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Multi-Objective Optimization for Trustworthy Tactical Networks: A Survey and Insights

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Multi-Objective Optimization for Trustworthy Tactical Networks: A Survey and Insights

Key words – multi-objective optimization, tactical networks, evolutionary algorithms, game theoretic approaches, trust-based applications, security, performance

Abstract – *Multi-objective optimization (MOO) is the process of optimizing multiple objective functions concurrently and systematically. Modern Army missions require a tactical network to achieve multiple objectives as multiple parties with different objectives are involved in collaborative mission execution. MOO problems have been studied extensively in the field of coalition formation based on evolutionary algorithms or game theoretic approaches. However, there has been no generic framework to consider MOO problems in tactical networks particularly when the goals must be achieved based on trustworthiness of participating entities. First, we provide a comprehensive survey of work on MOO formulation and solution techniques particularly in coalition formation. Second, we extensively discuss MOO techniques and methods that have been used for coalition formation. We specifically investigate the use of trust in the process of coalition formation. Third, we look into tactical applications in which trust plays a pivotal role for mission success. Finally, we discuss future research directions of MOO design for trustworthy tactical networks.*

1. Introduction

Military tactical networks are often faced with the challenges of optimizing multiple objectives where a coalition network may have multiple partners with different objectives but under a common goal. For example, a coalition network can be formed based on cooperation or collaboration of multiple coalition partners of different nature such as military organizations, non-government organizations (NGOs) and/or on-site civilian organizations or entities from different nations. They may have different utilities (or payoffs) to maximize even if they aim to collaborate for achieving a common goal. In addition, military tactical network protocols are required to be operable under resource constraints (e.g., battery life, computational power, bandwidth, and/or unreliable wireless transmission medium), lack of infrastructure (e.g., no centralized trusted entity), and/or highly hostile environments (e.g. security vulnerability due to network or physical attacks). In order to design tactical network protocols that are resilient against attackers, scalable under resource restrictions, and reconfigurable without any centralized trusted entities, tactical protocol designers must consider how to set and optimally achieve the multiple goals.

Multi-objective optimization (MOO) problems have been studied extensively in various multidisciplinary domains [19] because many real-world problems in economics and engineering are usually characterized by the presence of many objectives. A common technique is to represent multiple objectives by a single utility (or payoff) function which should be maximized. Since very often multiple objectives tend to be conflicting, the optimal solutions are not unique. As a result, MOO problems often have a set of *Pareto optimal solutions* referred to as the *Pareto frontier*. Navigation along the Pareto frontier allows designers to do trade-off analysis and select the best design for MOO [7].

In the field of coalition formation, many researchers have investigated MOO problems as one of tactical operations based on evolutionary algorithms or game theoretic approaches. However, no generic framework exists to consider MOO problems in tactical networks particularly when the goals must be achieved based on trustworthiness of participating entities.

The concept of trust has been studied extensively in many different disciplines such as philosophy, economics, psychology, sociology, autonomic computing, and organizational management [6]. *Merriam and Webster* dictionary defined trust as "assured reliance on the character, ability, strength, or truth of someone or something" [31]. Cho et al. [6] has summarized the definitions of trust derived from various domains.

This work aims to comprehensively survey existing work on MOO problem formulation and solution techniques particularly in coalition formation and to give insights on how to approach MOO issues in tactical coalition networks. In addition, we survey the use of trust in the process of coalition formation.

The rest of this paper is organized as follows. Section 2 explains the concepts of coalition formation, MOO, and MOO problems in coalition formation. Section 3 describes the key techniques/methods to solve MOO problems in coalition formation. Section 4 classifies the existing work on MOO for coalition formation with three categories based on the types of objectives. Section 5 discusses future research directions of MOO design for trustworthy tactical networks. Section 6 concludes the paper.

2. Multi-Objective Optimization (MOO) in Coalition Formation

2.1 Coalition Formation

According to Kahan and Rapoport [14], a coalition can be formed when three or more parties get together with a common interest that gives mutual benefits. In military tactical networks, a coalition comprises different entities such as countries and/or organizations (e.g., militaries, non-government, non-profit, and civilian organizations) that are involved in a military operation to pursue a common goal under a single command [30]. Many disciplines including economics, political science, mathematics, and computer science have different concepts of coalition [14]. However, the common aspect of coalition is to benefit mutually based on trust relationships between two parties, players and a coalition party (e.g., a coalition leader).

Military tactical networks often require forming a temporary coalition in order to execute a given mission where effective and efficient asset-task assignment is critical to successful mission completion. Under a common global objective of successful mission completion, the system may have multiple objectives to achieve while the involved parties may want to maximize their own utilities. In a typical scenario, the desirable outcome is successful mission completion while maximizing resource utilization for mission success and maintaining peaceful relationships among participating entities. This will enable the trust relationships among participating entities to be sustainable, which can positively affect future mission execution with the same coalition members.

2.2 Multi-Objective Optimization

Most engineering applications have multiple but conflicting objectives and simultaneous optimization of all objectives may not be possible [24]. For example, in a military tactical network, a commander may want to maximize mission performance while workloads should be equally distributed over all nodes and overall resource consumption should be minimized. Multi-objective optimization (MOO) is also known as multi-criteria optimization [24].

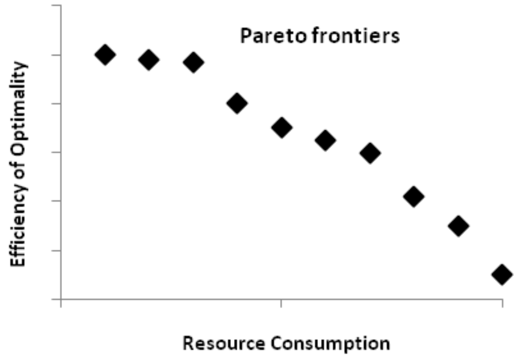

Fig. 1: Example of Multi-Objective Optimization.

Fig. 1 shows an example of the tradeoff observed in a MOO problem. The two conflicting goals are to maximize efficiency and to minimize resource consumption. MOO often yields a set of optimal solutions, called *optimal Pareto frontiers* [24].

Traditionally single objective optimization (SOO) has one objective function that may have multiple constraints. A SOO problem is often stated as follows:

$$\text{Optimize } \mathrm{f(X)} \tag{1}$$
$$\text{subject to } \mathrm{H(X)} = 0, \mathrm{G(X)} \geq 0$$

The function to be optimized is $\mathrm{f(X)}$ where vector X indicates the set of independent input variables. Functions $\mathrm{H(X)}$ and $\mathrm{G(X)}$ describe the problem constraints [9], [11]. A MOO problem can be stated as follows:

$$\text{Optimize } \mathrm{F(X)} = \{\mathrm{f_1(X), f_2(X), \ldots, f_n(X)}\} \tag{2}$$
$$\text{subject to } \mathrm{H(X)} = 0, \mathrm{G(X)} \geq 0$$

The functions to be optimized are $\mathrm{f_1(X), f_2(X), \ldots, f_n(X)}$ in $\mathrm{F(X)}$, and X is the set of independent variables. Similar to the SOO problem formulation, $\mathrm{H(X)}$ and $\mathrm{G(X)}$ specify the problem constraints. Often, multiple objectives may conflict, and thus the objective solutions may be conflicting as well. A solution may optimize one objective while it may compromise other objectives [9], [11].

3. Techniques and Methods in MOO for Coalition Formation

This section describes techniques and/or methods that are used to achieve MOO in coalition formation problems. We classify MOO techniques and methods into three categories: *conventional approaches*, *evolutionary algorithms*, and *game theoretic approaches*.

3.1 Conventional Approaches

Conventional approaches convert a MOO problem to a SOO problem. We discuss two main techniques: weighted sum and ε-constraints.

3.1.1 Weighted Sum

This technique creates a single objective function as a linear combination of the multiple objective functions

$$\text{Optimize } F_S(X) = \sum_{i=1}^{n} r_i f_i(X), \tag{3}$$

$$\text{subject to } H(X) = 0, G(X) \geq 0$$

$$0 \leq r_i \leq 1, i = \{1, \dots, n\}$$

$$\sum_{i=1}^{n} r_i = 1$$

Many works use this technique for multiple criteria decision making in which each weight represents the degree or priority level of that objective function [25], [26].

3.1.2 ε-Constraints

This method constructs a single objective function where only one of the functions is optimized while the remaining functions are constraints. The objective function can be stated as [9]:

$$\text{Optimize } f_i(X) \tag{4}$$

$$\text{subject to}$$

$$f_k(X) \leq \varepsilon_k, k = 1, \dots, n \text{ and } k \neq i$$

$$H(X) = 0, G(X) \leq 0$$

$f_i(X)$ is the function selected for optimization and the other (n-1) functions are modeled as constraints [11]. Matsatsinis and Delias [20] used ε-constraints to solve task allocation problems in multi-agent decision making systems.

3.2 Evolutionary Algorithms

Evolutionary algorithms (EAs) are categorized as metaheuristics, high-level algorithmic strategies that direct other heuristics or algorithms while searching through the feasible solution space in order to find an optimal solution in a SOO or MOO problem [11]. This technique has been used to solve NP-complete problems such as scheduling and the traveling salesman problem. Many works have used this technique to solve coalition formation (or task assignment or resource allocation) problems [2], [8], [9], [13], [23], [29]. This technique often finds close-to-optimal solutions in a polynomial time. Here we briefly discuss the general structure of evolutionary algorithms.

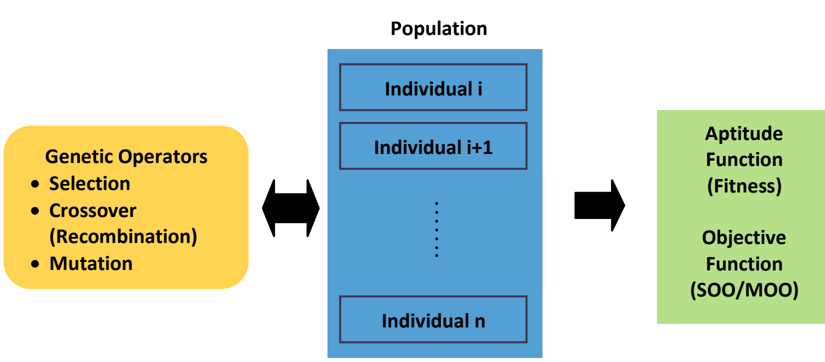

Fig. 2: The Structure of General EAs.

EAs have been used to solve combinatorial optimization problems whose optimal solutions can be obtained only with a very high computational overhead. As shown in Darwin's theory of evolution, the three fundamental components of evolution are: *replication, variation, and natural selection*. Replication forms a new entity from a previous one. Variations may occur during the replication. When the fittest entities win a competition, they are selected as survivors while the weakest ones die out. Mimicking the biological evolutionary process, EAs use the generic EA structure in Fig. 2.

An individual represents a solution to the problem. A population is the set of individuals that can be used to find an optimal value. The population can be improved by genetic operators that iteratively modify individuals of the population. An aptitude function estimates the fitness value of an individual solution. The objective function plays the role of the aptitude function. Genetic operators contribute to improving the individuals of the population. They include selection, crossover (recombination), and mutation. Selection is the step to select the best or fittest individuals. Crossover (i.e., recombination) is the process that can combine two elements of the current population to produce one or more offspring. Mutation transforms an individual into a new individual (i.e., a solution) [9], [11], [24].

Various types of evolutionary algorithms have been devised to solve resource assignment, such as quantum-based evolutionary algorithms [2], hierarchical evolutionary algorithms [8], genetic algorithms [9], [13], [23], simulated annealing [9], and hybrid particle swarm optimization algorithms [29].

3.3 Game Theoretic Approaches

Many coalition formation problems have been formulated using game theoretic approaches. We discuss two major approaches that have been popularly used: auction theory and coalition game theory.

3.3.1 Auction Theory

An auction can be performed when a seller (auctioneer) wants to sell any goods and there are buyers (bidders) who are willing to pay the price [17]. Similarly, in the coalition formation problem, a coalition leader wants to recruit its members to maximize its payoff and a potential bidder wants to join the coalition if the coalition gives the best gain by doing so. In this case, how to define a coalition payoff (i.e., the auctioneer's criteria to determine winners) significantly affects the member selection process and finally team composition. From a bidder's perspective, it will bid an item and commit itself to buy the item based on whether buying the item gives it the best individual payoff.

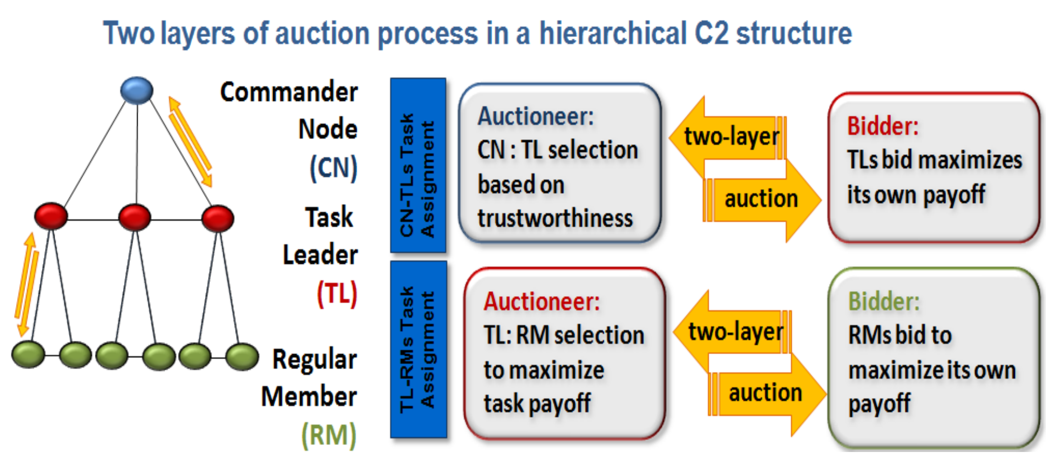

Fig 3. Example of Auction Process in Hierarchical C2 Structure.

Various types of auction-based algorithms have been proposed to solve coalition formation problems in the literature such as a single-item auction with multiple preferences [5], auction-based mechanism design for efficient bandwidth allocation [15], a reverse auction [10], and an auction with different bidding strategies (e.g., pessimistic or optimistic) [28].

In military tactical networks where an hierarchical structure is common with a commander and several task leaders, a two-layer auction process may be modeled from a commander to task leaders and then from task leaders to regular members. An example auction process that describes the hierarchical Command and Control (C2) structure is shown in Fig. 3. Note that decisions for bidding and winner determination (the winner selection process) are based on payoff maximization to individual bidders and task leaders.

3.3.2 Cooperative Game Theory

A cooperative game is a game in which groups of players, called coalitions, cooperate to obtain benefits by joining a grand coalition, the set including all coalitions. The game is a competition between coalitions of players. A cooperative game is also called a "coalitional game" [22]. Often strategic games assume that individual players are selfish and maximize their utility with no cooperation. The goal of the cooperative game is to model the situations in which the players work together or share some cost to benefit each other. However, players are selfish in that they are cooperative only if such behavior maximizes their utility [22].

In a cooperative game, two key elements must be specified: (1) a set of players; and (2) a characteristic function that estimates the value derived from different subsets of the players in the game. Let $\mathrm{N} = \{1, 2, \ldots, \mathrm{n}\}$ be the set of players and let i, where i runs from 1 to n, index each player differently. The characteristic function, denoted by v, computes the value of a subset S of N, denoted by $\mathrm{v(S)}$. $\mathrm{v(S)}$ is the value expected when the members of S form a coalition. That is, a cooperative game can be defined as a pair (N, v) where N is a finite set and v is a function that maps a subset of N to a value [22].

Function v can reflect the objective(s) of the system that should be attained in the coalition payoff. Each player computes its individual payoff based on its objective while a coalition estimates the expected payoff when a subset of members is chosen. Reward (or incentive) or penalty is used to enforce an individual player's behavior (or decision) to maximize the coalition payoff. Various versions of cooperative games have been used to solve coalition formation problems: using repeated cooperative games [12], hedonic games [25], and nontransferable utility cooperative games [27]. It should be noted that trust is considered in the payoff functions that impact the decisions of entities (i.e., players and coalition parties) [12].

While the MOO function is a linear combination of individual objective functions, it should be noted that the individual objective functions are typically non-linear functions of the variables of interest. One could consider a non-linear combination of the individual objective functions, reflecting prior knowledge about the interactions of the different objectives of interest.

4. MOO Classification

We classify existing work in MOO into three classes based on the concept of global welfare (system objectives) vs. individual welfare (individual objectives). The class 1 applies when there are no individual welfare functions. The class 2 is the case when all agents have identical individual welfare. The class 3 can be found when each agent may have its own individual welfare function.

4.1 Class 1 (C1): Global Welfare Only

MOO problems in this class deal with only multiple system/network objectives for global welfare. There are many works dealing with multiple criteria in engineering problems [2], [8], [9], [13], [29].

Balicki [2] examined a task assignment problem in a distributed system using a quantum-based multi-objective algorithm which adopts a new probabilistic representation called Q-bit. This work aimed to minimize workload and communication cost while maximizing system reliability. Dieber et al. [8] investigated an optimal set of configurations for a visual sensor network consisting of a large number of camera nodes based on an evolutionary algorithm. Here the objectives are to minimize overall energy consumption and data volume while maximizing quality-of-service in terms of the camera frame rate and resolution.

Donoso and Fabregat [9] studied a team formation problem in social networks seeking the best tradeoff between skill coverage and team connectivity. Member skill coverage should meet a required skill level while their trust relationships with other members should be close enough for active interactions. They applied genetic algorithm and simulated annealing to identify an efficient team composition satisfying both goals. Jin et al. [13] proposed an adaptive intelligent task allocation scheme based on genetic algorithm with the goals of maximizing network lifetime based on the balance of energy consumption among collaborative nodes while minimizing latency incurred in executing a task by providing sufficient processing power.

Yin et al. [29] examined an optimal task allocation problem in a distributed computing system where program modules need to be allocated to different processors to maximize the system reliability under resource constraints. This work formulated the MOO problem as a hybrid particle swam optimization problem to identify a near-optimal task allocation within a reasonable time.

4.2 Class 2 (C2) : Global Welfare and Individual Welfare

In this class of MOO problems, all agents have identical individual welfare functions. Game theoretic and market-based approaches have been proposed to solving this class of problems [3], [5], [6], [11], [16], [17], [28].

Breban and Vassileva [3] proposed a multi-objective security game mechanism to solve a security MOO problem. This work makes one of multiple security objectives as the main objective and uses other objectives as constraints. It investigates how Pareto frontiers may be generated for the main objective as the other constraints vary. The system, as a defender, maintains multiple objectives based on the attacker type while an attacker takes the role of a player to maximize its payoff by achieving its goal. Chang et al. [5] proposed a trust-based task assignment protocol that uses composite trust to select best team members to maximize the mission completion ratio while meeting an acceptable risk level where an individual entity aims to maximize its utilization. Cho et al. [6] proposed a combinatorial auction-based solution for multiple mission assignment in MANETs where the network has two goals in terms of minimizing communication overhead caused by mission assignment and maximizing mission completion ratio while each node aims to maximize its utilization. Goel and Stander [11] proposed a trust and motivation based clan formation method where self-interested agents want to maximize their payoff by joining, maintaining, or dissolving a clan. In this work, a coalition’s goal is to maximize its payoff by not missing cooperative opportunities but to minimize communication cost for forming a clan.

Koloniari and Pitoura [16] formulated the problem of clustered overlay network formation as a strategic game where nodes join a cluster based on their interest or content. The clustered overlay network has been used to efficiently exchange data relevant to the queries with less effort. An individual node has two conflicting goals: minimizing the cost for the recall of the queries with a sufficient number of cluster memberships (as fetching information from a node in the same cluster costs less) and minimizing the cost to maintain multiple memberships. The system has multiple objectives: speed of convergence to Pareto optimality, cost optimality (minimum cost for both recall and membership), load balance (minimum number of memberships and associated cost), and overhead minimization (movement of nodes, social cost, etc.). Lin and Huai [18] integrated trust into market-driven resource management decision making in Grid environments to achieve resource sharing, while accurately detecting malicious entities. In this work, a consumer tries to minimize the price of resource usage for its task completion under constraints of budget and deadline. A provider, forming a club for customers, aims to maximize the total revenue of its club and resource utilization while sharing resource only with trustworthy entities for effective resource usage. A club in this work mimics a coalition in game environments where a provider pursues global welfare.

Whitten et al. [28] presented a decentralized task assignment algorithm where each agent can make autonomous decisions but is restricted by constraints. This work used a consensus-based bundle algorithm for modeling different types of behavioral strategies. Both a task planner and an agent have the same goal to optimize task assignment in this work.

The commonality of MOO research in class C2 is that payoffs earned by individual entities often directly or indirectly contribute to global welfare. Therefore, in C2 MOO research, we observe that the goal of an individual entity and that of a coalition are well aligned and mutually beneficial to maximize their payoffs.

4.3 Class 3 (C3): Global Welfare and Individual Welfare with Different Individual Payoff Functions

In this class of MOO problems, the individual payoff functions are all different. This scenario is rare because most works deal with two-party objectives such as an individual entity vs. a coalition or system. Breban and Vassileva [3] studied a long-term coalition formation problem of both vendors and customers where each agent evaluates other agents based on trust. Each individual agent, either a vendor or a customer, joins a coalition based on its trust assessment to maximize the payoff, while the system aims at reducing the convergence time to reaching an equilibrium state for coalition formation. This work measured trust based on positive experience in transactions and similarity in preferences. This work is unique in that three-party objectives are being considered to solve a coalition formation problem. Meng et al. [21] presented a generic mathematical method for transforming the multi-objective problem into a multi-player game theoretic problem.

5. Future Research Directions and Insights

In this section, we envisage an example of coalition formation for trustworthy tactical network environments where multiple objectives may exist. A tactical network should be sustainable, that is, the system should meet the key characteristics of current/future warfare in military tactical networks. Leveraging the concept of sustainability in ecology and biology [1], a sustainable system should be *bearable* (or resilient) against hostile entities, *equitable* towards resource utilization, and *viable* (or survivable) under failure or lack of resources. Reflecting those key factors, we exemplify the system goals as (1) maximizing mission completion ratio and resource utilization in the presence of hostile or faulty entities (i.e., high resilience against hostility/failure); (2) maximizing load balance among nodes in the network (i.e., high equitability in resource usage); and (3) minimizing the delay to complete time-sensitive tasks (i.e., viability under time constraints).

We illustrate coalition formation in tactical networks with an example scenario in Fig. 4. In tactical networks, trustworthiness of participating entities is critical to successful mission completion. A coalition consisting of qualified members tends to achieve successful mission completion when the selected members behave as expected. If members of a coalition do not behave as expected, then the mission execution cannot continue and a new set of members should be selected for mission execution. This process will continue until the mission deadline. If the mission cannot be completed by the deadline due to untrustworthiness of the current members, the mission will fail. Otherwise, the mission is considered to have been executed successfully albeit with extra delay.

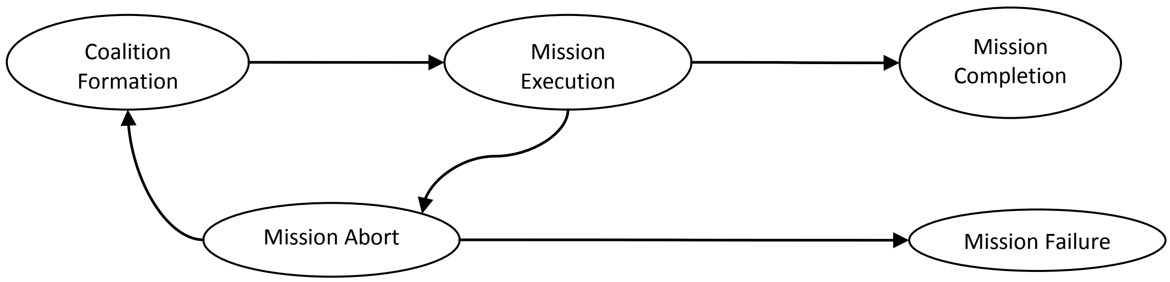

Fig. 4: Example Scenario of Coalition Formation in a Tactical Network.

Node trustworthiness can be evaluated from trust perspectives. Among the works surveyed in Section 4, [5], [9], [11] used trust to solve a coalition (or team, clan, alliance) formation or task assignment MOO problem. However, except for [5], they assumed that trust is already in place and can be used as a metric to help achieve MOO. Different from the existing work, Chang et al. [5] proposes a trust-based task assignment protocol to solve a MOO problem in a tactical coalition network. It captures trust based on multiple dimensions of an entity's trust under dynamically changing network environments (e.g., hostility, node failure or mobility), given task characteristics for tactical operations as input to the MOO problem. Trust is known to be related to risk. Hence, using trust/risk for node trustworthiness assessment for member selection and coalition formation can minimize mission abort and help satisfy multiple system goals in mission completion ratio, minimum delay, and efficient/effective resource utilization.

We suggest some future research directions for developing coalition formation MOO algorithms for trustworthy tactical networks as follows:

- Provide a mechanistic yet repeatable method to define critical multiple objectives, given targeted tactical operations and/or mission characteristics as input;
- Prioritize objectives according to mission characteristics or based on critical tradeoffs;
- Develop node behavior models reflecting the behaviors of entities in the targeted network environment;
- Develop attacker models reflecting the behaviors of malicious nodes (inside attackers);
- Develop trust-based MOO solution techniques allowing each entity to make decisions based on its trust assessment towards other entities, where trust assessment should take into account the unique properties of trust [6];
- Model as well define payoffs (or utilities) of all involved parties that would meet multiple objectives;
- Consider critical tradeoffs (e.g., minimum delay vs. fair resource sharing) in distributed and resource-constrained environments;
- Devise effective reward/penalty mechanisms to entice cooperative behaviors of individual entities to increase coalition and individual payoffs; and
- Devise effective and efficient optimization techniques to identify optimal solutions in resource constrained tactical network environments.

6. Summary

We performed a comprehensive survey on coalition formation problems with multiple objectives and techniques and methods to solve multi-objective optimization (MOO) problems in coalition formation. We discussed three main approaches used to model and solve MOO problems in coalition formation: conventional techniques, evolutionary algorithms, and game theoretic approaches. In addition, we classified MOO problems based on the design concept of global welfare vs. individual welfare. Trust has been used in solving coalition formation MOO problems where trust of entities may significantly affect the performance of attaining objectives in the system. Trust has been used in solving MOO problems arising in coalition formation where trust of entities may significantly affect the attainment of system objectives. Trust can play a significant role by suggesting heuristics leading to low complexity solutions that are not too far from the optimal solution.

However, in the literature, trust has been assumed to be in place and static, which is not realistic in practice. We suggested future research directions including trust-based MOO solution techniques to better solve coalition formation problems in tactical networks, taking into consideration the unique nature of trust and characteristics of tactical network environments.

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