producing good optimal and suboptimal solutions [11]. Another work demonstrates the effectiveness of an ACO algorithm based on Ant Colony System (ACS) approach and Monte Carlo (MC) simulation for the maximization under uncertainty of the expected net present value (NPV) of cash flows in the case of scheduling multi-mode projects [12]. In the case of handling many objectives in real-world portfolio problems, the authors in [13] have developed a hybrid metaheuristic approach based on ACO and preference incorporation that provides high-quality portfolios in comparison with the leading metaheuristics that are dealing with Pareto-front solutions. Recently, the work presented in [14] has shown that a MOACO algorithm permits to manage the risks inherent to project tasks realization. Many risk management methods and tools are based on the probability and impact concepts to assess the risk using qualitative and quantitative approaches [15]. In [16], the authors argue the necessity to improve the management of uncertainty in projects by transforming the existing project risk management processes into project uncertainty management. Indeed, risk exists whenever uncertainty exists [17]. In [18] [19] [20], the risk is regarded as uncertainty about the task durations. It is taken into account by stochastic models. In [21], the uncertainty is represented by fuzzy logic based models. Recently, in [22] the authors have proposed a model for coupling project management, risk management and a lesson learning system (LLS) methodologies. However, they have not developed a formal model with the corresponding algorithms to enhance experience reuse in projects risk management. As noticed in this brief panorama, there are no studies addressing the multi-objective optimization of project scenarios selection integrating the risks as an objective, particularly in the case of system engineering projects.

Thus, our **second contribution** consists in developing an approach which allows to improve the MOACO algorithm performance by a learning mechanism (MOACO-L). In the standard ACO algorithms, every time an ant has to make a choice, it evaluates a probability to reach the next nodes. This probability depends on local attractivity of these next nodes and on global attractivity (i.e. pheromone trails corresponding to experience feedback) but not on previous choices. Therefore, we propose to couple the MOACO algorithm with a learning mechanism (MOACO-L). Thus, the ants can learn useful information from past runs in order to influence the future choices taking into account the previous ones.

The problem formalization and its associated project graph are given in section II. The proposed method, based on MOACO-L algorithm, is presented in section III. The algorithm is developed using Ruby language and the resulting tests of the improved MOACO algorithm within a learning process are discussed in section IV. Finally, conclusions and perspectives are described in section V.

II. PROBLEM FORMALIZATION

The problem addressed in this paper is formulated by means of an acyclic and oriented project graph G. The graph G is defined by $G = (N, A)$. N is the set of nodes and A is the set of arcs connecting these nodes and representing the precedence constraints between them. An example of project graph is represented in Fig. 2.
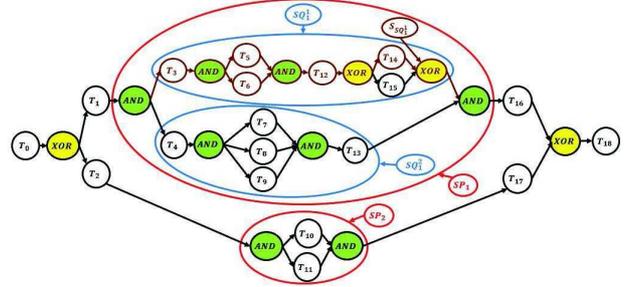

Fig. 2: Example of project graph.

The nodes of the graph represent tasks, conjunction logical operators (*AND*) and exclusive disjunction ones (*XOR*). The first and last nodes of the graph are fictive tasks. Each task node is associated with a triplet *(C, D, R)* corresponding to task cost value, its duration and the risk associated with these criterions. In our work, the risk is considered as an uncertainty about the achievement of project tasks. This uncertainty is related to the occurrence of undesirable events whose impacts increase the total cost of the project and/or its total duration. The uncertainties about the values of cost and duration criterions are represented as intervals. We assume that each interval has a minimum value being the nominal value of the criterion and a maximum value obtained from expert knowledge and/or past experiences [23]. A project P is defined as a set of tasks and/or sub-projects. P is represented by:

$$P = T^P \cup SP^P \tag{1}$$

where, T^P is the set of tasks of the project P and SP^P is the set of sub-projects of P. A sub-project is a sub-graph of the project graph G that starts with a divergence node *AND* and ends with a convergence node *AND*. A sub-project is characterized by its cost, duration and the uncertainty about their values. A sub-project consists of parallel sub-sequences. A sub-sequence may be composed of other tasks, and/or other sequential sub-projects, and/or convergence and divergence *XOR* nodes. A scenario S represents a project graph path. S is an ordered sequence of tasks (T_i) and/or sub-projects (SP_j) to realize. It is represented by:

$$S = \{T_i^r\}_{T^i \in T^P} \cup \{SP^r\}_{SP_j \in SP^P} \tag{2}$$

Each task T_i and each sub-project SP_j has a rank r corresponding to their orders in a given scenario S of the

project P. The total cost C_s of a scenario S of a project P, is defined by:

$$C_S = \mathbf{I}_{T_iES} [C_{T_i}, C^+_{T_i}] + I_{SP_jES} [C_{SP_j}, C^+_{SP_j}] = [C_S, C^+_S] \quad (3)$$

The total duration D_s of a scenario S of a project P, is defined by:

$$D_S = \mathbf{I}_{T_iES} [D_{T_i}, D^+_{T_i}] + \mathbf{I}_{SP_jES} [D_{SP_j}, D^+_{SP_j}] = [D_S, D^+_S] \quad (4)$$

where C^-_S and C^+_S are respectively associated with the nominal cost of a scenario S and its maximum cost in the case of occurrence of undesirable events. In the same way, D^-_S and D^+_S are respectively the nominal and maximal durations of the scenario S. $(C_{T_i}, C^+_{T_i}, D_{T_i}, D^+_{T_i})$ and $(C_{SP_j}, C^+_{SP_j}, D_{SP_j}, D^+_{SP_j})$ correspond respectively to tasks and sub-projects lower and upper bounds for cost and delay. Let SP_j be a sub-project of q *parallel* sub-sequences SQ^k_j ($k E \{1, \_, q\}$). Let $S_{SQ^k_j}$ be, a scenario corresponding to the sub-sequence k. The duration of the scenario $S_{SQ^k_j}$ is given by:

$$D_{S_{SQ^k_j}} = \mathbf{I}_{T_hES_{SQ^k_j}} [D_{T_h}, D^+_{T_h}] + I_{SP_lES_{SQ^k_j}} [D_{SP_l}, D^+_{SP_l}]$$
$$= D_{S_{SQ^k_j}}, D^+_{S_{SQ^k_j}} \quad (5)$$

Then, the duration of a sub-project SP_j is given by considering that every task or sub-project will be planned at their respective earliest starting date:

$$D_{SP_j} = MAX_{SQ_j} (D_{S_{SQ^k_j}}), MAX_k (D^+_{S_{SQ^k_j}})$$
$$k E SP_j \quad SQ^k_j \quad SQ_j E SP_j$$
$$= [D_{SP_j}, D^+_{SP_j}] \quad (6)$$

The Generalized Ordered Weighted Averaging operator (GOWA) **[24]** is a class of parametrized operators used to calculate the global risk R_s of a scenario S from uncertainties:

$$R_S = \sqrt[z]{w_C X (\frac{C^+_S - C_S}{C_S})^z + w_D X (\frac{D^+_S - D_S}{D_S})^z} \quad (7)$$

The expressions $(\frac{C^+_S - C_S}{C_S})$ and $(\frac{D^+_S - D_S}{D_S})$ represent respectively the percentages related to the increase of the nominal values of cost and duration of realization of the scenario S. w_C and w_D are weights satisfying $w_C + w_D = 1$, and z is a parameter such that $z E (-oo, +oo)$. In our model, $z = 2$ (quadratic mean). Therefore, R_S is the quadratic mean of the relative uncertainties on cost and delay.

III. PROPOSED MOACO-L ALGORITHM

The proposed MOACO-L algorithm is based on a single ant colony that will build solutions in the project graph by minimizing simultaneously the values of total cost, total duration and global risk. In each iteration, each ant builds its solution independently. Each arc (i, j) of the graph G contains three pheromone trails for each criterion of the triplet (C, D, R). The quantity of pheromone on (i, j) for each criterion $O E \{C, D, R\}$ is denoted by r^o_{ij}. All the ants of the colony are initialized from the first node of the project graph. Each ant f makes a choice from a node i to reach a node $j E N_i$ (N_i is the set of neighbors of i) using the following probability formula:

$$p^t_{ij} = \frac{(c^A_{ij})^f (D^A_{ij})^p (R^A_{ij})^a X (c^A_{ij})^f (D^A_{ij})^p (R^A_{ij})^{f3}}{\sum_{lEN_i} (c^A_{il})^f (D^A_{il})^p (R^A_{il})^a X (c^A_{il})^f (D^A_{il}) (R^A_{il})^{f3}} \quad (8)$$

For each node $j E N_i$, we have:

$$r^C_{ij} = \frac{q_{j:C}}{C_{T_j}} \quad (9) \qquad r^D_{ij} = \frac{q_{j:D}}{D_{T_j}} \quad (10) \qquad r^R_{ij} = \frac{q_{j:R}}{R_{T_j}} \quad (11)$$

where r^C_{ij}, r^D_{ij} and r^R_{ij} represent respectively the local attractivity of a node j regarding a node i, in terms of cost, duration and risk. $<p^C_C$, $<p^D_D$ and $<p^R_R$ are constants that ensure that r^C_{ij}, r^D_{ij} and r^R_{ij} are upper or equal to one. Theses constants are calculated as follows:

$$<p^C_C = MAX_{T_j ET^P} (C_{T_j}) \quad (12)$$
$$<p^D_D = MAX_{T_j ET^P} (D_{T_j}) \quad (13)$$
$$<p^R = MAX_{T_j ET^P} (R_{T_j}) \quad (14)$$

The risk measurement for a task T_j is denoted by R_{T_j} and calculated using the GOWA operator:

$$R_{T_j} = \sqrt[z]{w_C X (\frac{C^+_{T_j} - C_{T_j}}{C_{T_j}})^z + w_D X (\frac{D^+_{T_j} - D_{T_j}}{D_{T_j}})^z} \quad (15)$$

a and $f3$ are the weights associated with the global attractivity of pheromone trails and to the local attractivity. At the end of each iteration, all the ants of the colony which have reached the last node of the graph drop-off three quantities of pheromone $(r^C_{ij}, r^D_{ij}, r^R_{ij})$ associated to the three criterions (C, D, R) on each arc (i, j) belonging to their path (i.e. their scenario). The quantities of pheromone are initialized as (r^C_0, r^D_0, r^R_0) and are updated at each iteration:

$$r^C_{ij}(it + 1) = (1 - p) X r^C_{ij}(it) + I_{SE\{S_{it}\}} \frac{1}{C_S} \quad (16)$$
$$r^D_{ij}(it + 1) = (1 - p) X r^D_{ij}(it) + I_{SE\{S_{it}\}} \frac{1}{D_S} \quad (17)$$

$$r_{ij}^R(it+1) = (1-p) \times r_{ij}^R(it) + I_{SE\{S_{it}\}} \frac{1}{R_s} \quad (18)$$

p is the evaporation rate of pheromone trails and $\{S_{it}\}$ represents the set of scenarios made by all the ants of the colony at iteration (*it*). The weights $\grave{A}_j^C$, $\grave{A}_j^D$ and $\grave{A}_j^R$ are dynamic and vary at each new reached node. They allow to the MOACO-L algorithm to learn. The weights are defined by:

$$\grave{A}_j^C = \frac{Cp_j^c}{Cp_j^c + Cp_j^D + Cp_j^R} \quad (19)$$

$$\grave{A}_j^D = \frac{Cp_j^D}{Cp_j^c + Cp_j^D + Cp_j^R} \quad (20)$$

$$\grave{A}_j^R = \frac{Cp_j^R}{Cp_j^C + Cp_j^D + Cp_j^R} \quad (21)$$

with $\grave{A}_j^C + \grave{A}_j^D + \grave{A}_j^R = 1$. Cp_j^C, Cp_j^D and Cp_j^R represent the consumed capital percentage of cost, duration and risk to guide the ant f to reach the node $j \in N_i$ using the probability$_C$ formula$_D$ (8).$_R$ The aim of having dynamic weights $(\grave{A}_j^C, \grave{A}_j^D, \grave{A}_j^R)$ is to guide the ants in their choices by learning from their past choices. These percentages are calculated as follows:

$$Cp_j^C = \frac{C_j^g}{CpC_0} \quad (22)$$

$$Cp_j^D = \frac{D_j^g}{CpD_0} \quad (23)$$

$$Cp_j^R = {}^z\sqrt{w_C \times \frac{C^{g+} - C_j^g}{CpC_0^+ + CpC_0}}{}^z + w_D \times \frac{D_j^{g+} - D_j^g}{CpD_0^+ + CpD_0}{}^z \quad (24)$$

$$CpC_0 = [CpC_0, CpC_0^+] \quad (25)$$

$$CpD_0 = [CpD_0, CpD_0^+] \quad (26)$$

CpC_0 and CpD_0 are respectively the initial cost and duration capitals and they are represented as intervals in order to model the capitals about uncertainties on cost and delay capitals. C_j^g, D_j^g, C^{g+} and D_j^{g+} are respectively the nominal and the maximal cumulated costs and durations at the node j, such as:

$$C_j^g = I_{i\in Path_j} fC_i \quad (27) \qquad C_j^{g+} = I_{i\in Path_j} fC_i^+ \quad (28)$$

$$D_j^g = I_{i\in Path_j} fD_i \quad (29) \qquad D_j^{g+} = I_{i\in Path_j} fD_i^+ \quad (30)$$

$Path_j^t$ is the path of the ant f that includes all the visited nodes. Therefore, giving initial capitals to the ants permits to integrate a new bias into the probability formula (8). An ant which has consumed a great part of one of the three capitals will be influenced to choose next nodes that does not penalize this capital. Moreover, one can say that the ant learned from the path it uses in order to influence its future choices.

IV. EXPERIMENTS

A set of experiments has been done to validate our method and attest the efficiency of our proposed MOACO-L algorithm. The aim of these experiments is to make a comparative analysis between MOACO and MOACO-L algorithms. The algorithms were developed in the Ruby language and executed on desktop computer (Intel® Core™ i7 3.6 GHz processor). The set of experiments are made with a graph of 100 nodes organized following 23 sequential levels. Each level has a number of nodes that vary between 2 and 9 nodes. Every node of a level is connected to every node of the next level. The combinations give 44.10^{12} possible scenarios. The colony has 200 ants and the initial parameter settings that gives the best results are $q = \beta = 1$, $p = 0.05$, $r_0 = r_0^C = r_0^R = 1$, $z = 2$, $w_C = w_D = \frac{1}{2}$, $CpC_0 = [400000, 417000]$, $CpD_0 = [740, 790]$ and $\grave{A}_0^C = \grave{A}_0^D = \grave{A}_0^R = \frac{1}{3}$. These parameters have been evaluated empirically. The Fig. 3 represents a comparison between MOACO and MOACO-L algorithms using mean performance (Mean Perf) and the standard deviation (StdDevPerf). MeanPerf and StdDevPerf are defined as follows:

$$MeanPerf = MeanC \times MeanD \times MeanR \quad (31)$$
$$StdDevPerf = StdDevC \times StdDevD \times StdDevR \quad (32)$$

These values are calculated from the mean values of costs, durations and risks of the Pareto-optimal scenarios. The Pareto front is calculated at the end of each iteration (when the whole colony has reached the last node). The Fig.3 represents the results of the 600 iterations for the MOACO and MOACO-L algorithms.
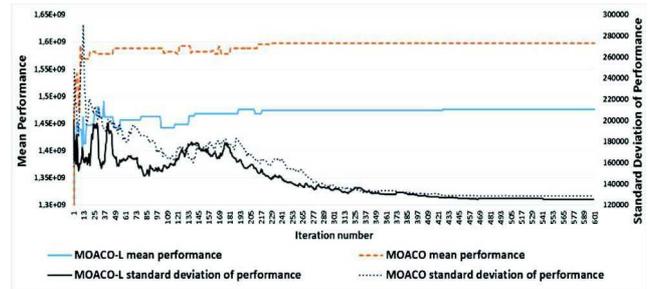

Fig. 3. Mean performance and standard deviation of performance of MOACO versus MOACO-L algorithms.

As shown in Fig. 3, the proposed MOACO-L algorithm gives better results than MOACO algorithm since it improves the mean performance in a reasonable amount of time. In fact, the MOACO-L algorithm generates Pareto-optimal solutions in 120.9 seconds versus 121.6 seconds for the MOACO algorithm. Furthermore, the learning mechanism allows the MOACO-L algorithm a better exploration of the search space because it stabilizes from the 426th iteration rather than the MOACO algorithm which stabilizes earlier (from the 222th iteration). Moreover, MOACO-L algorithm

provides efficient solutions in terms of cost, duration and risk. In fact, the MOACO-L algorithm is more performant than the MOACO algorithm with almost a difference of 8.84% for mean performance and almost a difference of 2.73% for standard deviation of mean performance.

V. CONCLUSION

In this article, we have proposed a MOACO-L algorithm for the optimization of project scenario selection under uncertainty by integrating a learning mechanism. We have shown that MOACO-L algorithm gives better results than the standard one. In future works, we expect to develop a knowledge model that interfere with our proposed optimization model in order to learn in an intelligent manner from previous projects experiences the uncertainties on costs and delays. The knowledge about the events and their impact on delays and costs capitalized during previous projects or defined by an expert on risk management has to be learned by a simulation method and introduced into the MOACO-L algorithm in order to guide the optimization.

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