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Conference Paper

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CISTER-TR-180105

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Abstract

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Analytical Hierarchy Process based Multi-Objective Multiple Traveling Salesman Problem

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I. Introduction

Today, the use of multiple unmanned aerial vehicles (UAVs) in the context of disaster management [1] is attracting increasing interest with the emergence of low-cost drones. One of the most challenging underlying problem is how to assign the UAVs to specific areas affected by a disaster event such as fire earthquakes or water floods, while minimizing several metrics of interests, also known as objectives. In its abstract form, the problem can be mapped to multiple traveling salesman problem (MTSP), where a set of agents have to visit a set of locations. Several studies addressed this problem by minimizing a single objective, such as the total traveled distance or the maximum traveled distance using centralized approaches [2], distributed approaches [3, 4], and auction-based approaches [5]. The limitation of the above mentioned works pertains to only focusing on one objective and ignores others that can be crucial to the application, such as the mission time or the consumed energy.

In the literature various works addressed the MTSP problem with multiple objectives optimization using different approaches. In this kind of problem, more than one optimal solution can be presented to optimize simultaneously all the objectives, referred to as Pareto optimal solutions. Most approaches are based on evolutionary computations algorithms such as [6, 7, 8]. Genetic algorithms (GA), local search, and Ant Colony Optimization (ACO) are the most common evolutionary methods used in the literature to find a set pareto-optimal solutions that provide the best trade-off among all objectives. However, these approaches have extensive computation overheads, and their convergence is challenging especially when applied for large problem instances. Some other approaches are proposed using mathematical models [9, 10], to represent the multi-objective optimization problem.

In this paper, we proposed a different approach that leverages the use of the Analytic Hierarchy Process (AHP) [11] to systematically determine the optimized weights for the different objectives. The benefit of the use of AHP is to effectively assign weight to objective functions based on their degree of critically in the application, and not just be common sense. In addition, we assess three different approaches to solve the multi-objective MTSP problem and select the best solution as the final output. Compared to the existing proposed approaches, especially, the evolutionary one, our solution presents a low computation overhead. Moreover, the choice of weights based on the AHP offers better results compared to the mono-objective results as shown in the performance evaluation section.

The remainder of the paper is organized in the following way. In Section 2, we provide some related works. Section 3 describes the problem formulation. In Section 4 we proposed our three-phase mechanism based on Analytical Hierarchy Process (AHP). A performance evaluation of the proposed solution is detailed in Section 5. We conclude with a discussion and future direction work in Section 6.

II. Related Works

In [12] authors proposed a new non-numerical method for Multiobjective Traveling Salesman called two-phase Pareto local search (2PPLS). In first phase each single-objective problem is solved separately using one of the best heuristics

978-1-5090-2255-7/16 $31.00 © 2016 IEEE

DOI 10.1109/ICARSC.2016.26

for the single-objective. In the second phase two Pareto local search is applied to every solutions of the initial phase using a 2-opt neighborhood with candidate lists. It is important to note that there is a need to solve a high number of weighted single-objective problems, before applying the Pareto local search, which may cause efficiency degradation. Also the integration of 2-opt process may achieve poor effectiveness with low efficiency when the number of feasible objective vectors is small, whereas it obtains desired effectiveness with low efficiency when the number of feasible objective vectors is large.

In [7] authors integrated ant colony optimization (ACO) to local search technique in order to resolve the multi-objective Knapsack problems (MOKPs) and the multi-objective traveling salesman problem (MTSPs). MOEA/D-ACO decomposes a multiobjective optimization problem into various single-objective optimization problems. Each ant is assigned to a sub problem, and each ant has several neighboring ants. A heuristic information matrix is maintained by each ant. The main issue related to this approach is the uncertain of the time convergence and the implementation complexity.

Shim et al. presented in [10] a mathematical formulation of the multi-objective multiple traveling salesman problems (MOmTSP). The proposed approach is not required to differentiate between the dominated and nondominated solutions. it's objective is to determine m cycles and cover a set of potential customers in order to maximize the corresponding benefit and minimizing the total traveled distance. An estimation of distribution algorithm (EDA) with a gradient search is used for the solution of the considered problem. The proposed approach works well when the users have prior knowledge about the problem to assign weights.

In [6] authors presented a detailed comparison between MOEA/D, and NSGA-II. The paper focus on the performance of the multiobjective travelling sales-man problem and studies the effect of local search on the performance of MOEA/D. Compared to MOEA/D, NSGA-II has no bias in searching any particular part of the Pareto front. All non-dominated solutions in the current population have equal chance to be selected for reproduction. However, this might not be efficient when sampling offspring solutions due to the following reasons. First, the non-dominated solutions might have very different structures in the decision space. Therefore, the possibility of generating high-quality offspring solutions by recombining these solutions is low. Second, the design of recombination operators is often problem-dependent. Efficient recombination operators for some combinatorial optimization problems are not always readily available. In MOEA/D, weight vectors and aggregate functions play a very important role to solve various kinds of problems. Overall MOEA/D has shown much better algorithmic improvement than NSGA-II. Again the weight process is considered an issue in this work.

Authors in [9] proposed a multi-objective mathematical programming approach that is capable of producing of accurate Pareto set. In this approach all Pareto optimal solution are divided into two popular problem, multi-objective travelling salesman problem (MOTSP) and multi-objective coverage problem (MOSCP). The Pareto set cannot guarantee a best solution for non-convex problems where the number of feasible objective vectors is small, and may waster the search effort. However the approach is very simple and easy to use especially for convex problems.

Most of the existing proposed approaches have been criticized mainly for their computational complexity, necessity for prior system knowledge to define weight for each objective and the lack of specifying sharing parameters. In this work we followed a three-phase mechanism based on Analytical Hierarchy Process (AHP) to define weights systematically for each objective depending on the application characteristics.

III. Problem Formulation

We consider the multi-objective multiple depot multiple traveling salesman problem, where a set of *m* robots, located at different depots, must visit a set of *n* target locations and return to their depots after mission completion.

The main objective is to find an efficient assignment of the target locations to the team of robots such that all the targets are covered by *exactly* one robot, and the cost is minimal. The cost is a function of multiple objectives such as minimizing the total traveled distance by all the robots, minimizing the maximum tour length of all robots, minimizing the mission time, minimizing the consumed energy, balancing the targets allocation, etc.

It is important to mention that a multi-objective optimization problem considers several conflicting objectives. This means that an efficient solution for one of the objectives could be an inefficient solution for another objective. In particular, the traditional optimization methods do not provide solutions that are good for all the objectives of the considered problem. A multi-objective optimization problem can be formulated through a mathematical model defined by a set of p objective functions, which must be minimized or maximized simultaneously. Formally, a multi-objective problem can be defined as

$$\begin{array}{ll} min/max & f1(X) \\ min/max & f2(X) \\ & . \\ & . \\ & . \\ min/max & fp(X) \end{array} \tag{1}$$

where X is the decision space.

Regarding the multi-objective multiple depot multiple traveling salesman problem, we consider a set of m robots $\{R_1,...,R_m\}$, which are initially located at m start locations or depots $\{T_1,...,T_m\}$. These m robots must repeatedly visit n targets' locations $\{T_m+1,...,T_m+n\}$, where each target must be visited *exactly* once. Each robot R_i starts from its depot T_i, then visits the list of ni allocated targets $\{T_{i_1},...,T_{i_{ni}}\}$ in that order, and finally returns back to its depot. The cost to travel from target T_i to target T_j is denoted as $C(T_i,T_j)$, where cost can be euclidean distance, consumed energy, time, etc.

Moreover, the objective functions can be classified into three categories. The first category includes objective functions that minimize the sum of the costs of all robots, such as minimizing the total traveled distance, minimizing the total consumed energy, etc. This category of objective functions is defined as:

$$minimize \quad \sum_{k=1}^{m}\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} x_{ijk}C(T_i,T_j) \tag{2}$$

subject to :

$$\sum_{k=1}^{m}\sum_{i=1}^{n+m} x_{ijk} = 1; \forall j = 1,..,n+m \tag{3}$$

$$\sum_{k=1}^{m}\sum_{j=1}^{n+m} x_{ijk} = 1; \forall i = 1,..,n+m \tag{4}$$

$$\sum_{i=1}^{n+m} x_{kik} = 1; \forall k = 1,..,m \tag{5}$$

$$\sum_{i=1}^{n+m} x_{ikk} = 1; \forall k = 1,..,m \tag{6}$$

$$x_{ijk} \in \{0,1\}; \forall i,j = 1,..,n+m \quad and \quad k = 1,..,m \tag{7}$$

Equation (3) and (4) ensure that each node is visited only once by a single robot. Equation (5) and (6) ensure that each robot starts from each corresponding depot and returns back to it. Finally, constraints (7) impose that the decision variables are binary.

The second category includes objective functions that minimize the maximum cost among all robots such as to minimize the maximum tour, minimize the mission time, which corresponds to the maximum time, etc. This category of objective functions can be modeled as:

$$minimize \quad \max_{k\in 1..m}\Big(\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} x_{ijk}C(T_i,T_j)\Big) \tag{8}$$

subject to same constraints defined in equations (3) to (7).

The third category of objective functions is related to balancing the workload among the robots, such as balancing the tours' length, the mission times, the number of allocated targets, etc. This category of objective functions can be modeled as:

$$\begin{aligned} &minimize \quad \sum_{k=1}^{m} |C_k - C_{avg}| \\ &C_k = \Big(\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} x_{ijk}C(T_i,T_j)\Big), k \in [1,m] \\ &C_{avg} = \frac{\sum_{k=1}^{m}\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} x_{ijk}C(T_i,T_j)}{m} \end{aligned} \tag{9}$$

C_k represents the tour cost for robot k. As already mentioned, the cost can refer to time, traveled distance, energy, etc. C_{avg} represents the average of tours cost.

In our system model, we assume that each robot has a global knowledge of the set of targets that must be visited and their locations. Moreover, each robot can estimate the cost between its current location and each target, such as the euclidean distance, the time, the energy, etc.

IV. Proposed Solution

A. General description

The proposed solution is a weighted-based approach, which means we assign to the objectives to be optimized different weights using the AHP process [11]. More precisely, we define the *global cost* as the sum of the weighted costs of the different objective functions under consideration.

Formally, let $W = (w_1,...,w_p)$ be a weight vector, where $0 < w_i < 1 \quad \forall i = 1,...,p$ and $\sum_{i=1}^{p} w_i = 1$. Then, the problem consists in optimizing the following function:

$$\begin{aligned} minimize \quad & g(x|W) = \sum_{i=1}^{p} w_i f_i(x) \\ \text{subject to :} \quad & x \in \Omega \end{aligned} \tag{10}$$

where Ω is the decision (variable) space and $f_i()$ is an objective function.

To generate the weight vector W, the Analytical Hierarchy Process (AHP) is used.

Figure 1 shows the general idea of the approach.First, the user introduces as input to the algorithm a comparison matrix indicating the importance (priority) of each objective function. Based on this comparison matrix, the AHP generates a weight vector. This weight vector is then used to compute the global cost as in Equation 10.

Then, three different approaches are executed as illustrated in Algorithm 1. Finally, the best solution from these three approaches are selected.

Algorithm 1 Proposed Solution General Algorithm

Input: Comparison matrix, Targets, Robots
Output: Best tours assignment
```
1: Begin
2:     Generate weight vector using AHP
3:     Market Based approach
4:     RTMA approach
5:     Balanced approach
6:     Select the best solution
7: End
```

B. The Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making approach, which can be used to solve complex decision problems [11]. The pertinent data are derived by using a set of pairwise comparisons. These comparisons are used to obtain the weights of the objectives, and the relative performance measures of the alternatives in terms of each individual decision criterion. If the comparisons

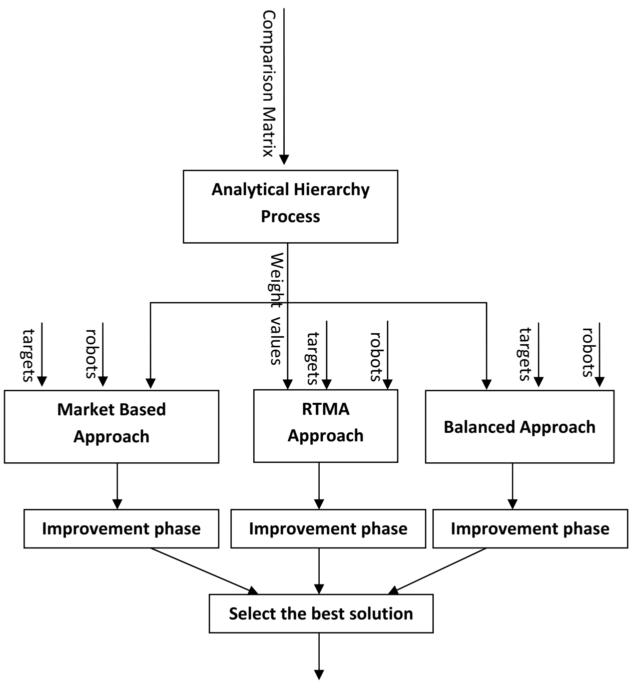


Figure 1: The proposed solution flowchart

are not perfectly consistent, the AHP provides a mechanism for improving consistency. Regarding a disaster management application, we consider three objective functions namely, the total traveled distance (TTD), the maximum tour (MT), and the deviation rate of tours lengths (DR). Indeed, in applications such as fire disaster the most important factor is the mission time, which is proportional to the maximum tour. Moreover, minimizing the total traveled distance and the deviation rate permits to minimize the total energy consumption and to balance the vehicles workload. Then, we consider the following comparison matrix.

$$A_{i,j} = \begin{pmatrix} & TTD & MT & DR \\ TTD & 1 & 1/2 & 1/3 \\ MT & 2 & 1 & 1/2 \\ DR & 3 & 2 & 1 \end{pmatrix} \tag{11}$$

Which means that the MT has two times more priority than the TTD and the DR has three times more priority than the TTD and two times more priority than the MT. Note that, the values of the comparison matrix describes the user preferences and are generally related to the applications use case. For example, in case of a disaster management application, the main priority criteria is the mission time which is proportional to the maximum tour. Some characteristics of the comparison matrix is that $a_{i,j} = \frac{1}{a_{j,i}}, \forall i,j$ and $a_{i,i} = 1$. From the comparison matrix we compute the eigenvalue λ and the eigenvector W that satisfy: $A_{i,j}W = \lambda W$. In this work, we use the $eig()$ Matlab function to compute the eigenvector. We obtained $W = \{0.2565, 0.4660, 0.8468\}$, the three numbers in the eigenvector are proportional to the relative weights of the three criteria. Because relative weights must sum up to 1, we have to normalize the eigenvector W by dividing each number in it by the sum of all numbers. The corresponding weight vector is $W = \{0.1634, 0.2970, 0.5396\}$.

Step	Robots	Bidding		Server side			Winner
		Target	Tour	TTD	MT	Global Cost	
1	R1	T1	280	280	280	280	R1
	R2	T5	486	486	486	486	
2	R1	T5	537	537	537	537	R1
	R2	T5	486	766	486	673	
3	R1	T6	748	748	748	748	R1
	R2	T6	562	1099	562	920	
4	R1	T2	1254	1254	1254	1254	R1
	R2	T2	1316	2065	1316	1815	

Table I: Step by step execution of the market-based approach

C. Market Based Approach

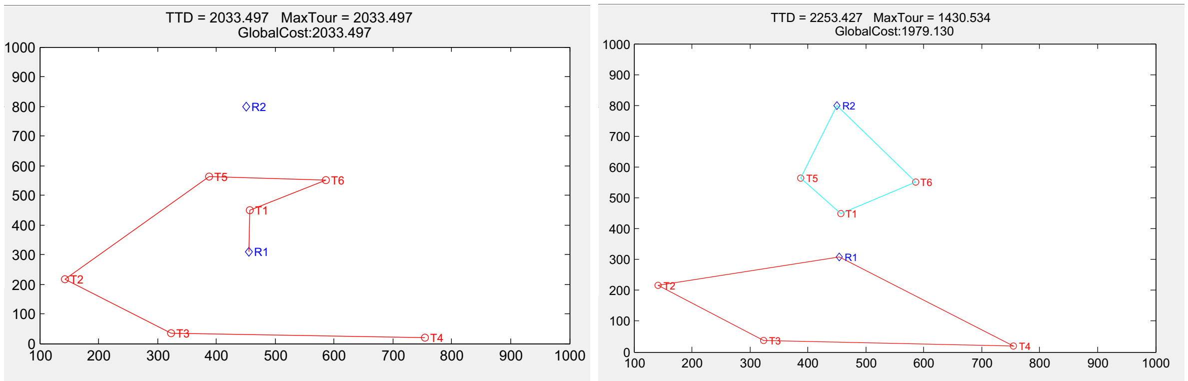
In the market-based approach, the different robots compete to visit the available targets. More precisely, each robot selects the best target, i.e, the target that has the minimum *local cost*. The *local cost* is defined as the weighted sum of the objective function costs for that robot. After the selection of a target, the robots send a *bid* to a central machine. The bid contains the selected target and the corresponding costs for each objective function. Upon receiving the different bids from robots, the central machine computes the *global cost* for each corresponding bid and then assigns the best target to its corresponding robot. Best target refers to the target with the minimum global cost.

Unlike local cost, the global cost considers all tour costs, such as the sum of all tours' length, the maximum of the tours' length, and the tours' length deviation rate. Robots continue the process of bidding until all targets are assigned. To illustrate the market based approach, we consider in Figure 2a a scenario with 2 Robots and 6 Targets, and two objective functions TTD and MT with the weight vector W={0.66, 0.33}, i.e TTD is 2 times more priority than MT. The different steps of the execution of the market based approach are cited in Table I. First $R1$ selects $T1$ and $R2$ selects $T5$. As the global cost when assigning $T1$ to $R1$ is less than the global cost when assigning $T5$ to $R2$, the assignment will be make to $R1$. The assignment process continues until all targets are allocated (Figure 2a).

D. RTMA-based Approach

The second proposed solution is inspired from [13], which we extended to take into account the multi-objective nature of our problem. In fact, the Robot and Task Mean Allocation Algorithm (RTMA) method proposed in [13] is restricted to single objective optimization. To illustrate these scenarios let's consider the example shown in Figure 2.

In this example, it is shown that the market-based approach does not give the best solution and that the RTMA approach outperforms the market-based one in this particular scenario.



(a) Market based approach

(b) RTMA based approach

Figure 2: Example of specific scenario (2 robots and 6 Tasks)

Indeed, in the market-based approach the global cost is 2033, however, in the RTMA approach the global cost is 1979, where the weight vector is $W = \{0.66, 0.33\}$.

The idea of the RTMA approach is to make robot choose the target that gives the best cost for the group instead of choosing the one that gives minimum cost for the robot itself. In other words, in RTMA the robot selects the target that seems to give optimized global cost instead of choosing the target that would give an optimized local cost. For this purpose, the cost is computed as the difference between the cost of the robot to visit a target minus the mean of the costs to visit all the targets by this robot. Formally, for a given robot, the RTMA cost to move from target T_i to target T_j is:

$$Cost_{RTMA}(T_i, T_j) = C(T_i, T_j) - \frac{\sum_{t=1}^{n} C(T_i, T_t)}{n} \quad (12)$$

where $C(T_i, T_j)$ is the (normal) cost to move robot from T_i to T_j and n is the number of targets. To better illustrate the RTMA cost, consider as example the Euclidean distance between two targets as the value of cost. The RTMA cost is:

$$Cost_{RTMA}(T_i, T_j) = D(T_i, T_j) - \frac{\sum_{t=1}^{n} D(T_i, T_t)}{n} \quad (13)$$

where $D(T_i, T_j)$ is the Euclidean distance between T_i and T_j.

In our work, for each robots, we compute the RTMA cost from its depot to each target. Then, each target is assigned to the robot having the low RTMA cost.

Returning to the example shown in Figure 2, the euclidian RTMA cost of robots $R1$ and $R2$ to each targets, starting from their corresponding depots is shown in Table II.

Targets	RTMA cost		Winner
	R1	R2	
T1	-147.1609	-173.9680	R2
T2	38.0983	134.7985	R1
T3	14.5316	249.0928	R1
T4	129.5453	313.1256	R1
T5	-24.0174	-280.4695	R2
T6	-10.9970	-242.5793	R2

Table II: RTMA assignment

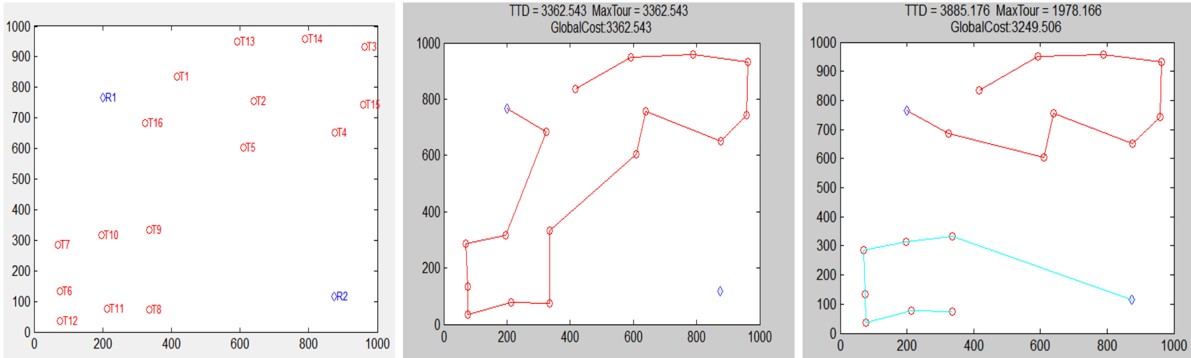
E. Balanced Approach

The idea of the balanced approach is to uniform or balance the number of assigned targets to each robots. More precisely, if we have m Robots and n Targets, each robot will be assigned approximately $\frac{n}{m}$ targets.

The behavior of robots in the balanced approach is close to the market-based one, except that *a robot exit the bidding process when it was assigned a sufficient number of targets.* The sufficient number of targets is no more than the number of targets divided by the number of robots, i.e $\frac{n}{m}$ targets. This ensures that targets are uniformly divided between robots and help in balancing tour lengths. This is illustrated in Figure 3 that shows an example of scenario where the balanced approach outperforms the market-based one and give a better solution. As shown in this figure, using the market-based approach all targets will be assigned to robot R_1, which leads to a global cost superior to the one resulted from the balanced approach, where targets are assigned uniformly between robot R_1 and R_2. More precisely, in the market-based approach, tour lengths of R_1 and R_2 are 3362.5 and 0, respectively. However, in the balanced approach they are 1978.16 and 1271.33, respectively.

F. The improvement Phase

Each of the approach described previously are followed by an *improvement phase* that tries to optimize the obtained result, i.e, in our case minimize the global cost. The word *improvement* can have different forms and can be obtained based on different criteria. In this work, the improvement is done based on the bidding on the *worst target*. More precisely, each robot, say R_i, computes its worst target, i.e, the target that introduces the biggest cost, and then bids with other robots on this target. If a robot, say R_j, can visit this worst target with lower global cost, the target will be removed from R_i tour and assigned to R_j.



(a) Initial configuration (b) Market based approach (c) Balanced based approach

Figure 3: Example of specific scenario (2 robots and 16 Tasks)

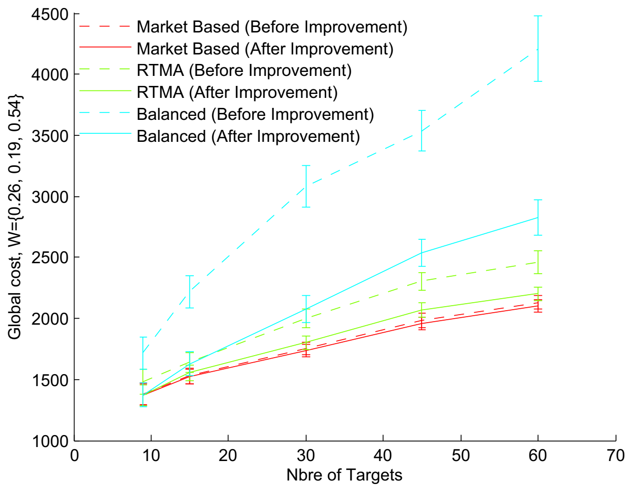


Figure 4: Comparison between the three proposed approaches and impact of the improvement phase

V. Performance Evaluation

In this section, we present the performance evaluation of the above three described approaches. We consider three objective functions, namely, the total travelled distance, the maximum tour, and the deviation rate. Therefore the considered global cost is:

$$Globalcost = \quad w_1 \sum_{k=1}^{m} C_k + w_2 \max_{k \in 1..m} (C_k) + w_3 \sum_{k=1}^{m} |C_k - C_{avg}|$$

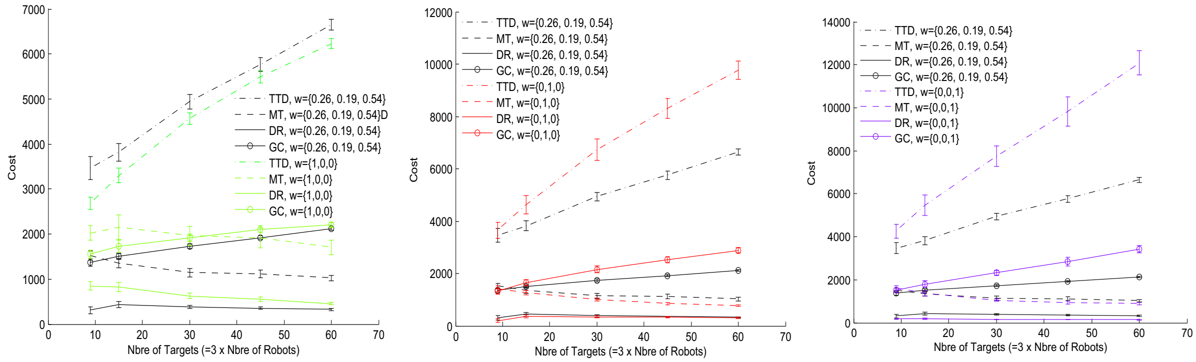
where C_k, C_{avg} are those of Equation 9, and $C(T_i, T_j)$ is the euclidian distance between the two targets T_i and T_j. Moreover, the following results are obtained using number of targets = 3 x number of robots, and number of robots varies in nr=[3 5 10 15 20]. In addition, targets coordinations are randomly chosen from a 1000 x 1000 space. For each configuration of number of robots and number of targets we generate randomly 30 scenarios and then we plot the mean of the obtained results from these 30 scenarios.

Figure 4 presents the comparison between the three proposed approaches and the impact of the improvement phase. In this figure, the weight vector is $w = \{0.26, 0.19, 0.54\}$. It is noted from the figure that, in large scenario, the Market-based approach shows a better result compared to the RTMA and the Balanced approaches. Moreover, it is clear from the figure that the *improvement phase* enhances the results and minimize the global cost especially for the *Balanced* and *RTMA* approaches.

In Figure 5, the proposed multi-objective approaches, where three objective functions were considered, was compared with the mono-objective approach, where a single objective function was considered. For the multi-objective approach, we used a weight vector $w = \{0.26, 0.19, 0.54\}$. Moreover, to consider a single objective function namely the total traveled distance, the maximum tour and the deviation rate, we used the following weight vector $w = \{1, 0, 0\}$, $w = \{0, 1, 0\}$ and $w = \{0, 0, 1\}$, respectively. Figure 5a, Figure 5b and Figure 5c present the comparison results of the the proposed multi-objective approach to the mono-objective approach, where we consider the TTD, the MT and the DR respectively. Regarding the global cost considering the three objective functions, it is clear from these sub-figures that the multi-objective approach outperforms the mono-objective one and gives a minimal global cost (plot in black color with circle). However, the single objective approach gives better results only in the specific objective function considered. More precisely, taking the example where the mono-objective approach considers the TTD (Figure 5a), in this case, it gives a minimum TTD cost than the multi-objective approach. This is obvious as the mono-objective approach favor only one criteria and omits others.

VI. Conclusions and Future Work

In this paper, we considered the problem of Multi-objective Multiple Traveling Salesman Problem. Three approaches where proposed, namely, a Market-based approach, an RTMA approach and a Balanced approach. Simulation results shows that the market-based approach outperforms the RTMA and the Balanced approach when large scenario is applied. Moreover, the comparison of the proposed multi-objective approach



(a) TTD (b) MT (c) DR

Figure 5: Benefit of the multi-objectives approach

with mono-objective solutions highlighted the benefit of our proposed approach. for further improvement we plan to compare the proposed approach with available multi-objective approach using existing benchmarks.

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