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Coalition formation problem: a capability-centric analysis and general model

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Abstract Coalition formation (CF) refers to reasonably organizing robots and/or humans to form coalitions that can satisfy mission requirements, attracting more and more attention in many fields such as multi-robot collaboration and human-robot collaboration. However, the analysis on CF problems remains limited. To provide a valuable study reference for researchers interested in CF, this paper proposed a capability-centric analysis of the CF problem. The key problem elements of CF are firstly extracted by referencing the concepts of the 5W1H method. That is, objects (*who*) form coalitions (*what*) to accomplish missions (*why*) by aggregating capabilities (*how*) in a specific environment (*where-when*). Then, a multi-view analysis of these elements and their correlation in terms of capabilities is proposed through various logic diagrams, structure charts, etc. Finally, to facilitate a deeper understanding of capability-centric CF, a general mathematical model is constructed, demonstrating how the different concepts discussed in this analysis contribute to the overall model.

Keywords coalition formation, capability aggregation, capability metric, mission requirement, environmental effect

1 Introduction

Multi-agent collaboration in the form of multi-robot collaboration, human-robot collaboration, and human collaboration is becoming a trend for accomplishing complex challenging missions [1–6]. For multi-agent collaboration, an important question is naturally raised: *Which agents can complement each other in capabilities and jointly accomplish missions better*? This implies a top-level decision-making problem named coalition formation (CF).

CF aims to form coalitions of objects according to the requirements of complex missions. In other words, some objects with various capabilities need to be picked out from many candidate objects according to mission requirements [7–9]. For example, during disaster rescue, multiple teams need to be formed and assigned to each disaster area according to the requirements of search and rescue [10]. Each object is denoted by a_i, $i \in \{1, 2, ..., n\}$. The set of all objects is denoted by $\Omega = \{a_1, a_2, ..., a_n\}$. These objects need to form m coalitions (each represented by S_k, $k \in \{1, 2, ..., m\}$) to accomplish corresponding m missions (each represented by T_k, $k \in \{1, 2, ..., m\}$). Define $S = \{S_1, S_2, ..., S_m\}$ as the decision variable of CF. The vectors $\boldsymbol{F} = (f_1, f_2, ..., f_p)$ and $\boldsymbol{G} = (g_1, g_2, ..., g_q)$ represent objective and constraint functions for different aspects, respectively. CF can be generally formulated as follows.

$$\min \boldsymbol{F}(S) = (f_1(S), f_2(S), ..., f_p(S)), \tag{1}$$

$$\text{s.t. } \boldsymbol{G}(S) \geqslant 0, \tag{2}$$

$$S_k \in 2^{\Omega}, \ \forall k \in \{1, 2, \ldots, m\}. \tag{3}$$

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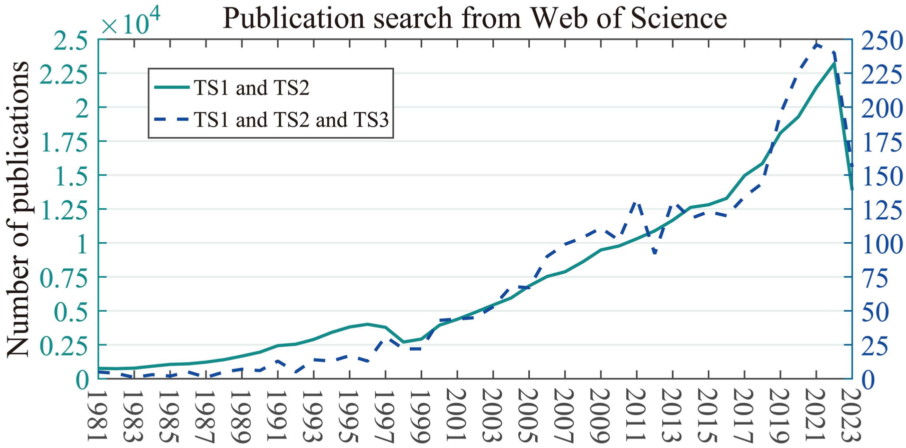

Figure 1 (Color online) The number of publications about TS1, TS2 and TS3 from Web of Science (1981–2023). TS1=((multi* OR swarm*) AND (UAV* OR UUV* OR UGV* OR agent* OR robot* OR (unmanned AND vehicle*) OR (role* OR staff* OR "human resource*"))). TS2=(cooperat* OR collaborat* OR coordinat*). TS3=((abilit* OR capabilit*) AND (coalition* OR team* OR group*) AND (form* OR configur* OR generat*)). The publications in 2023 only include data from January to September.

In human society, CF widely exists in human collaboration to accomplish missions, such as interdisciplinary healthcare, surgical operations, etc [11–14]. Human skills defined by missions are the basic criteria for forming coalitions to satisfy mission requirements [15]. Various skills can be viewed as a special level of qualification or responsibility to do work [11]. Besides, as artificial intelligence and robotics rapidly progress, robots show more and more powerful capabilities to work in multiple dimensions such as computing, sensing, and actuating. In multi-robot collaboration, what kind of robot coalitions are formed has a crucial influence on the performance of accomplishing complex missions such as multi-robot cooperative mapping, surveillance, etc [16–19]. Analogously, CF also exists in human-robot collaboration. A reasonable human-robot coalition depends on human skills, robot capabilities, and the co-adaptation between humans and robots [20, 21]. In total, CF has various civilian and military application backgrounds such as industrial production, disaster relief, transportation, military operations, etc [22–27].

In recent decades, CF research has attracted the interest of more and more scholars. We investigate related publications by searching topic (TS) terms, with three search items notated by TS1, TS2, and TS3, respectively. The definition of TS1 considers various objects in CF, e.g., robots and unmanned vehicles. The definition of TS2 aims at multi-agent collaboration. The definition of TS3 covers the possible synonyms of capability-centric coalition formation (CCF). The data of related publications from the Web of Science is shown in Figure 1. The number of publications of multi-agent collaboration (i.e., TS1 and TS2) or CCF (i.e., TS1 and TS2 and TS3) has been increasing steadily since the 21st century. Besides, the rising tendency of CCF publications remains consistent with that of multi-agent collaboration.

Scholars have analyzed the CF problem from some perspectives in review articles. Rizk et al. [28] analyzed coalition formation as a workflow in multi-agent systems and briefly introduced some concepts including offline and online coalition formation, single-task and multi-task agents, the uncertainties caused by lacking information on agent capabilities, etc. Mahdiraji et al. [29] introduced the definition of overlapping coalition structures, the task requirements on algebraic addition resources, etc. Other research articles also involved some concepts of CF, such as environmental effects on weapon mix [30] and optimization objectives of CF [31].

Referencing the 5H1W method, this paper firstly extracts the key problem elements. Then, this paper proposes a unified analysis of CF among objects, missions, environments, and coalitions in terms of capability aggregation, to provide a study reference and inspire research directions for researchers interested in CF. Furthermore, the capability-centric analysis will be indicated in the general mathematical model of CF. The features and contributions of this paper are summarized as follows.

- A holistic view of CF is presented through diagram analysis, focusing on the logic of problem elements in terms of capabilities.
- A multi-view analysis of objects is put forward based on logic diagrams covering a detailed summary of the types and hierarchical structure of objects, typical capabilities, and their relationships from the perspective of a control system, etc. Additionally, the capabilities are represented using a taxonomy-

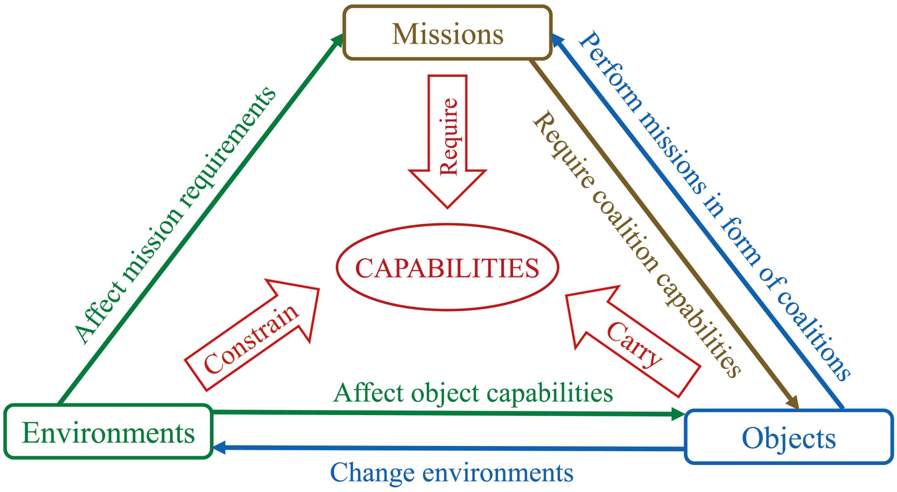

Figure 2 (Color online) The relationships among objects, missions, and environments in CF problems.

inspired approach, resembling the classification of species, genera, and families in biological taxonomy. Moreover, common mathematical operators are given to abstract and calculate the total capabilities of different objects within each coalition, offering a systematic framework for computation.

- The analysis delves into the capability requirements of missions on coalitions, taking into account capability aggregation and the hierarchical structure. Additionally, the analysis explores the effects of environmental factors on the capabilities of coalition members from the perspectives of traversability, transparency, connectivity, etc.
- A general mathematical model is constructed based on the capability-centric analysis. This model takes into account the environmental effects on object capabilities, mission requirements on coalitions, etc. By incorporating these factors, the model provides a holistic representation of the capability-centric interplay among environments, missions, and objects. Typical examples are provided to demonstrate how to mathematically describe a coalition formation and how to address specific considerations and distinctions in different CF problems.

The rest of this paper is organized as follows. First, a holistic analysis of CF elements is presented in Section 2. Then, the capability families, capability aggregation of objects, etc. are described in Section 3. The capability requirements of missions on coalitions are introduced in Section 4. Environmental effects on object capabilities are analyzed in Section 5. A general mathematical model is constructed in Section 6. Finally, Section 7 concludes this paper.

2 Holistic view of CF

Inspired by the 5W1H method, the CF problem can be viewed as: Objects (*who*) form coalitions (*what*) which can accomplish missions (*why*) by aggregating capabilities (*how*) in a specific environment (*where-when*) [32]. These elements and their relationships are analyzed around capabilities as depicted in Figure 2. Objects are the smallest independent units to form coalitions. Different objects possess one or multiple capabilities that enable them to accomplish missions together in the form of coalitions. Missions imply the capability requirements of coalitions. Various environmental factors influence the capabilities of objects and the requirements of missions. In turn, executing missions by coalitions also brings out changes in environments. The details of these elements will be presented in subsequent sections. Additionally, for clarity, the primary terms in this paper have been summarized and explained in Table 1.

In CF problems, due to different mission requirements and object capabilities, coalitions have the following characteristics which are also the criteria for classifying CF problems.

2.1 Number of simultaneous candidate coalitions

When an object becomes a member of one coalition, it may encounter two situations: a single coalition and multiple coalitions with respect to the number of simultaneous candidate coalitions.

Table 1 Terms and explanations

Term	Explanation
Coalition	The set of objects which collectively perform the same mission.
Single-coalition formation	The scenario in which one object belongs to only one candidate coalition.
Multiple-coalition formation	The scenario in which one object can belong to more than one candidate coalition.
Non-overlapping coalition formation	The scenario in which one object can only belong to at most one of several candidate coalitions under the scenario of multiple-coalition formation.
Overlapping coalition formation	The scenario in which one object can belong to different coalitions under the scenario of multiple-coalition formation.
Aggregation operator	The mathematical manner to abstract and calculate the total capabilities of coalitions.

Single coalition. There exists only a candidate coalition for objects, and in this case, each object faces only two potential outcomes: either becoming a coalition member or remaining outside the coalition. Once the coalition is formed, all coalition members need to perform one or more missions altogether. In the case where the coalition is engaged in multiple missions, the capability requirements of the coalition can be the integration of the capability requirements of all the missions.

Multiple coalitions. Each object has the potential to become a member of one or more candidate coalitions. In other words, in this case, CF needs to consider not only whether each object becomes a member of one coalition but also which coalitions it partners with.

2.2 Overlapping of coalitions

In the case that more than one coalition will be formed in a whole event, it is a question worth exploring whether the same object can become members of multiple coalitions to concurrently complete multiple missions.

Overlapping coalitions. Overlapping coalitions mean that the same object can be concurrently a member of different coalitions [29, 33]. The capabilities of objects should be shared among related coalitions. The objects can concurrently support capability requirements for these missions, such as processing power, communication bandwidth, etc [18]. For example, objects working as communication relays can serve multiple coalitions.

Non-overlapping coalitions. Non-overlapping coalitions mean that the same object can only become a member of one coalition. For example, it is impossible to require the same object to perform missions at different places at the same time. Additionally, even if the spatial constraint can be neglected, a non-sharable capability of the same object cannot cater to more than one coalition simultaneously either. For example, a robotic arm cannot simultaneously sort two items.

Remark 1 (Capability contribution to multiple coalitions)**.** The degree of involvement (DOI) needs to be considered in the case of multiple coalitions. DOI, a multi-dimensional vector, represents the contribution proportion of each object's resources (time, capabilities, etc.) in each coalition [34]. If multiple coalitions can share the same resource of one object, the DOI of the resource in these coalitions ranges from 0 to 1 [19, 33]. If the resource sharing is impossible, the DOI is 0 or 1.

3 Object analysis around capabilities and aggregation operators

3.1 Object types

In CF, the object refers to the smallest unit to form a coalition, including agents and agent-extending objects.

3.1.1 *Agents*

In this paper, an "agent" is viewed as an intelligent system, including humans and intelligent robots.

Humans. Humans are typical natural systems with high autonomy that can form coalitions to perform some operations. These coalitions formed around the same benefits and goals are human organizations oriented to different functions and purposes, such as economic coalitions and technological coalitions. In coalitions, humans often play important roles, such as commanders, planners, operators, and executants [35]. Humans can deal with emergencies and provide task-understanding capabilities, decision-making capabilities, and so on. Human organs are the carriers of various functions that can be viewed

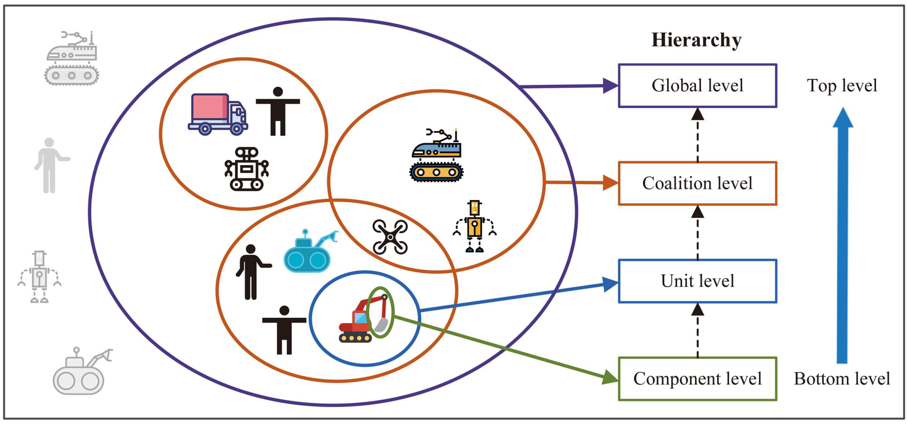

Figure 3 (Color online) The hierarchical structure of the studied objects in CF.

as the functional components of humans including brains for thinking and decision-making, hearts and lungs for maintaining life activities, limbs for performing operations, etc.

Intelligent robots. Robots with certain autonomy that can make decisions or perform some operations through programming and automatic control can be regarded as intelligent robots, such as autonomous ground vehicles and autonomous underwater vehicles [36–39]. Robots possess some self-contained functional components to complete missions such as robotic arms and visual sensors. It should be noted that for CF, these components are non-removable and cannot be viewed as an independent and complete unit to form coalitions.

3.1.2 *Agent-extending objects*

Agent-extending objects can provide energy, material resources, and information for agents to continuously run and execute tasks through its functional components. Agent-extending objects without autonomy depend on the control of matched agents. However, unlike the functional components of agents which are subsystems fixed on the agents, agent-extending objects are configurable when forming coalitions. Agent-extending objects are independent of agents and do not depend on any special agent. They are the option for coalitions and need to be optimized and configured according to mission requirements on coalitions. Robots without autonomy which need to rely on the control of humans or intelligent robots are regarded as agent-extending objects.

Remark 2. Objects composed of functional components can be viewed as the aggregation of various capabilities.

Remark 3. Agents should be able to manipulate the matched agent-extending objects under the constraints of physical space and cyberspace. For example, robot-extending objects can be temporarily installed or removed from intelligent robots under the restriction of their electrical interfaces and communication protocols, e.g., depth cameras. Human-extending objects can include hand-held tools, wearable tools, and manned platforms.

Remark 4. In human-robot coalitions, whether humans and robots can work cooperatively depends on their co-adaptation [40, 41]. Humans need the professional capability to manipulate robots and interpret robot signals, and robots also need to understand the instruction information of humans. According to mission requirements and robot autonomy, humans and robots can be in a parallel cooperative relationship or superior-subordinate relationship where robots are controlled by humans to different degrees.

3.2 Hierarchical structure

The hierarchical structure refers to the organizational structure of objects in CF. Analyzing the structure aims to clarify the concept of each level and the correlation between levels, contributing to the systematic problem sorting according to the relationships within and between adjacent structure levels. The structure levels from bottom to top include “component”, “unit”, “coalition” and “global”. The concise general view of the hierarchical structure is depicted in Figure 3.

Component level. “Component” level contains the functional components that are fixedly subordinate to objects. Components such as sensors and power supply subsystems enable objects to maintain their

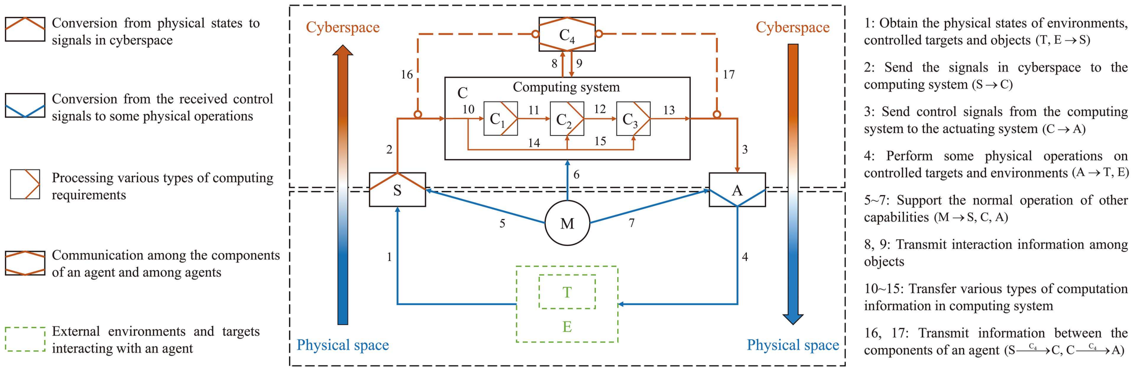

Figure 4 (Color online) The panorama of object capabilities from the perspective of a control system. S: sensing, A: actuating, M: maintaining, C: computing, C_1: cognizing, C_2: commanding, C_3: controlling, C_4: communicating, T: target, E: environment.

own functions and perform missions. For CF, the component level is a non-degradable atomic level.

Unit level. "Unit" level contains independent units that can be selected to form coalitions, i.e., the objects of CF (agents and agent-extending objects). Agent-extending objects and agents need to be matched to satisfy the capability requirements during forming coalitions. In terms of composition relationships, the unit can be viewed as a union set of non-degradable components. That is, $a = \cup_{v=1}^{v^{\mathrm{n}}} \mathscr{F}_v$, where a, $\mathscr{F}_v$ and v^{n} represent one object, one non-degradable component of the object and the number of the components, respectively.

Coalition level. "Coalition" level contains the sets (teams or groups) of units that are formed to satisfy mission requirements. Coalition formation in essence is to form one or multiple such sets. For dynamic situations, existing coalitions sometimes need to be adjusted according to changing mission requirements, and some units (coalition members) need to be dynamically added or removed to re-form new coalitions. The candidate range of these members may change and depend on time and space constraints in current environments and missions such as transfer distance and task priority, which may cover the original members, other coalition members, or idle units. The requirements on coalitions mainly include various capability requirements, such as sensing and actuating. The coalition capabilities required by various missions are distributed among different members. During mission execution, coalition members will work cooperatively [42].

Global level. From the perspective of mission complexity, there may be multiple missions, for which different coalitions are suitable. Complex temporal and spatial dependencies may exist between missions. From the perspective of overall missions, all missions are completed by multiple coalitions. This level is called "global" level. According to the overall requirements, multiple coalitions may need to be balanced and adjusted. The formation of coalitions may be parallel or sequential. Multiple coalitions may perform missions independently or cooperatively. Different relationships among coalitions will bring different constraints. For example, if coalitions work cooperatively, it may bring the total capability requirements, time and space constraints, and others on these coalitions. Besides, coalitions may be overlapping or non-overlapping with each other, depending on whether common members exist between coalitions.

3.3 Capabilities of objects

The capabilities of objects involve five common families as follows [43–45]. The conceptual diagram of object capabilities from a control system perspective is shown in Figure 4. Completing missions requires certain types of capabilities. These capabilities are usually scattered among different objects, so it is necessary to form coalitions to complete missions. The capabilities of objects can be represented as a class marked as B^{O}, $B^{\mathrm{O}} = \langle S, A, C, M, C_4 \rangle$.

Sensing (S). Sensing refers to the capability to obtain the physical states of environments (E), controlled targets (T), and themselves through various physical signal sensors such as gyroscopes. This capability can convert physical states into signals in cyberspace and send the signals to the computing system for further processing.

Actuating (A). Contrary to sensing, actuating realizes the transformation from signals in cyberspace to physical states. Actuating can convert received control signals from the computing system into some physical operations. These operations can act on controlled targets and environments, change their states, and achieve some desired purposes, e.g., mechanical arms grasping a workpiece. Agents can manipulate different agent-extending objects, which can also be regarded as an actuating capability.

Computing (C). Computing refers to the processing capability of data and information from sensors. Computing dominates the running of objects to deal with various computing requirements from cognizing (C_1), planning and decision-making (commanding, C_2), and controlling (C_3). Cognizing is the capability to process the acquired input and extracted information such as what and how controlled targets are. Decision-making, the kernel of computing, refers to determining what agents should do according to expected purposes, which is an important basis for judging whether a robot can be called an agent. Controlling is to solve how objects perform operations. The computing of objects can also be extended, such as processing huge data through cloud computing.

Maintaining (M). Maintaining refers to supporting the normal operation of other capabilities and ensuring the sustainability of one system by providing energy or material resources. The functions of maintaining include two aspects: internal maintaining and external maintaining, which mean keeping running and supporting the execution of tasks for the object itself or other objects, respectively.

Communicating (C_4). Communicating guarantees information interaction such as information sharing in multi-agent collaboration, and command and feedback transmission between superiors and subordinates. Communicating affects the rate and quality of information exchange among coalition members, which will have an impact on the efficiency of coalitions performing missions.

Remark 5. As a typical special case, moving is a kind of actuating capability. Different moving capabilities are suitable for missions in different environments.

Remark 6. If the components of an agent are not in the same location, the information transmission between these components also relies on communicating. In this case, the agent can be regarded as a networked system with scattered components but centralized control.

Remark 7. The above capabilities are usually spread among different objects. The carriers of these capabilities can be either the components of agents or agent-extending objects. In other words, these capabilities originate from the "component" level and will be aggregated from the bottom level to the top level.

Remark 8. As shown in Figure 4, when one object runs dynamically, logical relationships exist between the above capabilities. The operation relationship between sensing, computing, actuating, and the controlled targets (plus environments) can be regarded as a cycle "-S-C-A-T(E)-". Maintaining guarantees the normal operation of this cycle, and communicating keeps the interaction among objects.

3.4 Representation and metrics of capabilities

This part introduces the representation and metric set of object capabilities in the form of mathematical symbols.

The capabilities of objects can be sorted by imitating the concept of species, genera, and families in biological taxonomy. Several examples are given in Figure 5. This class includes the aforementioned capability families (sensing, actuating, computing, maintaining, and communicating), and each capability family includes specific capability genera, such as positioning and temperature measuring in the sensing family. Each capability genus in the aspect of cyber-physical systems possesses many different implementation means, that is, functional components (species), such as lasers and ultrasonic waves, to measure moving distance.

Generally, the capabilities can be evaluated by a tuple $\langle P_{\mathrm{SP}}, P_{\mathrm{AC}}, P_{\mathrm{ST}}, P_{\mathrm{CO}}, P_{\mathrm{DU}}\rangle$, where P_{SP}, P_{AC}, P_{ST}, P_{CO} and P_{DU} represent speed, accuracy, stability, coverage and duration, respectively. This can also be regarded as the performance of object capabilities. In this paper, it is uniformly assumed that the higher the capability value, the better the performance.

The focus of these evaluation items in different kinds of capability families is the same. However, the specific connotation is different. The speed can be the rate of energy supply, decision-making calculation, communication transmission, etc. The accuracy can be the measurement accuracy of sensors, the control accuracy of actuators, etc. The stability can be the disturbance-rejection capability of control systems, the reliability of information transmission, etc. The coverage can be the surveillance area of sensors, the range of information transmission, etc. The duration mainly refers to the sustainable time of one capability or the amount of remaining resources. These evaluation items can be measured by real values. In summary, the capability values represent the parameters of various functional components of objects.

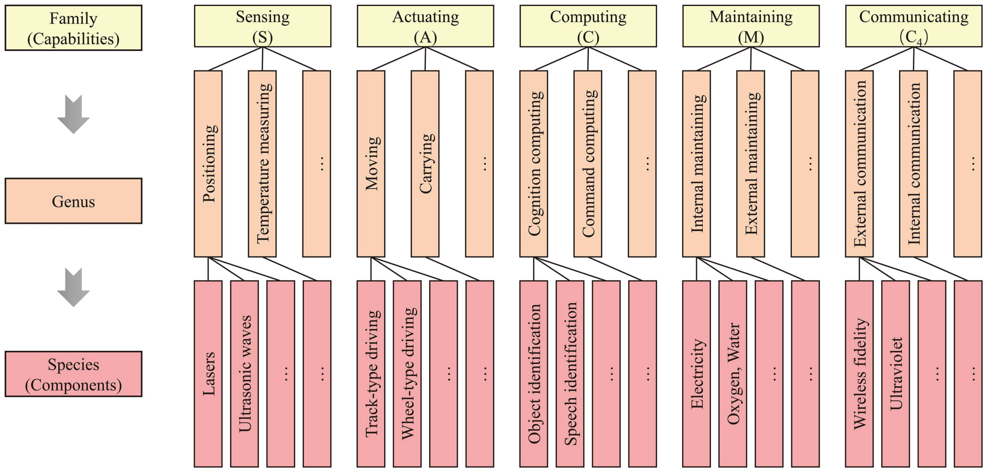

Figure 5 (Color online) Classifications of object capabilities.

The capability values can be formulated as $\boldsymbol{P} = [P_{\rm SP}, P_{\rm AC}, P_{\rm ST}, P_{\rm CO}, P_{\rm DU}] = \boldsymbol{L}(\mathscr{F}|\mathscr{E}_{\rm S})$, where $\mathscr{F}$ and $\mathscr{E}_{\rm S}$ represent one non-degradable functional component and its standard testing conditions, respectively. The function $\boldsymbol{L}(\cdot)$ represents the calculation method of capability values.

The capability metric set of one object should cover the evaluation items of all types of components. It can be represented by $\mathbb{P}^{\rm cm} = \{P_S^{\mathscr{F}}, P_A^{\mathscr{F}}, P_C^{\mathscr{F}}, P_M^{\mathscr{F}}, P_{C_4}^{\mathscr{F}} | \mathscr{F} \in a,\ \forall a \in S\}$, where $a \in S$ and $\mathscr{F} \in a$ represents one object in S and one component of the object, respectively. $P_{\triangle}^{\mathscr{F}} = \langle P_{\rm SP}, P_{\rm AC}, P_{\rm ST}, P_{\rm CO}, P_{\rm DU}\rangle$, $\triangle \in \{S, A, C, M, C_4\}$ represents the evaluation items of the component $\mathscr{F}$ regarding the capability family $\triangle$. The same evaluation items for the same type of component need to be included only once in $\mathbb{P}^{\rm cm}$.

3.5 Manner of aggregating object capabilities

The capabilities of each coalition are obtained by aggregating the capabilities of coalition members. The mathematical expression of capability aggregation is an important basis for coalition formation, laying the foundation for establishing CF models.

In this subsection, some aggregation manners (operators) are described to abstract and calculate the total capability of coalitions. Each object has various capabilities which can be represented in different forms. From the perspective of mathematical operations, the aggregation manner includes the algebra-based aggregation [46, 47], the set-based aggregation [18], and the logic-based aggregation [48]. The aggregation operators can act on any level within the hierarchical structure, aggregating capabilities from the bottom level to the current level.

Algebra-based aggregation. Some capabilities are measured by numerical values, such as the maximum acceleration and the maximum communication distance. For these capabilities, algebra-based aggregation operators are employed to aggregate these capabilities when forming coalitions, that is, the numerical operations of capabilities. The algebra-based aggregation operator is denoted as $G^{\rm A}(\cdot)$, including various specific operations such as addition, multiplication, minimization, and maximization, etc.

Set-based aggregation. Some capabilities are represented by sets, e.g., cover area. Aggregating these capabilities employs the set-based operators, including set intersection and set union. The set-based aggregation operator is denoted as $G^{\rm S}(\cdot)$.

Logic-based aggregation. Sometimes, the concern on capabilities may be described in the form of their presence or absence. In this case, when forming a coalition, we are concerned about whether all members of one coalition have certain capabilities or whether at least one member has certain capabilities. The logic-based aggregation operator is denoted as $G^{\rm L}(\cdot)$, including logic "AND", "OR" and their combinations.

Remark 9. Algebra-based and set-based operators are usually employed to aggregate the same capability. However, the logic-based operator is also employed to combine different capabilities. As shown in Figure 4, "-S-C-A-" is generally required in the cycle.

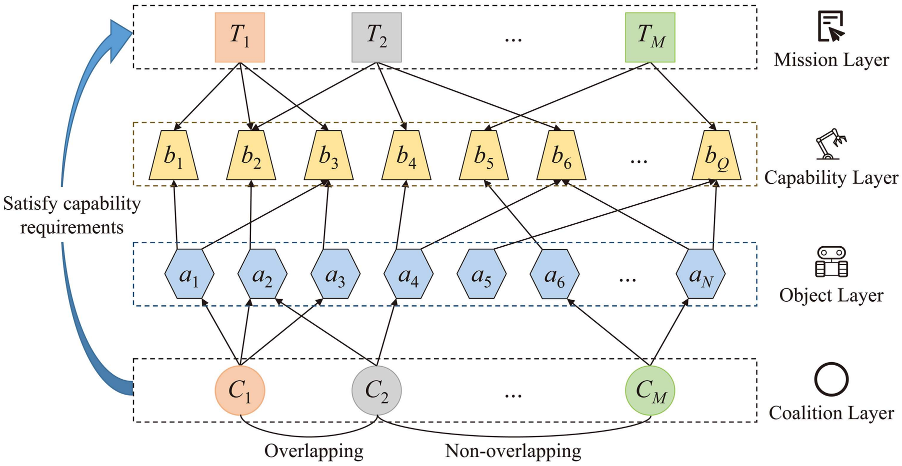

Figure 6 (Color online) The capability requirements of missions about coalition formation.

4 Mission analysis around capability requirements

Each object has limited capabilities and a single object cannot satisfy the capability requirements of complex missions. Therefore, coalitions made up of objects will be formed to aggregate the capabilities of each coalition member in order to complete missions. The capability requirements of missions in forming coalitions mainly reflect in various capabilities of objects described in Subsection 3.3.

4.1 Mission requirements on objects at "coalition" and "global" levels

The capability requirements of one mission refer to the requirements of the total capabilities of the whole coalition. The total capabilities of each coalition are computed by aggregating the capabilities of coalition members, which show influences on the "coalition" level. For different capabilities, various manners of aggregating capabilities are employed according to the capability characteristics, such as algebra-based aggregation, set-based aggregation, and logic-based aggregation. The capability requirement of missions is to have a lower limit on these aggregated capabilities of coalitions.

When forming multiple coalitions, it may be necessary to require the total capabilities of all coalitions, which shows effects on the "global" level. The requirements of multiple missions need to be integrated into the total mission requirements. The integration methods are related to the capability values and can be implemented in a manner similar to the aggregation operations summarized in Subsection 3.5. For example, for a consumable (reusable) capability, the total mission requirements may be the sum (maximum) of the requirements of these missions [49].

4.2 Formulation of capability requirements

For one coalition (the amalgamations of coalitions), the capability requirements can be formulated as $\boldsymbol{R}^{\mathrm{mi}} = \boldsymbol{H}(T|\mathscr{E}, \mathscr{T}, \mathscr{S})$, where T, $\mathscr{E}$, $\mathscr{T}$ and $\mathscr{S}$ represent one mission (multiple related missions), environmental factors (e.g., geography, weather, light field, flow field, electromagnetic field and confrontation), time and space, respectively. $\boldsymbol{R}^{\mathrm{mi}}$ represents the total capability requirements of T regarding the metric set $\mathbb{P}^{\mathrm{cm}}$ as introduced in Subsection 3.4. The function $\boldsymbol{H}(\cdot)$ represents the calculation method of capability requirements.

As shown in Figure 6, it is assumed that all capabilities in the capability layer will be aggregated by the algebra-based aggregation operator. The coalition C_1 consisting of objects a_1, a_2 and a_3, satisfies the capability requirement of the mission T_1 on the capabilities b_1, b_2 and b_3. The capability b_3 is jointly supported by the objects a_1 and a_3 in an algebraic addition manner.

5 Environment analysis around effects on capabilities

According to the characteristics of constituent elements, environmental factors include geography, weather, light field, flow field, electromagnetic field, and confrontation (game). Environments usually restrict ob-

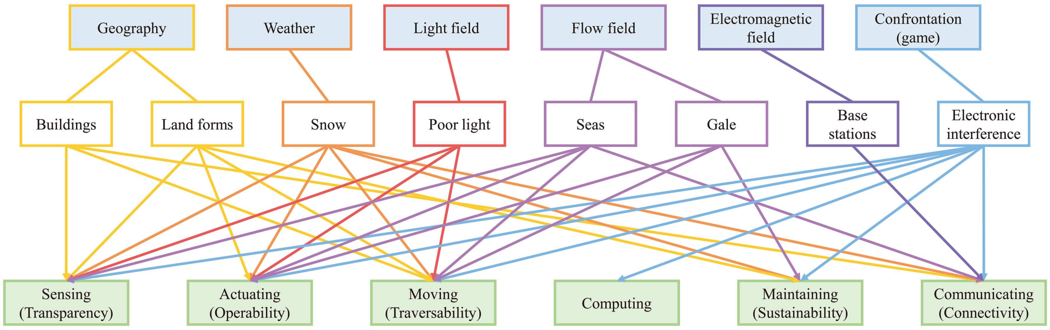

Figure 7 (Color online) Examples of various environmental factors affecting different capabilities.

ject capabilities. Figure 7 shows the capabilities of objects are affected by different environmental factors. One factor of the environment may affect more than one capability, and one capability may be affected by multiple environmental factors.

5.1 Effects of environmental factors on object capabilities

The effects on objects are mainly reflected by traversability, transparency, connectivity, operability, and sustainability.

Transparency. The sensing capabilities of objects can be affected by geographical conditions (e.g., buildings), light fields (e.g., poor light), etc.

Operability. The actuating capabilities of objects can be affected by geographical conditions (e.g., landforms), weather (e.g., snow), etc.

Traversability. The moving capabilities of objects can be affected by geographical conditions (e.g., buildings), flow fields (e.g., seas), etc.

Sustainability. The maintaining capabilities of objects can be affected by geographical conditions (e.g., landforms), weather (e.g., snow), etc.

Connectivity. The communicating capabilities of objects can be affected by electromagnetic fields (e.g., base stations), confrontation (e.g., electronic interference), etc.

5.2 Formulation of environmental effects on object capabilities

The above environmental effects ultimately manifest in the capability values of objects. For example, environmental effects on traversability mean the changes in the maximum speed at which objects can move.

The environmental effects can be formulated as $[\omega^{\mathrm{en}}_{\mathrm{SP}}, \omega^{\mathrm{en}}_{\mathrm{AC}}, \omega^{\mathrm{en}}_{\mathrm{ST}}, \omega^{\mathrm{en}}_{\mathrm{CO}}, \omega^{\mathrm{en}}_{\mathrm{DU}}] = \boldsymbol{E}(\boldsymbol{P}|\mathscr{E}, \mathscr{T}, \mathscr{S})$, where $\omega^{\mathrm{en}}_{\mathrm{SP}}, \omega^{\mathrm{en}}_{\mathrm{AC}}$, $\omega^{\mathrm{en}}_{\mathrm{ST}}, \omega^{\mathrm{en}}_{\mathrm{CO}}$ and $\omega^{\mathrm{en}}_{\mathrm{DU}}$ represent the coefficients of capability change for the capability values within $\boldsymbol{P}$ in terms of speed, accuracy, stability, coverage and duration, respectively. The function $\boldsymbol{E}(\cdot)$ represents the calculation method of the coefficients for different environments $\mathscr{E}$, time $\mathscr{T}$ and space $\mathscr{S}$. These coefficients usually range from 0 (capability disabled) to 1 (no effect), and sometimes are even larger than 1 (capability enhanced).

$P^{\mathrm{en}}_{\mathrm{SP}}, P^{\mathrm{en}}_{\mathrm{AC}}, P^{\mathrm{en}}_{\mathrm{ST}}$, $P^{\mathrm{en}}_{\mathrm{CO}}$ and $P^{\mathrm{en}}_{\mathrm{DU}}$, updated by $P^{\mathrm{en}}_{\#} = \omega^{\mathrm{en}}_{\#} \times P_{\#}$ ($\# \in \{\mathrm{SP}, \mathrm{AC}, \mathrm{ST}, \mathrm{CO}, \mathrm{DU}\}$), represent the speed, accuracy, stability, coverage and duration after being affected by environmental factors regarding one capability, respectively. Obviously, the object capabilities are jointly constrained by environmental factors and the cyber/physical properties of functional components. For example, the GPS-based navigation of vehicles works well outdoors but fails indoors due to signal blocking.

As analyzed in Section 3, the environment-effected capabilities should also be aggregated from the bottom level (the "component" level) to the top level (the "global" level). For a set of objects, their total capabilities can be calculated by aggregating those of all objects regarding each specific capability.

5.3 Effects of environmental factors on missions

The environment not only influences the capabilities of objects but also has an effect on the capability requirements of missions. In essence, the capability requirements are shaped by the specific environmental conditions in a particular time and space, as depicted by the formula $\boldsymbol{R}^{\mathrm{mi}} = \boldsymbol{H}(T|\mathscr{E}, \mathscr{T}, \mathscr{S})$ in Section 4.

The characteristics of environments, including dynamics and uncertainty, will cause changes in mission requirements. Due to the effects of environments on the capabilities of objects and mission requirements, sudden changes in the environment may alter the total capabilities of coalitions and potentially lead to mission failure for coalitions.

6 General mathematical model of capability-centric CF

Various objects with complementary capabilities can form coalitions to satisfy mission requirements. Based on the above analysis, the key elements of CF problems are summarized as follows.

Decision variables (S). When $m = 1$, the model represents the single-coalition formation problem; otherwise, when $m > 1$, the model represents the multiple-coalition formation problem. For the non-overlapping CF problem, $S_{k_1} \cap S_{k_2} = \emptyset$ ($\forall k_1 \neq k_2$, $k_1, k_2 = 1, 2, ..., m$). For the overlapping CF problem, $S_{k_1} \cap S_{k_2} \neq \emptyset \wedge S_{k_1} \neq S_{k_2}$ ($\exists k_1 \neq k_2$, $k_1, k_2 = 1, 2, ..., m$). When $S_{k_1} = S_{k_2}$ ($\exists k_1 \neq k_2$, $k_1, k_2 = 1, 2, ..., m$), there exists a coalition that executes more than one mission.

Constraints. The CF problem includes two classes of constraints, i.e., mission-related and mission-unrelated constraints.

- *Mission-related constraints* (Eq. (5)). Mission-related constraints originate from missions or the relationships among missions, e.g., the capability requirements on coalitions (the "coalition" level) and the amalgamations of coalitions (the "global" level). This implies the influence of environmental factors, information lack, variability, and uncertainty in object capabilities and mission requirements, etc [50]. The dynamics and uncertainty associated with environmental factors present challenges when solving CF problems. $X_l(S)$ denotes coalitions or the amalgamations of coalitions. When $X_l(S)$ represents any coalition ($X_l(S) \in S$), the constraint represents the capability requirements of the corresponding mission on the coalition; When $X_l(S)$ represents the universal set of all coalition members ($X_l(S) = \cup_{k=1}^{m} S_k$), the constraint represents the total capability requirements on all coalitions; When $X_l(S) \subset \cup_{k=1}^{m} S_k$, the constraint represents the total capability requirements on several coalitions which can cooperate in performing missions.
- *Mission-unrelated constraints* (Eq. (6)). Mission-unrelated constraints originate from objects, environments, and so on, rather than missions. The constraints include non-overlapping (overlapping) requirements between any two coalitions, the threshold of resource contribution of objects (the sum of DOI in each coalition is limited), etc. In terms of resource utilization, all objects may be used to form coalitions ($\cup_{k=1}^{m} S_k = S$); otherwise, the union of all coalitions is a proper subset of S ($\cup_{k=1}^{m} S_k \subset S$).

Optimization objectives (Eq. (4)). CF is usually a multi-objective optimization problem ($p \geqslant 2$). For CF, the optimization objectives are commonly cost minimization and expected performance maximization as shown in Table 2 [19, 24, 31, 33, 51–60]. Coalition costs include resource-usage costs, communication costs, etc. Expected performance includes the number of missions satisfied, expected utility, etc.

The general mathematical model of capability-centric CF can be formulated as follows. Firstly, the representation of coalitions and the amalgamations of coalitions is given in a uniform form $X_l(S) = \{x | x \in \psi, \forall \psi \in \vartheta_l(S)\}$. $\vartheta_l(S) \in \Theta(S) = 2^S/\emptyset$[1], $l \in \{1, 2, ..., 2^m - 1\}$ represents one set of coalitions (e.g., $\vartheta_l(S) = \{S_1, S_2\}$). $X_l(S)$ represents the set of all objects that exist in each coalition of the set $\vartheta_l(S)$ (e.g., $X_l(S) = \{x | x \in S_1 \vee x \in S_2\}$).

$$
\begin{aligned}
&\min \boldsymbol{F}(S) = (f_1(S), f_2(S), ..., f_p(S)), &(4)\\
&\text{s.t. } \boldsymbol{G}^{\text{agg}}(X_l(S)) \geqslant \boldsymbol{R}_l^{\text{mi}}, \ \forall l \in \{1, 2, ..., 2^m - 1\}, &(5)\\
&\quad\ \ \boldsymbol{G}^{\text{un}}(S) \geqslant 0, &(6)\\
&\quad\ \ S_k \in 2^{\Omega}, \ \forall k \in \{1, 2, \ldots, m\}, &(7)
\end{aligned}
$$

where $\boldsymbol{G}^{\text{agg}}(\cdot) = (G_1^{\text{agg}}(\cdot), G_2^{\text{agg}}(\cdot), ..., G_{q_{\text{re}}}^{\text{agg}}(\cdot))$ represents the vector of aggregation operators to aggregate capabilities. $G_j^{\text{agg}}(\cdot) \in \{G^{\text{A}}(\cdot), G^{\text{S}}(\cdot), G^{\text{L}}(\cdot), ...\}$, $j \in \{1, 2, ..., q_{\text{re}}\}$ is used to aggregate the jth capability of $X_l(S)$ regarding the metric set $\mathbb{P}^{\text{cm}}$, where q_{re} denotes the number of capability metrics. $\boldsymbol{R}_l^{\text{mi}}$ represents the vector of the capability requirements of missions on $X_l(S)$. $\boldsymbol{G}^{\text{un}}(\cdot)$ denotes the vector of mission-unrelated constraints on coalitions.

1) $\Theta(S)$ represents the power set of S with the empty set removed.

Table 2 Typical optimization objectives in CF

Optimization objectives		Descriptions	References
Cost minimization	Resource-usage cost minimization	$\sum_{k=1}^{m}\sum_{a_i\in S_k} u_{ik}$ represents the usage cost of object resources, where u_{ik} ($u_{ik}\geqslant 0$) is the cost of a_i using capabilities to perform T_k.	[19, 51, 52]
	Distance (time) cost minimization	$\sum_{k=1}^{m}\sum_{a_i\in S_k} d_{ik}$ represents the total distance traveled by all coalition members to mission locations, where d_{ik} ($d_{ik}\geqslant 0$) is the distance between a_i and T_k.	[31, 51, 53]
	Communication cost minimization	$\sum_{k=1}^{m}\sum_{a_i\in S_k}\sum_{a_{i'}\in S_k, i'\neq i} c_{ii'}$ represents the total communication cost between coalition members, where $c_{ii'}$ ($c_{ii'}\geqslant 0$) denotes the communication cost between a_i and $a_{i'}$.	[33, 54]
Expected performance maximization	System efficiency maximization	$\sum_{k=1}^{m} e_k$ represents the total efficiency of all coalitions, where e_k ($e_k\geqslant 0$) represents the efficiency of the coalition S_k depending on the coalition composition.	[31, 55]
	Number of missions satisfied maximization	$\sum_{k=1}^{m}\tau_k$ represents the number of all satisfied missions, where τ_k ($\tau_k\in\{0,1\}$) indicates whether S_k can satisfy the requirements of T_k. If satisfied, $\tau_k=1$; otherwise $\tau_k=0$.	[24, 31, 56]
	Expected utility maximization	$\sum_{k=1}^{m}\mu_k$ denotes the total expected utility of all coalitions, where μ_k represents the expected guerdon paid for S_k. If S_k can satisfy the requirements of T_k, $\mu_k>0$; otherwise $\mu_k=0$.	[33, 57]
	Total arrival time minimization	$\sum_{k=1}^{m} S_k^{\mathrm{at}}$ and $\max\{S_1^{\mathrm{at}}, S_2^{\mathrm{at}},\ldots,S_m^{\mathrm{at}}\}$ denote two different arrival time of coalition members for coalitions working in serial and parallel manners, respectively.	[58]
	Coalition size minimization	$\lvert\cup_{k=1}^{m} S_k\rvert$ represents the number of all objects within coalitions, where the function $\lvert\cdot\rvert$ represents the size of any input set.	[59, 60]

Table 3 Typical examples of CF problems

Cooperative transportation	Objects	Missions	Environments
	Robots with various skills, such as griping, vision, grabbing, etc.	The cooperative transportation task requires multi-dimensional skills; cooperation can be achieved when some robots transport the item and others are involved in coordination and navigation along the desired trajectory and/or clearing obstacles along the path.	A dynamic environment.
	Decision variables	Constraints	Objectives
	$x^i=1$ represents that the robot a_i is a member of the coalition S; $x^i=0$, otherwise.	$\vee_{i=1}^{n} x^i b_j^i \geqslant d_j$, $j\in\{1,2,\ldots,q_{re}\}$ represents that the coalition possesses each skill required by the task, where b_j^i, $d_j\in\{0,1\}$ and $\vee$ represents the logical OR operation.	$\min\sum_{i=1}^{n}\left(\varphi^i x^i+\mu^i x^i\right)$ is to minimize the sum of the cost and travel distance of coalition members for the task, where φ^i and μ^i represents the cost and travel distance of the robot a_i for the task T, respectively.
Emergency resource allocation for concurrent incidents	Objects	Missions	Environments
	Rescue agencies with multiple emergency resources.	When a natural disaster occurs, rescue agencies should form coalitions to response quickly and efficiently to incidents; each rescue agency can be involved in executing more than one rescue task and allocating its emergency resources to several different incidents at the same time.	Natural disasters, such as floods, volcanic eruptions, earthquakes, and tsunamis.
	Decision variables	Constraints	Objectives
	w_j^{ik} $\left(w_j^{ik}\geqslant 0\right)$ represents the amount of the jth emergency resources contributed by the rescue agency a_i for the coalition S_k.	(1) $\sum_{i=1}^{n} w_j^{ik}=d_j^k$, $j\in\{1,2,\ldots,q_{re}\}$, $k\in\{1,2,\ldots,m\}$ represents that the total emergency resources of each coalition satisfy the corresponding incident's request, where d_j^k $\left(d_j^k\geqslant 0\right)$ is the amount of the jth emergency resource required by the incident T_k; (2) $\sum_{k=1}^{m} w_j^{ik}\leqslant b_j^i$ ensures that there is no emergency resource conflict, where b_j^i $\left(b_j^i\geqslant 0\right)$ is the amount of the jth emergency resource owned by the rescue agency a_i.	$\min\lambda_1\sum_{i=1}^{n}\sum_{k=1}^{m}\left(\gamma^{ik}\sum_{j=1}^{q_{re}} w_j^{ik}\right)$ $+\lambda_2\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{j=1}^{q_{re}}\left(\phi_j^i w_j^{ik}\right)$ is to minimize the weighted sum of the total travel time and the total cost of the allocated emergency resources, where γ^{ik}, ϕ_j^i, λ_1 and λ_2 represent the minimal arrival time for a_i to deliver unit emergency resource to T_k, the unit cost of the jth emergency resource of a_i and two weights with a range of $[0,1]$, respectively; and $\lambda_1+\lambda_2=1$.

Two typical examples are provided in Table 3 to achieve a deeper mathematical understanding of coalition formation. Each example is accompanied by a summary of the object, mission, and environment, along with the corresponding elements of the mathematical model. Through these two examples, specific considerations and distinctions of different types of CF problems can be discerned.

Cooperative transportation in a dynamic environment can be viewed as a single-coalition formation problem where tasks are tackled one by one. The transportation task requires diverse skills like pushing, lifting, vision, and grabbing, and so a heterogeneous rather than a homogeneous coalition of robots is required [48]. For the same item transported, the coalition size is determined by the state of the environment. Emergency resource allocation for concurrent incidents in natural disasters can be considered as an overlapping coalition formation problem [51]. In this case, it's crucial to take into consideration not only the assignment of each object to specific coalitions but also the level of its capability contribution within each coalition (i.e., the degree of involvement). The different rescue missions in natural disaster environments require various emergency resources, demanding swift responses from rescue agencies.

7 Conclusion

This paper conducts a thorough analysis of objects, missions, environments, and their interrelation in CF, with a focus on capabilities as the central theme. The whole analysis is carried out by means of diagram illustration, which helps to visualize the relationships and connections between these elements. Moreover, a general mathematical model is developed by combining the capability-centric analysis. It is hoped that this paper will provide a fresh perspective for understanding CF and serve as a valuable study reference for researchers interested in this topic.

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