Resilience Optimisation for Next Generation Drone Logistic Networks

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The paper will present a novel approach to the design optimisation of a resilient Drone Logistic Network (DLN) for the delivery of medical equipment. It is proposed a digital blueprint methodology that integrates Digital Twin (DT) models and optimisation tools, with the goal to optimise both the network topology and the delivery planning-scheduling over the defined network.
The DLN is a complex system being composed of a high number of different classes of drones and ground infrastructures which interconnections give rise to the whole network behaviour. Uncertainty, that comes in different forms, affects at different levels the subsystems and the whole network.
The paper will present the generative network optimisation which is the approach used to define, by design, the network topology and configuration that are optimal for the defined Key Performance Indicators. It will then focus on the operational optimisation problem which, for a predefined DLN, aims at determining the optimal drone's planning and scheduling considering also the uncertainty on the environment and the possible unexpected events.

Keywords: Digital Blueprint, Digital Twin, Physarum Optimisation, Drone Logistic Network, Vehicle Routing Problem, Complex System, Graph Theory, Resilience, Scheduling, Planning.

ACO Ant Colony Optimisation
DAE Differential Algebraic Equation
DLN Drone Logistic Network
DT Digital Twin
MH-PO Multi Headed Physarum Optimiser
MOP Multi-Objective Problem
NHS National Health Service
NOP Network Optimisation Problem
PSO Particle Swarm Optimisation
SoS System of Systems
UC Use Case
VRP Vehicle Routiong Problem

1. Introduction

During the last years more efforts has been spent on researching new solution for distributed healthcare network systems. Some experiments about medical delivery with the use of drones have already been done in the recent past. A trial near Rome by Leonardo and Telespazio Li et al. (2020) was completed in 25 minutes by drone while the road journey along the coast took of 45-60 minutes. In F. V. Daalen and Geerlings (2017) it has been established that below a tournaround time of 4 hours there are no negative effects on biological samples. Matternet Matternet (2020) announced in 2020 a collaboration with lab facilities in Berlin to transport patient samples from hospitals in

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Berlin by drone to lab facilities run by Labor Berlin. This is in addition to the flights Matternet have undertaken in Switzerland with Swiss Post, transporting laboratory samples between two hospitals. Microbiological specimens including blood cultures were transported by drone as a test in T. K. Amukele and Zhang (2016) and compared with stationary specimens to assess whether such specimens are affected by drone transport. For the microbes used in the trial no significant impact was found on the time to produce a positive result for the specimens flown for 30 minutes. Flight tests for medical delivery have been successfully conducted also in Spain Quintanilla García et al. (2021).

Working in this direction the UK government is currently investing in the realisation of an autonomous Drone Logistic Network (DLN) that allows the delivering of medical equipment and assistance to remote areas. The CAELUS project, financed by the UK Industrial Strategy Future Flight Challenge Fund, has the aim of further explore the use of drone delivery systems for the dispatching of medical items. This paper presents part of the results produced during the first project phase. The CAELUS' main goal is the realisation of a digital blueprint - a combination of a Digital Twin (DT) models of the complex network and a set of optimisation tools - of the DLN with a twofold applicability.

The first application of the digital blueprint corresponds to the design process of the whole DLN such to be optimal for the given key performance indicators as defined by the stakeholders. This task takes place in advance of the physical network construction and it is entirely performed in the virtual environment simulation. The design problem translates to a multi-objective generative network optimisation Gao et al. (2019) where the network is iteratively defined, simulated and improved. The indicators considered in this work are: capital costs of investment and operational cost of the delivery, delivery time and resilience under internal and external unexpected events. In particular, the resilience is considered as the ability of the whole network system to absorb negative and unpredictable events and recover after the failure.

For this generative network optimisation, a biologically-inspired methodology has been developed which extend the work proposed in Masi (2013). It is inspired by the behaviour of the by Physarum organism and it has shown to perform well in many engineering problems including network topology T. Nakagaki (2000) and Steiner tree problems A. Tero (2000).

The methodology includes two integrated steps: the generation of a sub-optimal delivery network that is progressively optimised and the simulation over the generated network of the drone delivery system. The former is a Network Optimisation Problem (NOP) while the latter, with the task of selecting the correct drones and finding the optimal routing and scheduling, can be classified as a Vehicle Routiong Problem (VRP).

The second task performed by the digital blueprint is the network operational problem: the on-line simulation of the DT during the actual operational life of the DLN and optimisation of its scheduling and planning. Once the physical network system is operative, sensor data can be collected from the physical systems and used to refine the DT models. The digital blueprint is used in this phase to simulate many possible scenarios affected by uncertainty in the medium-short period of time, and determine the optimal actions to take.

The paper will first present briefly the generative network optimisation problem and its algorithmic methodology, then the operational optimisation problem and its algorithmic solution. It will finally explain the application and the solutions presented.

2. Digital Twin Models

The DT models are one of the fundamental components of the digital blueprint. They are refined by real data flowing from the physical systems in the network and allow to simulate many possible scenarios without taking any risk on the physical infrastructures. For each one of the network components a corresponding DT has been developed while their integration gives rise to the DT of the whole network system. Even if the DT models are not presented in the current paper, they are however an integral part for the proposed methodology.

3. Generative Optimisation of a Logistic Network

The Generative Optimisation of a logistic network method integrates both NOP and VRP. The former component defines the network topology by choosing which nodes and links to use and all the discrete properties associated to them. This part refers to both ground and aerial infrastructures. The latter optimisation component instead simulates the whole DT system over the created network and defines the optimal planning and scheduling strategy for the items delivery together with all the optimal values of the continuous problem variables. Since multiple conflicting goals are considered the design methodology translates in the Multi-Objective Problem (MOP):

$$\begin{aligned} \text{minimise} \quad & \mathbf{f}(G, \mathbf{x}) = [f_1, f_2, ..., f_m]^T \\ \text{subject to} \quad & c_i(G, \mathbf{x}) \leq 0, \quad i = 1, ..., n \\ & \mathbf{x} \in \mathbb{X} \end{aligned} \tag{1}$$

where G is the set of all possible nodes and links that can be selected to generate the delivery network, $\mathbb{X} \subset \mathbb{R}^n$ the parameter space of mixed-integer variables, $m, n \in \mathbb{N}$, $m \geq 2$ and $\mathbb{Y} = \{\mathbf{f}(G, \mathbf{x}) \text{ s.t. } \mathbf{x} \in \mathbb{X}, g_j(G, \mathbf{x}) \leq 0, j = 1, ..., n\}$ the feasible objective space.

4. Multi-Headed Physarum Decision Making

The algorithm that has been developed to solve the Generative Optimisation problem is the Multi Headed Physarum Optimiser (MH-PO), a meta-heuristic approach based on multiple adapting populations that allow for combinatorial optimisation and discrete decision making. *Physarum Policefalum* is a single-celled multi-nucleate slime mould that in its *plasmodium* state is formed of a network of veins called *pseudopodia*. The organism presents interesting bio-intelligence behaviour that allows it to adapt and move in order to find sources of food or amicable environments. This capacity is made possible by the mechanisms of extension and retraction of the veins that are coupled with the flow of both chemical-physical signals and food nutrients. The algorithm belongs to the family of swarm intelligence methodologies that includes also Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) to whom it shows some similarity Hickey and Noriega (2008). A first work on the Physarum algorithm has been proposed in Masi (2013). The multi-headed extension and integration with the generative network optimisation will be published soon in a specific work.

5. Operational Optimisation: planning and Scheduling

The second problem application of the digital blueprint regards the actual operation of the DLN. Given a predefined network topology and set of terrestrial and areal infrastructures, the goal here is to decide the optimal planning and scheduling of drones over the DLN. The DLN can both be a virtual model as a result of the network optimisation problem or a physical and operative network system. The optimisation algorithm for planning and scheduling needs to be able to define optimal planning under nominal conditions, to consider also the effect of uncertainties on the system dynamics and finally to be able to overcome possible systems disruptions.

6. Planner

An agent-based model has been developed to simulate and understand the behaviour of the network infrastructures and the flying fleet of drones over the variation of internal and external conditions. A decision agent node has been implemented for the definition of the optimal network operations. It takes in input the on-line information on the operative network and on the delivery requests and defines as output the optimal drone scheduling by minimising the key performance indicators time-to-delivery and risk of the trajectory. In order to achieve this goal the ground infrastructure congestion dynamics over the DLN is also simulated.

7. Application - Network Optimisation

It is here described the practical application for the proposed generative optimisation methodology. The main goal is to design an optimal DLN for the delivery of medical items and assistance in the Scottish territory for the National Health Service (NHS). The results presented in the following refer to the delivery of biological samples from Hospitals to Microbiological Laboratories. This is a representative Use Cases (UCs) as identified in the preliminary phase of the project.

The list of ground infrastructures considered in the model includes: Hospitals (H), Laboratories (L), Airports (A), Charging Stations (CS) and Drone Ports (DP). H, L and A represent infrastructures already existing and functioning in Scotland while DP and CS are new infrastructures that could be created and for which new locations need to be identified. A set of drones with different properties and performances are also considered. The problem consists in the definition of the optimal network topology and combination of nodes properties in order to optimise the medical delivery where the nodes H represent the pick-up points and the L the delivery points of the nested VRP.

The optimisation problem is represented by the geographical map of the real Scottish ground infrastructures as plotted in Fig. 1. The map includes 13 H, 19 L, 3 A and 24 additional stations for which different types of ground infrastructures (CS or DP) can be selected.

7.1. *Optimisation Metrics*

Many key performance metrics have been identified. The three most important, in the following of the section, have been selected and included in the optimisation framework.

7.1.1. *Cost*

The cost estimation is decoupled in Capital Expenditures (CapEx) and Operational Expenditures (OpEx).

The former refers to the cost needed to acquire, upgrade, and maintain physical assets. CapEx refer to Hub infrastructure (airport, drone port) and new ground infrastructure Network Points (charg-

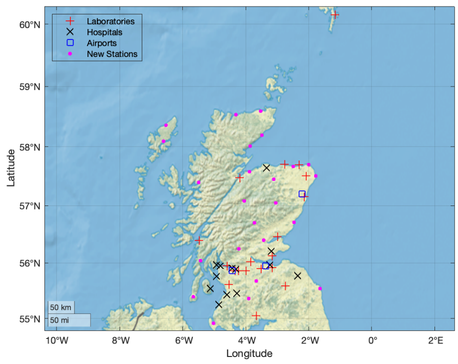

Fig. 1. DLN map of the ground infrastructures: 3 Airports (black square), 13 Hospitals (blue square), 19 Laboratories (green square) are given and 24 additional stations (blue points). DLN map stations, problem 1: map of the ground infrastructures.

ing points, short term stock holding, temperature control systems, data provision, communication with drones).

The latter instead, OpEx, depend on the time of flight for each drone and on man-hour required to operate the system.

for a station i

$$C^i_{CapEx} = C_{nominal}(1 + \delta_{capacity}) \quad (2)$$

7.1.2. *Time to Delivery*

Nominal time for the delivery per unit of delivered item in steady state conditions:

$$\text{KPI}_2 = \frac{T_{tot}}{X} \quad (3)$$

Time T_{tot} is the sum of preliminary process time, flight time between stations, process time through intermediate stations and analysis time at the lab for a single drone:

$$T_{tot} = T_{prep} + T_f + T_{inter-CS} + T_{analysis} \quad (4)$$

The preparation time consider the worst case between time for flight DP to H, and internal H transport/preparation of payload:

$$T_{prep} = \max(T_f^{\text{DP}\rightarrow H}, T^H_{transp/proc}) \quad (5)$$

The time of flight depends on the nominal path lenght and type of drone chosen (consider uncertainty on environment conditions):

$$T_f = \sum_{link-k} \frac{L_k}{v_{drone}} \tag{6}$$

Charging time and transport/processing of drones in intermediate stations is proportional to the number of drones transiting through the station (global quantity of the whole network) and inversely proportional to the CS capacity:

$$T_{inter-CS} \propto \frac{N_{drones}}{C} \tag{7}$$

The analysis time is proportional to the total volume of work of the selected laboratory (global quantity of the whole network):

$$T_{analysis} \propto V_{Lab,tot} \tag{8}$$

The total capacity of transported items X is

$$X = \frac{V_{items}}{C_d n} \tag{9}$$

with n the number of concurrently flying drones that is the minimum between the number of available drones $N_{d,tot}$ and the maximum capacity of the airline corridor $N_{max,link}$:

$$n = \min(N_{d,tot}, N_{max,link}) \tag{10}$$

7.1.3. *Resilience*

The resilience of a complex System of Systems (SoS) is considered to be the ability of the whole system to absorb shocks due to internal or external unexpected events, to evolve, to adapt and finally to recover functionalities totally or partially after the failures.

An explanatory example of the metric that has been adopted in the paper is presented in the following and it refers to Figs. 2 and 3. In particular, Fig. 2 represent a DLN were nodes (ground infrastructures) include 13 charging stations CH, 1 hospital H and 1 laboratory L while links refers to all feasible airways connections. Each station and airway is characterised by specific properties as defined by the resilience model presented below. The nominal flow of deliveries transits through the highlighted links in Fig. 2: H, CS-7, CS-10 and L. The flow quantification, normalised to 1, is plotted in Fig. 3 and refers to time below 100. We suppose, as in Fig. 2, that a failure happens at time $t_0 = 100$ which make CS-7 unusable. Fig. 2 shows that the DLN allows for a reorganisation of the delivery plan using station CS-12. The mission after the failure can still be accomplished but, as in Fig. 3, due to the longer trajectory required and to the different properties of the new selected station and links, the new flow is lower than the nominal one. Quantification of resilience is made restricting the analysis between the time instant when the failure happens, t_0, and the time instant when the system recovers (in this case only partially). For the failure of node i the resilience is calculated as:

$$R_i = \frac{\int_{t_0}^{t_r} Q_i(t)dt}{t_h - t_r} \tag{11}$$

where Q_i is the flow after the i-th failure. The global metrics is finally calculated by making each station fail and averaging all the results.

The resilience metrics is based on the dynamical flow analogy based on differential equations. Using the state-space approach, the system of mixed DAE is represented in matrix form by the *state equation* and the *output equation*:

$$\begin{aligned} \{\dot{p}(t)\} &= \left[\mathcal{A}\right] \cdot \{p(t)\} + \left[\mathcal{B}\right] \cdot \{u(t)\} \\ \{Q(t)\} &= \left[\mathcal{C}\right] \cdot \{p(t)\} + \left[\mathcal{D}\right] \cdot \{u(t)\} \end{aligned} \tag{12}$$

where the *state matrix* $\left[\mathcal{A}\right]$ can be calculated as:

$$\left[\mathcal{A}\right] = \left[\mathbf{C}\right]^{-1} \left[\mathbf{K}\right] \tag{13}$$

where $\left[\mathbf{C}\right]$ is the diagonal matrix of capacitance:

$$\mathbf{C} = \begin{bmatrix} C_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & C_{nn} \end{bmatrix} \tag{14}$$

calculated as

$$\mathbf{C} = \mathbf{I_c}\{c\} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \tag{15}$$

with $\mathbf{I_c}$ the identity matrix and $\{c\}$ the vector of capacitance of each node in the network, and $\left[\mathbf{K}\right]$ is the matrix of conductance:

$$\mathbf{K} = \begin{bmatrix} K_{11} & \cdots & K_{1n} \\ \vdots & \ddots & \vdots \\ K_{n1} & \cdots & K_{nn} \end{bmatrix} \tag{16}$$

calculated as:

$$\mathbf{K} = \mathbf{I_k}\{k\} = \begin{bmatrix} I^k_{11} & \cdots & I^k_{1n} \\ \vdots & \ddots & \vdots \\ I^k_{n1} & \cdots & I^k_{nn} \end{bmatrix} \begin{bmatrix} k_1 \\ \vdots \\ k_n \end{bmatrix} \tag{17}$$

with $\mathbf{I_k}$ the incidence matrix of order zero and $\{k\}$ the vector of conductance of each link in the network.

The *input matrix* $[B]$ is:

$$[\mathcal{B}] = \left[\mathbf{C}\right]^{-1} \left[\mathbf{U}\right] \tag{18}$$

where $\left[\mathbf{U}\right]$ represents the boundary conditions.

Once the vector of p is calculated, also the flow Q can be found by mass balance equations summarised in the second line of Eq. (12) that is the *output equation* with $[C]$ the output matrix and $[D]$ the direct transmission matrix and it allow to calculate the volumetric flow through the network.

In particular, in analogy with an hydraulic network, we consider for the generic i-th node (reservoir):

$$C_i = \frac{A_i}{9.81\rho_i} \tag{19}$$

with A_i the section and ρ_i the density.

With the same hydraulic analogy, the conductance for the generic i-th link (pipe) given by the Hagen-Poisuelle formula:

$$K_i = \frac{1}{R_i} = \frac{\pi r_i^4}{8\mu_i L_i} \tag{20}$$

Flows parameters related to nodes and links are considered to be variable with respect to the system conditions. Indeed, each node has a defined maximum capacity represented as the maximum pressure in the flow model $p_{i,max}$. When this threshold is reached the node (station) start to be saturated. This is modelled by varying ρ as

$$\rho_i = \begin{cases} \rho_{i,0} & \text{if } p_i \leq p_{i,max} \\ \rho_{i,0} M_i(p_i - p_{i,max}) & \text{if } p_i > p_{i,max} \end{cases} \tag{21}$$

when a further threshold is reached, $p_{i,MAX}$ the node fails.

An analogous approach is implemented for the links. A threshold capacity is given for each link ij. For a higher flow than $Q_{ij,max}$ the airways are congested, with a variation of the viscosity μ_{ij}

$$\mu_{ij} = \begin{cases} \mu_{ij,0} & \text{if } Q_{ij} \leq Q_{ij,max} \\ \mu_{ij,0} M_i(Q_{ij} - Q_{ij,max}) & \text{if } Q_{ij} > Q_{ij,max} \end{cases} \tag{22}$$

This allows to model the degradation of performance of stations (nodes) and airways (links) due to saturation and congestion and also the cascade of failures through the network system.

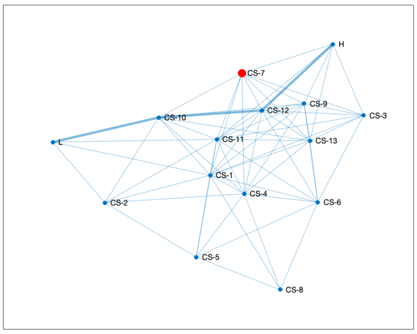

Fig. 2. Resilience metrics example. A charging station is consider unusable due to a failure. A new alternative trajectory is possible. It is highlighted between source H and sink L passing through CS-12 and CS-10.

8. Application - Operational Optimisation

It is here presented an application for the operational optimisation problem. The test case consists in the trajectory optimisation for an a intra-urban blood culture transport delivery in Edinburgh between Western General Hospital and Royal Infirmary of Edinburgh at Little France. A risk map is created based on the ground information on population density and avoiding areas and it is used to define the trade-off between the minimisation of the flight trajectory length and the associated risk of impact on the ground.

Uncertainty is also defined on the environmental conditions (wind speed and temperature) and

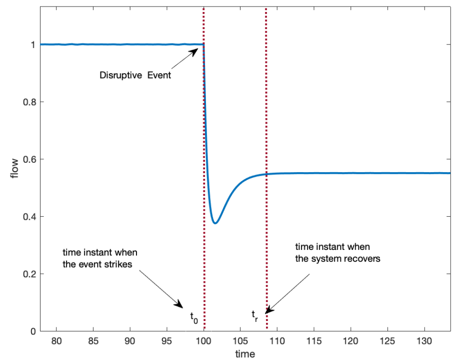

Fig. 3. Resilience metrics example. Normalised flow in the Logistic Network in Fig. 2 before and after failure of station CS-7. The network is able to absorb part of the shock and recover. The performance after the failure is however lower than in the nominal case. The resilience is calculated as in Eq. (11) as function of the area below the flow curve and the time distance $t_r - t_0$.

its propagation allows to identify robust trajectory plans against the impact risk on the ground.

A final test case is presented for the definition of the optimal planning over the whole DLN for an entire fleet of drones. It is here used the planner agent node which simulate the dynamics of the network and define the optimal planning and scheduling.

9. Results

Figs. 2 and 3 refers to the first optimisation problem: the generative network optimisation. In particular they explain the definition of resilience as it is defined and optimised: a network resilient solution is able to sustain possible node failures and continue to finalise the scheduled deliveries by adapting the scheduling and planning at the new network conditions. In particular, as in Fig. 3, resilience is a dynamic property.

Figs. 4 to 9 show instead the results for the second optimisation problem: the operational network optimisation.

The planner algorithm can solve the deterministic multi-objective optimisation for the flight trajectory. Fig. 4 shows the trade-off on the solutions between flight distance and risk on the ground impact.

The corresponding Pareto front of the solutions plotted in Fig. 4 is then presented in Fig. 5.

In Fig. 6 the uncertainty on the environment conditions is also considered and propagated through the models to quantify its effects on the performance indicators. This uncertainty quantification is used by the Planner optimisation algorithm to define robust solution on the optimal trajectory as in Fig. 7 where the different Pareto front are represented for different levels of threshold on the environment uncertainty.

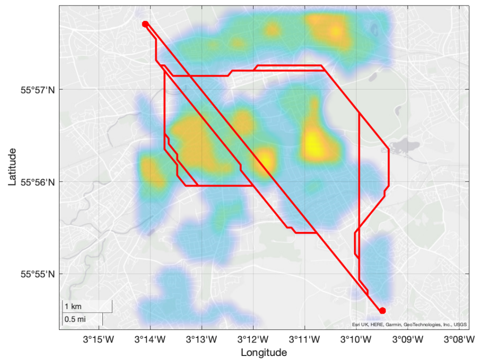

Fig. 4. Risk map over Edinburgh. Optimal trajectories between origin and destination that shows the trad-off between minimising distance and risk.

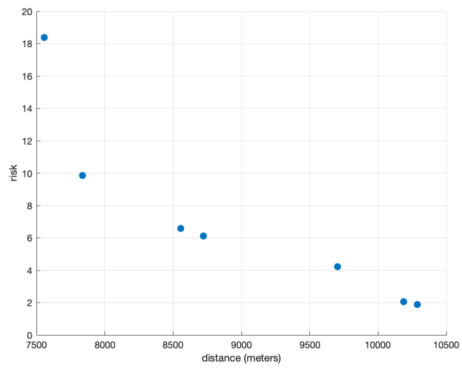

Fig. 5. Pareto front of solutions showing drone's trajectories' distance and risk.

Acknowledgement

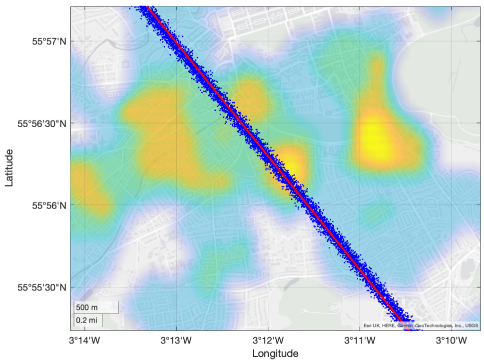

Fig. 6. uncertainty propagation of impact on the ground.

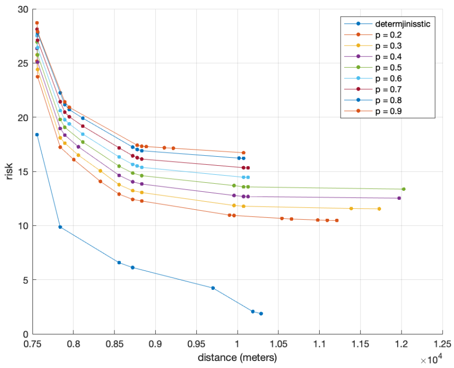

Fig. 7. pareto front distance vs risks for different levels of uncertainty

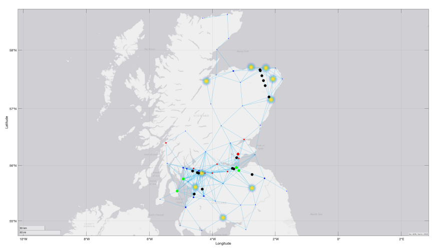

Fig. 8. visualisation of the Agent Based model simulation for the production of the optimal delivery plannings. Yellow points show terrestrial infrastructures that have failed.

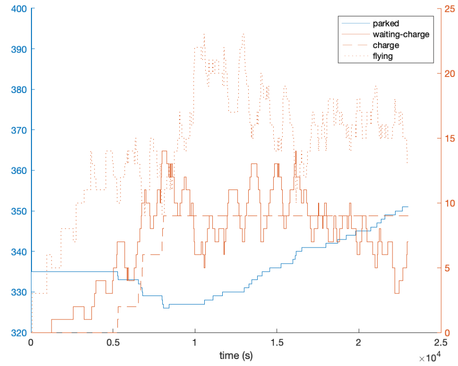

Fig. 9. time online evolution of network metrics.

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