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A Distributed Algorithm for UAV Cluster Task Assignment Based on Sensor Network and Mobile Information

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Abstract: Cluster formation and task processing are standard features for leveraging the performance of unmanned aerial vehicles (UAVs). As the UAV network is aided by sensors, functions such as clustering, reformation, and autonomous working are adaptively used for dense task processing. In consideration of the distributed nature of the UAV network coupled with wireless sensors, this article introduces a Rational Clustering Method (RCM) using dense task neighbor information exchange. The Rational Clustering Method (RCM) is an algorithm for dense task neighbor information exchange that can be used to cluster objects according to their shared properties. Each object's task neighbors, and the similarities between them, are calculated using this method. Starting with the task density of its neighbors, the RCM algorithm gives each object in the dataset a weight. This information exchange process identifies a UAV units' completing tasks and free slots. Using this information, high-slot UAVs within the communication range can be grouped as clusters. Unlike wireless sensor clusters, task allocation is performed on the basis of available slots and UAV longevity within the cluster; this prevents task incompletion/failures and delays in a densely populated UAV scenario. Cluster sustainability or dispersion is recommended when using distributed state learning. State learning transits between the pending task and UAV longevity; an intermediate state is defined for task reassignment amid immediate cluster deformation. This triple feature-based distributed method balances tasks between failures, overloading, and idle UAVs. The RCM was verified using task processing rate, completion ratio, reassignment, failures, and delay. Task processing rate was increased by 8.16% and completion ratio was increased by 10.3% with the proposed RCM-IE. Reassignment, failure, and delay were all reduced by 12.5%, 9.87%, and 11.99%, respectively, using this method.

Keywords: clustering; sensor network; state learning; task assignment; UAV

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1. Introduction

Unmanned aerial vehicles (UAV) are aircraft without persons on board. UAVs, also known as drones, perform certain tasks without human actions, processed via remote sensing and internet connection. A sensor network is used in UAVs to maximize the efficiency of vehicles [1] and combines multiple sensor nodes that identify particular objects from a database. Dedicated sensors are primarily used in a sensor network that provides exact details to management systems [2]. Monitoring and analysis are achieved using dedicated sensors. The particle swarm optimization (PSO) method is mainly used in sensor networks to perform optimization [3]. PSO reduces computation costs and increases efficiency, providing optimal information to perform tasks in UAVs. A wireless sensor network (WSN) is a low-cost technology used for UAVs [4]. Sensor nodes are used in WSNs to capture exact details about objects and produce data for the processing unit. WSNs are also used in UAVs to classify data based on certain types and functions. WSNs reduce delay time in computation, which enhances the efficiency and effectiveness level of UAVs [5].

UAV clustering techniques are mainly designed to improve the communication range among users and vehicles. Clustering strategies are primarily used in multi-UAV scenarios to increase the feasibility level of vehicles [6]. The reinforcement learning (RL)-based clustering technique is used for UAV task management systems. RL identifies essential tasks based on priorities and characteristics [7]. The RL clustering technique improves the decision-making accuracy level, which maximizes the UAVs' performance. Task management requires a proper plan and strategy to perform tasks; as such, the UAV clustering technique provides optimal and effective planning data that reduces the delay time in performing tasks [8]. The cluster-based planning strategy is also used for UAVs in task management systems. The cluster-based method identifies essential factors and features that are needed to be performed in task management [9]. The feature extraction technique is used in the present study to extract essential features based on specific functions. Multi-UAV clusters are used in clustering techniques that provide the necessary data related to tasks and the operation of task management [10]. Artificial intelligence (AI) is an emerging technology in various applications and systems and utilizes human-like intelligence to perform certain tasks in machines, mainly computers [11]. AI techniques reduce labor or worker ratio in many fields. The AI-based clustering technique is used for task-handling processes and is mainly used for multi-task offloading in UAVs [12]. AI tackles the problems presented in task offloading and increases the accuracy level in problem prediction, which improves the efficiency of task management systems. The UAV clustering technique is used in task handling; it controls the server and provides individual tasks to every server [13]. The UAV clustering technique uses specific algorithms to provide good communication services to management systems and detects disasters anticipated during task planning. The task-handling method requires accurate information to perform further tasks in UAVs [14]. AI-based, large-scale task offloading methods are used in task handling to maximize effectiveness levels in UAVs. The UAV clustering technique is used in the current work to identify required communication resources and produce data for task handling systems [15]. For UAV (Unmanned Aerial Vehicle) cluster task assignment using sensor network and mobile data, the Rational Clustering Method (RCM) is a crucial component of the distributed algorithm. The RCM is an effective method for rapidly evaluating the relative value of alternative clustering assignments with respect to a specific criterion of interest. This allows for a low-overhead method of delegating tasks to different UAVs. Moreover, it enables UAVs to modify their cluster assignment depending on the circumstances. This is especially helpful when the UAVs' applications require them to quickly adjust to new conditions. Through the use of the RCM, the distributed algorithm can more efficiently determine which UAVs should be assigned which tasks, resulting in better overall performance.

In this work, we introduce a decentralized algorithm for assigning tasks within UAV clusters by utilizing data gathered from sensor networks and mobile devices. To efficiently utilize a large fleet of unmanned aerial vehicles (UAVs), the algorithm takes into account data from a sensor network and each vehicle's location while in flight. There are two components to this algorithm. To begin, we use the UAVs' locations to create a graph structure, with each UAV serving as a node and edge weights determined by the physical distance between them. Second, the UAVs are given missions based on the data gleaned from the mobile devices and the sensor network. Different algorithms are used to optimize task assignment based on the type of task being performed. The unmanned aerial vehicles (UAVs) can begin their missions once the task allocation is finalized. Regarding the assignment of tasks to UAV clusters, the Rational Clustering Method (RCM) is a decentralized algorithm that takes into account data from sensor networks and mobile devices. To accomplish this, the RCM algorithm facilitates extensive communication between tasks through the use of dense task neighbor data. The RCM algorithm considers where the UAVs are, what they need to do, and how the communication network is set up. Due to its decentralized nature, the RCM algorithm facilitates rapid responses to shifting conditions by minimizing the need for human intervention in task allocation. The algorithm also guarantees a fair distribution of work between UAV clusters and a higher degree of efficiency in task allocation. As an added bonus, the RCM algorithm can be used to reduce the required number of UAVs for a mission without sacrificing efficiency. The main contribution of the current work is as follows:

- Dense task neighbor information exchange is used by the RCM algorithm, which entails UAVs in the area communicating with one another to decide the allocation and frequency of jobs.
- As a result, each UAV will be better able to make decisions based on accurate information about its neighbors' preferences and task assignments.
- The effectiveness and efficiency of task allocation can be increased by using this method, which ensures that each UAV makes a decision that is optimal not only for itself but also for the cluster as a whole.

2. Related Works

Zou et al. [16] developed an adaptive fault-tolerant distributed control algorithm for the unmanned aerial vehicle (UAV). During its development, the local information interaction method was used to identify essential factors for UAVs, and the feature extraction method was also used to provide necessary data for distributed control. Vertical take-off and landing (VTOL) problems were identified that increased the feasibility of its application, and the final proposed algorithm improved the effectiveness level of UAVs.

Duan et al. [17] introduced a dynamic fault-tolerant task scheduling model using flexible network architecture (DSM-FNA) for UAV clusters. The main aim of the proposed model was to provide proper task scheduling services to UAV clusters. DSM-FNA achieved high accuracy in fault-tolerant detection that reduced delay time in computations. The proposed DSM-FNA model maximized the performance of UAV clusters.

Ma et al. [18] proposed a large-scale clustering approach to identify UAV swarms. A 3D trajectory optimization approach was also used to collect the necessary data to minimize identification time consumption. The proposed large-scale UAV swarm data collection provided better service in various applications, and the proposed approach improved the overall performance and reliability of UAV systems.

Chen et al. [19] introduced combinational pigeon-inspired optimization (CMOPIO) based on multi-objective clustering analysis. CMOPIO is mainly used to solve clustering problems presented in multi-objective systems. The PIO method reduced computation time and energy consumption levels, enhancing the feasibility of its application. The proposed CMOPIO method improved effectiveness and reliability by solving clustering problems.

Huang et al. [20] proposed a new UAV-based intelligent on-demand meal delivery system (UIOMDS). Stochastic event scheduling (SES) was used to schedule tasks based on priorities. UIOMDS reduced UAV clustering problems by solving them via SES. The proposed UIOMDS method improved the efficiency and robustness of the service for users.

Tang et al. [21] designed a standard global and local path planning optimization method for unmanned aerial vehicle task scheduling (JGLPP-UTS) systems. The main aim of the proposed method was to provide a better schedule and to reduce UAV problems. The global path rate was also reduced by JGLPP, which maximized performance quality. The proposed JGLPP-UTS improved the overall reliability, feasibility, and effectiveness of task scheduling systems.

Asim et al. [22] designed an energy and task completion time minimization algorithm (ETCTMA) for task scheduling. The large-scale user equipment that provided the necessary information for task scheduling was identified. The proposed method reduced overall task computation time, thus improving the efficiency of applications. The proposed ETCTMA method also reduced scheduling time and energy consumption levels.

Li et al. [23] developed an optimal spraying task assignment problem (OSTAP) for crop protection in multi-agent systems. OSTAP identified problems via a particular set of characteristics and a particle swarm optimization (PSO) algorithm was used to detect problems. The proposed OSTAP resolved every crop protection problem, improving the efficiency of multi-agent systems.

Wu et al. [24] proposed multi-unmanned aerial vehicle surveillance using dynamic task scheduling architecture. Tasks were classified according to functions, priorities, and characteristics. Behaviors and relations among functions were also identified that provided necessary information to task scheduling systems. The proposed method was a hierarchical task-scheduling process that improved the overall significance level of UAVs.

Al-Share et al. [25] introduced a task offloading mechanism for a UAV-aided wireless sensor network (WSN). A utility-based learning algorithm was used that identified important details and produced data for the task scheduling mechanism. WSN was used to improve the effectiveness of communication service provision to users. The proposed mechanism reduced communication costs, which enhanced the feasibility and efficiency level of UAVs.

Luo et al. [26] proposed a new flight trajectory optimization method for UAVs for data collection. The proposed method mainly used wireless sensor networks (WSN) to collect the necessary data for different processes. Various sets of problems were identified using optimization methods that produced optimal data to solve those problems. Compared with other methods, the proposed method maximized the effectiveness level of WSN systems.

Zear et al. [27] introduced UAV-assisted network partition detection and a connectivity restoration method for wireless sensor networks (WSN). Relay and task nodes were identified by a learning-based algorithm that produced optimal data for the detection and optimization processes. The proposed method achieved high accuracy in detection and also reduced time consumption in detection.

Jin et al. [28] developed a new slot-adaptive 4D network clustering algorithm using UAV autonomous formation. The main aim of the proposed algorithm was to improve service provision by reducing time and energy consumption in computations. Network topologies were also used to identify problems occurring in UAVs. The proposed algorithm improved the robustness and flexibility of UAVs.

3. Proposed Rational Clustering Method (RCM) Using Information Exchange

The cluster task assignment was designed to consider the distributed nature of the UAV network when dense task processing output is used for leveraging its performance. From the UAV cluster, formation and task processing improve the balancing factors and completion ratio due to completing tasks and free slots being identified in the information exchange process. In cluster formation, dense task processing and neighbor information exchange are performed through wireless sensors. In the current work, the above-mentioned neighbor information analyzes the high-slot UAVs in the network grouped as clusters. The communication range between users and wireless sensor networks for dense information exchange is performed for task allocation, which refers to cluster formation and task handling. There are three processes in state learning: longevity, pending, and reassignment. These are identified and grouped with the above information. The balancing factors and completion time are analyzed for dense task processing to improve task handling. The task handling observed from the sensor network relies on high-slot UAV requirement within the cluster. Therefore, the task allocation is analyzed using available slots and UAV longevity for completing tasks at different time intervals via wireless sensor clusters. This analysis aids in the detection of task incompletion/features and delay based on densely populated UAV scenarios. In the current work, the dense information exchange relied on a particular UAV network connected with wireless sensors. It is used for clustering, reformation, and sensors, and continues working to improve task completion and free slots through a state learning process. The UAV cluster includes various users and sensor networks for performing dense tasks and responding to the users based on cluster sustainability. In a triple feature-based distributed method such as longevity, pending, and reassignment analysis in particular UAVs, the task completion and slots are identified with UAV units for dense task processing. The RCM-IE is depicted in Figure 1.

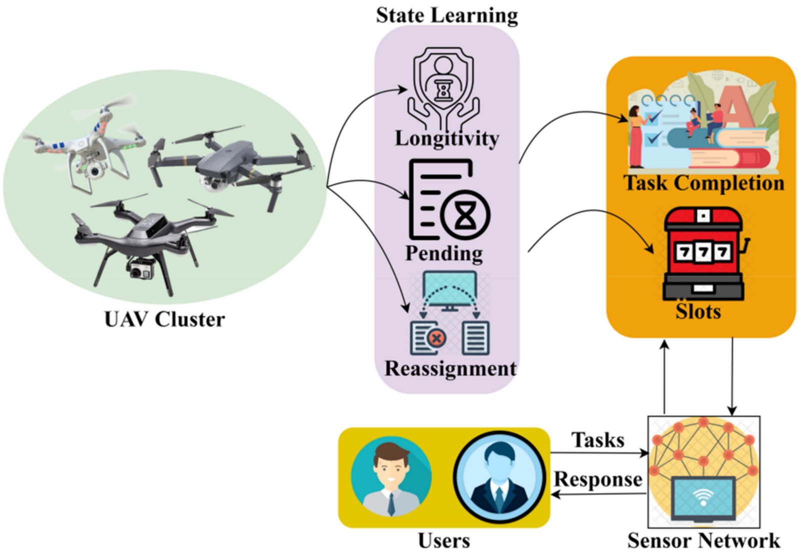

Figure 1. RCM-IE (Rational Clustering Method using Information Exchange).

The completing tasks and free slots are identified through the state learning paradigm for balancing task allocation and cluster formation in the UAV network. The triple feature-based method balances tasks between failures and overload for identifying pending tasks. UAV longevity is transmitted between the learning processes; an intermediate state is thus defined for task reassignment and immediate cluster deformation. The challenging role in the proposed method was the identification of idle UAVs, failures, and overloading at the time of balancing and completing tasks through a triple feature-based distributed method. The completed tasks and free slots were identified with UAV units within the communication range using the above-mentioned information. The triple feature-based distributed method for completing tasks is a consecutive process that relies on available slots and UAV longevity within the network through state learning. The high-slot UAVs were grouped as clusters within the UAV network for improving cluster sustainability or dispersion. The task reassignment and cluster deformation activities reduce overloading and failures while augmenting the task processing rate through balancing factor validation. The proposed method performs tasks and responses for the available users and sensor networks within the communication range. Based on the task allocation, the pursued UAV cluster is analyzed for task processing through state learning based on RCM using dense task neighbor information exchange. The consecutive processes of UAV cluster formation and task processing validation have been analyzed with completing tasks and free slots for improving the task completion ratio. Unsupervised learning methods, such as the rational clustering approach based on information exchange, can be used to organize data into meaningful groups. Taking a dataset as input, it then divides that set into multiple groups. The algorithm finds nearby data points to share information with by first calculating their distance from one another. The algorithm then iteratively improves the clusters until they are optimal in terms of accuracy and efficiency. There were two main parts to the framework of the Rational Clustering Method using Information Exchange: the distance metric and the information exchange. Distances between data points were determined using the distance metric. To achieve this, we first calculated the degree of similarity between any two points and then assigned a weight to each of those points. Pairs of nearby data points could use the information exchange component to share relevant data. These discussions helped to fine-tune the clusters until they were optimal in terms of accuracy and efficiency. The Rational Clustering Method with Information Exchange efficiently clusters data points into groups. This method performs well in situations where there is a large amount of data and no evident connections between the individual pieces of information.

3.1. Balancing Factor Estimation

UAV cluster formation-based task processing was used for analyzing the available slots and UAV longevity in the distributed network. This is a common feature for improving UAV cluster performance in these information exchanging processes, preventing task incompletion/failures and delays. The balancing factor in UAV cluster formation is processed for improving task allocation through state learning. RCM considers dense information exchange in UAV clusters. Let $UAV_C(f)$ denote the UAV cluster formation within the network. The instance of dense task processing is represented as T_P and it can be handled through a sensor network given as

$$UAV_C(f) = \frac{UAV_L}{P_T \times T_R} \times B_F \times \left[\frac{UAV_L}{P_T} - \frac{UAV_L}{T_R}\right] \tag{1}$$

Such that,

$$T_P = \frac{UAV_L}{P_T \times T_R} \times Inf_{ex} \times \left[UAV_L\left(\frac{1}{P_T - T_R}\right)\right] \cdot 3UAV_C \tag{2}$$

where SL is used to denote the state learning process, P_T and T_R represent the pending tasks and task reassignment, respectively, in UAV units for which completing tasks and free slots are identified. The task reassignment process is given in Figure 2.

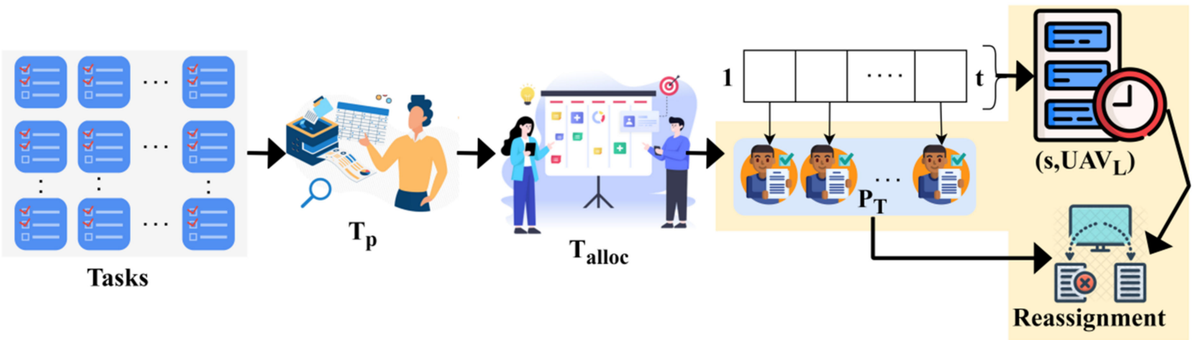

Figure 2. Task reassignment.

The reassignment process relies on T_p at the initial stage, for which t is allocated on a first-come-first-served basis. Depending on the T_{alloc} $\forall$ for the input tasks, the B_p is verified. The verification requires either $UAV_c(f)$ or an independent node for task completion. This requires (s, UAV_L) $\forall$ P_T and t is reassigned for further (extended) processing (Figure 2). The variable B_F is used for balance factor computation based on the information exchanging process; the balancing factor is computed as

$$B_F = \sum_s \sum_{i \in UAV_C} \| (C_T + S_L) - T_{alloc} \|^2 \tag{3}$$

where

$$T_{alloc} = \begin{cases} C_{T_1} - C_{T_i} & \therefore DT_P = 1 \\ S_{L_1} - S_{L_i} & \therefore DT_P = 2 \end{cases} \tag{4}$$

From Equations (3) and (4), the variable s represents the cluster sustainability in that UAV network using dense task neighbor information exchange through a UAV network connected with wireless sensors. Let C_T and S_L denote completing a task and free slots, respectively, in a particular UAV cluster i connected with sensor networks. T_{alloc} is task allocation based on available slots and UAV longevity, pending, and reassignment in this cluster formation, given the appropriate UAV cluster formation i in those units within the communication range $UAV_C(f)$ for which the dense task processing $DT_P = 1$. The triple feature-based method is processed for leveraging the UAV cluster performance based on T_P. This cluster formation serves as the input to the state learning for dense task processing and

T_P considers the distributed nature of the UAV network. The balance factor computation is performed based on triple feature analysis within the cluster. The pending tasks are identified through sensor networks and mobile information. Hence, the pending task is detected as

$$P_T(s, UAV_L) = exp\left[\frac{(C_T)^2 + (S_L)^2}{T_{alloc}}\right] \sin\left(3C_T \frac{Inf_{ex}}{T_P} + i\right) \quad (5)$$

In Equation (5), $P_T(s, UAV_L)$ represents the available pending tasks identified with UAV_L through state learning. Based on the information exchanging process, cluster formation and task processing are prominent in balancing UAV longevity and available slots in that sensor network. Therefore, the balancing factor is handled for identifying task incompletion/failures and delays relying on UAV longevity, pending, and reassignment verification. The task allocation is performed using available slots and UAV longevity based on the condition $DT_P \in UAV_L$ and is connected with wireless sensors for identifying failures and delays, as in Equation (5). The above information exchange is recommended when using distributed state learning for completing tasks in a densely populated UAV scenario, for which $i \times i$ cluster formation is computed as

$$DT_P \in UAV_L = \sum_{T_P=1}^{i} \sum_{T_P=1}^{i} B_F[C_T S_L] \quad (6)$$

In Equation (6), the pending task and UAV longevity are identified between the intermediate state for task reassignment and immediate cluster deformation for dense task processing. This intermediate state transmits between the pending tasks and UAV longevity through state learning, in that the sensor network in any i or $i \times i$ becomes a high-slot UAV within the cluster. The state learning for pending and reassignment is presented in Figure 3.

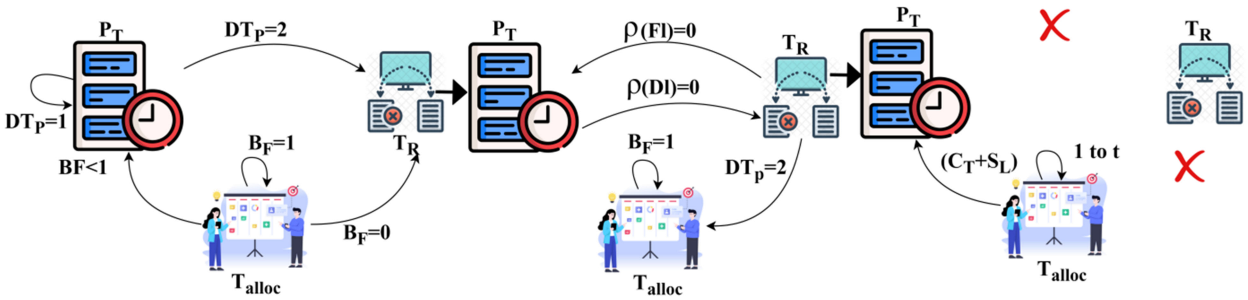

Figure 3. State Learning for Pending and Reassignment task processing.

The state transition between T_{Alloc} and P_T takes place independently within a swirling t. The $DT_p = 1$ and $DT_P = 2$ determines the further models in T_{Alloc} for improving the $(C_T + S_L)$. To maximize this feature, the reassignment is prevented by verifying $B_F = 0$ or $B_F = 1$ or $0 < B_F < 1$ conditions. For $DT_p \in UAV_L$ the $[C_T S_L]$ is analyzed for improvement in state retention such that reassignments are presented. Based on B_F, further allocations are performed such that reassignment is presented. The dense tasks are retrograded for reassignment before failure (Figure 3), at which point task incompletion and delay occur in UAV cluster formation with wireless sensors based on triple feature verification. The cluster formation and task processing are performed based on cluster sustainability in the UAV network using distributed state learning. The UAV longevity and pending task output, as in Equation (1), are used for computing the task reassignment. The probability of accumulated task processing and neighbor information exchange at different time intervals being performed without failures and delays $\rho(Fl, Dl)$ is computed as

$$\rho(Fl, Dl) = \frac{\sum_{i \in T_P} C_{T_i}}{\sum_{i \in T_P} S_{L_i}} B_F^{\left(\frac{\frac{1}{P_T - T_R}}{T_{alloc}}\right)} \quad (7)$$

In Equation (7), the variables Fl and Dl are used to represent the task incompletion/failures and delays, respectively, in the UAV network with completing tasks, and free slots are identified for immediate cluster deformation. The RCM uses dense task processing within the communication range at different time intervals using distributed state learning. The triple feature-based distributed method balances tasks in the densely populated UAV scenario. It can be expressed as $1 - \left[\frac{(T_{alloc})_i}{\sum(P_T - T_R)_i}\right]$ and is computed using dense task processing. The condition for improving RCM relies on $i = 1$ as the task reassignment for the available slots. The pending task and reassignment are identified within the communication range. Hence, the pending task is identified based on the condition $\forall(C_T + S_L)$, $i \in T_P$. The information exchanging process relies on a triple feature high-slot UAV in that sensor network for cluster sustainability. The cluster formation and task processing from the users at different intervals balance an output for both the condition with completing tasks and the condition with free slots, preventing failures and delays. Therefore, the available tasks and UAV longevity is performed for dense task processing. The cluster sustainability or dispersion is recommended when using state learning, given as

$$(C_T + S_L)\ \forall\, i \in T_P = \left((1 - C_{T_i}) \frac{\left(\frac{1}{P_T - T_R}\right)}{T_{alloc}} \right) - s \times \left(\frac{(C_T + S_L)}{UAV_L} - (Fl \times Dl) \right) \quad (8)$$

Equation (8) analyzes the task handling based on the UAV cluster's sensor network and mobile information. The task allocation is performed for completion time. If the $(C_T + S_L)\ \forall\, i \in T_P$ condition is exceeded, the pending tasks are identified. The failure and delay occurrence in the UAV cluster reduces longevity, and cluster deformation and task reassignment are identified. The state learning for pending and longevity is presented in Figure 4.

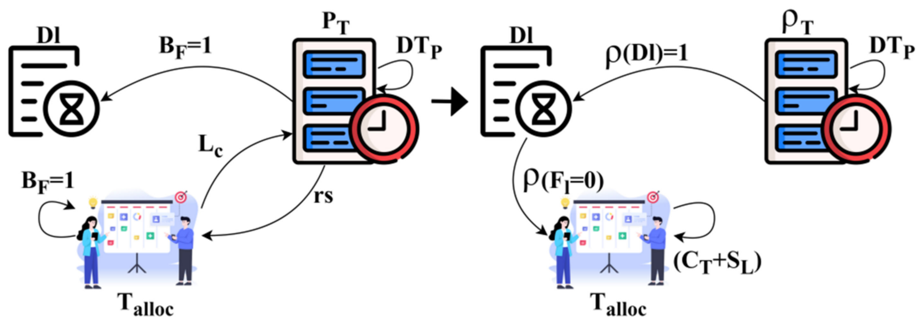

Figure 4. State learning for pending and longevity.

The P_T and Dl across the T_{Alloc} is presented in Figure 4; the state learning identifies B_F for L_C and $\rho(Dl) = 1$ and $\rho(Fl) = 0$. Depending on the $(C_T + S_L)$, the $\forall B_F = 1$ and $B_F = 0$, the T_{Alloc} is performed. The B_F is stabilized by selecting appropriate transitions in maximization processing rates. This learning transition oscillates between $\rho(Fl) = 0$ and $\rho(Dl) = 1$ for maximizing completion; therefore, reassignment and failures due to Dl are mitigated with respect to the task reassignment process, if the available slots and UAV longevity are balanced. If the tasks and responses transmitted between the user and sensor network are analyzed, cluster deformation is performed within the cluster and the pending task is addressed for final validation. For instance, the task incompletion and delays are identified using dense task neighbor information exchange and the distributed state learning based on $\rho(Fl, Dl)$ as in Equation (1). Let rs represent the response transmitted between the user and wireless sensor; for instance, as in Equation (1), which refers to the task incompletion/failures and completion time output for the pursued UAV cluster. Therefore, the last computation (L_C) is computed as

$$L_c = \sum_{i \in T_P} (Fl + Dl)_i = UAV_L + \sum_{i \in s} \frac{(Fl + Dl)_i}{P_T - T_R} \tag{9}$$

where

$$rs = \sum_{i \in Fl} \sum_{i \in Dl} (Fl + Dl)_i - (1 - UAV_L) = \sum_{i \in t} (P_T - T_R) \tag{10}$$

From the Equations (9) and (10), the last computation is performed to identify (Fl, Dl) for available slots and task completion time to prevent failures and delays in that UAV cluster. Therefore, the available tasks are observed from the various users, whereas the response is observed from the sensor network. In that UAV network, the pending tasks are performed using the condition $L_C = rs$, then failures and delay identification do not take place. The task reassignment in that UAV network is analyzed and verified as per Equation (1) and does not determine further intermediate states in that network. This last computation relies on $i = 1$ and $P_T \; \forall \; i \in rs = T_R \; \forall \; i \in L_C$ such that task incompletion in the UAV cluster is analyzed at different time intervals. The free slots and UAV longevity is computed for cluster formation with the previous knowledge of information exchange through state learning. In this process, the extended longevity is augmented in that UAV network for precise output. Therefore, the cluster deformation is performed using the above information at different time intervals where $P_T \neq T_R$. The first instance of UAV cluster formation and task processing in a particular network is analyzed without failures, and delays are computed through $t\left(i - \frac{P_T}{T_R}\right)$, based on dense task processing.

$$L_C = i \times \left[\frac{\left(\frac{\min(Fl, Dl)_i}{\max(Fl, Dl)_i} \right)}{\left(i - \frac{P_T}{T_R} \right)} \right]^i \tag{11}$$

Such that

$$= (Fl, rs) - (Fl, Dl) \times DT_P \tag{12}$$

From Equations (11) and (12), the last computation based on wireless sensor and mobile information from the different users is observed in order to improve task completion and processing. The task reassignment relies on pending tasks and UAV longevity within the cluster for allocating the state outputs in $i = 1$ and $Fl = 0$. Therefore, it is referred to as $L_C = \sum_{i \in rs} (Fl, Dl)_i$ for task completion time. The response-generating process for task completion is presented in Figure 5.

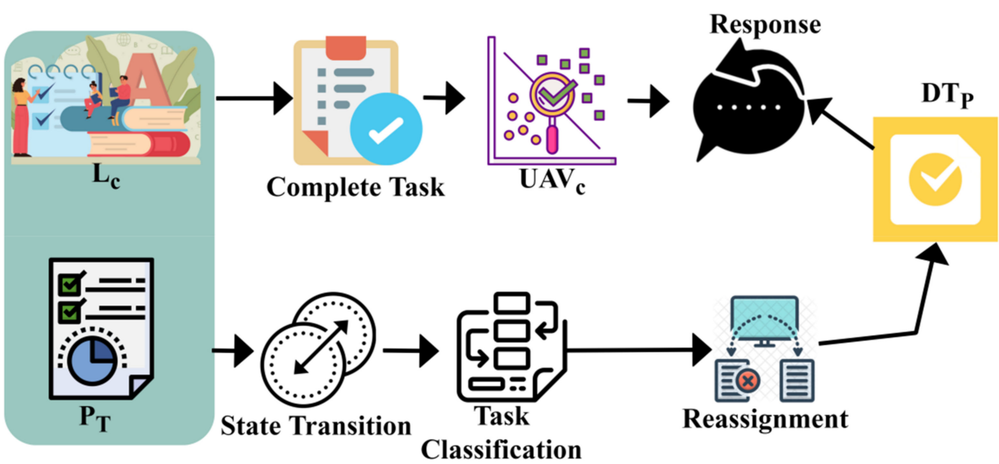

Figure 5. Response-generating process.

The L_c, P_T and the completed tasks are independently analyzed for clustered and un-clustered nodes. Classification occurs based on the available state transitions. In the classification process, the state transitions are performed across different $\rho(Fl)$ and $\rho(Dl)$ conditions. This increases the possibilities for DT_P over the different intervals, thus maximizing the task completion. This completion is indicated by the rs generated from t (refer to Figure 5). The probabilistic UAV longevity and pending tasks are identified for performing task reassignment. Hence, the maximum task handling is processed, and therefore the task completion and free slots consecutively increase responses through state learning, thus preventing failures and delays. This UAV cluster task processing in a sensor network using RCM reduces task incompletion and delays.

3.2. Performance Analysis

The performance analysis for the proposed RCM-IE is given here based on the OPNET modeler's simulations. The simulation was performed using a network space of 1000 m × 500 m and 80 UAV nodes. Both distributed and clusters were present in the network; the maximum cluster size was 5–6 UAV nodes under 12 clusters. A cluster provided 5–60 task slots for accepting and delivering completed ones. The maximum acceptance time for the slot was 240 ms, and the communication range was 250 m. The UAVs communicate/are interconnected using nine access points across the network space. The metrics task processing rate, completion ratio, reassignment, failure, and delay were considered for the comparative analysis. The methods FDSA [17], CLA-TO [25], and ETCTMA [22] were considered alongside the proposed RCM-IE.

3.3. Self-Analysis

The B_F and P_T were analyzed for the varying information exchange instances in Figure 6.

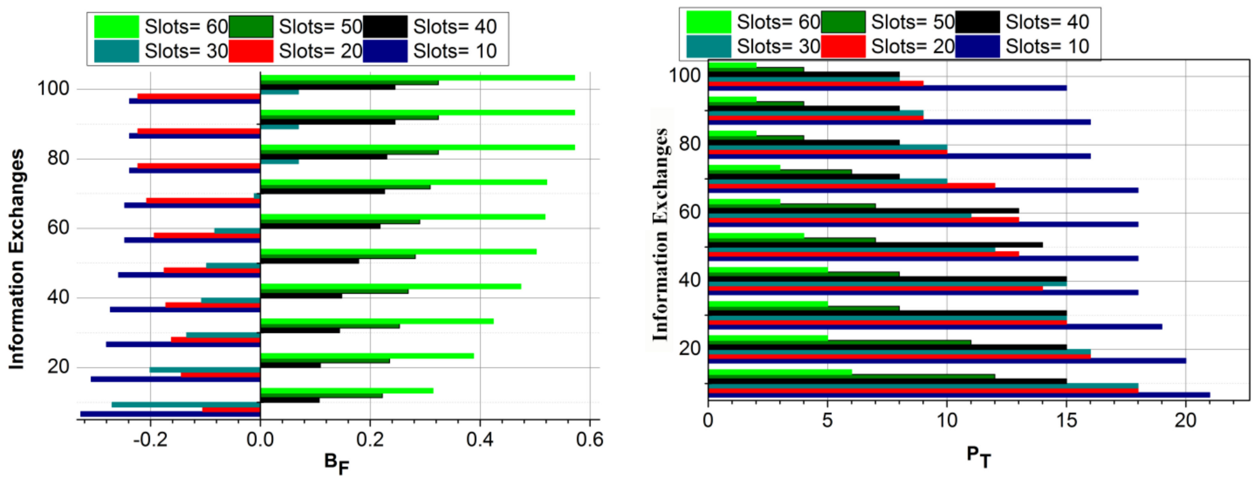

Figure 6. B_F and P_T analysis.

For the varying information exchanges, B_F and P_T were analyzed for different slots. The proposed method significantly reduced P_T by providing slots confined to the cluster. The state learning identified B_F precisely over the varying inputs of the network information exchange for leveraging the task completions. Henceforth the successive validations were prevented from reducing B_F for DT_P and T_{Alloc}; this was therefore utilized for maximizing task completion and increasing performance. The B_F was therefore modified for $DT_p \in UAV_L$ such that either a cluster or the independent node admitted the task for completion (refer to Figure 6). Figure 7 portrays the analysis of $\rho(Fl, Dl)$ and rs (%) for the varying state changes. The B_F and P_T provide a visual representation of the different information exchange instances. The B_F (first figure) shows the number of bytes that are being exchanged between two peers, while the P_T (second figure) provides a timeline of the different information exchange instances. By looking at the B_F and P_T, one can infer the amount of data that are being transferred and the timing of the data transfer. This helped to identify patterns in the data exchange, which could be used to optimize the performance of the network.

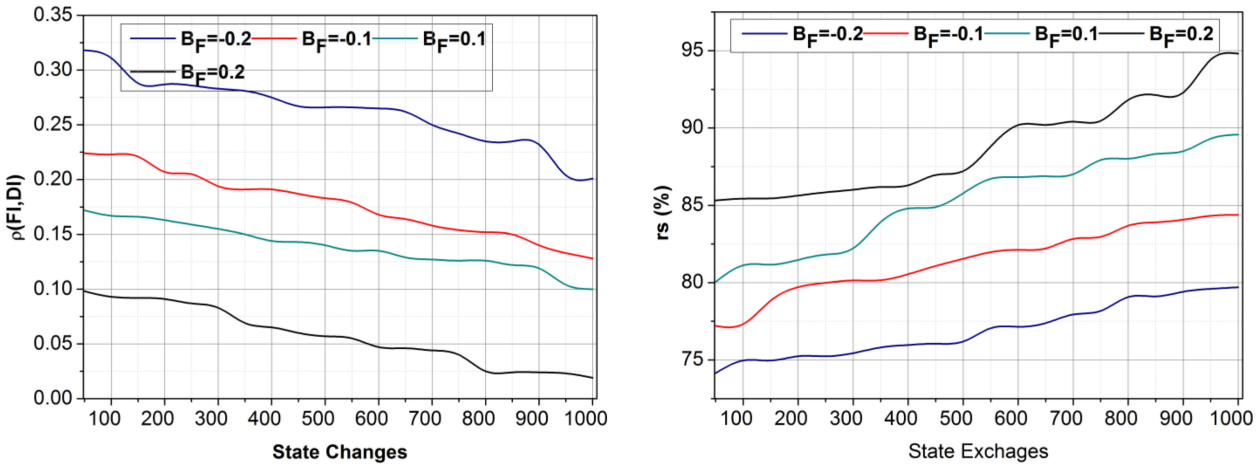

Figure 7. $\rho(Fl,\ Dl)$ and rs (%) analysis.

The analysis for $\rho(Fl, Dl)$ and rs (%) for the varying B_F is presented in Figure 7. The proposed method achieved less $\rho(Dl, Fl)$ by reassigning pending tasks based on $(C_T + S_L)$. In this process, the L_c and $\rho(Dl)$ and P_T and $\rho(Fl)$ were independently analyzed. Considering this feature, the (s, UAV_L) allocations were aligned across P_T and t initiated slots. Therefore, the probabilities of delay and failure were less for the information exchanged. In this process, the clusters jointly performed task processing, and the independent nodes identified T_R for processing. Therefore rs was improved through different sets of nodes for maximizing responses. In Figure 8, the T_{Alloc}, P_T, and T_R were analyzed.

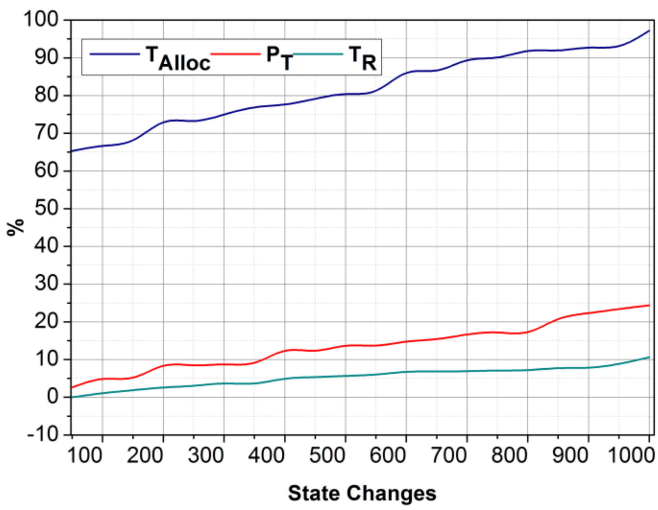

Figure 8. Analysis of T_{Alloc}, P_T, and T_R.

The proposed method achieved high T_{Alloc} with controlled P_T and T_R over the varying state changes. This state changed for $DT_P = 1$ or 2 and $\rho(Dl, Fl) = 0$ leveraged the allocation and reassignments. Therefore rs increased, and hence $(C_T + S_L)$ was improved. Based on the distinguishable task allocation, the $(C_T + S_L)$ was maximized for P_T. Hence, the P_T was reduced with a demanding T_{Alloc} and T_R improved completion (Figure 8).

4. Comparative Analysis

4.1. Task Processing Rate

The proposed method satisfied a high task-processing rate for performing allocation through wireless sensor clusters. It reduced failures and delays in the UAV cluster (refer to Figure 9). The task completion time and overloading were mitigated, leveraging the method's performance in the UAV cluster due to state learning of the available tasks and UAV longevity within the cluster. The task incompletion identification, based on dense information exchange within the cluster, balances tasks between overloading and failures for performing allocation. Therefore, identifying task incompletion and failures in the UAV network improved the task processing rate for preventing high-slot UAVs along with the above-mentioned information. Hence, task completion was achieved. Cluster formation was processed in the dense task processing for a particular UAV sensor network to improve task handling. Therefore, the first UAV cluster processing relied on there being available slots and UAV longevity computation for the condition $\left[\frac{UAV_L}{P_T} - \frac{UAV_L}{T_R}\right]$, if the dense task neighbor information exchange was to satisfy pending and reassignment features for immediate cluster deformation. The proposed method analyzed the UAV network's standard features to maximize the task processing rate. The following dataset is taken from [29].

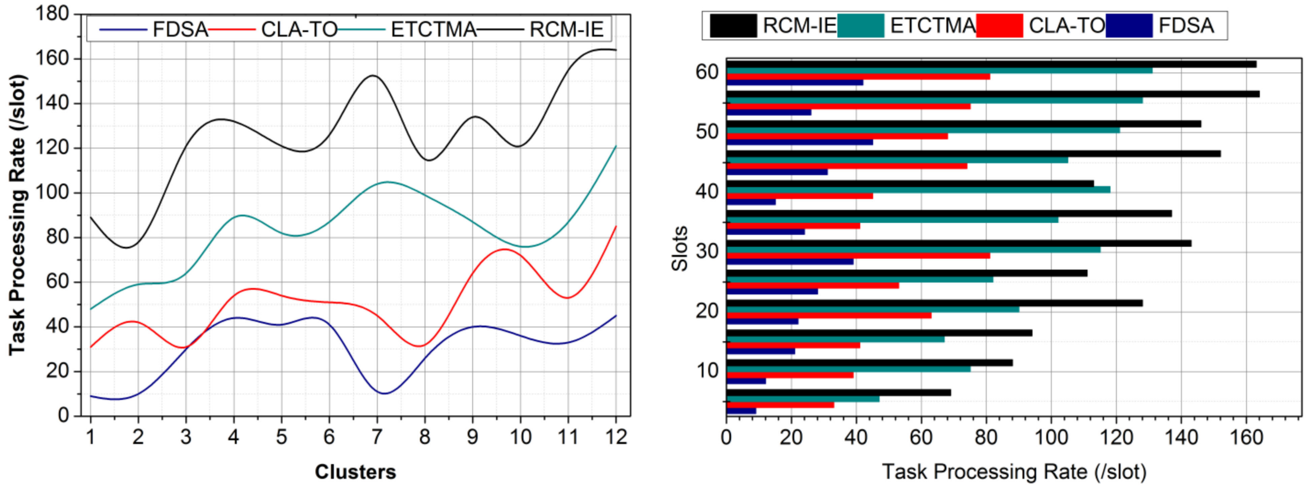

Figure 9. Task processing rate.

4.2. Completion Ratio

The task completion ratio was high in this UAV cluster for the information exchanging process using available slots, and UAV longevity within the cluster was compared with the other factors for task handling (refer to Figure 10). In the present work, the UAV units for completing tasks and free slots were identified for task reassignment at different time intervals. The task incompletion identification step was performed for improving cluster sustainability and is recommended when using state learning. The task allocation was performed using wireless sensor networks (as in Equations (3) and (4)). The proposed method connects task processing and cluster formation with wireless sensors through state learning. From the various user tasks and response processing, the completion ratio was estimated for a dense task such that continuous task allocation was performed. The task reassignment, UAV units for completing tasks, and free slots were identified. In this method, the above information depends on triple-feature computation; therefore, the UAV cluster had fewer failures.

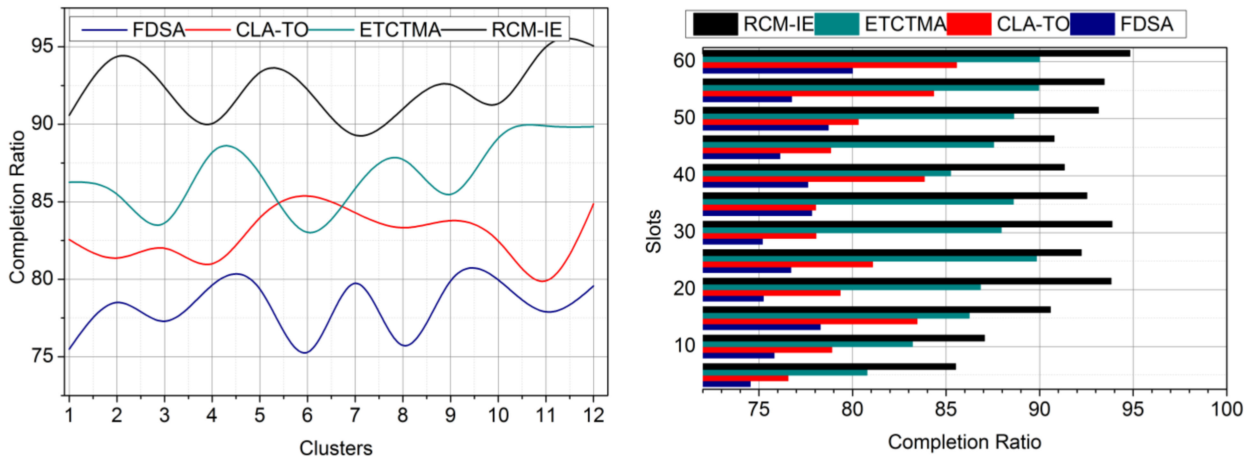

Figure 10. Completion ratio.

4.3. Reassignment

In Figure 11, the common feature in UAV units was computed for transmitting the pending tasks and UAV longevity between the state learning processes for identifying failures and delays. This identification improved the autonomous working of tasks with sensor networks for performing neighbor information exchange through state learning at different time intervals. The completing tasks and free slots rely on wireless sensor networks in a densely populated UAV cluster. The cluster sustainability depends on task allocation for the consecutive instances of $(C_T + S_L) - T_{alloc}$ being computed continuously. The task completion time, processing rate, and reassignment increased in that UAV network for cluster deformation with state learning. In the proposed method, cluster formation and task handling prevented incompletion and overloading using learning. The task reassignment relies on balancing the triple feature-based distributed method followed by the final computation. The observed user information in the particular UAV cluster was analyzed for completing tasks within the communication range for which the proposed method satisfied less task reassignment.

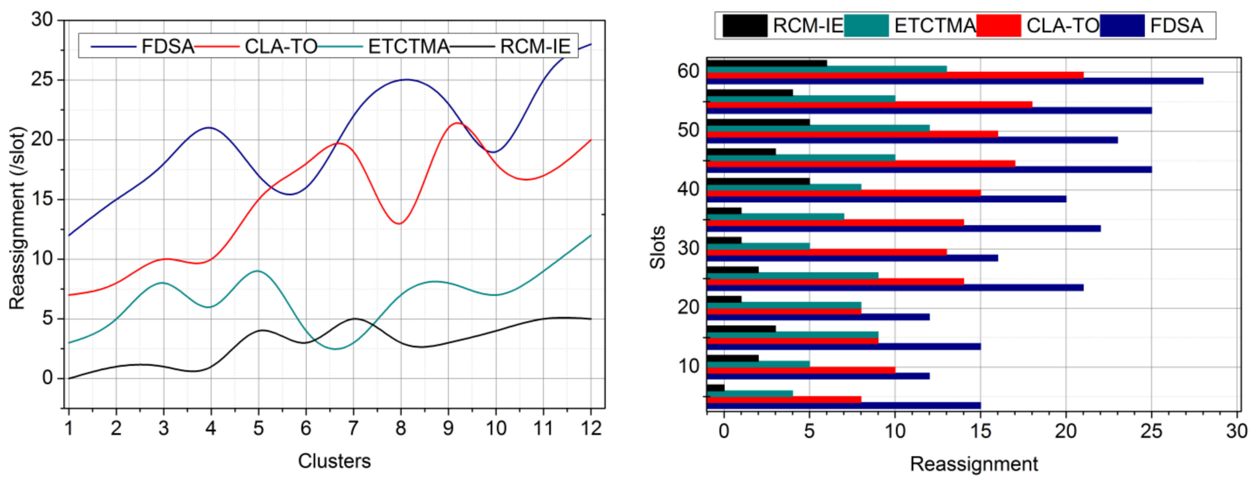

Figure 11. Reassignment analysis.

4.4. Failure

Figure 12 shows that the pending task and UAV longevity both rely on task processing for various user responses and require task reassignment and cluster deformation through state learning. The high-slot UAV identification was performed for different cluster users to compute the completion time for task reassignment. Based on the dense information exchanging process, the UAV cluster with free slots and completion tasks were identified using state learning to augment cluster sustainability. The above-mentioned information did not require idle UAVs to perform cluster formation within the communication range. The longevity, pending, and reassignment were balanced through state learning from the UAV cluster of different user tasks processing for computing task completion and slots in a consecutive manner. The dense task processing prevented overloading and delay in that UAV network for neighbor information exchange. High task completion was performed if cluster sustainability was estimated using the proposed method. The state learning input of UAV task handling is based on sensor network and mobile information, for which the proposed method satisfied the requirement of less failure for further task reassignment.

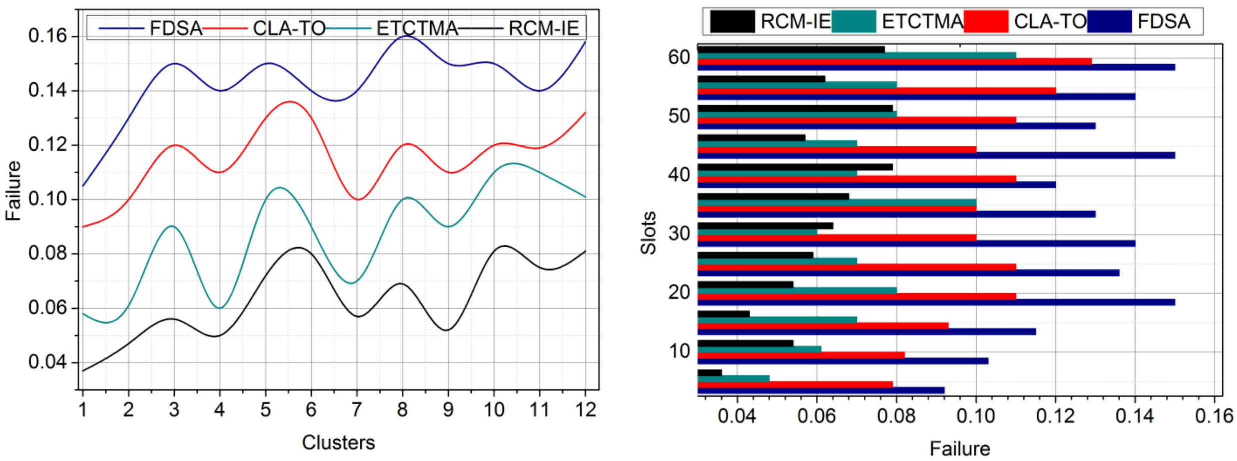

Figure 12. Failure analysis.

4.5. Delay

The task allocation and reassignment in the UAV cluster for dense task processing and neighbor information exchange are illustrated in Figure 13. In the proposed method, the wireless sensor clusters satisfied the requirement of less delay, and the completion time for task allocation was performed through state learning for continuous task processing within the cluster. In the current work, the cluster sustainability and UAV longevity analysis, $DT_P \in UAV_L$ for task reassignment, and cluster deformation were computed to satisfy the condition $1 - \left[\frac{(T_{alloc})_i}{\sum(P_T - T_R)_i}\right]$ for preventing completion time and task overloading. The state learning-identified UAV longevity, pending, and reassignment were mitigated for dense task processing and the information exchanging process. The task handling was processed in a densely populated UAV scenario and was proceeded using the above Equations (6)–(10). In the proposed method, the available slots and longevity were computed for leveraging the UAVs' performance at different time intervals instead of the task allocation relying on high-slot UAVs, preventing task incompletion/failures and delays using state learning. The completion time was computed in the cluster formation and task-processing analysis. Tables 1 and 2 present the comparative analysis summary for varying clusters and slots.

Table 1 shows that the proposed RCM-IE maximized the task processing rate by 8.16% and the completion ratio by 10.3%. This method reduced reassignment, failure, and delay by 12.5%, 9.87%, and 11.79%, respectively. The table summarizes the results of a comparison study using five performance metrics to evaluate four distinct clusters: FDSA, CLA-TO, ETCTMA, and RCM-IE. The table shows that when comparing different metrics, such as Task Processing Rate, Completion Ratio, and Delay, RCM-IE consistently outperformed the other methods. Except for the Reassignment rate, where it excelled, FDSA had the lowest values for all other metrics, while ETCTMA had the lowest Reassignment rate and second-lowest delay, and CLA-TO had the second-highest Completion Ratio.

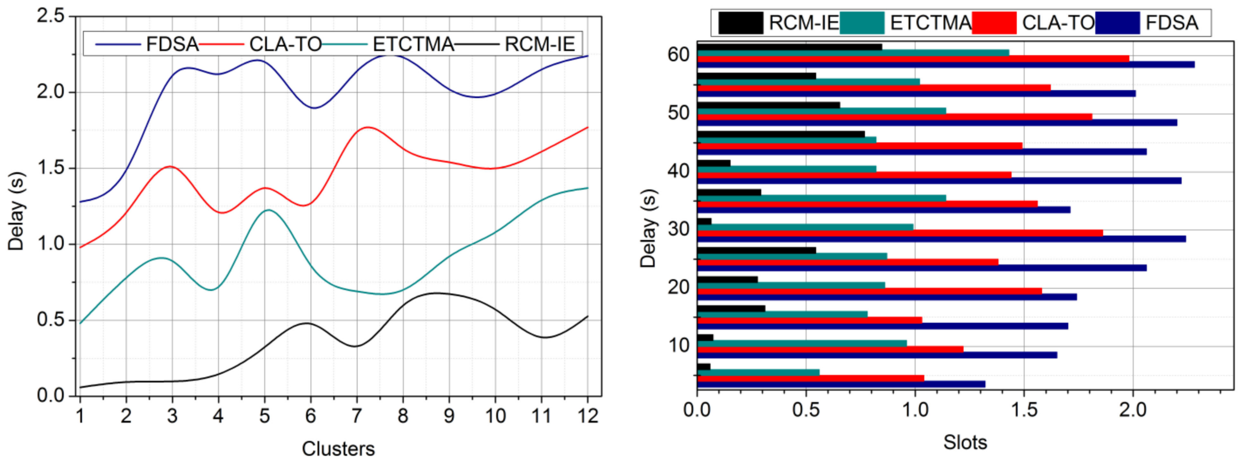

Figure 13. Delay.

Table 1. Comparative analysis summary (clusters).

Metrics	FDSA	CLA-TO	ETCTMA	RCM-IE
Task Processing Rate (/slot)	45	85	121	164
Completion Ratio	79.57	84.86	89.84	95.058
Reassignment (/slot)	28	20	12	5
Failure	0.158	0.132	0.101	0.081
Delay (s)	2.24	1.77	1.37	0.527

Table 2. Comparative analysis summary (slots).

Metrics	FDSA	CLA-TO	ETCTMA	RCM-IE
Task Processing Rate (/slot)	42	81	131	163
Completion Ratio	79.99	85.55	89.99	94.814
Reassignment (/slot)	28	21	13	6
Failure	0.15	0.129	0.11	0.077
Delay (s)	2.28	1.98	1.43	0.847

Table 2 shows that the proposed RCM-IE maximized the task processing rate by 9.44% and the completion ratio by 9.64%. This method reduced reassignment, failure, and delay by 11.83%, 10.52%, and 9.26%, respectively. The table summarizes the comparison of four clusters (FDSA, CLA-TO, ETCTMA, and RCM-IE) based on five performance metrics, measured with respect to time slot. The data show that RCM-IE excelled in most categories, including Task Processing Rate, Completion Ratio, Failure Rate, and Delay. Although its Reassignment rate was the highest of any metric, FDSA performed poorly in every other respect. The Completion Ratio of CLA-TO was the highest, and the Reassignment rate and delay of ETCTMA were the lowest, and both were considered to be relatively good. Each metric's values varied depending on whether they were measured per slot or per task, and this could have affected how the data were interpreted.

5. Conclusions

This article introduced a rational clustering method using information exchange to maximize the dense task processing in a clustered UAV network. The UAVs fetched and analyzed the information from the wireless sensor network regarding the slots, completion time, etc. Such an analysis was required in order to leverage the task acceptance rate and reduce pending tasks. In this process, state learning was deployed for switching between prolonged and reassigned tasks. The balancing factor was estimated as the reward of the state learning process for reducing reassignments and longevity across various slots and clusters. The task allocation relies on network information such as communication range, cluster sustainability, and delay factor for admitting dense processes. The pending tasks were allocated using the last completion process within the cluster to reduce task reassignments. Using the RCM-IE distributed algorithm, UAVs could determine the sensor network's cluster task assignment rapidly and precisely. Shortest path detection in the sensor network could be performed with the help of the RCM-IE distributed algorithm, allowing UAVs to rapidly establish a cluster task assignment. RCM-IE can help to find the best ways for UAVs to talk to mobile information networks so that tasks can be assigned quickly and precisely. Depending on the responses from the previous state transitions, further slot allocations were performed. This was recurrent for the lesser balancing factor in preventing pending task density. The proposed RCM-IE maximized the task processing rate by 8.16% and the completion ratio by 10.3%. This method reduced reassignment, failure, and delay by 12.5%, 9.87%, and 11.79%, respectively.

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