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RESEARCH ARTICLE

# Intelligent Scheduling Algorithms for the Enhancement of Drone-Based Innovative Logistic Supply Chain Systems

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**ABSTRACT** The integration of advanced technologies such as artificial intelligence, the Internet of Things, and location-tracking technologies has revolutionized our daily lives by enhancing the functionality of logistical services. However, these advancements have also placed significant pressure on the current supply networks and have impeded further growth within the logistics industry. This article presents an inventive logistic supply chain solution utilizing drone-based delivery to tackle the logistic supply chain issues. The proposed solution goal is to minimize the maximum required time to finish all assigned delivery tasks. A set of sophisticated algorithms was developed based on the combination of dispatching rule, randomization, and iterative methods to optimize the performance of the supply chain processes and effectively accomplish the aim of time savings. The deployed system enables the management of a larger volume of shipments and increases the efficiency of logistic supply chain management. The experimental results demonstrate that the proposed algorithms can decrease the maximum duration required to complete the delivery operations assigned to the drones in 1520 cases. The algorithm that exhibited the highest level of performance was the *MID* algorithm, which attained a staggering percentage of 87.7%, an average deviation from the optimal solution of 0.001, and an execution time of 0.0215 s. Moreover, after comparing their outputs, the *MID* algorithm was determined to outperform the top two algorithms in the literature.

**INDEX TERMS** Algorithms, delivery, drones, logistics, monitoring, supply chain, path-select, optimization.

## I. INTRODUCTION

The logistics industry is progressively relying on drones as a transportation option in the future. Drones have the potential of several benefits in contrast to conventional means of order delivery [1]. These advantages include swiftness, dependability, confidentiality, and the capacity to surpass weather impediments such as blizzards and floods, topographical hindrances like harsh terrain, a dearth of roads, and immunity to traffic [2], [3]. Hence, the utilization of drone transport systems has the potential to shorten the delivery duration and improve the efficiency of logistical operations [4], [5], primarily in locations with high population density, traffic congestion, or inadequate

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infrastructure. Correspondingly, there has been an upsurge in the application of drones for supplying goods and rendering medical and emergency aids in such environments [6]. Advancements in drone technology and more cost-effective computing and manufacturing processes are driving greater utilization of drones [7], which in turn is leading to a transformation of how logistics operations are conducted.

This paper presents a modern logistics system that relies on drones as a basis for transportation, distribution, and supply operations. By utilizing drone services for modern logistics, a vast array of advantages is anticipated, such as decreased transportation expenses and time, thus resulting in a boost in profits. Moreover, it can enhance emergency services and medical supplies, thus preserving lives. The logistics sector can benefit from the proposed system, as it can improve response time when the availability of goods is limited, leading to increased efficiency. Moreover, there is room for enhancement in the caliber of services provided within modern logistics frameworks.

Logistics support firms worldwide are demonstrating a growing preference for distribution schemes that heavily depend on drones. These businesses utilize diverse techniques in their transportation logistics that hinge on drones. Some have developed completely automated logistics systems that exclusively rely on drones as their primary carrier [8], [9]. During these operations, the proposed system records a substantial volume of data to continuously monitor the shifts in drone movement and trace their routes. In [10], the researchers put forth various ideas to utilize the capabilities of fifth-generation communication technologies and guarantee seamless data transfer of massive volumes.

When managing logistics, time is crucial, particularly in transportation operations, logistical support, and deliveries. Saving time for the logistics support system provides greater flexibility to the subsystem responsible for transportation and deliveries to complete all assigned tasks accurately and effectively. Thus, this research aims to address the problem of scheduling delivery tasks assigned to drones to reduce the maximum completion time required to perform all assigned tasks. This research's primary objective is to use the latest technologies and reduce the response time needed to meet the requirements of a modern logistics system. Achieving this goal will provide more time for the system, increase its effectiveness, and contribute to reducing expenses and risks, enabling authorities and organizations to use drones optimally.

Additionally, recent global changes have revealed the inadequacy of traditional supply systems to keep pace with sudden changes in the work environment, especially if they are comprehensive, as illustrated during the recent earthquake that struck southern Turkey and northern Syria [11]. The earthquake has led to the destruction of infrastructure, including large parts of road networks, leaving authorities unable to use traditional means to provide essential and medical needs for those affected [12]. This disaster highlighted the importance of air transportation, especially drones, due to their ability to reach affected areas and provide necessary relief materials or medical supplies to those affected, regardless of their location, which was one of the decisive factors in saving dozens of affected individuals.

Finally, the objectives of this research are detailed as follows:

- Design a support system model based on a task generator to employ the developed algorithms in the scheduler.
- Presents a new mathematical model related to the studied problem based on the functional objective, minimizing the mission completion time.
- Developing a novel approach to solve the supply chain logistic delivery problem based on drones as the prime transportation means to optimize the drone-based supply chain logistics delivery.
- Many techniques were used to achieve the developed algorithms, including dispatching rule, randomization, iterative methods, and the minimum of some developed algorithms to generate new algorithms.
- Evaluate the performance of the developed algorithms experimentally by metrics inspired by literature using the provided instances.
- Provide metaheuristic-adaptable algorithms capable of supplying the required solution and attaining the desired goal in a tolerable execution time.

The rest of the paper is organized as follows. Section II provides a detailed discussion of the state-of-the-art regarding the presented problem. Section III presents the innovative logistic supply chain based on drones, including a figure describing an overview of the modern logistical support system. The mathematical modeling is presented in Section IV. Section V presents the proposed algorithms. The experimental results are discussed in Section VI. Finally, the conclusion is presented in Section VII.

## II. LITERATURE REVIEW

Recently, there has been considerable development and dramatic change in logistics operations, supply operations, and order delivery. Traditional approaches can no longer respond to the continuous changes and challenges that appear regularly. These changes result in high prices, delayed delivery times, failure to adapt to the rising demand and high competition with competitors in this industry.

Many researchers in this field have made fruitful efforts to address these challenges, as logistics systems have been developed and many previously unknown services and prospects have emerged, in addition to the availability and usability of drones in many fields and various applications. In continuation of these efforts, researchers in [8] presented a comprehensive survey of the literature that has been proposed so far in the design and modeling of logistics services for drone-based delivery systems to determine the levels of performance that can be achieved using the proposed approaches. Several research challenges related to drone-based parcel delivery systems were also discussed as well as the problems that need to be solved.

Many researchers proposed strategies and concepts to incorporate drones' abilities and technologies in logistical transportation to enhance supply operations. For example, the authors in [13] demonstrated a technique that combines many drones to build a larger drone capable of transporting heavier items. The researchers highlighted the problems and solutions that may be used to overcome the barriers of this technology and make it feasible to utilize it to contribute to the growth of the drone-based transportation industry.

Other solutions presented by [14], [15] and [16] suggested using a combined truck-drone structure, where the main routing part is performed by the truck while the drone performs the last mile delivery. A suggested solution for the Traveling Salesman Problem was developed by researchers in [17] to enhance the drone-truck routers while delivering and distributing packages to increase the efficiency of these systems. These methods allow access to more than one customer but require the presence of the required packages in advance on the truck. Appropriate infrastructure is also required, and challenging terrains or extreme weather conditions such as floods or accumulated snow cannot be handled by this solution, which may limit the ability of the truck to reach some customers. Despite these obstacles, this solution can be integrated with other solutions to bypass the previously mentioned limitations.

Many researchers have proven the feasibility of using drones as a reliable component, so the use of drones has spread in many sectors. For example, the authors in [18] presented drones as a potential transporter for biologic samples; their research concluded that while drones achieved modest gains for short-distance transportation, long-distance transport models with proper scheduling and sufficiently high drone speeds offer more promising time reductions. Additionally, the authors in [5] used drones equipped with smart capsules to introduce a verified method of transporting blood products, a method that is designed especially for an urban environment.

A development that would be contrary to what had been expected, the authors in [19], based on their findings, concluded that there is an inverse relationship between the level of perceived privacy risk and the intention to utilize drone delivery services. As the perceived risk increases, the willingness to adopt such services tends to decline. The inclination towards privacy directly impacts privacy concerns, while both privacy concerns and legal safeguards affect how much risk is perceived in terms of privacy. Additionally, the perceived level of usefulness has the most significant impact on consumers' inclination to embrace drone technology for delivery purposes.

The authors in [4] reviewed drone-based parcel delivery techniques. According to the authors, drones may be the ideal mode of delivery. However, the field is relatively new and requires more research to address various concerns, including determining priority for fulfilling customer requests. What is the most efficient course for drones to follow when there are no consumers to attend, and how can drone delivery schedules be refined to create a planned cost-efficient route.

The increasing intricacy of logistics operations and the requirement to manage a lengthy and dispersed chain, which can even extend to the final stages of production, underscores the challenge of effectively handling post-production stages of products and goods. Addressing these challenges prompted researchers to seek innovative solutions. For example, the authors in [20] presented a software architecture to model a smart warehouse model that can alleviate the problems of warehouse logistics to enhance efficiency and handle logistics chain complexity in warehouse logistics.

The aforementioned studies have demonstrated a variety of methods and approaches that utilize drone technologies to facilitate logistical supply objectives. Additionally, it was suggested that to fully utilize the proposed systems and attain the desired feasibility, particularly in terms of cost and transportation time, there is a necessity for a proficient scheduling mechanism. Drone scheduling algorithms are about the optimization of drone flight and can have other features, for example, determination of finishing time, use of drones, battery optimization, and battery recharging issues.

Scheduling for system optimization was presented by many researchers; for example, optimizing drones for maximum flying time durations was presented by the authors in [7], air ambulance optimization in [21] and computer networks optimizations in [22].

Therefore, this research introduces a supply chain control scheme that utilizes drones as the primary transporter, with the assistance of intelligent algorithms, to optimize the effectiveness of the proposed approach by reducing the overall task execution time. Additional tasks can be completed through the proposed system by utilizing the saved time, resulting in maximum benefits with no added infrastructure or cost. This approach ensures both the financial and technical feasibility of the proposed system. This research presents a set of algorithms to minimize the maximum completion time required by drones in any monitoring system to finish all given tasks regarding logistics task distribution. Several heuristics presented by [23], [24], [25], [26], and [27], [28] were used to develop the proposed algorithms.

In the literature, there is a lack of algorithms that can produce a good solution with low execution time, especially for hard instances such as those found in the supply chain and logistics domains. Moreover, to the best of our knowledge, there are now similar approaches in the literature that address the presented problem as solved by the supposed approach.

## III. INNOVATIVE LOGISTIC SUPPLY CHAIN BASED ON DRONES

A supply chain based on drones has been developed to manage the delivery of goods efficiently and effectively. The delivery process depletes valuable time and drone resources, particularly the flying time of the drone, which impacts the performance of the logistical system responsible for distributing goods to different areas within cities and jurisdictions. Therefore, careful management of drone resources will significantly impact the overall performance of the logistic system and generate several alternatives to reduce costs and improve system performance.

In this research, a modern logistics system is presented. The system relies on an intelligent interactive console working through a set of developed intelligent algorithms to reschedule tasks assigned to drones and reduce the total time required to complete all tasks. The new scheduling allocates more tasks in the same amount of time, thereby increasing the number of deliveries without incurring additional time costs. This system can also provide necessary data on the drone's flight from launch to arrival, which the algorithms presented in this research use to update the task scheduling processes and increase the efficiency of the logistics support system.

An overview of the general components of the modern logistical support system is shown in Figure 1.

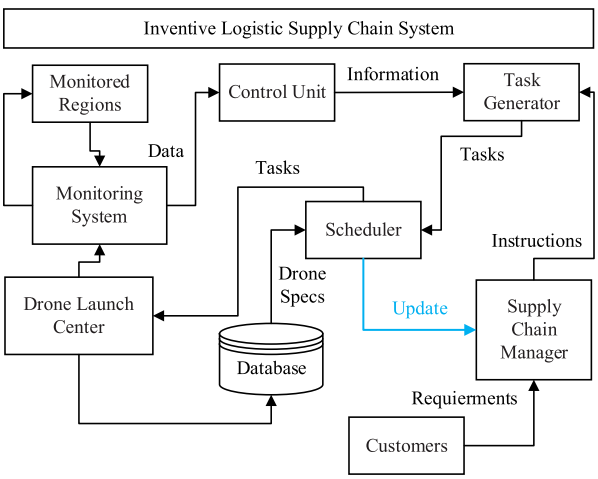


**FIGURE 1.** **Overview of the modern logistical support system.**

In the suggested approach, the monitoring system collects all necessary logistical data and transmits it to the control unit for processing. The resulting information has the details of all logistic requirements, the distance to be traveled, and the necessary data on the status and location of each drone. This information is sent to the task generator. The supply chain manager's instructions are employed in the task generator to map the provided information into distinct tasks. The scheduler receives the drone fleet's technical specifications, such as each drone's status, range, remaining flying time, the number of available drones, and any other required data needed to complete the assigned tasks without any problems or complications. In the scheduler, a group of intelligent algorithms utilizes these facts to assign the given tasks to optimize the use of the drone fleet.

In this model, the transportation and supply teams will amend the way they work according to the updates received from the relevant authorities, as the logistical transportation system benefits from the information received from the developed monitoring system to issue updated directives. The status of each request and each drone within the components of the transportation system is continuously updated, and this, in turn, updates the control unit data, thus updating the system information and then updating the instructions and directions issued to the transportation teams, which will lead to improving and accelerating delivery operations.

With the continuous flow of updated data, new tasks are generated for each monitored area to match the recent changes at all times, including updates within delivery operations. Each time a new task is submitted, the intelligent algorithms refresh the drone's available tasks to minimize the maximum total time required to finish all assigned tasks.

The novel aspects of the proposed approach are listed as follows:

- This study has never been studied in literature with the same objective function and constraints.
- Novel algorithms based on dispatching rule, randomization, and iterative methods were developed to solve the presented proven NP-hard problem. The presented methods were proven to generate the desired solution.
- Using drones as the principal carrier in logistical supply operations between a warehouse and distribution centers in the city's neighborhoods.
- A scheduler component that can enhance the supply chain logistic system forms the basis of a broad model. Integrating this model into the supply chain logistic system as an embedded system is possible by designing a hardware component, also known as the scheduler. This component can effectively utilize the developed algorithms to oversee and regulate the drone-powered delivery infrastructure. By incorporating this component, the system can initiate the use of the drone to fulfill necessary tasks and accomplish the desired enhancements autonomously, without any need for user involvement.

## IV. MATHEMATICAL MODELING

In the proposed system, many sub-distribution areas, referred to as "Regions" in this context, are established within each city as shown in Figure 2. The sub-distribution centers spread within the city are launched from the main distribution center by the drones. The distance between the main center and the sub-distribution centers is accurately known and saved in the data entered into the control unit. The missions are carried out by the drones from the main center to the sub-centers, and the sub-center to be visited by the drone is determined in advance based on the distance, flight time, and the type of parcels to be delivered. All of this data is saved in the control unit to be considered when tasks are assigned to the drones. Delivery tasks per region are assigned to drones within a limited time specified by the capabilities and technical specifications of the used drones.

The desired goal of the proposed system is not just assigning the required tasks to the available drones. Instead, the system aims to search for the best distribution that

**TABLE 1.** Summary of related work.

| Reference | Objective | Domain | Used Techniques | Outcome |
|---|---|---|---|---|
| [8] | To determine the levels of performance that can be achieved using the analyzed approaches. | Logistics drone-based models | Structured and scalable classification framework | A categorization to outline the parameters and simplify evaluating a diverse range of drone-based logistics schemes. Research gaps in the reviewed works. |
| [13] | To build a larger drone capable of transporting heavier items. | Drone-based transportation industry. | Mixed integer linear programming (MILP. Ruin-and-recreate metaheuristic with problem-tailored removal and insertion operators. | Combined drones (C-drone) to transport heavier items.. |
| [14] | To serve many customers and offer pickup and drone delivery services. | Combined truck-drone delivery services | Mixed-integer linear programming (MILP) Two-stage heuristic algorithm and simulated annealing algorithm. | Two-stage solution approach. |
| [15] | To present a cost-effective pickup and drone delivery service. | Combined truck-drone delivery services | Mixed integer-linear programming. An exact branch-and-cut with a heuristic. | A graph-based approach.. |
| [16] | To minimize the total cost and the value loss for perishable goods distribution. | Combined truck-drone delivery for perishable goods during epidemic. | Two-phase hybrid heuristic with K-means clustering. The extended Non-dominated Sorting Genetic Algorithm-II. | Delivery routes optimization model. |
| [18] | To save transporting of biologic samples time. | Drone-based biologic transport. | Comparable study with two ground distance models, urban model and rural district | A conceptual approach. |
| [5] | To validate urban areas drone-based delivery system equipped with a smart capsule blood products transportation. | Blood products drone-based delivery | Monitored smart capsule. Comparable study based on hemolytic tests. | Drone-based delivery system with a smart capsule. |
| [4] | To discuss the various suggested approaches' respective performance levels. | Logistics drone-based delivery systems | Reviewing studies on drone-based delivery logistic systems. | Highlights solutions and concepts of drone-based logistic delivery systems. Current issues with drone-based delivery methods. The expected new research avenues for drone-based package delivery systems. |
| [20] | to lead warehouse logistics to new levels of efficiency by solving warehouse environments problems | Warehouse management | Integrate machine learning and computer vision tasks into a complicated architecture for managing sophisticated logistical processes. | Smart warehouse model environment. |
| Our model | To minimize the maximum required time to finish all assigned delivery tasks. | Supply chain drone-based logistics delivery | Developed algorithms based on the combination of dispatching rule, randomization, and iterative methods. | Inventive drone-based logistic supply chain management system. Optimizing drone-based logistics supply chain. Managing a large fleet of drones. |

enables all the required tasks to be completed in less time. This combination is the solution to the presented problem, which the proposed system will achieve through a set of algorithms developed for this purpose. Additionally, this combination represents the maximum utilization and optimal management of all available resources. The presented

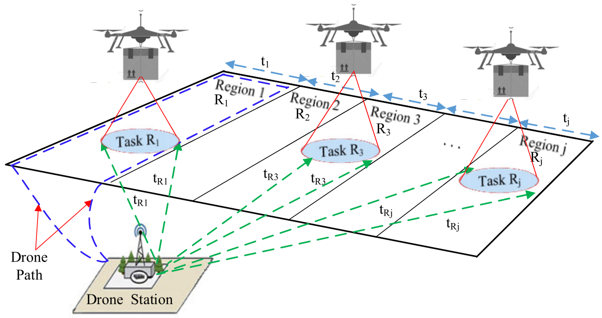


**FIGURE 2.** An overview of the drone controlling system.

problem is formulated as follows: drones are grouped at the drone station, identified as $DS$. Each drone is identified as $D_i$ $\forall i = \{1, \cdots, d\}$, where $d$ represents the total number of drones at $DS$. The concerned city is partitioned into equal regions, and each region is denoted by $R_j$ $\forall j = \{1, \cdots, r\}$, where $r$ is the total number of resulted regions.

Within the drone station, the distance between the launching points of each drone is negligible and assumed to be equal to zero. The flying time from any point within the drone station to any region $R_j$ is known as the going time and is denoted by $t_{R_j}$. The flying time from any region $R_j$ in the city to any point in the drone station is known as the returning time. In this context, the drone departure and return times are the same. The required time to finish the assigned tasks in any region $R_j$ is denoted by $tf_j$.

*Proposition 1:* The required time to move from any point at the drone station, complete the assigned task, and return to the drone station is detailed in Equation 1

$$mt_j = 2 \times t_{R_j} + tf_j \; \forall j = \{1, \cdots, r\}. \tag{1}$$

The time $mt_j$ will be known as mission time.

The cumulative time after finishing the assigned task in region $j$ by any drone is denoted by $M_j$. The calculation of $M_j$ will be as follows: $M_j = M_k + mt_j, \forall j = \{1, \cdots, r\}$, Where $k$ is the last region visited by the assigned drone. If region $j$ is the first region visited by the assigned drone, then $M_j = mt_j$. The time required by all drones to finish all the assigned tasks is known as the mission completion time and will be denoted by $Mc$ and will be calculated as described in Equation 2.

$$Mc = \max_{1 \le j \le r} M_j. \tag{2}$$

The completion time of each drone is denoted by $C_i$ $\forall i = \{1, \cdots, d\}$. The $Mc$ value described in Equation 2 can be written as detailed in Equation 3.

$$Mc = \max_{1 \le i \le d} C_i \tag{3}$$

This research aims to schedule the assigned tasks in the regions of interest within the city to minimize the maximum completion time $Mc$.

The mathematical model is formulated using the mixed-integer linear programming model. To derive the mixed-integer linear programming model, we introduce the binary variable $x_{ij}$ as follows:

$$x_{ij} : \begin{cases} 1 \text{ if region } R_j \text{ is scheduled to drone } D_i \\ 0 \text{ otherwise} \end{cases}$$

The mixed integer linear programming model related to the studied problem is described in Equation 4.

$$Minimize Mc \tag{4}$$

Subject to:

$$\sum_{i=1}^{d} x_{ij} = 1, \forall j \in \{1, \cdots, r\} \tag{5}$$

$$\sum_{j=1}^{r} mt_j x_{ij} \le Mc, \forall i \in \{1, \cdots, d\} \tag{6}$$

$$x_{ij} \in \{0, 1\}, \forall j \in \{1, \cdots, r\}, \forall i \in \{1, \cdots, d\} \tag{7}$$

$$Mc \ge 0 \tag{8}$$

The minimization of $Mc$ is the objective function that is described in Equation 4. While Equation 5, is the constraint related to the obligation of the assignment of any region $j$ to exactly one drone. The condition expressed in Equation 6 is related to the constraint of the total assigned time for each drone. Whereas the total scheduled region with time $mt_j$ for a drone $i$ is less or equal to $Mc$ for all regions. Equation 7 is the constraint that declares $x_{ij}$ as a binary variable. Finally, Equation 8 is the constraint that obliges the maximum completion time for all drones to be positive.

*Example 1:* Suppose a city is divided into nine regions that three drones will visit to perform specific tasks. Table 2 shows the total time to finish the assigned task of each region.

**TABLE 2.** The elapsed time required for each region in Example 1.

| j | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $mt_j$ | 41 | 33 | 28 | 22 | 31 | 36 | 18 | 42 | 52 |

Firstly, applying the shortest time algorithm to solve the problem. This algorithm prioritizes the region with the minimum mission time to be scheduled first. Figure 3 illustrates the resulting schedule after applying this algorithm.

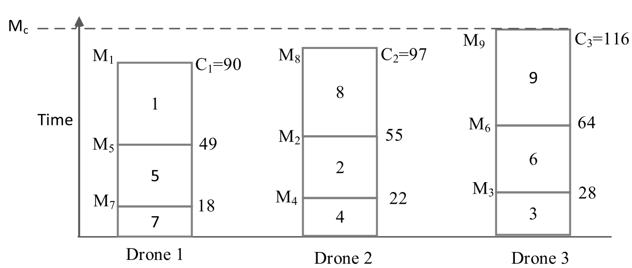


**FIGURE 3.** Schedule applying algorithm 1 for Example 1.

Figure 3 shows that drone $D_1$ visited regions 1, 5, and 7. While drone $D_2$ visited regions 2, 4, and 8. For drone

$D_3$, regions 3, 6, and 9 are visited. Consequently, the total completion time for $D_1$, $D_2$, and $D_3$ are 90, 97, and 116, respectively. Therefore $Mc = \max(90, 97, 116) = 116$. Now, apply another algorithm, the longest-time algorithm, to solve the same problem. This algorithm prioritizes the region with the maximum mission time to be scheduled first. Figure 4 illustrates the resulting schedule when applying the second algorithm.

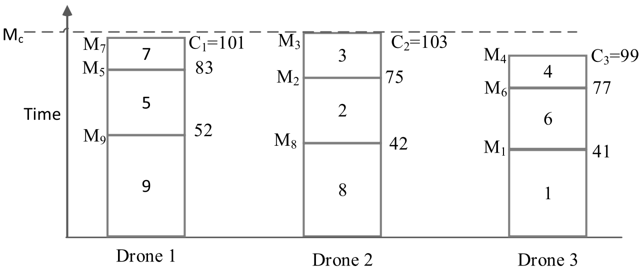


**FIGURE 4.** **Schedule applying algorithm 2 for Example 1.**

Figure 4 shows that drone $D_1$ has visited regions 5, 7, and 9. In comparison, drone $D_2$ visited regions 2, 3, and 8, and drone $D_3$ visited regions 1, 4, and 6. Consequently, the total completion time for $D_1$, $D_2$, and $D_3$ are 101, 103, and 99, respectively. Therefore $Mc = \max(101, 103, 99) = 103$.

The assumptions of the proposed approach are as follows:

- The drone's battery range is assumed to be sufficient to reach any region within the city.
- The drones are assumed to be identical.
- If a drone finishes its task, it will return to the drone station. If there is another task for the same drone in another region, then its setting preparation time is assumed to be negligible.

## V. PROPOSED ALGORITHMS

A set of six algorithms were proposed to solve the presented problem. These algorithms are based on the dispatching rule, randomization, and iterative methods. The combination of these methods gives a good result. It is noticed that there is no dominating algorithm among the given algorithms. To better enhance the obtained results, select the minimum of the two algorithms *IRR* and *DLR*, which will produce a new algorithm *MID*. While the minimum of *DLR* and *IRD* will create the algorithm *MDI*. The first thing to notice here is that the obtained results of *MID* will be better than *IRR* and *DLR* algorithms' results. The same notice applied for the results of *MDI* compared to *DLR* and *IRD* results.

### A. LONGEST COMPLETION TIME ALGORITHM (LCT)

This algorithm is based on the dispatching rule. The first step in this algorithm is to arrange the given tasks according to the non-increasing order of their mission time $mt_j$ values. Then, assign the region of interest to the drone that has the minimum completion time until the assigned tasks are finished.

### B. ITERATIVE RANDOM REGION ALGORITHM (IRR)

This algorithm has been developed based on the randomization method and is operational as follows. The first step involves classifying the concerned city into three types. For the first type, a monitored area is selected to be scheduled based on the region index. In contrast, for the second type, the selected area is scheduled based on the increasing order of their mission time. The scheduling of the third type is performed based on the non-increasing order of their mission time. For a certain type, any region from the set of given regions in the extent of the concerned city is randomly selected, and the selected area is assigned to the drone that has the minimum completion time. This process is iterated until all regions are assigned. This process is iterated many times. Therefore, the selection process is performed *lmt* times for each type. In this context, integers in the range of $x$ and $y$ will be derived by the function $RaM(x, y)$, while the function $AgN(j)$ will assign the area $j$ to the drone that has the minimum completion time. The function $InC()$ will sort the given regions in an increasing order based on their mission time, while $DeC()$ will sort the regions in a non-increasing order based on their mission time. The iteration number *lmt* for this algorithm is fixed experimentally at 1000. The name of this algorithm will be *IRR*. The detailed steps of the algorithm *IRR* are shown in Algorithm 1.

**Algorithm 1** Iterative Random Region Algorithm (*IRR*)

Initialize $kind = 1$
**for** ($kind = 1$ to 3) **do**
  **if** ($kind = 2$) **then**
    Call $InC(Re)$
  **else**
    **if** ($kind = 3$) **then**
      Call $DeC(Re)$
    **end if**
  **end if**
  **for** ($e = 1$ to $lmt$) **do**
    Set $st = r$
    **while** ($st \geq 1$) **do**
      Set $k = RaM(1, st)$
      Call $AgN(k)$
      Set $st = st - 1$
    **end while**
    Calculate $Mc^{e}_{kind}$
  **end for**
  Calculate $Mc_{kind} = \min\limits_{1 \leq e \leq lmt} Mc^{e}_{kind}$
**end for**
Calculate $Mc = \min\limits_{1 \leq kind \leq 3} Mc_{kind}$
Return $Mc$

### C. D-REGIONS WITH LCT AND RANDOM CHOICE ALGORITHM (DLR)

This algorithm is initiated by dividing monitored regions into two parts. The *LCT* algorithm schedules the first part, and the second part is scheduled randomly, i.e., any remaining regions are randomly selected. The preparation of the first part is performed based on multiplication by the number of drones, denoted by $D$ and referred to as the multiplier. For instance, the $LCT$ algorithm is applied to the first $2 \times d$ regions, and the rest of the regions are randomly selected and allocated to the drone with the minimum completion time. In this case, the multiplier $D$ is equal to 2. Afterward, the process is iterated $lmt$ times. The next step is to increase the multiplier $D$ to 3 and repeat the process, and so on, until $D \times d < 60$ and $D \times d < r$. This algorithm will be identified as $DLR$. The detailed steps of the algorithm $DLR$ are presented in Algorithm 3.

**Algorithm 2** D-Regions With $LCT$ and Random Choice Algorithm ($DLR$)

Set $D = 1$
Call $InC(Re)$
**while** $(D \times d < 60)$ **do**
  **for** ($e = 1$ to $lmt$) **do**
    Set $st = r, k = 1$
    **while** $(k \leq D \times d)$ **do**
      Call $Asg(j)$
      Set $st = st - 1$
      Set $k = k + 1$
    **end while**
    **while** $(rest \geq 1)$ **do**
      Set $k = RaM(1, st)$
      Call $AgN(k)$
      Set $st = st - 1$
    **end while**
    Calculate $Mc_D^e$
  **end for**
  Set $D = D + 1$
**end while**
Calculate $Mc_D = \min_{1 \leq e \leq lmt} Mc_D^e$
Calculate $Mc = \min_{D} Mc_D$
Return $Mc$

### D. ITERATIVE RANDOM DRONE CHOICE ALGORITHM (IRD)

The randomization method will be employed in this algorithm. The selection of the region to be assigned is randomly performed in this algorithm, and this step will be repeated until all regions are assigned. After that, the selection process will be repeated to choose drones randomly to generate a different schedule for each iteration. This algorithm will consist of three variants, namely, the selection of the region to be scheduled based on the region index, the selection of the region to be scheduled based on the increasing order of the region mission time, and the selection of the region to be scheduled based on the decreasing order of the region mission time. The best solution obtained will be returned after the execution of all these variants. In practice, the iteration loop is executed $lmt$ times. The complexity of $IRD$ is $O(n^2)$.

### E. MINIMUM IRR-DLR (MID)

This algorithm is derived after the execution of $IRR$ and $DLR$ algorithms. This algorithm's first step is executing $IRR$ and $DLR$. The second step is to return the minimum value among the results obtained from $IRR$ and $DLR$. The detailed steps are as follows: First, call the algorithms $IRR$ and $DLR$. The solutions returned by $IRR$ and $DLR$ are denoted by $Mc_{IRR}$ and $Mc_{DLR}$, respectively. The value returned by $MID$ is $Mc_{MID} = \min(Mc_{IRR}, Mc_{DLR})$. The functions $FCIRR()$ and $FCSDLR()$ implement the algorithms $IRR$ and $DLR$, respectively. The resulting $MID$ algorithm is described below.

**Algorithm 3** D-Regions With $LCT$ and Random Choice Algorithm ($DLR$)

Set $Mc_{IRR} = FCIRR(PK)$
Call $Mc_{DLR} = FCSDLR(PK)$
Calculate $Mc_{MID} = \min(Mc_{IRR}, Mc_{DLR})$
Return $Mc_{MID}$

### F. MINIMUM DLR-IRD (MDI)

This algorithm is derived after the execution of $DLR$ and $IRD$ algorithms. This algorithm's first step is executing $DLR$ and $IRD$. The second step is to return the minimum results among $DLR$ and $IRD$ obtained values. The detailed steps are performed as follows: First, call the algorithms $DLR$ and $IRD$. The $DLR$ and $IRD$ returned solutions are denoted by $Mc_{DLR}$ and $Mc_{IRD}$, respectively. The value returned by $MDI$ is $Mc_{MDI} = min(Mc_{DLR}, Mc_{IRD})$.

## VI. RESULTS AND DISCUSSION

This research implemented the developed algorithms using C++ on a Windows 10 operating system machine equipped with a Core i5 6200 CPU @ 2.30GHz 2.40 GHz, and 8.00 GB RAM. The Instances subsection shows that the generated instances are composed of four classes. Classes A and B are based on uniform distribution, while C and D are based on normal distribution. The subsection presents the metrics that will be used to assess the performance of the developed algorithms. The algorithms will be compared based on the average gap, percentage, and time calculations. The discussion subsection displays the overall results of the developed algorithms. After that, the obtained results when the number of drones $d$, number of regions $r$, and when the pair $(r, d)$ changes will be displayed.

### A. INSTANCES

The proposed algorithms performance evaluations require two types of distributions to generate the required instances. The first type is the uniform distribution, denoted by $U[]$, and the second is the normal distribution, denoted by $N[]$. Two classes of each distribution type are generated, each having a different method of generating $mt_j$. The required instances are generated using these four classes. These classes are described as follows:

- Class A: $U[20, 120]$.
- Class B: $U[65, 260]$.
- Class C: $N[80, 30]$.
- Class D: $N[100, 50]$.

The selected total number of regions $r$ and the total number of drones $d$ are shown in Table 2.

**TABLE 3.** Number of regions and drones choice.

| r | d |
|---|---|
| 7,10,13 | 2,3,4 |
| 18,22,26,30 | 2,3,4,5,8 |
| 50,100,250 | 10,15,20 |

In this context, ten different instances are generated for each class for each $r$ and $d$ value. Table 2 shows the total number of generated instances as $(3\times3+4\times5+3\times3)\times10\times4 = 1520$.

The data used in this work was inspired by the research presented by [29]

### B. METRICS

The below metrics are used for the performance evaluation of the developed algorithms.

- $\overline{M}$ the best $Mc$ the value returned after all algorithms are executed.
- $M$ the $Mc$ value returned when executing the studied algorithm.
- $gp = \frac{M-\overline{M}}{\overline{M}}$.
- $Ap$: the average $gp$ over instances.
- $Pe$ the percentage of instances when $M = \overline{M}$ is reached.
- *Time* the average running time of the algorithm. The time is calculated in seconds. The character "-" is denoted if the time is less than 0.0001 s.

### C. DISCUSSION

In this subsection, the performance results of the developed algorithms will be reviewed based on the presented assessment parameters. Table 4 displays the overall results of the developed algorithms. The results of the conducted study indicated that the algorithm that demonstrated the highest level of performance is the *MID* algorithm, as evidenced by its success rate of 87.7%, an average gap of 0.001, and an execution time of 0.0215 seconds. The *IRR* algorithm, possessing a success rate of 70.5%, an average gap of 0.004, and a runtime of 0.0110 seconds, emerges as the second most effective algorithm.

**TABLE 4.** Overall results for all algorithms.

| | LCT | IRR | DLR | IRD | MID | MDI |
|---|---|---|---|---|---|---|
| Pe | 24.5% | 70.5% | 48.5% | 27.9% | 87.7% | 56.4% |
| Ap | 0.021 | 0.004 | 0.006 | 0.064 | 0.001 | 0.004 |
| Time | 0.0000 | 0.0110 | 0.0105 | 0.0041 | 0.0215 | 0.0146 |

Table 5 presents the $Ap$ values for each number of regions $r$. For *MDI*, the minimum average gap of less than 0.001 is achieved when $r = 7$. As for *MID*, the minimum average gap of less than 0.001 is reached when $r$ takes the values of $\{7, 10, 13, 18, 22, 26, 30, 50\}$. The average gap is greater than 0.001 for only two values of $r = \{100, 150\}$. On the other hand, for *LCT* and *DLR*, the gap is always greater than or equal to 0.001 for all values of $r$.

**TABLE 5.** The *Ap* values for each number of regions *r*.

| r | LCT | IRR | DLR | IRD | MID | MDI |
|---|---|---|---|---|---|---|
| 7 | 0.026 | 0.000 | 0.007 | 0.000 | 0.000 | 0.000 |
| 10 | 0.032 | 0.000 | 0.010 | 0.004 | 0.000 | 0.002 |
| 13 | 0.046 | 0.000 | 0.010 | 0.007 | 0.000 | 0.003 |
| 18 | 0.024 | 0.002 | 0.006 | 0.032 | 0.000 | 0.005 |
| 22 | 0.028 | 0.004 | 0.009 | 0.019 | 0.000 | 0.005 |
| 26 | 0.030 | 0.001 | 0.007 | 0.032 | 0.000 | 0.006 |
| 30 | 0.009 | 0.001 | 0.002 | 0.029 | 0.000 | 0.002 |
| 50 | 0.012 | 0.015 | 0.003 | 0.243 | 0.000 | 0.003 |
| 100 | 0.001 | 0.017 | 0.010 | 0.214 | 0.009 | 0.010 |
| 250 | 0.002 | 0.005 | 0.005 | 0.133 | 0.004 | 0.005 |

Table 6 illustrates the $Ap$ values for each number of regions $d$. For *MDI*, the minimum average gap of less than 0.001 is reached when $d = 2$. While for *MID*, the minimum average gap of less than 0.001 is reached when $d = \{2, 3, 4, 5\}$. On the other hand, for *LCT* and *DLR*, the average gap is always greater than or equal to 0.001 for all values of $d$. The maximum average gap of 0.288 is obtained by *IRD* when $d = 20$.

**TABLE 6.** The *Ap* values for each number of drones *d*.

| d | LCT | IRR | DLR | IRD | MID | MDI |
|---|---|---|---|---|---|---|
| 2 | 0.012 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 |
| 3 | 0.029 | 0.000 | 0.006 | 0.004 | 0.000 | 0.002 |
| 4 | 0.033 | 0.000 | 0.008 | 0.015 | 0.000 | 0.005 |
| 5 | 0.033 | 0.002 | 0.007 | 0.038 | 0.000 | 0.007 |
| 8 | 0.031 | 0.009 | 0.013 | 0.078 | 0.001 | 0.008 |
| 10 | 0.000 | 0.010 | 0.003 | 0.125 | 0.003 | 0.003 |
| 15 | 0.009 | 0.008 | 0.005 | 0.177 | 0.002 | 0.005 |
| 20 | 0.005 | 0.020 | 0.010 | 0.288 | 0.008 | 0.010 |

Table 7 illustrates the *Time* values for each number of regions $r$. This table shows that the minimum time of less than 0.0001 s is reached for *LCT* when $r = \{7, 10, 13, 18, 26, 30, 50\}$. In comparison, the maximum time of 0.1235 s is reached for *MID* when $r = 250$. For the algorithm *MID*, the minimum execution time is 0.0021 s, which is reached when $r = 7$.

Figure 5 illustrates the fluctuations in the execution time when the parameters $r$ and $d$ are altered. Until an $r$ value of 25, the algorithms exhibit comparable execution times, however, the *MDI* algorithm outperforms other algorithms in terms of speed.

**TABLE 7.** The *time* values for each number of regions *r*.

| r | LCT | IRR | DLR | IRD | MID | MDI |
|---|---|---|---|---|---|---|
| 7 | 0.0000 | 0.0015 | 0.0005 | 0.0008 | 0.0021 | 0.0013 |
| 10 | 0.0000 | 0.0020 | 0.0011 | 0.0010 | 0.0031 | 0.0021 |
| 13 | 0.0000 | 0.0026 | 0.0022 | 0.0012 | 0.0048 | 0.0034 |
| 18 | 0.0000 | 0.0035 | 0.0039 | 0.0019 | 0.0074 | 0.0058 |
| 22 | 0.0008 | 0.0040 | 0.0049 | 0.0026 | 0.0084 | 0.0066 |
| 26 | 0.0000 | 0.0048 | 0.0065 | 0.0022 | 0.0113 | 0.0087 |
| 30 | 0.0000 | 0.0055 | 0.0086 | 0.0027 | 0.0141 | 0.0113 |
| 50 | 0.0000 | 0.0140 | 0.0082 | 0.0052 | 0.0222 | 0.0134 |
| 100 | 0.0001 | 0.0262 | 0.0221 | 0.0090 | 0.0483 | 0.0311 |
| 250 | 0.0001 | 0.0635 | 0.0600 | 0.0199 | 0.1235 | 0.0799 |

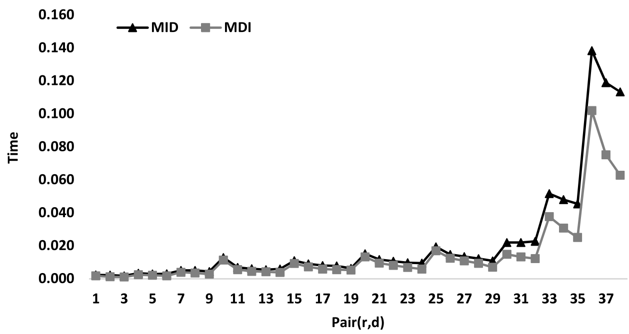


**FIGURE 5.** The time variation when the pair (*r*, *d*) changes.

### D. COMPARISON WITH RESULTS IN LITERATURE

This subsection discusses the best-proposed algorithm *MID* with the two best algorithms developed in [7]. These two algorithms are *IDST* and *RED*. Indeed, we coded the last algorithms developed in [7] over the 1520 instances generated in this paper and compared the obtained results. The minimum value of *Mc* returned after running all three algorithms *IDST*, *RED*, and *MID* is calculated and denoted by $Mc_{lit}$. The percentage of each algorithm is calculated based on $Mc_{lit}$. Table 8 presents the number of instances when the studied algorithm is equal to $Mc_{lit}$, the related percentage, and the related average gap. Table 8 shows that the proposed algorithm *MID* outperforms those in the literature in 76.4% of cases, with an average gap of 0.002. However, *IDST* reaches the best solution in 32.2% of cases with an average gap of 0.013, and *RED* reaches the best solution in 44.3% of cases with an average gap of 0.010.

**TABLE 8.** Comparison with results in literature.

| | IDST | RED | MID |
|---|---|---|---|
| Number | 490 | 673 | 1161 |
| Pe | 32.2% | 44.3% | 76.4% |
| AP | 0.013 | 0.010 | 0.002 |

## VII. CONCLUSION

The logistics concept has experienced notable modifications due to various factors, including technological advancements and external events such as epidemics, earthquakes, lockdowns, and precautionary protocols. These changes necessitated fresh and imaginative approaches to fulfill novel conditions. This research presented an innovative drone-based logistics supply chain system to upgrade the quality of logistics services. The improved response time and effective resource management offered by this innovative approach aim to overcome any existing challenges in the field. The proposed approach utilizes drones that follow precise instructions issued by the monitoring system to guarantee that they reach their target and complete the assigned tasks without any issues. The monitoring system uses the drones' captured data to determine the sequence of upcoming assignments, select the appropriate drones, and identify the regions to be visited next. The time factor plays a crucial role in determining the efficacy of logistics supply chain systems. The system's success crucially depends on various time-related factors like take-off, arrival time, delivery, and system update time, as well as recognizing upcoming tasks. In response to those challenges, this research offered an approach to minimize the maximum time required to finish all assigned tasks. Several algorithms were developed and experimentally evaluated using 1520 unique instances to minimize the maximum completion time required to complete all assigned tasks. The results demonstrated that the proposed method was highly successful in boosting the operational effectiveness of the supply chain logistics system. After comparing the *MID* algorithm to two top-performing algorithms in existing literature, it was revealed that the *MID* algorithm outperformed both.

The limitations of the proposed approach can be summarized as follows: The proposed approach does not provide an exact solution to the presented NP-hard problem. Only one objective was addressed in this context, and other objectives like battery life or power consumption were not considered. Moreover, more constraints, such as the battery charging state and the drone's technical specifications, like speed and range, were all assumed to be identical. Finally, for each region, this work assumed that only one drone could visit that region during a certain task. The performance evaluation of the developed algorithms for the proposed system was performed using only randomly generated data. The future work of this study is to collect actual data from logistics delivery institutions, specifically from drone-based deliveries, to highlight and measure the efficacy of drone-based models.

For future work, the developed algorithms can be adapted to solve problems in other domains, especially those interested in green applications, for example, green transportation and monitoring. Moreover, meta-heuristics and neighborhood search algorithms can be used to enhance the presented algorithms. Also, lower bound calculations may be used as the basis for performance measurements instead of comparing the results of algorithms with each other. Finally, branch and bound algorithms may be utilized to reach an exact solution to the developed algorithms for the presented problem.

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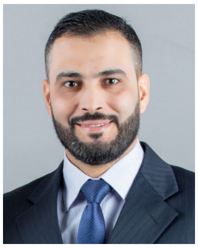

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