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Generative Optimisation of Resilient Drone Logistic Networks

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***Abstract*—This paper presents a novel approach to the generative design optimisation of a resilient Drone Logistic Network (DLN) for the delivery of medical equipment in Scotland. A DLN is a complex system composed of a high number of different classes of drones and ground infrastructures. The corresponding DLN model is composed of a number of interconnected digital twins of each one of these infrastructures and vehicles, forming a single digital twin of the whole logistic network.**

The paper proposes a multi-agent bio-inspired optimisation approach based on the analogy with the Physarum Policefalum slime mould that incrementally generates and optimise the DLN. A graph theory methodology is also employed to evaluate the network resilience where random failures, and their cascade effect, are simulated. The different conflicting objectives are aggregated into a single global performance index by using Pascoletti-Serafini scalarisation.

***Index Terms*—Physarum Optimisation, Digital Twin, Drone Logistic Network, Vehicle Routing Problem, Complex System, Graph Theory, Resilience**

ACO Ant Colony Optimisation
CMOP Constraint Multi-Objective Problem
DAE Differential Algebraic Equation
DLN Drone Logistic Network
DLND Drone Logistic Network Design
DT Digital Twin
LRP Location-Routing Problem
KPI Key Performance Indicator
MH-PO Multi Headed Physarum Optimiser
MOO Multi-Objective Optimisation
NHS National Health Service
NOP Network Optimisation Problem
PSO Particle Swarm Optimisation
SoS System of Systems
TSP Travelling Salesman Problem
UC Use Case
VRP Vehicle Routiong Problem

This work is founded by the project CAELUS, UK Industrial Strategy Future Flight Challenge Fund

I. Introduction

It has been recognised in these last years (and the covid-19 pandemic increased the supporting evidence) that a distributed healthcare network can improve tremendously the efficacy and efficiency of our healthcare systems. Working in this direction the UK government is currently investing in the realisation of a autonomous Drone Logistic Network (DLN) that allows the delivering of medical equipment and assistance to remote areas.

Some experiments about medical delivery with the use of drones have already been done in the recent past. In Rwanda drones are used successfully for the delivery of blood from central storage facilities [1], [2]. In Baltimore trials are currently performed for delivering kidneys for transplants [3]. A trial near Rome by Leonardo and Telespazio [4] was completed in 25 minutes by drone while the road journey along the coast took of 45-60 minutes. In [5] the effect of drone transportation has been analysed on biological samples and it has been established that below a tournaround time of 4 hours there are no negative effects. Matternet [6] announced in 2020 a collaboration with lab facilities in Berlin to transport patient samples from hospitals in 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 [7] 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 [8]. In [9] there is an interesting study for the reliability of dreon delivery of authomatic external defibrillators that takes into consideration stochastic demands and meteorological conditions.

The work presented in this paper, as part of the CAELUS project financed by the UK Industrial Strategy Future Flight Challenge Fund, wants to do a further step. The goal is indeed to design and produce a whole DLN that is optimal from many Key Performance Indicators (KPIs). It is indeed required to minimise the capital costs of investment and the operational cost of the delivery, to allow fast areal routing, scheduling and planning and finally to design such a delivery network to be resilient under internal and external unexpected events.

As highlighted in [10] emerging attention of the research field is put on the development of approaches for the generation network optimisation since it is a difficult problem with a wide range of applicability. It has been furthermore recognised the importance of cross-fertilisation between engineering approaches and the biologic field that generated bio-intelligent systems through hundreds of thousand years of evolution.

Within the immense biological realm, in the last years researchers have focused their attention to the single multi-nucleate cells Physarum Polycephalum slime mould which shows an excellent intelligence in constructing biological network in the existing experiments, including the network topology [11] and Steiner tree problems [12].

We present then a Physarum-inspired network optimisation methodology that extend the work proposed in [13]. The algorithm is called Multi Headed Physarum Optimiser (MH-PO) since multiple cooperative Physaria are modelled and evolved during each generation.

The methodology includes two integrated approaches: 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 drone and finding the optimal routing and scheduling, can be classified as a Vehicle Routiong Problem (VRP).

The complex DLN system is modelled as a Digital Twin (DT): a virtual copy has been developed for each component of the physical system and their interconnection generates the DT of the whole system. Due to the computational cost of simulating the DT, a surrogate-based approach is implemented that improve the speed of the optimisation convergence.

The design problem translates in a Multi-Objective Optimisation (MOO) Problem since many KPIs are considered. A Pascoletti-Serafini scalarisation approach is implemented.

Particular attention is given in the paper to the quantification of the network resilience that is considered as the ability of the whole network system to absorb negative and unpredictable events and recover after the failure.

The remainder of the paper is organised as follows. First we give a definition of the Drone Logistic Network Design (DLND) problem and we briefly describe the generative approach. Second, we describe the improved MH-PO algorithm and its specificity for the generative optimisation method. Third, we describe the Use Case (UC) in section V and present the problem formulation and the optimisation metrics. Finally the conclusions are given based on the results.

II. Drone Logistic Network Design

The DLND is a type of Location-Routing Problem (LRP) [14] that aims to find simultaneously the optimal decision on the location of the DLN facilities and on the routing of the fleets of drones. The problem has an influence on the drone supply chain planning at three different levels of the organisation: strategic, tactical, and operational. From a strategic perspective, it deals with the decisions on the location of ground stations, their infrastructure types, the type and number of drones used in the network and the allocation of customers. The tactical decisions includes the transportation modes among stations and the allocation of drones to *depot*. Lastly, the operational-level decisions include the VRP for the fulfilment of customer demands. We propose here a generative optimisation approach for the solution of the DLND problem. The method, MH-PO, is indeed based on an iterative procedure that progressively define sub-optimal DLN, evaluate them and produce improved solutions. It is to be noticed that the total number of network's nodes and links is fixed in advance before starting the optimisation process. It is the optimisation task to select a sub-set of them o be used to generate the network. The links' costs are calculated on-line during the simulation and saved in memory. This can be particularly advantageous for high dimensional and/or high costly problems where only a sub-set of all the solutions is analysed by the optimiser and the remaining part of node combinations is not considered and simulated.

III. Multi-Headed Physarum Decision Making

The MH-PO is a meta-heuristic approach based on multiple adapting populations that allow for combinatorial optimisation and discrete decision making. 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 [15]. Physarum-inspired algorithms have however demonstrated to be particular promising and efficient in solving complex optimisation tasks. *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 with its phases and its workflow is summarised in algorithm 1 while the main algorithm's parameters are listed in table I.

A. Initialisation

First all the parameters defining the MH-PO in table I are defined (line 1 in algorithm 1).

B. Construction

The construction phase is repeated at each generation (lines 3-13 in algorithm 1) and it is used to define a sub-optimal DLN which will then be progressively improved through following generations. At each step of the construction, each agent evolves adding a single new link. Two alternatives methods are possible: ramification to an unexplored new link or movement in the already existing network. The choice is stochastic with a probability threshold $p_{ram,0}$ as in line 6. In the former case a set of new possibilities are evaluated and saved in memory while in the latter all the previously generated links that are feasible are considered. The flow through each of these veins ij is modelled with the Hagen-Poisuelle equation:

$$Q_{ij} = \frac{\pi r_{ij}^4}{8\mu} \frac{\Delta p_{ij}}{L_{ij}} \tag{1}$$

where r_{ij} is the vein radious, μ the dynamic viscosiy, L_{ij} is problem-specific heuristic that model the cost of the link and Δp the pressure gradient.

The flow matrix in eq. (1) is then used to decide where to move with a weighted roulette approach:

$$p_{ram,i-j} = \begin{cases} \frac{Q_{ij}}{\sum_{j \in N_i} Q_{ij}} & \text{if } j \in N_i \\ 0 & \text{if } j \notin N_i \end{cases} \tag{2}$$

The construction phase evolves a single head of the MH-PO for each *pick-up* station and defines the corresponding *delivery* one for the nested VRP.

The construction phase needs to satisfy a set of rules. Some of them are problem independent and correspond to generic settings of MH-PO: the maximum number of times a node can be visited by the same agent and the possibility to exclude a link if in a previous generation it resulted unfeasible. There are then some problem specific rules. The network needs to have directional links that connect *depots* to *pick-up* and *pick-up* to *deliveries*. *additional* stations can be included between the two end points, but the order (*depots*, *pick-up*, *deliveries*) has to be satisfied. A constraint on the link is also considered and it refers to the energy limit given by the battery.

Finally, the termination criterion is achieved when all pick-up stations are connected to a delivery one. At this point the Physaria construction of the current agent can be stopped (line 5 in algorithm 1).

C. Matching criteria

During the construction phase or after the network has been finalised, a set of rules are implemented in order to match the different components of the agent.

D. Network Definition

Once the construction phase is terminated, the information collected during the optimisation process is used to generate the DLN. The network is defined by the selected nodes by the current Physarum's generation and by all the feasible links calculated up to this point. To be noticed that it is a multi-layer network where each type of drone corresponds to a single layer.

E. Global quantification

The network is used to quantify the global performance metrics of the Physarum's solution (line 16 of algorithm 1).

F. Vein's Update

As discussed in [13] two methods are used in the literature to model the flow through the Phsarum's veins: the fluid-style that is based on a mass-balance system equation and the ACO-style that is based on the analogy with ACO's pheromone deposition and evaporation. The latter has shown to outperform the former and is used in the current implementation.

Vein's extension and retraction happens through the dilation and evaporation processes. In particular, at the end of each k-th agent's evolution (lines 18-20) the Physarum's veins radii are dilated based on the formula:

$$\left.\frac{d}{dt} r_{ij}\right|_{\text{dilation}} = f\left(Q_{ij}\right) = m \frac{r_{ij}^{(k)}}{L_{tot}^{(k)}} \tag{3}$$

where m is the linear dilation coefficient and is fixed a priori.

After all agents have constructed their sub-optimal network the radii retraction is applied:

$$\left.\frac{d}{dt} r_{ij}\right|_{\text{contraction}} = -\rho r_{ij} \tag{4}$$

with ρ the evaporation coefficient.

Taking inspiration from the amoeba Dictyostelium discoideum (Dd) a dilation of the best solution is also included:

$$\left.\frac{d}{dt} r_{ij_{\text{best}}}\right|_{\text{elasticity}} = GF r_{ij_{\text{best}}} \tag{5}$$

where GF is the growth factor of the best chain of veins and $r_{ij_{\text{best}}}$ the best vein's radii.

G. Restart mechanism

To avoid stagnation on local minima, a restarting criterion is implemented on the value of all the vein's radii and applied when a fixed a-priori percentage of agents at the current generation converges to the same solution:

$$r_{ij} = \mathcal{R}(r_{ij}) = r_0 \tag{6}$$

TABLE I: Optimiser parameters

symbol	explanation
r_0	starting radius
m	linear dilation coefficient
ρ	evaporation coefficient
GF	growth factor for best solution
GF_{graph}	growth factor from graph theory
N_{gen}	number of generations
N_{phys}	number of virtual physarum
N_{agents}	number of virtual agents
$p_{ram,0}$	initial probability of ramification
$p_{ram,\delta}$	reduction factor of probability of ramification
$p_{child,loc}$	probability of choosing a child from the same physarum
$p_{child,glo}$	probability of choosing a child from other physaria
λ	weight on ramification
$\vec{\omega}$	objective functions weight vector

Algorithm 1 Optimisation Algorithm

```
Initialise parameters in table I
for each generation do
    for each agent do
        while construction condition do
            for each active Physarum do
                if ν ∈ U(0,1) ≤ p_ram then
                    Create new decision path building missing
                    links and nodes for the selected physarum
                else
                    Move in the existing graph
                end if
                Update shared information
            end for
        end while
        Look for possible matching
        Define Drone Delivery network
        Calculate global metrics
        Update surrogate model
        Graph analysis of the generated network
        for each Physarum do
            Update veins with dilation
        end for
    end for
    for each Physarum do
        Update veins with evaporation and dilation of the best
        solution
    end for
    Check on minimum and maximum vein's radius
    if restart condition then
        Update all radii to r_0
    end if
end for
```

H. Surrogate-based approach

Since the DT is computationally expensive it is here proposed a surrogate-based approach. During the construction phase the lower fidelity but faster surrogate is used. Once the network is completed and the global metrics are evaluated, instead, the higher fidelity models are evaluated and the response surface is update.

IV. Algorithm Complexity

The MH-PO optimisation algorithm can solve the Travelling Salesman Problem (TSP), the VRP and their variants. These optimisation problems are NP-complete and an exhaustive search of their optimal solution suffers of the curse of dimensionality having a computational complexity greater than $\mathcal{O}(n!)$ with n the number of nodes. The Generative Optimisation Problem is even more computationally complex that TSP and VRP since both network topology and drone mission planning needs to be optimised. The global convergence of MH-PO on the generative problem can not be proved as for any other optimisation strategy in the literature. MH-PO is however complete. It is indeed based on a stochastic search on the parameter space that plays with the trade-off between exploration and exploitation. Probability on any possible decision is updated, increased or reduced, but it remain strictly positive for all the optimisation run allowing for any possible solution evaluation as the simulation time increase. The algorithmic complexity grows with $\mathcal{O}(n)$.

V. Application

Through a stakeholder engagement in CAELUS, four types of products for delivery applications have been identified as promising for the DLN: laboratory samples, blood products, chemotherapy and medicine delivery. We focus here on the delivery of biological samples from Hospitals to Microbiological Laboratories. Four types of ground facilities are considered in the problem: Hospitals (H), Laboratories (L), Airports (A) and New Facilities NF. H, L and A correspond to already existing facilities with a given location while for the NF a grid of possible new locations has been defined. Different types of infrastructures are included that can be coupled with the listed ground stations: Take-off and Landing Infrastructure (TL-I), Drone Charging Infrastructures (DC-I) and Drone Ports infrastructures (DP-I). Each one of these is given with different capacities. An heterogeneous fleet of drones is defined with different properties and performances.

The task of the DLND is to generate an optimal DLN that will autonomously and optimally deliver by drones the laboratory samples from H to A starting from *depots*.

VI. Problem Formulation

Given the list of ground facilities A, L, H and NF which sizes are respectively n_A, n_L, n_H and n_{NF} and the list of infrastructures that can be attached are also given, we define the ground stations as the combination of a ground facilities and one or more infrastructures. Four types of stations can be defined: *depot*, *pick-up*, *delivery* and *additional*. Nodes with facility A or with infrastructure DPI are classified as *depot*. Nodes with a facility H are *pick-up*. Nodes with a facility L are *delivery*. The remaining nodes are classified as *additional*. A node can assume more than one of these definitions: combination of L and DPI is indeed both a *delivery* and a *depot* node.

The DLN can now be represented as the network $G(N, L)$ where N is the set of all nodes (ground stations) and L the set of all feasible links (flight connections).

We define three KPIs that are used to drive the optimisation process: the total network cost C_{tot}, the total time to delivery T_{tot} and the network resilience R_{net}.

The optimisation solver deals with the following tasks: (i) to choose a subset of *depot*, *delivery* and *additional* nodes between the ones given in input, (ii) to define for each of the selected ground facilities its set of infrastructures, (iii) to define the heterogeneous fleet of drones specifying numbers and types, (iv) to assign drones to *depots*, (v) to calculate a set of optimal routes for the drone-based delivery.

The general formulation of the DLND can be described with the following Constraint Multi-Objective Problem (CMOP) formulation:

$$\begin{aligned} \text{minimise} \quad & \mathbf{f}(G, \mathbf{x}) = [C_{tot}, T_{tot}, R_{net}]^T \\ \text{subject to} \quad & c(G, \mathbf{x}) \leq 0 \\ & \mathbf{x} \in \mathbb{X} \end{aligned} \tag{7}$$

In eq. (7) G and $\mathbf{x}$ are the decision variables. The MH-PO defines at each generation a sub-graph $G_P(N_P, L_P)$ that is used o quantify the metrics T_{tot}, C_{tot} and R. $\mathbf{x} \in \mathbb{X} \subset \mathbb{R}^n$ is the vector of mixed-integer variables of the DTs. $\mathbf{f}$ is the vector of objective functions with C_{tot} the total network cost, T_{tot} the total time to delivery and R_{net} the network resilience. The mathematical formulations of C_{tot}, T_{tot} and R_{net} are presented in section VII. The constraint function c assure feasible scheduling of drones on the predefined DLN with regards to the battery's energy consumption. $\mathbb{Y} = \{\mathbf{f}(G, \mathbf{x})$ s.t. $\mathbf{x} \in \mathbb{X}$, $g_j(G, \mathbf{x}) \leq 0$, $j = 1, ..., n\}$ the feasible objective space.

$K_d = [1, 2, ..., n_d]$ number of total drones $\tau_d = [1, 2, ..., p]$ number of types of drones.

$K_s = [1, 2, ..., n_s]$ number of total station

$K_l = [1, 2, ..., n_l]$ number of total workers

A. Approach Novelty

The optimisation approach is used to solve the generative DLND problem: the methodology does not only optimise drone's planning, routing and scheduling, but also generate an optimal network, by defining stations and their locations, over which the delivery is performed.

During the generative optimisation phase many scenarios are considered and simulated. Solutions are saved in an archive and are used in the next generations of the MH-PO and as a benchmark for the operational phase of the DLN.

VII. Optimisation Metrics

This section presents the mathematical formulation of the KPI used in the optimisation problem. Different fidelity models have been developed to analyse the DLN. An Agent based model is coupled with the DTs of all the network's subsystems. Its fidelity depends on the fidelity of the used DTs. A flow model based on the analogy with the non-Newtonian flow has been developed to study the transient behaviour of the DLN. It is here used to quantify resilience. For the total cost and total time functions are here given the description of the lower fidelity models while it is left for a future publication the detailed description of all the developed models.

A. Network Cost

The cost model includes all the expenditures that are required for the construction (Capital Expenditures) and operation (Operational Expenditures) of the DLN. It is defined as the sum of fixed and variable costs. Fixed cost, that includes transportation and facility costs, is the sum of the costs for drones, stations, labor and the vehicle maintenance:

$$C_{fix} = \sum_{i \in K_d} c_{d,i} + c_{d,i}^m + \sum_{i \in K_s} c_{s,i} + \sum_{i \in K_L} c_{l,i} \tag{8}$$

where $c_{d,i}$ and $c_{d,i}^m$ are the cost of the i-th drone and its maintenance respectively, $c_{s,i}$ is the cost of the i-th station and $c_{l,i}$ is the cost of the i-th worker. In eq. (8), $c_{s,i}$ is the sum of all the i-th station's infrastructures. The variable cost instead depends on the network operation and it considers the efficiency of each vehicle η^k, the price of source of power c^k, and the distance of travel d^k:

$$C_{var} = \sum_{k \in K_d} \sum_{i,j \in L_P} c^k d_{ij} \eta^k N_{ij} \left(w^k + W^k \right) \tag{9}$$

where w^k is the average weight per shipment of i-th drone, W^k is the i-th drone's weight and $N_{ij} \geq 0$ the number of drones flying on the link.

Finally, the total Network cost is weighted sum of C_{fix} and C_{var} where the latter is considered for 10 years period.

$$C_{tot} = w_{c,1} C_{fix} + w_{c,2} C_{var} \tag{10}$$

B. Time to Delivery

This model quantifies the nominal time for the delivery of medical items in a steady state flow delivery conditions.

A set of delivery requests are first defined and an optimal plan on the network is first calculated.

The total time to delivery is the sum of the total travelling time and the total processing time at the stations.

$$T_{tot} = \sum_{k \in \tau_d} \sum_{i,j \in L_P} \frac{d_{ij}}{v^k} N_{ij}^k + \sum_{k \in \tau_d} \sum_{i \in N_P} P_i^k(N_i) \tag{11}$$

The travelling time in eq. (11) is function of the distance d_{ij} between the connected nodes $i, j \in N_P$ as in the defined scheduling, of the k-th drone's type velocity v^k and the number of drones of the k-th type flying the link N_{ij}^k. The processing time depends on the drone type, on the station type and on the number of drones concurrently processed at the station. Indeed depots and intermediate stations require processing time only for take-off and landing. For any station with a charging infrastructure, the charging time is calculated as function of the station capacity $C_{s,i}$ and the number of drones landed:

$$P_{charge,i}^k = t_{charge}^k + \frac{N_i}{C_{s,i}} \tag{12}$$

For pick-up stations, the processing time has an additional component calculated as the difference between the time required for preparing the medical package and the time interval between the started order and the landing of the drone T_0:

$$P_{pickup,i}^k = \max(0, T_{package} - T_0) \tag{13}$$

Finally, for the delivery station the additional component for the medical samples analysis is considered:

$$P_{delivery,i} = t_a \frac{N_i}{C_{s,i}} \tag{14}$$

C. 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. 3 to 6. It is represented the DLN for Scotland medical delivery were nodes (ground infrastructures) include 3 Airports, 13 Hospitals and 19 Laboratories and 24 additional stations 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. The flow quantification, normalised to 1, is plotted in fig. 1 and refers to time below 100. We suppose that a failure happens at time $t_0 = 100$ which make a station unusable. **??** 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. 1, 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:

$$R_i = \frac{\int_{t_0}^{t_r} Q_i(t)dt}{t_h - t_r} \tag{15}$$

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 Differential Algebraic Equations (DAEs) is represented in matrix form by the *state equation* and the *output equation*:

$$\begin{aligned} \{\dot{p}(t)\} &= \left[\mathcal{A}\right] \cdot \{p(t)\} + \left[\mathcal{B}\right] \cdot \{u(t)\} \\ \{Q(t)\} &= \left[\mathcal{C}\right] \cdot \{p(t)\} + \left[\mathcal{D}\right] \cdot \{u(t)\} \end{aligned} \tag{16}$$

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

$$\left[\mathcal{A}\right] = \left[\mathbf{C}\right]^{-1} \left[\mathbf{K}\right] \tag{17}$$

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

$$\mathbf{C} = \begin{bmatrix} C_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & C_{nn} \end{bmatrix} \tag{18}$$

calculated as

$$\mathbf{C} = \mathbf{I_c}\{c\} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \tag{19}$$

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:

$$\mathbf{K} = \begin{bmatrix} K_{11} & \cdots & K_{1n} \\ \vdots & \ddots & \vdots \\ K_{n1} & \cdots & K_{nn} \end{bmatrix} \tag{20}$$

calculated as:

$$\mathbf{K} = \mathbf{I_k}\{k\} = \begin{bmatrix} I_{11}^k & \cdots & I_{1n}^k \\ \vdots & \ddots & \vdots \\ I_{n1}^k & \cdots & I_{nn}^k \end{bmatrix} \begin{bmatrix} k_1 \\ \vdots \\ k_n \end{bmatrix} \tag{21}$$

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:

$$\left[\mathcal{B}\right] = \left[\mathbf{C}\right]^{-1} \left[\mathbf{U}\right] \tag{22}$$

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. (16) 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):

$$C_i = \frac{A_i}{9.81\rho_i} \tag{23}$$

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:

$$K_i = \frac{1}{R_i} = \frac{\pi r_i^4}{8\mu_i L_i} \tag{24}$$

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

$$\rho_i = \begin{cases} \rho_{i,0} & \text{if } p_i \leq p_{i,max} \\ \rho_{i,0} M_i (p_i - p_{i,max}) & \text{if } p_i > p_{i,max} \end{cases} \tag{25}$$

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}

$$\mu_{ij} = \begin{cases} \mu_{ij,0} & \text{if } Q_{ij} \leq Q_{ij,max} \\ \mu_{ij,0} M_i (Q_{ij} - Q_{ij,max}) & \text{if } Q_{ij} > Q_{ij,max} \end{cases} \tag{26}$$

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.

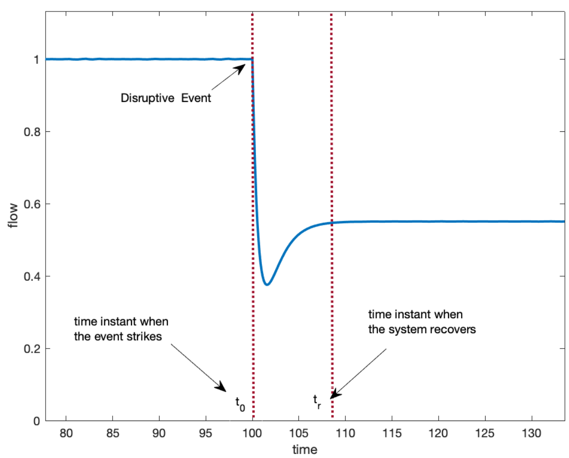

Fig. 1: Resilience metrics example. Normalised flow in the Logistic Network before and after failure of station CS-7. The network is able to absorb part of the shock and recover. The performance after the failure is however lower than in the nominal case. The resilience is calculated as in eq. (15) as function of the area below the flow curve and the time distance $t_r - t_0$.

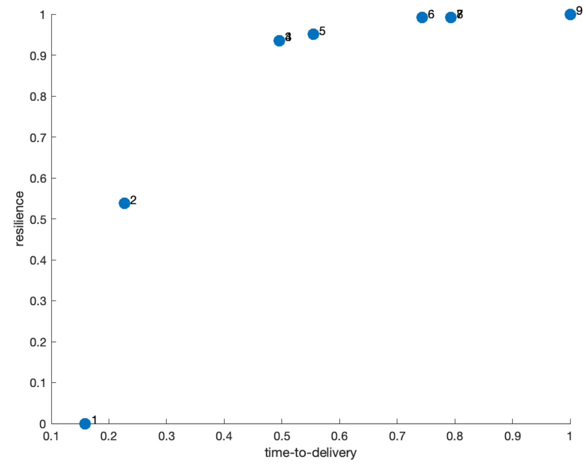

Fig. 2: Results of problem 1. Optimal Pareto front showing the trade-off between resilience and time-to-delivery.

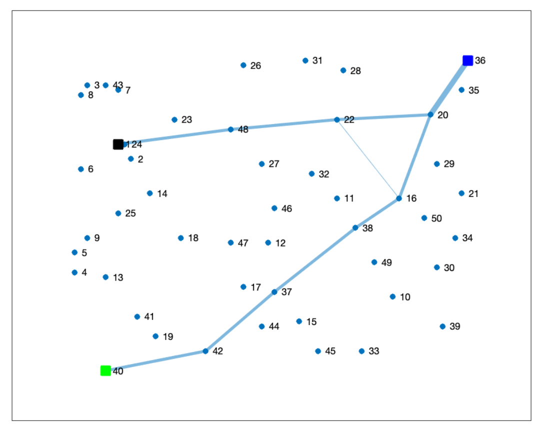

Fig. 3: Results of problem 1. Drone Logistic Network corresponding to solution 1 in fig. 2

VIII. Results

Results of the first DLN optimisation are plotted in figs. 2 to 6. fig. 2 shows the Pareto front of the optimal set solution explaining the trade-off between the two competing objective functions resilience and total time-to-delivery (with a constant weight associated to the cost function). The two extreme solutions 1 and 9 are further analysed in figs. 3 to 6. fig. 3 shows the optimal graph topology when only the time-to-delivery is optimised and minimum importance is given to the network resilience. In fig. 4 it is shown what happens when a node (station 16) fails: no alternative path is possible in order to connect source (Hospital) to sink (Laboratory) nodes and the mission fails. Similar results are obtained if any other charging station fails. On the other side, fig. 5 shows the optimal graph topology when the utility function assigns most of the importance to the network resilience and time-to-delivery is considered to be not important. Here many stations are selected for the DLN even if most of them are not included in the nominal path. With respect to the previous solution, here the cost is higher and the nominal time of delivery plan is also worse. However, as in fig. 6, after a failure on a stations along the nominal path, the network is able to re-plan its strategy and the mission is still accomplished even if with a lower performance. Similar results of fig. 6 are obtained if any different node becomes unusable.

IX. Conclusions and Future Work

In this paper we presented a novel bio-inspired optimisation methodology, MH-PO, for the solution of the generative DLND for the delivery of medical items for the National Health Service (NHS). MH-PO takes advantage from the concurrent evolution of multiple Physaria populations and, besides the network design problem, can also solve the classical shortest path, TSP and VRP with high performance. Particular attention has been put on the development of a resilience metric and its use as one of multiple optimisation objectives. Pascoletti-Serafini scalarisation approach has been adopted to deal with the MOO.

We decided to focus in this publication on the optimisation methodology while leaving for later publications the detailed presentation of the developed DT and of the approaches used for uncertainty quantification and surrogate-assisted optimisation.

Acknowledgment

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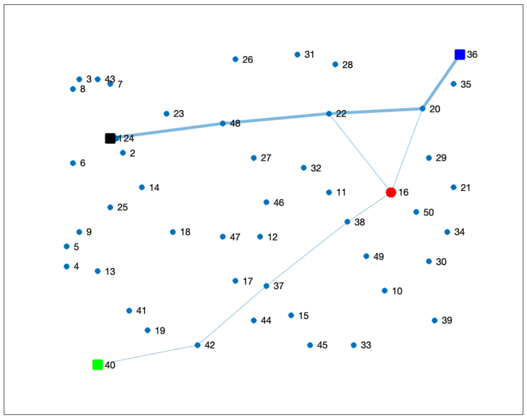

Fig. 4: Results of problem 1. Drone Logistic Network corresponding to solution 1 in fig. 2 after failure of station 16. No alternative path is possible.

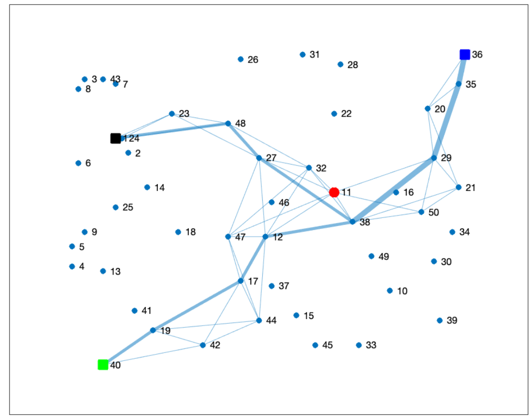

Fig. 6: Results of problem 1. Drone Logistic Network corresponding to solution 1 in fig. 2 after failure of station 11. An alternative path is possible.

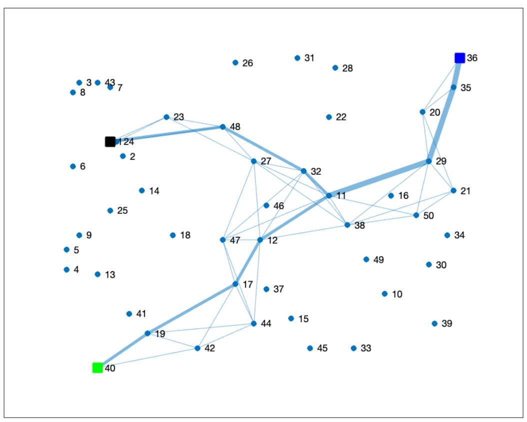

Fig. 5: Results of problem 1. Drone Logistic Network corresponding to solution 9 in fig. 2

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