



U.S. Army Research, Development and  
Engineering Command

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



***TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.***

**ICCRTS 2013, Paper ID: 082**

**Jin-Hee Cho \***, Ing-Ray Chen<sup>+</sup>, Yating Wang<sup>+</sup>, Kevin Chan \*, Ananthram Swami \*

\*US Army Research Laboratory

<sup>+</sup>Virginia Tech

- Motivation
- Contributions
- Multi-Objective Optimization (MOO) in Coalition Formation
  - Coalition Formation
  - Multi-Objective Optimization (MOO)
- MOO Techniques for Coalition Formation
  - Conventional Approaches
  - Evolutionary Algorithms
  - Game Theoretic Approaches
- MOO Classification based on Nature of Individual Objectives
- Current ARL Efforts
- Future Research Directions and Insights

- Multiple objectives may exist in tactical networks:
  - Coalition partners with different objectives
  - Multiple system goals with restricted resources
- Examples of system goals are:
  - Sustainability / survivability
  - Resilience
  - Scalability
  - Reconfigurability for agility
  - Resource efficiency
- Multiple goals may conflict:
  - Performance vs. security
  - Accuracy vs. efficiency
  - Effectiveness vs. survivability



- Used a novel classification developed to categorize existing work on coalition formation for MOO
- Delivered the overview of research trends in solving coalition formation MOO problems in terms of used techniques
- Showed the recent trends that use trust concept to solve MOO problems in tactical networks

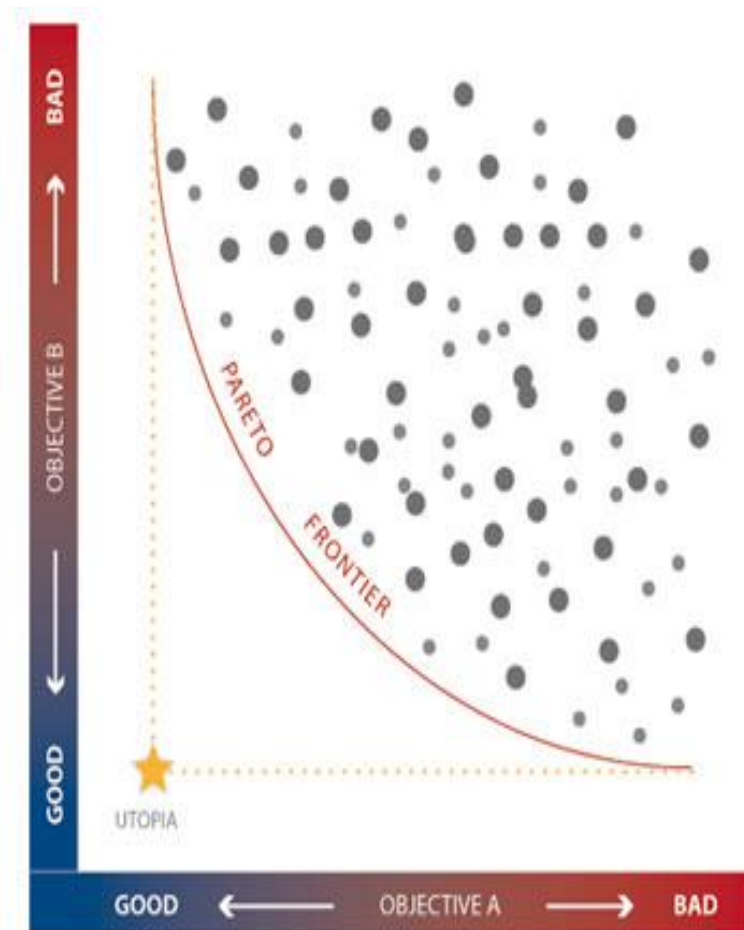
According to Kahan and Rapoport (1984):

*A coalition can be formed when three or more parties get together with a common interest that gives mutual benefits.*



- The common aspect of coalition is **mutual benefits based on trust relationships between two parties**
- Examples:
  - Asset-task assignment for successful mission completion with multiple coalition partners
  - Service composition to maximize service (mission) satisfaction in battlefield situations
  - Achieving sustainability for future performance while satisfying the current performance based on effective/efficient resource allocation

- An example of MOO in a military tactical network:
  - Maximize mission performance;
  - Maximize load balance over all nodes;
  - Minimize overall resource consumption
- MOO often yields a set of optimal solutions, called *optimal Pareto frontiers*



Source: <http://www.enginsoft.com/>

## Single-Objective Optimization (SOO)

Optimize  $f(X)$

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

## Multi-Objective Optimization (MOO)

Optimize  $F(X) = \{f_1(X), f_2(X), \dots, f_n(X)\}$

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

- Function  $f(X)$  is to be optimized;
- Vector  $X$  indicates the set of independent input variables
- Functions  $H(X)$  and  $G(X)$  describe the problem constraints

## Convert a MOO problem to a SOO problem

- **Weighted Sum**: creates a single objective function (OF) as a linear combination of the multiple OFs

$$\begin{aligned} \text{Optimize } F_S(\mathbf{X}) &= \sum_{i=1}^n r_i f_i(\mathbf{X}), \\ \text{subject to } H(\mathbf{X}) &= 0, G(\mathbf{X}) \geq 0 \\ 0 \leq r_i &\leq 1, i = \{1, \dots, n\} \\ \sum_{i=1}^n r_i &= 1 \end{aligned}$$

- Used in multiple criteria decision makings
- Each weight: the degree or priority level of the respective OF
- Individual OFs are typically non-linear functions of the variables of interest

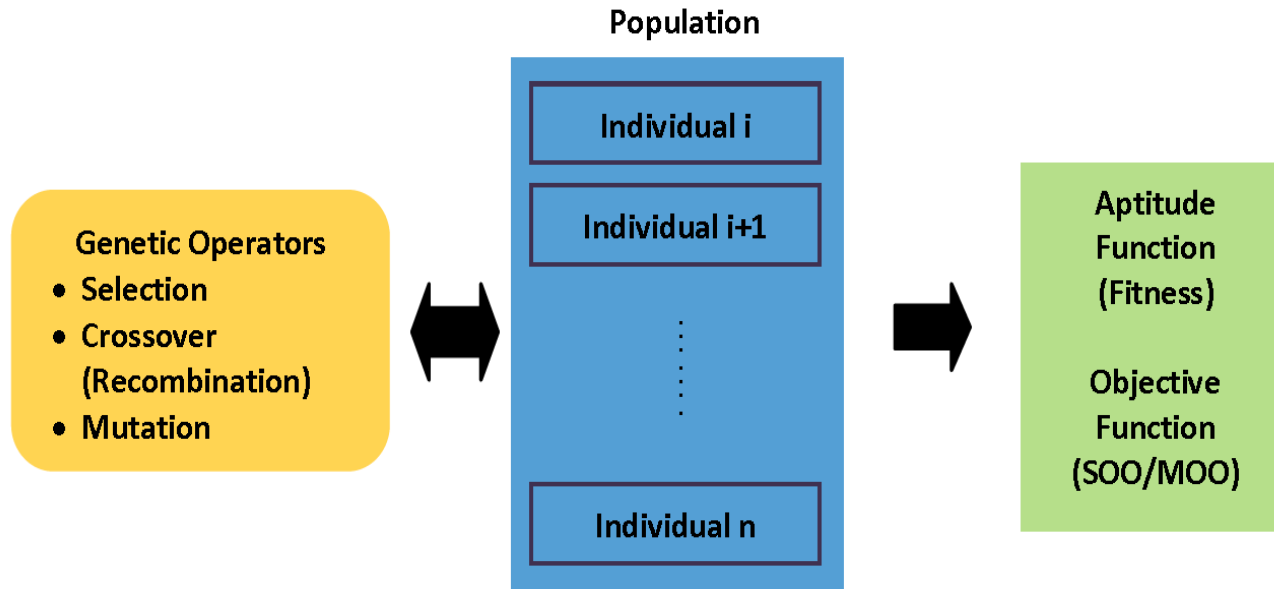


## Convert a MOO problem to a SOO problem

- **$\epsilon$ -Constraints**: constructs a single OF where only one of the functions is optimized while the remaining functions are constraints

$$\begin{aligned} & \text{Optimize } f_i(X) \\ & \text{subject to} \\ & f_k(X) \leq \epsilon_k, k = 1, \dots, n \text{ and } k \neq i \\ & H(X) = 0, G(X) \leq 0 \end{aligned}$$

- $f_i(X)$  is the function selected for optimization and the other (n-1) functions are modeled as constraints

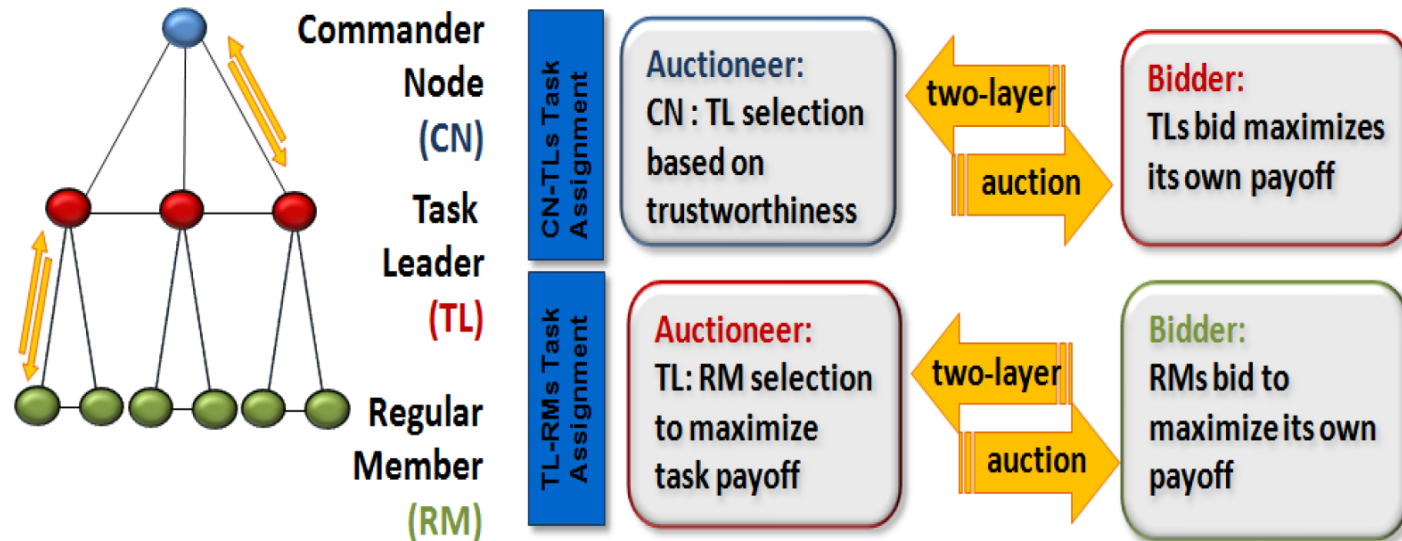


The Structure of General EAs.

- Categorized as metaheuristics, high-level algorithmic strategies that direct other heuristics or algorithms
- Search through the feasible solution space to find an optimal solution
- Mainly used for NP-Complete problems (e.g., combinatorial optimization prob.)
- Often finds **close-to-optimal solutions in a polynomial time**



### Two layers of auction process in a hierarchical C2 structure



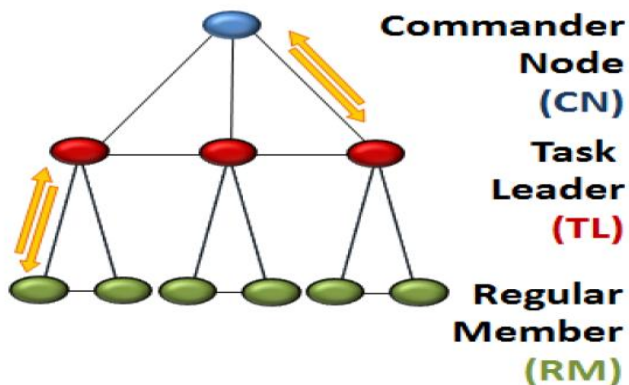
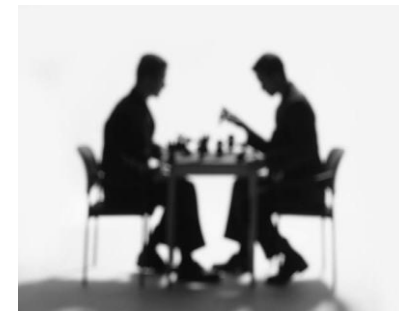
Example of Auction Process in Hierarchical C2 Structure.

## Auction Theory

- In a coalition formation problem:
  - A coalition leader wants to recruit its members to maximize its payoff;
  - A potential bidder wants to join the coalition if the coalition provides the best gain by doing so

### Cooperative Game Theory (aka. Coalitional game)

- A cooperative game is a game in which groups of players, called coalitions
- Player: joins a coalition that maximizes its own individual payoff (selfish)
- Coalition leader: chooses players to maximize its own coalition
- The goal of the cooperative game is to maximize a grand coalition's payoff

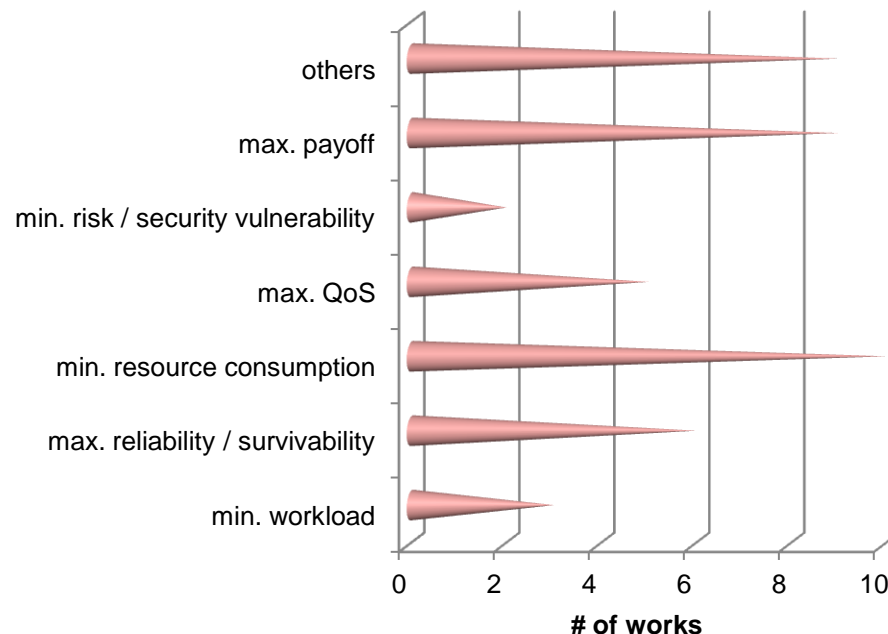
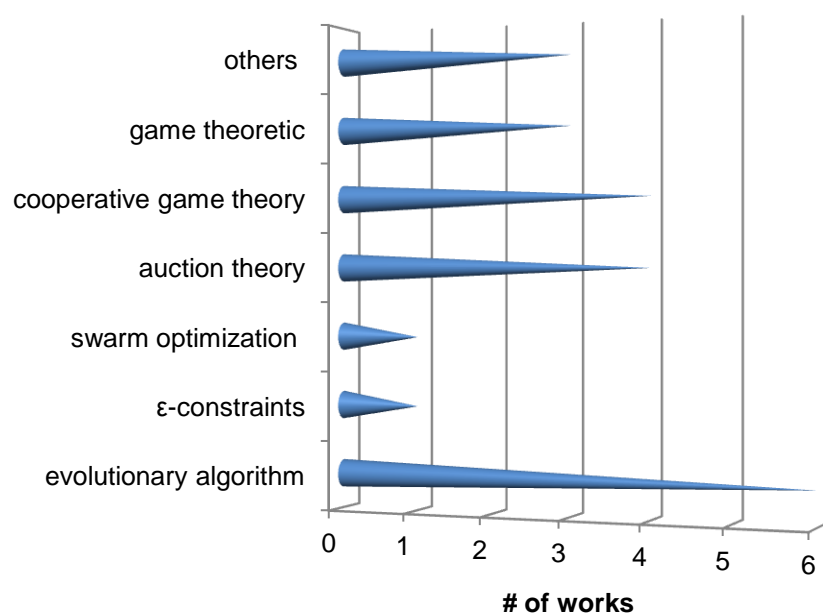


Compose compositions of all teams under a mission to maximize the payoff of mission team

Select a member to maximize the payoff of a task team by TL

Join a task team to maximize the payoff of an individual member

Example of cooperative game process in hierarchical C2 structure



- Literature review for 2002-2012; 22 works
- Dominant approaches are Evolutionary algorithms and game theoretic approaches
- Main objectives are closely related to resource constraints and system payoffs

- **Class 1 (C1):** No individual objectives
- **Class 2 (C2):** Individuals have identical objectives
- **Class 3 (C3):** Individuals have different objectives

In all three classes, system objectives must also be optimized

## C1: System Objectives Only (no trust is considered)

Author(s)	System/coalition objectives	Techniques/Solutions	Problem
Balicki (2009)	Minimize workload and cost; maximize system reliability	Quantum-based evolutionary algorithm	Task assignment
Dieber et al. (2011)	Minimize energy consumption and data volume; maximize quality-of-service	Evolutionary algorithm	Task allocation
Jin et al. (2012)	Maximize network lifetime; minimize latency for task execution	Fitness function based on genetic algorithms	Task allocation
Matsatsinis and Delias (2003)	Maximize speediness of task execution and assignments functionality; minimize risk due to allocation decision	$\epsilon$ -constraints	Task allocation
Notario et al. (2012)	Maximize task execution quality; minimize energy and bandwidth consumption	Genetic algorithm	Task assignment
Yin et al. (2007)	Maximize reliability; Minimize resource (memory / computational power) consumption	Hybrid particle swam optimization	Task allocation



## C2: System Objectives and Identical Individual Objectives (no trust is considered)

Author(s)	Individual objectives	System/coalition objectives	Techniques/Solutions	Problem
Cho et al. (2011)	Maximize node utilization	Minimize communication overhead caused by mission assignment; Maximize mission completion	Combinatorial auction	Mission assignment
Edalat et al. (2012)	Minimize bid waiting time	Minimize energy consumption and delay in task assignment	Reverse auction in cooperative game	Task allocation
Genin and Aknine (2010)	Maximize node utilization, given resource constraints and task requirement	Maximize coalition payoff	Similarity and frequency based selection algorithms	Coalition formation
Koloniari and Pitoura (2012)	Minimize cost for queries recall and membership maintenance	Minimize the convergence time to optimality, load balance, membership and recall cost, and required overhead	Cluster formation game	Formation of clustered overlays
Nardin and Sichman (2010)	Maximize a payoff as a share of the coalition payoff	Maximize throughput and valuation; minimize delay	Hedonic coalition game	Task allocation
Saad et al. (2011)	Customer: Maximize service satisfaction as a share of coalition payoff	Provider: Maximize revenue in wireless network service as coalition payoff	Nontransferable payoff coalitional game	Resource allocation
Singh et al. (2011)	An agent: maximize its utilization by being assigned to tasks	Task planner: maximize task assignment	Consensus-based bundle algorithm	Task assignment



## C3: System Objectives and Different Individual Objectives (no trust is considered)

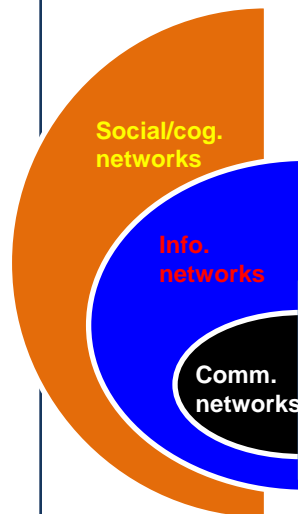
Author(s)	Individual objectives	System/coalition objectives	Techniques/Solutions	Problem
Meng et al. (2010)	Maximize an individual player's objective where each individual has a different objective	Minimize computational cost; Maximize optimality accuracy	Nash equilibrium, cooperative, and evolutionary game	Generic MOO solution

## Trust has been used to solve coalition formation (task assignment) with multiple objectives

	Author (s)	Individual Objectives	System Objectives	Techniques	Problem
C1	Dorn et al. (2011)		Maximize skill coverage and team connectivity	Genetic algorithms / simulated annealing	Team formulation
C2	Chang et al. (2012)	Maximize node utilization	Maximize mission completion ratio under a given a risk constraint	Auction-based	Task assignment
	Guo et al. (2009)	Maximize membership period	Maximize efficiency and security in business process	Trust and self-confidence based	Coalition formation
	Huo et al. (2011)	Maximize an individual payoff	Maximize the profit of the supply chain alliance	Cooperative game	Alliance formation
	Mikulski et al. (2011)	Maximize an individual payoff	Maximize trust synergy; minimize trust liability	Cooperative game	Coalition formation
	Griffiths and Luck (2003)	Maximize an individual payoff	Maximize coalition payoff; Minimize resource consumption	Congregating; cooperation-based clan formation	Clan formation
C3	Breban and Vassileva (2002)	Vendor: Maximize sales Customer: Minimize prices	Maximize stability of an optimal formation of coalitions	Trust-based coalition formation	Coalition formation

**Goal:** The proposed task assignment technique is to:

- Meet multiple system objectives using composite trust-based member selection process
- Reduce complexity significantly for finding close-to-optimal solutions
- Conduct comparative performance study of the proposed technique



**Composite Trust**

- Social Connectedness
- Reciprocity
- Competence
- Integrity

**Trust Aggregation**

- Direct evidence
- Indirect evidence

$$T_{ij}^X(t) = \alpha T_{ij}^{D-X}(t) + (1 - \alpha) T_{ij}^{ID-X}(t)$$

**Multiple Objectives**

$$P_{MOO} = P_{MC} + U - D$$

Maximize mission completion ratio ( $P_{MC}$ )

Maximize resource utilization ( $U$ )

Minimize delay to task completion ( $D$ )

Importance

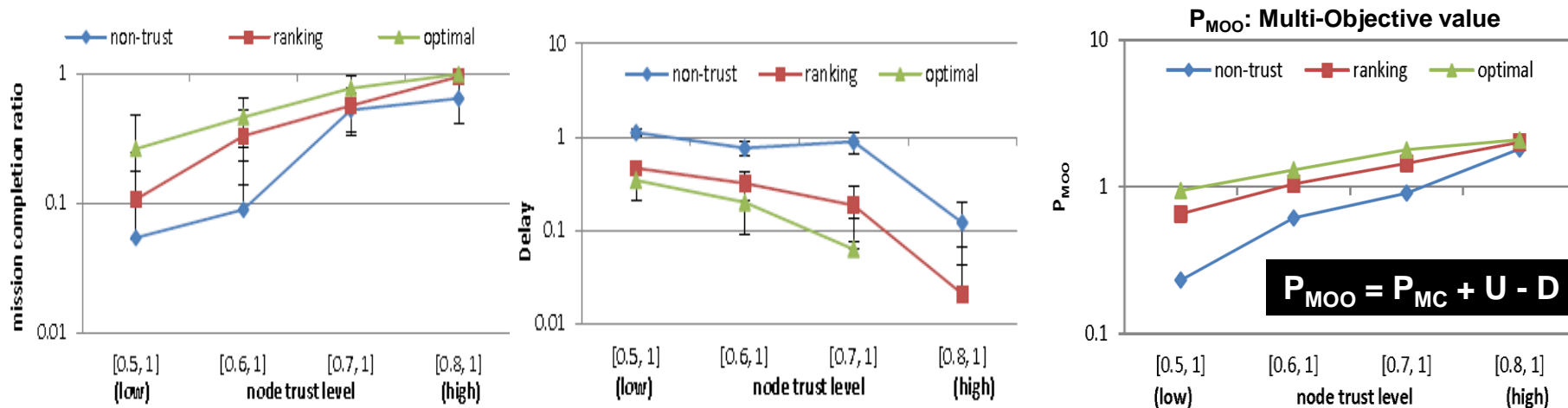
Urgency

Difficulty

**Task Model**

## Composite trust based member selection improves performance with less complexity

**Non-trust:** no trust used; **ranking:** trust-based; **optimal:** optimal solution using ILP



- Higher mission completion ratio ( $P_{MC}$ ) and node utilization ( $U$ ; not shown) and lower delay ( $D$ ) with more trustworthy nodes
- Higher multi-objective value ( $P_{MOO}$ ) with more trustworthy nodes

**Result: Trust ranking-based selection outperforms non-trust-based scheme while performing close to the optimal solution**



**Goal:** The proposed service composition and binding technique is to:

- Meet multiple system objectives by maximizing MOO function
- Improve performance objectives by making trust-based decisions
- Conduct comparative performance study of the proposed technique and non-trust baseline scheme

## Multiple Objectives

$$MOO = \sum_{m \in \mathcal{T}} (Q_m - D_m - C_m) = Q - D - C$$

Maximize Quality-of-Information (Q)

Minimize Delay (D)

Minimize Cost (C)

Competence

**Composite Trust**

Integrity

**Service Composition Specification (SCS)**

$$SCS = \langle [S_0], [S_2, S_4], [S_3], [S_7], [S_4, S_8], [S_2] \rangle$$

**Service selection criteria:**

- abstract service type  $S_i$
- service requirements in terms of:
  - ✓ Quality of Information (Q)
  - ✓ Delay (D)
  - ✓ Cost (C)

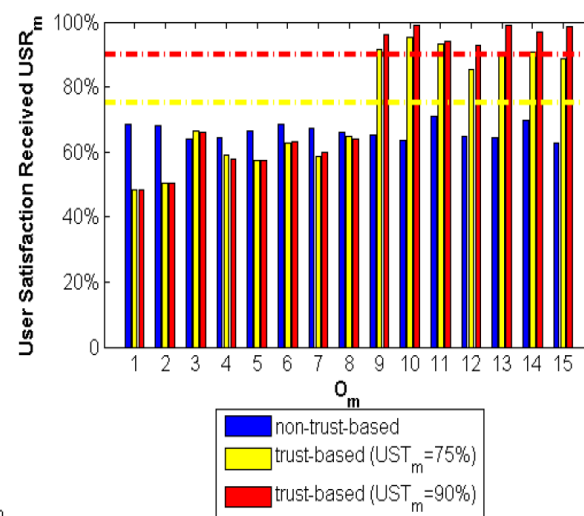
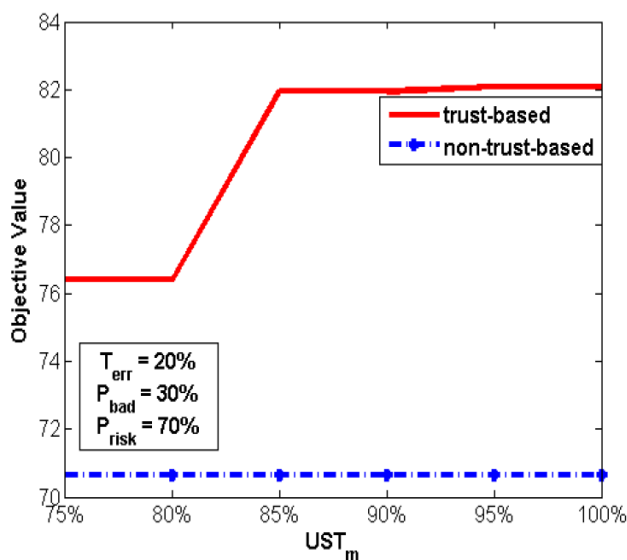
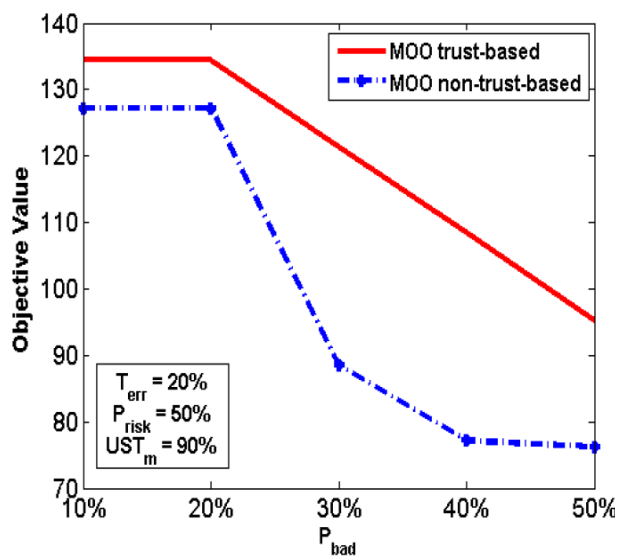
**User Satisfaction Received (USR<sub>m</sub>):** User satisfaction level based on received service provision over advertised service quality

$$USR_m = \text{Min} \left( \frac{Q_m^{\text{true}}}{Q_m^{\text{advertised}}}, \frac{D_m^{\text{advertised}}}{D_m^{\text{true}}}, \frac{C_m^{\text{advertised}}}{C_m^{\text{true}}} \right)$$



## Trust weighted qualification assessment improves performance objectives

$T_{err}$ : trust estimation error;  $P_{bad}$ : % of bad nodes;  $P_{risk}$ : % of risk taking by malicious nodes



$UST_m$ : User satisfaction threshold for operation  $m$

$USR_m$ : User satisfaction received based on advertised quality of service provision

**Result: Trust-based scheme shows higher resilience against % of malicious entities (and various intensity of malicious activities) with higher MO values /  $USR_m$**

- Provide a systematic yet repeatable method to define critical multiple objectives;
- Develop node behavior (attack) models;
- Define payoffs (or utilities) of all involved parties and/or reward/penalty mechanisms
- Devise effective and efficient MOO techniques

***Thank You!***

U.S. Army Research Laboratory

**Jin-Hee Cho**

[jinhee.cho@us.army.mil](mailto:jinhee.cho@us.army.mil)

301.394.0492

2800 Powder Mill Rd.

Adelphi, MD 20783