

Distributed Limited Resource Allocation and Energy-Expenditure Learning for Advanced Air Mobility

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This paper addresses the problem of assigning drones to charging stations that have a limited number of spots to service drones, such as charging, battery reloading, maintenance, etc. The objective is the minimize the overall energy cost of drones. We proposed a new service model for drone operations for Advanced Air Mobility (AAM). A data-driven method is proposed to estimate the energy expenditure of drone flights using a Recurrent Neural Network (RNN). A heuristic distributed allocation algorithm is then proposed to solve the problem, namely Hungarian-based Distributed Limited Resource Allocation Algorithm (HBDLRAA). The simulation results show that the proposed RNN-based method can produce a stable prediction given noisy flight data. The proposed HBDLRAA generates drone allocation that satisfies the given constraints.

I. Introduction

The coming needs of the future society have inspired us to extend the research on the different aspects of the topic of unmanned aerial vehicles (UAVs), or drones. NASA has exerted significant and serious efforts towards enabling Advanced Air Mobility (AAM) to resolve the current challenges in transportation and aircraft operations [1]. AAM will cover travel across local, regional, intraregional, and urban areas, enabling consumers to access to on-demand air mobility, cargo and package delivery, healthcare applications, and emergency services through an integrated and connected multi-modal transportation network [2, 3]. The NASA Revolutionary Vertical Lift Technology project is developing UAM VTOL aircraft designs that can be used to focus and guide research activities in support of aircraft development for emerging aviation markets[4]. Soon in the future the sky will be filled by different kind of VTOL UAVs for different purposes [5].

In the conceptualized future aviation for AAM, the increasing levels of greenhouse gases due to the growing number of fuel-driven vehicles have gotten the attention of researchers and governments of many countries in the last two decades. A study shows that 26% of the worldwide carbon dioxide (CO₂) emissions are caused by traffic [6]. Clean-energy drones, such as electric drones, have been witnessed in shipping goods while significantly reducing the emissions caused by traffic. Large VTOL UAVs are being investigated by the industrial, government, and academic stakeholders for the future transportation of humans and cargo for AAM. There is a pressing need to charge electric drones to minimize downtime and keep vehicles moving quickly. To minimize downtime, fast-charging stations (FCSs) are considered. However they include issues such as EVs generally having shorter cruising range than their gasoline-powered counterparts due to the limited capacity of the EV battery, so they frequently need to charge their vehicle. One of the key issues on FCSs was considered by [7]. They address the FCS deployment problem, incorporating the elastic charging demand in a stochastic manner. The relationship between fleet vehicle downtime and the number of charging stations has been studied by [8]. By modeling the fleet operations of a major car-sharing service provider, they jointly optimize charging station allocation in terms of the number and location of charging stations and the assignment of EVs to charging stations. For electric VTOL (eVTOL) aircraft, an FCS is usually a subsystem of a vertiport. Vertiport operators will face the same question of how eVTOLs should be managed such that the overall energy consumption and downtime could be minimized.

In addition, there is a push to maximize the usage of renewable energy. Hussain et al. [9] proposed an optimization strategy for sizing a battery energy storage system (BESS) within an FCS by considering cost reduction, peak shaving, and resilience enhancement. A large increase in energy produced from renewable sources (such as wind and solar) is needed to assure the sustainability and dependability of electricity delivery in the expanding metropolis. However, because it is dependent on varying weather conditions, renewable energy supply is much more erratic and intermittent than traditional supply. In order to optimize home energy usage, demand response approaches are being researched to

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shift device usage to periods of low demand [10]. It takes time for these devices to replenish their energy banks from renewable sources like solar, water, and wind. It is essential for charging stations to perform intelligent scheduling to minimize the drong energy cost while meeting the charging demand under constraints in charging stations, such as a limited number of charging spots. Allocation of limited resources was propounded as the central concept underlying adaptive strategies [11–13]. A variety of methods and algorithms have been developed to find the optimal solution, such as game theory and optimization theory [14–16].

In this paper, we consider the scenario where a drone operator manages a number of heterogeneous drones (e.g., small and large drones) located at a number of drone stations (e.g., for charging and maintenance) at different locations. The drone operator is to provide package (e.g., fast food) delivery services for different companies (e.g., McDonald, Starbucks, etc.). At a certain time period, the drone operator receives on-demand delivery requests and sends drones to pick up packages at designated companies, deliver packages to requested locations, and return to a drone station for charging or battery reloading. The objective of the drone operator is to minimize the overall drone energy cost while satisfying the constraints of drones and drone stations, such as the maximum number of drones that a station can accept, the maximum energy capacity of a drone, and the maximum drone speed and payload.

The contribution of the paper includes two solution methods to address the aforementioned problem, which is broken into two sub-problems. The first subproblem is to estimate the energy expenditure required for a drone to travel to a destination from its current location, and the second subproblem is to allocate drones to stations with constraints. An energy-expenditure estimation method uses historical data from a drone's previous flights and projects how much energy is required for the drone to reach a destination. Current physics-based methods suffer from model accuracy and difficulty of identifying key parameters in the model. We propose to leverage data-driven machine-learning techniques such as a Recurrent Neural Network (RNN) to improve accuracy. The resource allocation solution proposes to allocate all the available limited resources in charging stations to meet the demand for all drones. In this work, we propose a distributed assignment method to solve resource allocation with constraints.

The remaining of the paper is structured as follows. Section II introduces the problem formulation. Section III presents the fundamental of RNN and the methodology of applying RNN for energy expenditure estimation. Section IV presents the proposed allocation algorithm. Section V presents the results and discussions of the work. Finally, Section VI concludes the paper with potential future work.

II. Problem Formulation

In the resources-allocation problem we consider in this paper, we assume that N_c charging stations run by a drone operator are to serve N_d drones at a particular time instant. The index sets for N_c charging stations and N_d drones are defined as $\mathbb{S}_{c,N_c} \triangleq \{1, \dots, N_c\}$ and $\mathbb{S}_{d,N_d} \triangleq \{1, \dots, N_d\}$, respectively. Charging station $C_i, \forall i \in \mathbb{S}_{c,N_c}$, can only provide LoC_i charging bays. Let $LoC \triangleq \{LoC_i\}, \forall i \in \mathbb{S}_{c,N_c}$, be the set stores the numbers of limited charging bays for all charging stations. Let e_{ij} be the energy expenditure for drone j to travel to station i , which can be calculated using the positions of a drone and a charging station. Let binary variable $x_{ij} \in \{0, 1\}, \forall i \in \mathbb{S}_{c,N_c}, \forall j \in \mathbb{S}_{d,N_d}$, specify whether or not charging station i is allocated to drone j , i.e., $x_{ij} = 1$, if charging station i is allocated by drone j and 0 otherwise.. Then, the limited resource allocation problem can be formulated as a linear sum assignment problem (LSAP)

$$\min_{x_{ij}} \sum_{i=1}^{N_c} \sum_{j=1}^{N_d} (e_{ij} x_{ij}) \quad (1)$$

$$\text{s.t. } 1 \leq \sum_{j=1}^{N_d} x_{ij} \leq LoC_i, \forall i \in \mathbb{S}_{c,N_c}, \quad (2)$$

$$\sum_{i=1}^{N_c} x_{ij} = 1, \forall j \in \mathbb{S}_{d,N_d}. \quad (3)$$

Inequality (2) represents that the maximum number of drones assigned to charging station i is no greater than LoC_i . Equation (3) indicates that a drone is only assigned to a single charging station.

III. Energy Expenditure Estimation using RNN

A. Introduction of RNN

RNN is a type of artificial neural network in which connections between nodes can form a cycle, allowing the output of some nodes to influence the input received by other nodes in the same network [17, 18]. This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable-length sequences of inputs. It can demonstrate temporal dynamic behavior because of this. RNNs can process input sequences with varying lengths by using their internal state (memory) [19, 20].

B. RNN-Based Energy Expenditure Estimation

To estimate the energy expenditure for drone i traveling to station j , e_{ij} , a drone will sample its states (e.g., motor speeds, battery power remaining, etc.) at particular intervals as it travels and stores the data into an array within its internal memory. When the drone decides to stop at a charging station, the drone will negotiate with its connected drones to find an optimal charge station by solving the LSAP problem described in Eqns. (1) to (3) in a distributed manner.

The historical data a drone has stored will be used to by a recurrent neural network (RNN), a type of neural network that can handle sequential data and inputs of varying lengths. RNNs can store information from previous inputs by maintaining crucial information to generate the following output of the sequence. Previous outputs are then used as inputs for the next step. Applications for RNNs are seen in handwriting recognition [21], sentence building [22], speech recognition [23, 24], and target trajectory prediction [25].

An RNN is a natural fit as the data collected by each drone is collected as a time series and behaves as sequential data. All requesting drones will also have historical data that varies in different lengths depending on how long the drone has already flown and the interval at which it samples its states. Similar to the drone sampling the remaining battery power at particular intervals, the RNN will determine the predicted energy expenditure for each interval until it reaches the destination. The sum of the energy for each interval will be the total amount of energy necessary for the remainder of the drone's flight. The predicted needed energy will be an input for the proposed task allocation algorithm to be presented in the next section.

The work will utilize the data set developed in [26], which contains nearly eleven hours of flight time and covers approximately 65 kilometers of flight distance using the DJI Matrice 100 quadcopter. The drone flies the same triangular pattern for all 201 flights and utilizes onboard sensors, including GPS, IMU, voltage and current sensors, and an ultrasonic anemometer, to collect accurate data regarding states, power consumption, and wind speeds. Rodrigues et al. [26] used different combinations of payload weights (0g, 250g, and 500g), velocities (4 m/s, 6 m/s, 8 m/s, 10 m/s, and 12 m/s), and cruise altitude (25m, 50m, 75m, 100m) for each flight to allow for varying operational parameters. We believe the data set fits the need of the project as it implements package delivery and contains data needed to estimate EPM. The data set does not contain values for EPM but contains all the elements necessary to calculate the EPM. Equation (4) is used to calculate the EPM for each time step.

$$EPM = \frac{voltage * current}{velocity} \quad (4)$$

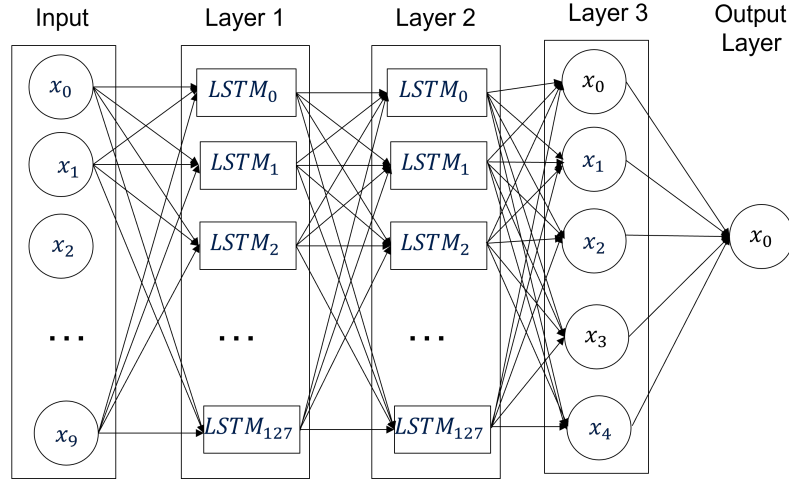
Historical data on a drone's flight is valuable when predicting future behaviors and state information. Therefore, we take recent flight information as a sequence and train a neural network to predict the EPM. The neural network for the project is designed around the RNN, which has the advantage of utilizing data sequences. The RNN contains multiple Long Short-Term Memory (LSTM) cells that can maintain only relevant information to make predictions. Our neural network is a five-layer network that takes in ten variables for the last fifteen timesteps. Table 1 shows the input variables for the RNN. The middle layers of the network consist of two LSTM layers, each containing 128 cells, and one dense layer with five neurons. The output layer predicts the EPM for the given future time step. Figure 1 shows the network architecture.

IV. Distributed Limited Resource Allocation Algorithm (DLRAA)

The proposed DLRAA is based on the well-known Hungarian method and a heuristic strategy to handle resource constraints. We will first introduce the Hungarian algorithm and present the new Hungarian-based heuristic assignment algorithm to handle resource constraints.

Table 1 Neural Network Input Variables for Energy Prediction

Variable	Unit
Wind Speed	m/s
Wind Angle	deg
Position x	m
Position y	m
Position z	m
Roll	deg
Pitch	deg
Yaw	deg
Velocity Magnitude	m/s
Linear Acceleration Magnitude	m/s^2

**Fig. 1 Network Architecture for Proposed RNN.**

A. Hungarian Method

Kuhn [27] presented the Hungarian method, as summarized in Algorithm 1, to solve the assignment problem where the number of agents is equal to the number of tasks. It is proven that the Hungarian method provides an optimal solution in polynomial time. The Hungarian algorithm performs using a cost matrix, $C \triangleq [c_{ij}]$, and the assignment process can be interpreted as a procedure for solving a maximum-weight matching problem where the cost matrix, C , is manipulated iteratively to obtain an assignment with the minimal global cost. To achieve this, the smallest entry in each row and each column of the cost matrix is subtracted from the other entries of each row and column, respectively. When a conflict takes place, i.e., two or more agents select the same task, Step 5 in Algorithm 1 is applied to find the smallest entry of each row to resolve the conflict. This process is repeated until a conflict-free assignment is obtained. Note that Algorithm 1 is a deterministic process in the sense that given the same cost matrix, C , it always produces the same assignment X and resulting $Cost$.

B. Hungarian-Based DLRAA (HBDLRAA)

Following the problem formulation in Section II, we propose a heuristic method to solve this constrained multi-task allocation problem described in Eqns. (1) to (3). We first define the cloned station set and the pseudo drone as follows.

Definition 1 (Cloned station). A *cloned station* is a copy of a given drone station whose attributes (e.g., capacity, position, etc.) are the same as the given station.

Algorithm 1 Hungarian Algorithm [28]

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1. **Procedure** $(X, Cost) = \text{HUNGARIAN}(C)$ % Matrix C is an $n \times n$ cost matrix that can be computed using the attributes of agents and tasks; matrix X is the assignment matrix, and $Cost$ is the overall cost induced by using the assignment matrix X .
 2. Given the cost matrix, C :
 3. Step 1: Subtract the smallest entry in each row from all the entries of its row.
 4. Step 2: Subtract the smallest entry in each column from all the entries of its column.
 5. Step 3: Draw lines through appropriate rows and columns so that all the zero entries of C are covered and the minimum number of such lines is used.
 6. Step 4:
 7. **Procedure:** (T)est for optimality :
 8. **If** the minimum number of covering lines is n ,
 9. An optimal assignment of zeros is possible and the assignment is finished.
 10. **End If**
 11. **If** the minimum number of covering lines is less than n ,
 12. An optimal assignment is not yet possible. Proceed to Step 5.
 13. **End If**
 14. **End Procedure**
 15. Step 5: Determine the smallest entry not covered by any line. Subtract this entry from each uncovered row, and then add it to each covered column. Return to Step 3.
 16. **End Procedure**
 17. Return X and $Cost$.
 18. **End Procedure**
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Definition 2 (Pseudo drone). A *pseudo drone* is the drone whose cost to reach any station is infinite.

Definition 3 (Pseudo station). A *pseudo station* is the station of infinite cost for a drone to arrive at.

In this paper, the cost for a drone, j , to travel from its current location to a charging station, i , is defined as the energy expenditure, i.e., $c_{ij} = e_{ij}$, where $e_{ij} = \text{EPM}_j \cdot d_{ij}$. Symbol EPM_j is the energy per meter in units of J/m that is estimated by the proposed RNN method, and symbol d_{ij} is the distance between drone j and station i .

Algorithm 2 Hungarian-Based Distributed Limited Resource Allocation Algorithm (HBDLRRA)

For all charging stations in $\mathbb{S}_{c, N_c}$,

1. **Procedure:** $[X, Cost] = \text{HBDLRRA}(N_c, N_d, LoC)$
 2. Create $(LoC_k - 1), \forall k \in \mathbb{S}_{c, N_c}$, cloned stations for every charging station.
 3. Define $N_c^A \triangleq \sum_i^{N_c} LoC_i$ as the number of total original and cloned stations.
 4. **If** $N_c^A > N_d$
 5. Add $\beta = N_c^A - N_d$ pseudo drones.
 6. **End If**
 7. **If** $N_c^A < N_d$
 8. Add $\gamma = N_d - N_c^A$ pseudo stations.
 9. **End If**
 10. Build $N_c^A \times N_c^A$ cost matrix $C = [c_{ij}]$, where c_{ij} is the energy expenditure for drone j to travel to station i .
 11. $[X, Cost] = \text{HUNGARIAN}(C)$, where $X = [x_{ij}]$.
 12. **End Procedure**
-

The main novelty of the proposed HBDLRRA lies in how the limited resources, i.e., the limited number of drone spots in a charging station, in the cost matrix that is used by the Hungarian matrix. Algorithm 2 summarizes the main procedure of HBDLRRA. According to the limited spots of every charging station, cloned stations are created (line 2). Depending on the relationship between the number of total spots and the number of drones, pseudo drones and pseudo stations will be added to create a squared cost matrix (line 10) for the Hungarian algorithm (lines 4-9). The allocation result is generated by using the Hungarian algorithm (line 11).

It should be noted that when the number of drones is greater than the total number of spots, i.e., $N_d > N_c^A$, there

will remain $N_d - N_c^A$ drones assigned to pseudo stations. In this case, we assume that the HBDLRRA can be applied one more time to allocate the remaining drones to stations that will be served in the next time period.

V. Numerical Results

A. Results of Energy Expenditure Estimation using RNN

We trained the neural network with the stochastic gradient descent method called Adam with learning of 0.001. The learning rate is critical as it determines the step size taken toward the global/local minimum. A small learning rate takes smaller step sizes but increases the risk of falling into a local minimum. A more significant learning rate takes larger step sizes but increases the risk of overshooting the global minimum. The neural network also utilizes the sigmoid activation function for each perceptron, which outputs values between zero and one. We choose the sigmoid activation function as EPM can only be positive values. Another important hyperparameter is the lookback, which determines the number of previous time steps used to predict the next time step. We trained the neural network with a lookback of fifteen to provide the neural network with sufficient data to observe a pattern and predict the EPM for the next time step.

The neural network was trained for a total of 500 epochs. The training data included only level flight data where the altitude did not change for more than one meter. For each level flight portion, the first 70 percent of the data was used for training, while the last 30 percent was used for validating. EPM was calculated by dividing the product of the current and voltage by the three-dimensional instantaneous velocity vector.

The results show that the neural network can train a model to predict the necessary EPM for future time steps with relatively small errors. Figure 2 shows the network training for one particular data set.

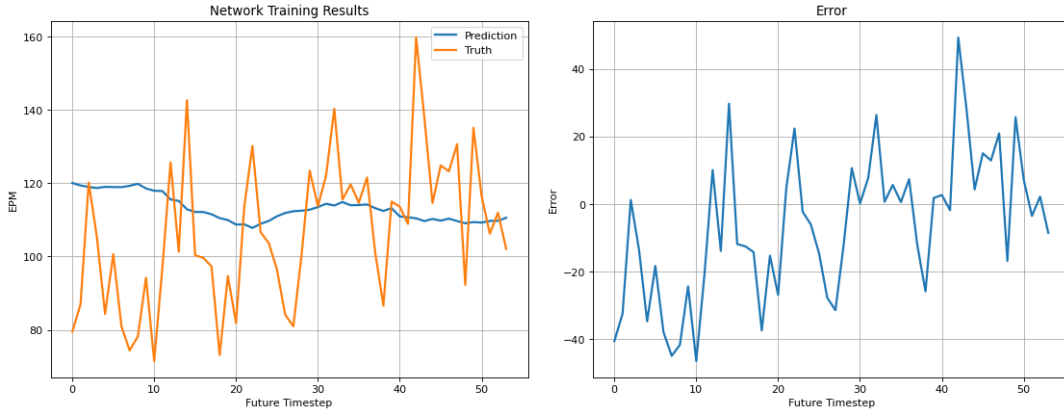


Fig. 2 RNN-predicted EPM values overlaying the true EPM values (left) and the prediction errors (right).

We observe a lot of variation within the EPM signal, which is credited to the sensors' noise and the UAV's instantaneous velocity. Figure 3 shows the current and voltage for the entire flight, while the velocity for an entire flight is also shown in Figure 4. We can see from the figures that there is much variation in the current, voltage, and velocity signals. Combining the variations in all three signals when calculating the EPM magnifies the variation observed in the actual signal of Figure 2. The predicted EPM in Figure 2 does not have considerable variation. However, the trained model shows promising results with the predicted EPM, as the predicted signal is roughly the average of the actual signal for the flight portion.

B. Result of Resource Allocation using DHBDLAA

In the simulation, we selected a representative scenario where five charge stations serve 10 drones. Every charging station has a limited number of spots. The allocation result is illustrated in Table 2 and Fig. 5. The EPM value is selected as $110 J/m$ based on the result in Fig. 2. Note that EPM values would be different for heterogeneous drones. Therefore, the energy cost will be reflected by both distance and EPM values.

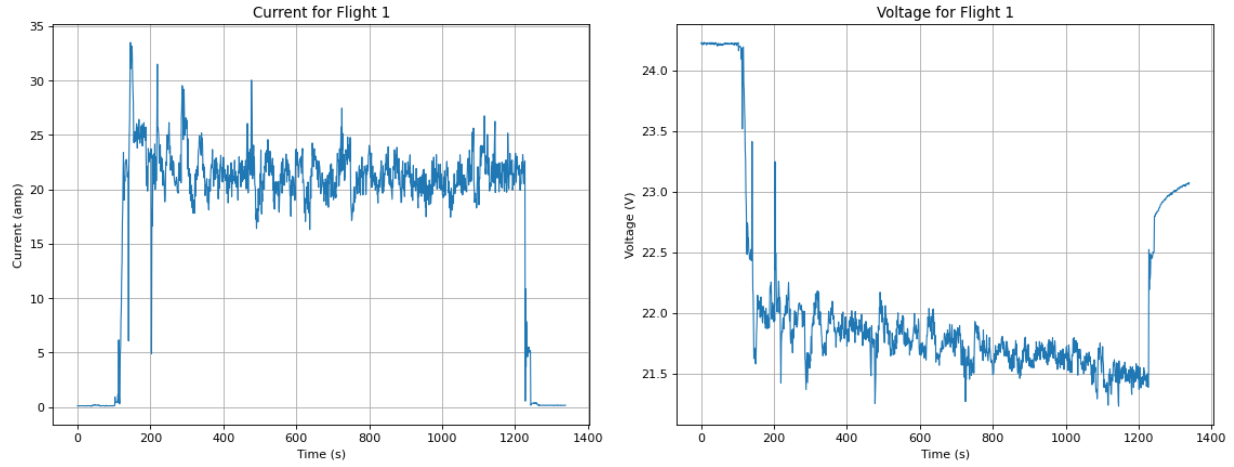


Fig. 3 Voltage and current evolution for a sample drone flight.

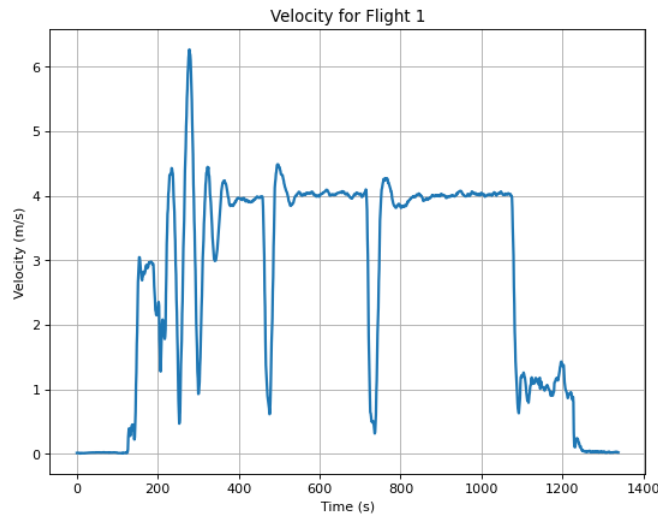


Fig. 4 Velocity evolution for a sample drone flight.

Table 2 Allocation Result of A Sample Case

Charging Stations	Max Drones Spots	Drone Allocation			
CS_1	3	D_3	D_7	D_{10}	
CS_2	4	D_2	D_6	D_9	D_{11}
CS_3	3	D_1			
CS_4	2	D_5	D_8		
CS_5	1	D_4			

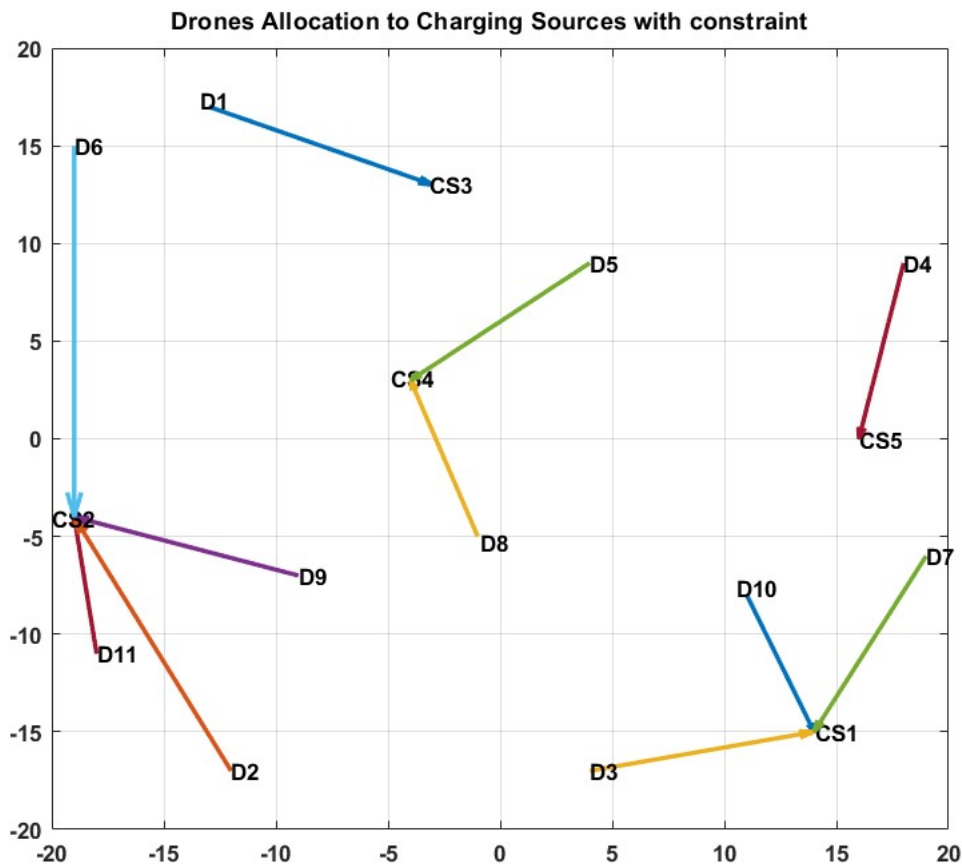


Fig. 5 Result of drone allocation to charging stations with constraint in a selected scenario.

VI. Conclusion

In this paper, we present a novel resource allocation method to minimize overall energy consumption for drone operations. The proposed Recurrent Neural network for energy consumption estimation shows a satisfactory estimation result given noisy flight data. The proposed allocation algorithm was implemented in a selected scenario and the result shows its effectiveness in generating the allocation while satisfying the constraints. In our future work, we will further test the performance of the proposed methods in various cases and compare them with relevant approaches.

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