Modeling Drone Deliveries Using Petri Nets: An Evaluation on Collision Recovery and Energy Efficiency

Leonel Feitosa∓, Vandirleya Barbosa∓, Luis Guilherme Silva∓, Iure Fé∓,
Fabíola M. C. de Oliveira⋆, Luiz Fernando Bittencourt¶, Huber Flores§ and Francisco Airton Silva∓

***Abstract*— The growing adoption of drones for goods delivery has emerged as a potentially viable solution. By operating through aerial routes, drones significantly reduce delivery times and expand operational reach. However, covering large areas requires prolonged flights, leading to high battery consumption and an increased risk of collisions, particularly in densely populated regions. This study presents a Stochastic Petri Net model to evaluate drone performance, focusing on metrics such as utilization, delivery rate, mean mission time, and drop probability. Additionally, energy consumption and carbon footprint metrics were investigated to assess the environmental impact of drone operations. The model incorporates factors such as strategic recharging points and collision probability, providing insights into drone performance under high-demand scenarios.**

I. Introduction

In recent years, the adoption of drones for deliveries has revolutionized the logistics sector, offering solutions for transporting goods in commercial and hospital settings [1]. The global drone delivery market was valued at US$1.68 billion in 2023, with growth forecast to reach US$4.35 billions by 2027, driven primarily by the Asia-Pacific region (39%), followed by North America and Europe [2]. In addition to optimizing routes and delivery times, cooperative drones increase operational capacity, enabling greater efficiency in the distribution of packages and the management of large volumes [3]. In the commercial and hospital sectors, transporting goods by drones has shown potential to meet demands in hard-to-reach areas [4]. Simulation models, such as Stochastic Petri Nets, are used to predict the performance of these systems, considering factors such as delivery rate, drone utilization, and mean mission time. These tools allow not only the optimization of resource allocation but also the identification of operational bottlenecks, especially in densely populated regions with high demand.

Despite their promise, delivery drones can be expensive, ranging from a few thousand dollars to up to US$60,000, depending on characteristics such as size and payload capacity. Using sensors combined with neural networks, these drones are capable of avoiding obstacles with low resource consumption and navigating autonomously in environments with high obstacle density, corners, and dead ends without getting stuck or colliding. When considering using a set of drones to meet specific delivery demands, methods that allow evaluating their performance for capacity planning before acquisition are necessary to ensure more informed decisions.

Using drones in deliveries is reshaping logistics by offering cost reduction, faster transport, and access to remote areas. However, obstacles and unpredictable conditions in dense urban environments raise the risk of collisions. While some solutions lessen these risks, further improvement is necessary. Stochastic Petri Nets (SPNs) allow probabilistic modeling of drone performance, supporting analysis of demand handling and collision likelihood. Unlike Markov chains, SPNs intuitively represent concurrency and synchronization. This work employs SPNs to assess drone utilization and collision probability in continuous package deliveries.

This research proposes an SPN model to evaluate drone performance in delivery operations, considering factors such as recharge time, demand arrival rate, and collision probability. This approach combines delivery logistics, energy use, and failure recovery, unlike existing robotics models found in the literature. The model, with 23 transitions and 19 locations, represents real-world scenarios and explores the relationship between cooperative drone use and package deliveries. It evaluates several performance metrics, including utilization, delivery rate, average mission time, crash probability, energy consumption, and carbon footprint, providing a comprehensive view of drone operations.

We present related work in Section II. Section III describes the scenario, the proposed model and its metrics. In Section IV, we present the case studies with numerical results, analyzing the impact of variables such as the arrival rate of new deliveries and the probability of collision. Finally, Section VI presents the conclusions of the work and suggestions for future research.

II. Related Work

The use of drones for delivering goods has evolved considerably in recent years, driven by technological advances that allow for greater efficiency and safety in operations. Studies have explored different aspects of these deliveries. The study by [5] proposes a model to improve the distribution of medical supplies during public health emergencies, considering

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∓Leonel Feitosa, ∓Vandirleya Barbosa, ∓Luis Guilherme Silva, ∓Iure Fé are with Federal University of Piauí, Brazil {leonelfeitosa, vandirleya.barbosa, luis.e, iure.fe, faps}@ufpi.edu.br

⋆ Fabíola M. C. de Oliveira is with Federal University of ABC, São Paulo, Brazil fabiola.oliveira@ufabc.edu.br

¶ Luiz Fernando Bittencourt is with Unicamp, São Paulo, Brazil bit@ic.unicamp.br

§Huber Flores is with University of Tartu, Estonia huber.flores@ut.ee

constraints such as contactless delivery and drone capacity. The work by [6] seeks to optimize drone routing in simultaneous deliveries and collections, evaluating the impact of speed and battery on system efficiency. [7] analyze the sizing of the drone fleet and delivery time, highlighting the reduction in the time spent transporting medicines. However, these investigations do not explicitly consider the probability of collision between drones or the need to recharge, which are essential aspects to ensure the viability of continuous large-scale operations.

On the other hand, some research has explored these challenges, seeking solutions to improve delivery safety and autonomy. In the context of recharge, the study by [8] proposes a model to design transport networks for biomedical materials, optimizing the allocation of demand and the use of recharging stations without requiring significant reconfigurations. The work by [9] uses Petri Nets to simulate and evaluate delivery strategies, seeking to reduce time and operational costs. The study by [10] explores flight planning methods aimed at extending the autonomy of drones through distributed recharging stations. [11] analyze fleet optimization in direct deliveries of time-sensitive products, considering battery replacement under different operating conditions. In parallel, other research addresses collision prevention in air delivery services. The study by [12] evaluates three geometric approaches to mitigate risks in high-traffic spaces, allowing drones to dynamically adjust their trajectories in dense urban environments. Finally, the work by [13] proposes using Petri Nets for drones to monitor and evaluate the behavior of other drones at runtime, detecting deviations and ensuring greater precision in operations.

Table I summarizes the related works, highlighting the evaluated metrics, the methods used, and the consideration of essential aspects such as battery recharge and collision probability. In this context, this work stands out by simultaneously integrating delivery logistics, collision probability, and drone recharge into an SPN-based model. This modeling captures probabilistic interactions, allowing a more comprehensive analysis of complex operational scenarios. Another distinguishing feature is the dynamics of collisions and repairs, including the time to replace drones, an aspect absent in the analyzed works.

III. Proposed Modeling

This section presents the model developed to analyze drone performance in deliveries, describing the base scenario with charging points, the proposed SPN model, and the evaluation metrics.

A. Drone Delivery Scenario

Figure 1 presents the scenario of package delivery by drones. The drones are programmed to make deliveries, departing from the origin point (A) which can be a distribution center or a strategically located logistics base toward the destination (C), with an intermediate stop to recharge (B), inspired by the work of [8]. This intermediate point is selected considering factors such as proximity to the main route, the ability to serve multiple drones simultaneously, and safety, ensuring recharging without operational interruptions. During recharging, the drones are connected to automated stations that use drone charging technologies. After recharge, the drones resume their journey towards the final destination (C). Upon reaching the destination, the drones are recharged again, ready to return to the distribution center and begin a new mission.

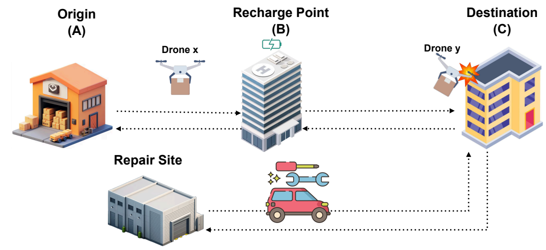


Fig. 1. Overview of drone package transportation scheme considering a recharge point and drone collision.

In addition to optimized routes and strategic recharging, the logistics are designed to deal with eventualities such as collisions with objects. A repair and maintenance team is immediately called to collect the crashed drone in collision situations. The repair involves a detailed analysis of the damage, which may include replacing parts, recalibrating sensors, or completely replacing the drone, depending on the extent of the problems identified. Crashed drones are taken to the technical analysis site, where a decision is made on whether to repair or discard them according to the criteria established in [14]. Combining optimized routes, strategic recharging, repair or replacement of drones in the event of a collision, and energy efficiency results in a fast and reliable delivery system [12].

B. Proposed SPN Model

The model was built and simulated using the Mercury tool (version 5.0.1) [15]. Figure 2 presents the proposed SPN model, in which all transitions are of the *infinite server semantics* type, that is, simultaneous *tokens* can be triggered while the transition in question is enabled [16]. The *tokens* represent resource units or system states and are used to describe the dynamics of the model, indicating, for example, the flow of packages or drones throughout the process steps. This type of modeling is widely used to capture the interaction between components in complex systems [17].

Figure 2 highlights the structure of the model, considering the architecture with battery recharge points and collision probability. The initial phase of the system refers to the reception of packages in the delivery system, in which `AD` (*Arrival Delay*) represents the interval between the arrivals of the packages for delivery. The place `PG` marks the point on the route where the delivery packages enter the system, and at the place `PQD` (marking C), the delivery drones wait in position. The activation of the transition `AB` indicates that the delivery drones have received the packages and are departing on a delivery mission, starting at `A0`. The drones recharge at transition `Charge1` before reaching the recharge

TABLE I

RELATED WORK.

Works	Metrics	Evaluation Method	Drone Recharging	Collision Probability
[5]	Travel time, service time	Mathematical Model	×	×
[8]	Number of trips, distance traveled	Mathematical Model	✓	×
[9]	Operation rate, delivery time, utilization rate of drones, total number of packages delivered	Petri Nets	✓	×
[6]	Energy, time, number of drones	Route Optimization Model	×	×
[13]	Real-time reliability	Petri Nets	×	✓
[7]	Response time	Experiment	×	×
[12]	Collision rate, mean travel time	Markov Chain Model and Simulation	×	✓
[10]	Total travel time, energy consumption, number of stops at charging stations	Mathematical Model and Simulation	✓	×
[11]	Number of battery replacements, number of drones, energy consumption	Mathematical Model and Simulation	✓	×
This work	MMT, drone utilization, delivery rate, energy consumption, carbon footprint	Stochastic Petri Net	✓	✓

point represented by place `B0`, which symbolizes arrival at destination B shown in Figure 1. After reaching point `B0`, the drones are ready to continue their journey at place `B1`, departing from B to C at transition `BC`, until they reach destination C at place `C0`. Upon arriving at `C0`, transition `Charge2` is triggered to begin recharging, preparing at place `C1` for the return journey. To begin the return journey, the `CB` transition directs the drones from origin C to destination B. At place `B1_R`, the drones reach destination B and recharge their batteries at transition `Charge1_R`. When the battery is charged, they prepare at place `B0_R` to continue the return journey, leaving origin B for destination A, as indicated by transition `BA`. Arrival at destination A (place `A0_R`) is marked by transition `Charge0`, where recharging occurs, and the drones wait in position at place `PQD` to begin a new mission.

During the mission process, collisions with fixed obstacles may occur. The probability of a collision occurring is modeled in the immediate transitions `TI1_C, TI2_C, TI3_C, TI4_C`. If a collision occurs, the *token* will proceed to place `PC`; otherwise, it will proceed through the immediate transitions `TI1_S, TI2_S, TI3_S, TI4_S`. The `TC` transition represents the time associated with the support team to locate the crashed drone and return to the evaluation site, which is reached when the *token* arrives at place `PA_1`. The beginning of the analysis is marked by the transition `TA`, after which the *token* (drone) can follow `TIR`, if repair is possible, or `TIS`, if the drone needs to be replaced by a new one. If the `token` follows `TIR`, it will arrive at the repair location at place `PR`, and then will go through transition `TR` until it is replaced in the fleet at `PQD`. If the `token` follows `TIS`, the drone will arrive at place `PS` and will wait a deterministic time associated with `TDS` before the replacement is carried out. Finally, it will be replaced in the drone fleet at place `PQD`.

From this modeling, metrics that describe the system operation can be obtained, such as mean mission time, drone utilization, and delivery rate. In addition, two other energy-related metrics were evaluated: energy consumed and carbon footprint, providing insight into the environmental impact of drone operations. These metrics help us understand the impact of different variables on the delivery process.

The mean response time (*MRT*) can be obtained from Little's Law [18]. The law indicates that the MRT is given by multiplying the number of requests within the system by the inter-arrival time (AD). In the model, the inter-arrival time resides in the transition named AD, located at the left end of the model. In this article, the requests are the drones, and we call the MRT the mean mission time (MMT). Thus, the number of elements in the system is the sum of the *tokens* in all the places where the drones pass. Since there is a single capacity place (PQD) in the presented model, this sum can be easily obtained by $C - EspPQD$, where C is the total number of drones and $EspPQD$ represents the expected number of *tokens* in the PQD place at that time. $EspPlaceName$ represents the statistical expectation of having *tokens* in "PlaceName," where $EspPlaceName = (\sum_{i=1}^{n} P(m(Place) = i)\times i)$, and n is the maximum number of *tokens* that the $Place$ can contain, where $P(m(Place) = i)$ denotes the probability of having exactly i tokens in that place, and $m(Place)$ is the marking function that returns the number of tokens in $Place$. In other words, $EspPlaceName$ indicates the expected value of *tokens* in that place at a given time or in steady-state conditions. Therefore, the equation corresponding to Little's Law for MMT used in our model is expressed in Equation 1:

$$\text{MMT} = (C - Esp\{PQD\}) \times AD. \tag{1}$$

The utilization of drones is the division of the expected number of *tokens* in a place through which the executed *tokens* pass by the respective total capacity. The mean processing utilization is given by Equation 2, noting that $C - EspPQD$ returns, for this model, the number of elements within the system:

$$\text{U} = \frac{C - Esp\{PQD\}}{C}. \tag{2}$$

The Delivery Rate (DR) is given by the sum of the throughput. The calculation of the throughput of a (place, transition) pair is given by dividing the expected number of *tokens* in that place ($Espplace$) by the time of that transition ($Ttransition$). Thus, DR is given by Equation 3:

$$\text{DR} = \frac{Esp\{B0\}}{T\{BC\}}. \tag{3}$$

Equation 4 presents the calculation of the Energy Consumed (EC) metric, which represents the total energy used by drones during the execution of a mission. The value is estimated based on the expected number of *tokens* in

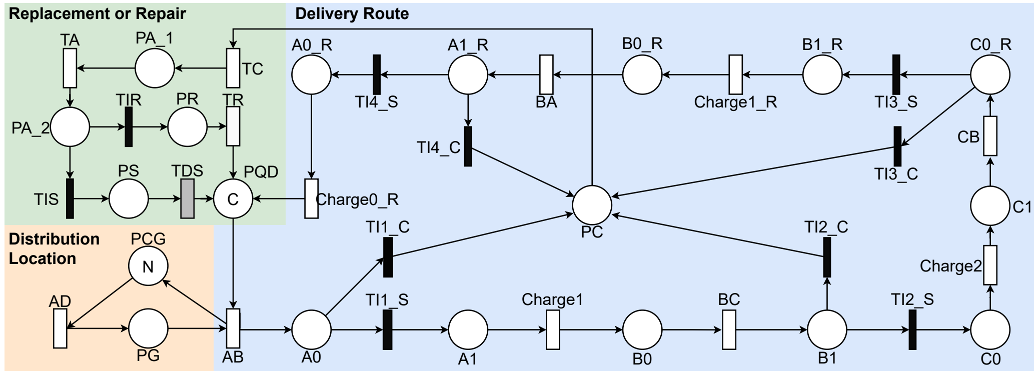


Fig. 2. Stochastic Petri Net (SPN) model to evaluate drone delivery logistics.

the model places that represent active states of the system, such as waypoints, recharging, and drone operation. This value is multiplied by $OP\_Drones = 0.08\,\text{MJ/km}$, which corresponds to the energy consumed by the drone while it is active, and by $TimeOP$, which represents the duration of the mission [19]. The resulting value expresses the total amount of energy consumed by the drones to complete a mission.

$$\text{EC} = \left(\left(\begin{array}{l} E\{A0\} + E\{A1\} + \\ E\{B0\} + E\{B1\} + \\ E\{C0\} + E\{C1\} + \\ E\{C0\_R\} + E\{B1\_R\} + \\ E\{B0\_R\} + E\{A1\_R\} + \\ E\{A0\_R\} + E\{PC\} + \\ E\{PA\_1\} + E\{PA\_2\} + \\ E\{PS\} + E\{PR\} \end{array} \right) \times OP\_Drones \right) \times TimeOP \tag{4}$$

The Carbon Footprint (CF) metric, presented in Equation 5, quantifies the environmental impact of energy consumption, considering the carbon emission factor (CEF):

$$\text{CF} = CEF \times EC. \tag{5}$$

CEF represents the amount of CO_2 equivalent emitted per unit of energy consumed. In the context of this work, which involves the operation of drones, the CF allows us to estimate the emissions associated with the electricity used during the missions. For Austria, a country whose energy matrix is mostly renewable, the CEF value is 0.0874 $kgCO_2$-eq/kWh [20], which is the value adopted in this study to calculate the carbon footprint of drone operations.

IV. Case Studies

This section presents the case studies that uses the proposed model. For the model parameters, we initially used the values shown in Table II for the transition times; these mean times were based on the article by [9] and companies that provide drone repair services [14], [21]. In the following case studies, the arrival rate is varied from 1 to 300 packages per hour for Figure 3. For the Collision Probability in Figure 3(d), AD was set at 0.2 packages/h and N as the number of packages to be delivered at 750. It is worth noting that these parameters are configurable and may be different for each reality depending on the type of drone, distances, among other parameters.

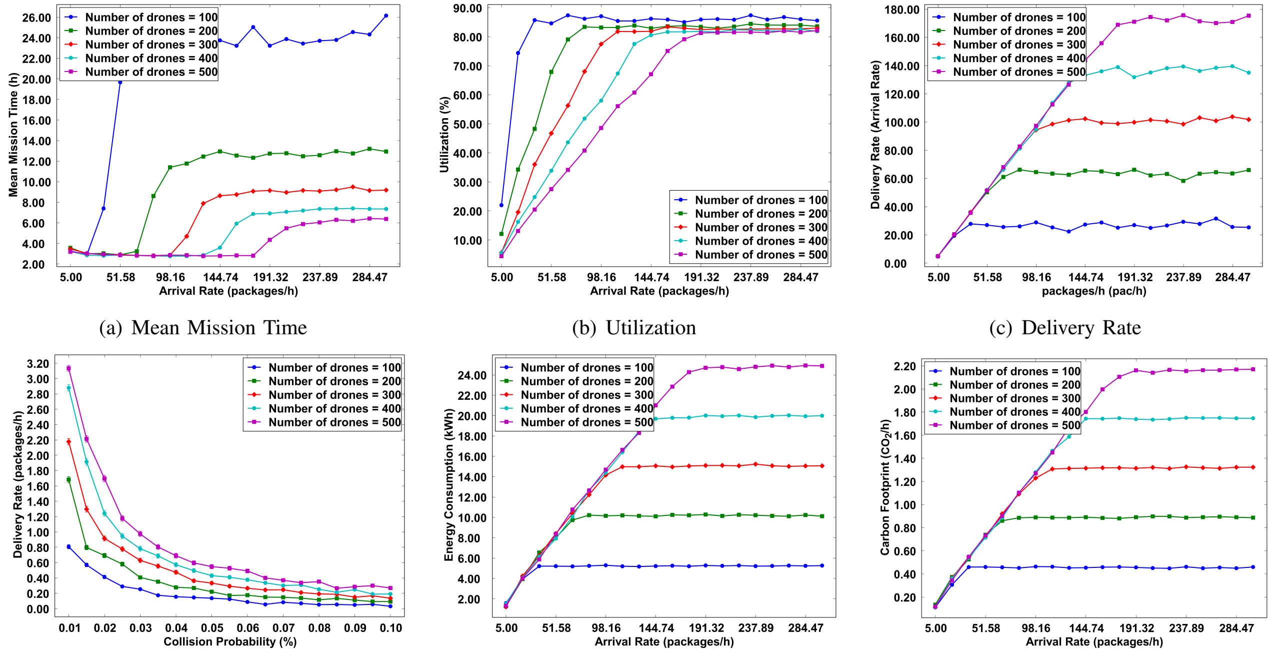
TABLE II
Parameters used to feed the model.

Components	Value (h)
Transportation time (AB, BC, CB, BA)	0.5
Battery recharge time (Charge1, Charge2, Charge1_R, Charge0_R)	0.16
Time to collect drone from crash site (TC)	8.0
Time to analyze drone (TA)	48.0
Time to repair drone (TR)	120.0
Time to replace drone (TDS)	0.5

Figure 3 presents the results of the analysis of the impact of varying the number of drones (100, 200, 300, 400, and 500) on different performance metrics, considering arrival rate and collision probability as variables. These values were based on the approach used by [22], who demonstrated the feasibility and applicability of different drone capacities in a *blockchain*-based delivery system.

Figure 3(a) shows the mean mission time (MMT) as a function of the arrival rate. The distance between the curves highlights that for 100 drones, the mean mission time exceeds 26 hours at higher arrival rates, while for 500 drones it remains around 6 hours. The sharp growth observed for 100 drones demonstrates limitations in processing capacity when the system is under pressure. For instance, at an intermediate arrival rate (around 164 packages/h), the configuration with 200 drones results in mission times of approximately 13 hours, while the configuration with 500 drones maintains MMT near 2.7 hours. At the initial rates, all configurations perform similarly, showing low and stable MMT values. Increasing the number of drones reduces mission time, since MMT grows primarily due to the accumulation of packages in the system at high arrival rates.

The results presented in Figure 3(b) show the utilization of drones as a function of the arrival rate. For 100 drones, utilization quickly reaches 85%, while 500 drones, for the same arrival rate below 50 packages/h, maintain values around 22%. The growth angle is less pronounced as the number of drones increases, indicating a more balanced system. For example, at 87 packages per hour, utilization is 85% for 100 drones and around 50% for 400 drones, showing a difference in performance. At lower rates, all configurations



(a) Mean Mission Time
(b) Utilization
(c) Delivery Rate
(d) Delivery Rate x Drones Collision Prob.
(e) Energy Consumption
(f) Carbon Footprint

Fig. 3. Performance results of the drone delivery system in different scenarios.

show low utilization, which indicates greater responsiveness to low demands. At higher rates, a stabilization is observed at high utilization.

Figure 3(c) shows the delivery rate as a function of the arrival rate. The distance between the lines reveals that the delivery rate for 100 drones is limited to approximately 28 packages/h, while 500 drones can deliver up to 175 packages/h. The growth angle is consistent and linear in configurations with higher capacity, while it is more irregular for smaller configurations. A notable point is that, at 144 packages/h, configurations with 400 drones reach 133 packages/h, compared to 65 packages/h for 200 drones. At the starting point, all configurations show equivalent delivery rates at low demands. In the end, configurations with 500 drones demonstrate superior delivery capacity compared to the others.

The results in Figure 3(d) show the relationship between the delivery rate (in packages per hour) and the collision probability. For lower probabilities, such as 1%, there is a clear difference between the scenarios: the rate reaches about 3.13 packages/h with 500 drones and only 0.81 packages/h with 100 drones. As the probability increases, all configurations show a decrease in performance. From 5% onwards, the curves begin to converge. At 10%, the values narrow to a range between 0.03 and 0.27 packages/h. This indicates that, as collisions become more frequent, the number of drones has less impact on the final delivery rate, limiting the system's ability to respond to demand.

Figure 3(e) shows the relationship between energy consumption (in kWh) and package arrival rate (packages/h). For the configuration with 100 drones, the lowest consumption is observed among the scenarios, with values that remain constant around 5.2 kWh. When doubling the fleet to 200 drones, consumption stabilizes around 10 kWh from 67 packages/h onward. With 300 drones, consumption increases slightly, reaching around 15 kWh and remaining stable at higher arrival rates. Scenarios with 400 and 500 drones present consumption levels of 20 kWh and 25 kWh, respectively. Although larger fleets provide greater delivery capacity and reduced mission times, this scalability comes with a higher energy cost.

Figure 3(f) shows the carbon footprint (in CO_2/h) as a function of the package arrival rate (packages/h). For the configuration with 100 drones, the carbon footprint remains below 0.5 CO_2/h throughout the entire analyzed interval, indicating more environmentally controlled consumption. When doubling the fleet to 200 drones, there is an increase, stabilizing at around 0.9 CO_2/h from 67 packages/h onward. With 300 drones, the values increase, remaining around 1.3 CO_2/h even as the arrival rate rises. For 400 drones, a more significant increase is observed, with values exceeding 1.7 CO_2/h and stabilizing around 1.8 CO_2/h. The configuration with 500 drones presents the highest carbon footprint, reaching around 2.2 CO_2/h under the heaviest load scenarios. Although larger fleets ensure superior performance and higher delivery rates, this comes with a proportionally greater environmental impact.

V. Discussion

Room for improvement is evident even though our work shows that drone delivery trajectories and processes can be effectively modeled using Petri nets. The modeling approach enables a structured and probabilistic representation of system behavior, including concurrency and synchronization, which are essential features in complex drone delivery systems. However, real-world deployment scenarios often involve variations in drone size, processing units, battery capacities, sensor technologies, and compliance with regional manufacturing standards. These differences can significantly affect performance metrics such as mission time, energy consumption, and delivery rate.

To address this, our model incorporates adjustable, technology-specific parameters, allowing it to be tailored to distinct drone types and operational constraints. This flexibility supports sensitivity analysis and comparative studies, helping researchers and practitioners understand how changes in hardware or software components may impact system behavior. For example, users can alter processing speed, battery efficiency, or collision tolerance in the model to simulate alternative configurations or evolving technological capabilities.

Drone swarms can also benefit from our method, which supports the simulation of multiple drones operating collaboratively in parallel missions. Future extensions may incorporate inter-drone communication and decentralized task allocation to support more realistic swarm-based delivery scenarios, such as task allocation, shared charging infrastructure, inter-drone communication, and more drones. By modeling diverse swarm formations and their interactions with environmental and logistical elements, it becomes possible to identify optimal configurations for distinct routes.

VI. Conclusion

In this work, we have proposed to use Stochastic Petri Nets to analyze the performance of drone delivery services. The developed model allows the evaluation of metrics such as mean mission time, drone utilization, package delivery rate, energy consumption, and carbon footprint. The presented model is configurable. The results confirm that the increase in the number of drones reduces delivery times and increases delivery rates. For example, in a scenario with 164 packages per hour and 200 drones, the MMT was reduced from nearly 14 hours to 2.7 hours by increasing the number of drones to 500, highlighting the importance of fleet planning. Larger fleets, however, also result in higher energy consumption and carbon footprint. Future work intends to incorporate evaluations using reliability metrics into the model, allowing for better analysis. A validation will also be carried out using a simulator to confirm the accuracy and applicability of the proposed model. Additionally, a sensitivity analysis will be conducted using Design of Experiments (DoE) to evaluate the influence of different parameters on the system's behavior.

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