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Foresighted real-time hierarchical resource scheduling in dynamic multi-domain satellite networks

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Recently, satellite networks have emerged as a competitive solution for enabling widespread service deployment by overcoming geographical constraints. As the range of supported services continues to grow, multi-domain satellite networks (MDSNs) that integrate diverse services have emerged as a transformative paradigm [1]. In an MDSN, each domain refers to a group of satellites dedicated to a specific service [2]. However, the independent, heterogeneous nature of these domains, along with dynamic mission arrivals and fluctuating resource availability, poses challenges for resource allocation and scheduling [3]. Consequently, there is a pressing need for an efficient collaborative resource management framework for MDSNs to ensure long-term mission success while enabling rapid decision-making. Related work is summarized in Appendix A.

In this study, we propose a foresighted real-time hierarchical resource scheduling (FRHRS) framework, which integrates efficient decision-making with adaptive coordination to enhance mission completion. At the upper layer (UL), we develop an intelligent real-time decision-making mechanism that dynamically adjusts the resource allocation mode (whether cross-domain or intra-domain) to optimize long-term scheduling. Guided by these UL decisions, the lower layer (LL) employs a lightweight mission realization path-planning algorithm based on resource cost to enable rapid resource assignment for mission execution. The outcomes of mission execution are then fed back to the UL for iterative refinement, forming a hierarchical feedback loop that enhances multi-domain coordination and efficiency. Extensive evaluations demonstrate that the proposed framework outperforms existing benchmark methods in both mission completion rate and runtime efficiency.

System model. We consider an MDSN which can be denoted as $\mathcal{D} = \{d_1, d_2, \dots, d_K\}$ consisting of K domains, each of which contains a set of intra-domain satellites $N_S^{d_k}$. $\mathcal{N}_S = \{N_S^{d_1}, N_S^{d_2}, \dots, N_S^{d_K}\}$ denotes the set of all satellites in the MDSN. There is a group of ground stations (GSs) represented by $\mathcal{N}_G$, which receive data from each domain. The set of the arrived missions of domain d_k in time slot t is represented as $\mathcal{M}_t^{d_k}$, and all the missions in slot t constitute the set $\mathcal{M}_t$. The scheduling period $\mathcal{T}$ is divided into T time slots as $\mathcal{T} = \{1, 2, 3, \dots, T\}$. The satellites in each domain continuously store, compute, and offload the computed missions to the GSs.

The primary objective of network resource scheduling is to maximize the number of completed missions in the MDSN through satellite collaborative scheduling. To support the formulation of the scheduling strategy, the system model is structured into three components: the mission model, channel model, and energy consumption model. Specifically, the mission model formalizes representation of missions, the channel model captures transmission capability of communication links, and the energy model quantifies power usage.

We construct the problem $\mathcal{P}$ to maximize the number of scheduled missions in MDSN, under the relevant constraints.

$$\mathcal{P}: \max \sum_{t \in \Gamma} \begin{cases} \mathcal{P}_t^{NCD}: \sum\limits_{d_k \in \mathcal{D}} \sum\limits_{m \in \mathcal{M}_t^{d_k}} \sum\limits_{\tau \in T_w^t} \sum\limits_{i \in \mathcal{N}_S^{d_k}} \sum\limits_{j \in \mathcal{N}_G} w_{i^\tau j^\tau}^m, \\ \mathcal{P}_t^{CD}: \sum\limits_{m \in \mathcal{M}_t} \sum\limits_{\tau \in T_w^t} \sum\limits_{i \in \mathcal{N}_S} \sum\limits_{j \in \mathcal{N}_G} w_{i^\tau j^\tau}^m, \end{cases}$$
$$\begin{aligned} \text{s.t.}\ & \text{Flow conservation constraints,} \\ & \text{Storage \& link capacity constraints,} \\ & \text{Energy \& computing constraints.} \end{aligned}$$

The problem $\mathcal{P}$ includes both cross-domain scheduling $\mathcal{P}_t^{CD}$ and non-cross-domain scheduling $\mathcal{P}_t^{NCD}$. The scheduling process is organized into a sequence of successive rolling time windows, each with a length of T_w. Additionally, the binary variable $w_{i^\tau j^\tau}^m$ represents the selection of the inter-satellite link for mission transmission. The details of the system model and problem formulation can be found in Appendix B.

Algorithm design. The FRHRS framework consists of an upper layer and a lower layer, as shown in Figure 1(a). Missions are scheduled by the intra-domain until the upper layer decides to schedule across domains. In practice, determining whether to implement cross-domain scheduling to optimize mission completion throughout $\mathcal{T}$ is a sequential decision problem that boils down to a Markov decision process (MDP). The MDP tuples can be described as follows.

State. In the t-th time slot, the state of MDSN can be defined as $S^t \triangleq \{S_{\mathcal{B}}^t, S_{\mathcal{C}}^t, S_{\mathcal{D}}^t, S_{\mathcal{E}}^t, S_{\mathcal{F}}^t\}$, which consists of storage state information $S_{\mathcal{B}}^t$, communication state information $S_{\mathcal{C}}^t$, energy state

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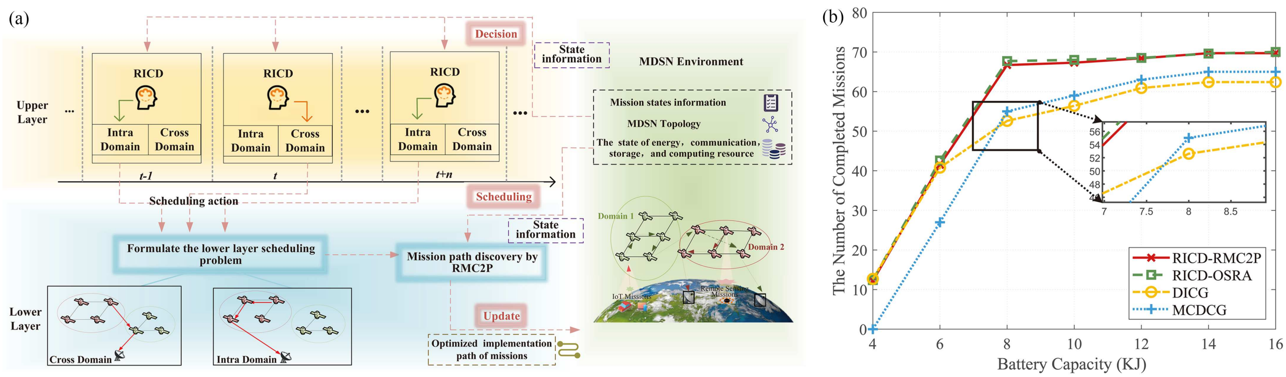

Figure 1 Proposed FRHRS framework and corresponding mission-completion performance. (a) Overall framework of the proposed FRHRS; (b) the number of completed missions versus the number of battery capacity.

information $S_{\mathcal{D}}^t$, and mission state information $S_{\mathcal{E}}^t$, $S_{\mathcal{F}}^t$ of all satellites in MDSN.

Action. The action in t-th time slot is represented as $a_t \in \mathcal{A}$, where the binary action space $\mathcal{A} \in \{0, 1\}$ corresponds to the approaches of two types of subproblems, i.e., intra-domain scheduling and cross-domain scheduling.

Reward. The reward is obtained by solving the subproblems generated by the actions in the upper layer. Specifically, if $a_t = 0$, the reward is achieved by intra-domain scheduling and can be denoted as $r_t = \sum_{d_k \in \mathcal{D}} r_t^{d_k}$, where $r_t^{d_k}$ denotes the scaled count of completed missions in domain d_k.

We propose a real-time intelligent cross-domain decision-making (RICD) algorithm to solve the problem of dynamic real-time cross-domain resource scheduling (RT-CDRS). The mapping from the MDSN state to action in the t-th time slot can be denoted as $\theta_t : s_t \to a_t$. The continuous mapping over $\mathcal{T}$ is referred to as a policy, which can be represented as $\xi = \{\theta_1, \theta_2, \ldots, \theta_T\}$. The cumulative expected reward of MDSN within T time slots under the state s_t and a policy ξ can be expressed as $\mathcal{R}(s_t, \xi) = \mathbb{E}\left[\sum_{m=0}^{T-t} \gamma^m \cdot r(s_{t+m}, \theta_{t+m}^{\xi}(s_{t+m}))\right]$, where $\mathbb{E}[\cdot]$ denotes expectation function, γ represents discount factor. The goal is to find the optimal policy ξ^* to maximize the number of completed missions in MDSN, i.e., $\xi^* = \arg\max_{\xi \in \Xi, \mathbf{s}, \mathbf{a}, \mathbf{r}} \mathcal{R}(s_0, \xi)$, where Ξ is the set of all feasible strategies. Among various DRL algorithms, we employ the dueling double deep Q-learning network (D3QN) due to its superior performance and the straightforward structure [4].

During the scheduling process at the lower layer, it is required to (1) determine the mission realization path, (2) calculate the remaining resource state, and (3) provide the upper layer with the reward for a decision taken according to the current states. We first focus on rapidly identifying a feasible realization path for a specific mission, based on the decision made at the upper layer. The realization path includes a sequence of inter-satellite transmissions and the selection of computing nodes, represented by the variables v_{it}^m and $w_{it\,jt}^m$, respectively. These problems are slow to solve due to numerous variable constraints. Therefore, we propose a rapid mission realization path planning (RMC2P) algorithm with low complexity. The details of algorithm design and complexity analysis can be found in Appendix C.

Simulation. We consider an MDSN with up to six heterogeneous domains comprising 24, 12, 12, 16, 20, and 24 satellites, respectively, deployed at altitudes between 550 and 1414 km with inclinations between 42° and 53°, and connected to seven geographically distributed GSs.

Figure 1(b) illustrates the impact of satellite battery capacity on the number of completed missions. As battery capacity increases, the performance of all methods improves and gradually approaches a plateau, indicating that energy ceases to be the primary limiting factor once sufficient capacity is available. Our proposed RICD-RMC2P algorithm closely matches the optimal satellite resource allocation (OSRA) that relies on an exact solver for path planning. Moreover, under large battery capacities, the proposed RICD-RMC2P completes 21.8% and 28.8% more missions than the myopic cross-domain column generation (MCDCG) strategy and the domain isolation column generation (DICG) strategy, respectively. The detailed simulation configurations, benchmark design, results, and analysis are provided in Appendix D.

Conclusion. In this study, we investigated the RT-CDRS problem in MDSN. We proposed the FRHRS framework, which optimizes overall mission completion throughout the entire scheduling period and the effectiveness of mission realization path planning through synergy between UL and LL. Numerical experiments validate the superiority of the proposed algorithm over the benchmark methods. The limitations of this study and future directions are discussed in detail in Appendix E.

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Supporting information Appendixes A–E. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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