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OPTIMAL POWER HARNESS ROUTING FOR SMALL-SCALE SATELLITES

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Abstract This paper presents an approach to optimal power harness design based on a modified ant colony optimisation algorithm. The optimisation of the harness routing topology is formulated as a constrained multi-objective optimisation problem in which the main objectives are to minimise the length (and therefore the mass) of the harness. The modified ant colony optimisation algorithm automatically routes different types of wiring, creating the optimal harness layout. During the optimisation the length, mass and bundleness of the cables are computed and used as cost functions. The optimisation algorithm works incrementally on a finite set of waypoints, forming a tree, by adding and evaluating one branch at a time, utilising a set of heuristics using the cable length and cable bundling as criteria to select the optimal path. Constraints are introduced as forbidden waypoints through which digital agents (hereafter called ants) cannot travel. The new algorithm developed will be applied to the design of the harness of a small satellite, with results highlighting the capabilities and potentialities of the code.

Keywords – Small satellite, Ant Colony Optimisation, discrete optimisation, multi-objective, harness, routing, bundle

NOMENCLATURE

ρ/ξ	Global/Local Pheromone evaporation constant
τ_0	Initial pheromone level
τ_{ij}	Pheromone edge between node i and j
η_{ij}	Heuristic information
C	Eucledian distance between source and sink
α	Pheromone influence parameter
β	Heuristic information influence parameter
γ	Bundling heuristic info influence parameter
q_0	Explorability parameter
q	Random real number
p_{ij}	Probability of moving to node j from node i
k	Ant index with k = 1,2...m
m	Number of ants per colony
n	Number of nodes contained in T^+
J_i^k	Candidate list of node i, ant k
T^+	Best-so-far path
L^+	Length of best-so-far path
m_{term}	Iteration termination criterion
d	m_{term} sizing parameter (≥ 0.4)
I_{last}	Optimisation termination criterion
n_{Col}	Number of colonies
I_{max}	Definite optimisation termination criterion

1 INTRODUCTION

Designing the harness subsystem of satellites has always posed various challenges. Numerous design parameters need to be taken into consideration in order to ensure the uninterrupted and undistorted flow of power and data as well as staying well within the volume and mass constraints of the satellite. So far the harness subsystem design has been based mainly on the experience of the designer(s) as well as trial and error techniques during the satellite Assembly, Integration and Verification (AIV) phase [1]. This leads to non optimal designs occasionally, creating obstacles during the subsystems' integration, problems due to mass and volume constraints or disruptions and distortions in intrasatellite communications due to high noise level affecting the satellite hardware. Hence, optimising the harness subsystem is essential for enhancing the robustness of a small-satellite design and ensuring the mission's success. This work comes to bridge the gap between designing experience, optimal design and automation of the harness design procedure. With the help of advanced optimisation and simulation techniques, cre-

ating an optimal design of the harness subsystem for small-scale satellites automatically is now possible, greatly contributing to minimising the designer workload as well as avoiding critical errors and discrepancies. The approach adopted here is to discretise the available space that can be used for cable routing and transform, as consequence, the problem from continuous to a combinatorial one. Cable routing can be considered a Non-deterministic Polynomial-time hard (NP-hard) problem in three dimensions where a set of digital agents starting off from the same node (source) search for the optimal route towards a specified point (sink) within the discrete search space. Stochastic programming techniques have been widely used for routing optimisation problems like the Travelling Salesman Problem (TSP) with an extensive bibliography found on metaheuristics such as the Ant Colony Optimisation (ACO) [2]. While continuous optimisation offers great accuracy, it is unnecessary to treat this particular problem with such high accuracy. Increasing the density of the discretised search space can provide the necessary accuracy for finding high quality solutions in an efficient manner. The ACO metaheuristic has been widely used in solving 2D routing problems, such as the Quadratic Assignment Problem (QAP), Job-shop Scheduling Problem (JSP), Vehicle Routing Problem (VRP), Sequential Ordering Problem (SOP) [3] and less often in 3D problems like automatic pipe routing [4]. Here, an ACO inspired algorithm, opportunely modified in order to take into account the particular nature of the harness problem, is detailed. The application of the obtained algorithm to a simplified test case, shows the capabilities of the code to find optimal paths from source to sink, both when the length of the cables is the only objective function to take into account and when a bundling function is considered to push all the cables to follow a common path. Statistical results are shown and commented. A summarising section with anticipations on future work ends the paper.

2 HARNESS OPTIMISATION

As previously stated, once the available internal space is discretised, harness optimisation can be considered as a NP-hard combinatorial problem, much like the well known Travelling Salesman one (TSP). It has been demonstrated that nature inspired algorithms such as the Ant Colony System (ACS) can provide fast and high quality solutions to large scale combinatorial problems. [5]

2.1 Ant Colony System

The Ant Colony System (ACS) was developed by Dorigo and Gambardella as an evolution of the first and still naive algorithm based on ants' behaviour, namely the Ant System (AS) [2]. Introducing a number of changes, the ACS is an improved variable of the AS able to find satisfactory solutions for real case problems.

All ant-based algorithms utilise a common basic idea. Ant colonies use positive feedback (pheromone deposition), negative feedback (pheromone evaporation) and shared knowledge (pheromone matrix) encouraging the cooperation between agents in order to achieve the best result possible. All the aforementioned knowledge passes to the ants in the form of the pheromone parameter. Every ant has access to a common pheromone matrix, where good solutions receive a pheromone enhancement while worse solutions receive a pheromone decrease. After each iteration, knowledge is accumulated in the form of pheromone trails being deposited on the available search space, thus leading each ant colony to learn from previous experience using the pheromone matrix. Therefore, each ant's step takes into account the experience accumulated so far (pheromone trails) as well as any heuristic information used per colony in order to minimise the objective function. The ACS algorithm utilises a set of key operations throughout each ant step, as described below in Algorithm 1.

Algorithm 1 ACS algorithm

Set values for $m, I_{last}, \tau_0, q_0, \alpha, \beta$
Define candidate list $J_i \ \ \forall i \in [search \ space]$
while I_{max} not met **do**
   Place all ants on start
   for k = 1:m **do**
      while not terminate **do**
         Calculate η_{ij}
         Decide next j^k using Eq. (2)
         Perform a local pheromone update on arc ij using Eq. (4)
      end while
   end for
   Calculate the length of all tours T^k
   Find T^+
   Perform a global pheromone update on T^+ using Eq. (5)
end while

Initially the algorithm specifies the values of initial parameters. The ants start exploring the search space, forming possible optimal pathways. Once all ants of the colony complete their tours, pathways'

lengths are measured, the shortest pathway, T^+, is enhanced with pheromone and all ants start a new search for more solutions. This iterative procedure continues until the definite optimisation termination criterion, I_{max}, is met, resulting in acquiring the optimal path. A more detailed description of the steps included in Algorithm 1 is found below.

1. Set values for the number of ants per colony, m, optimisation termination criterion, I_{last}, explorability parameter, q_0, pheromone influence parameter, α, heuristic influence parameter, β. The initial pheromone level of the search space, τ_0, is calculated as follows

$$\tau_0(t) = (n \cdot L_{nn})^{-1} \qquad (1)$$

with L_{nn} being the length of the nearest neighbour tour, performed using the nearest-neighbour algorithm [6], n the total number of nodes included in the search space.

2. Define the candidate list of every node in the search space, J_i, with $i \in [search\ space]$. The ACS ants' exploration is based on candidate lists i.e a set of nodes J_i^k in the vicinity of node i where ant k is situated at. Unvisited nodes contained in the candidate list are examined first, having priority over the rest of the nodes contained in the search space.

3. While the definite optimisation termination criterion, I_{max}, is not met

4. Place all ants on the starting node.

5. For all the ants of the colony, m

6. While the ants have not terminated their tour

7. Calculate the length heuristic for edge ij, $\eta_{ij} = L_{ij}^{-1}$, with L_{ij} being the eucledian length of edge ij.

8. Define the next ant step, j, on the basis of the *pseudo-random proportional rule*. The transition of ant k situated on node i, to node j, is decided according to Eq. (2)

$$j = \begin{cases} \arg\max_{u \in J_i^k} \left\{ [\tau_{iu}(t)]^\alpha [\eta_{iu}]^\beta \right\} & \text{if } q \leq q_0 \\ J & \text{if } q > q_0 \end{cases} \qquad (2)$$

where q is a random real number uniformly distributed over $[0, 1]$, q_0 is a tunable parameter in the interval $(0, 1)$, $J \in J_i^k$ selected according to the transition probability distribution below

$$p_{ij}^k(t) = \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta}{\sum_{l \in J_i^k} [\tau_{il}]^\alpha \cdot [\eta_{il}]^\beta} \qquad (3)$$

where τ_{ij} is the pheromone level of edge ij, α and β are positive influence parameters. Likewise, τ_{il} is the pheromone level of edge il and η_{il} is the heuristic value of edge il with l being every node contained in J_i^k. Tuning q_0 enhances the exploitation or exploration option, where $q \leq q_0$ aims in exploiting the available knowledge of the problem whereas $q > q_0$ aims in exploring the available search space.

9. Perform a local pheromone update on edge ij, also known as online update. While exploring the search space, ants perform a local pheromone update after each step. Once ant k performs a step from node i to node j, it updates the pheromone level of edge ij according to Eq. (4)

$$\tau_{ij}(t) \leftarrow (1 - \xi) \cdot \tau_{ij}(t) + \xi \cdot \tau_0(t) \qquad (4)$$

where τ_{ij} is the pheromone level of edge ij, ξ is the pheromone evaporation rate parameter, τ_0 is the initial pheromone trail value.

The *local pheromone update* is performed in order to enhance the exploration of the discretised space and create more possible solutions. This is achieved by subtracting a fraction of the initial pheromone trail level found on edge ij, making this edge less appealing to the following ants, thus favouring the exploration of non visited pathways. By shuffling ants' paths with the use of the local pheromone update, the probability of finding better solutions and avoiding stagnation is increased.

10. End the while condition

11. End the for loop.

12. Calculate the length of each ant's tour, T^k, on the basis of eucledian distance.

13. Find the best-so-far tour, T^+, corresponding to the shortest-so-far tour length

14. Perform a global pheromone update on all the edges included in the best-so-far tour, T^+, according to the *global pheromone update rule*

$$\tau_{ij}(t) \leftarrow (1 - \rho) \cdot \tau_{ij}(t) + \rho \cdot \Delta\tau_{ij}(t) \qquad (5)$$

where ij are the nodes comprising T^+, ρ is the pheromone evaporation rate parameter and

$$\Delta\tau ij(t) = (L^+)^{-1}$$

3

with L^+ being the length of T^+ The *global pheromone update* allows colony members to spread all acquired experience among them, promoting synergy between ants thus leading to a faster convergence to the optimal solution.

15. End the while condition.

In the following of the section, first mean heuristics of the general ACS are detailed, then the harness environment is described, and, latter, the ACS is modified for harness optimisation.

2.2 Harness simulator

Initially a 3D representation of the satellite is created. The volume of the satellite is expressed by a parallelepiped, and each subsystem is described by a prism located at a specified point within the parallelepiped, based on the current configuration of the satellite. Interfaces of the satellite subsystems are set accordingly, as well.

The available inner satellite space is then discretised using a 3D structured mesh, and for each node i a candidate list J_i is defined, and Cartesian coordinates, (x_i, y_i, z_i), are stored as well.

A second step takes into account the presence of the subsystems, then all the nodes intersecting the prisms representing the subsystems are eliminated from the mesh, and all the candidate lists are modified as well. In this way, ants can only *see* the true available space.

2.3 3D ACOHARN

While optimising satellite cabling poses some similarities with the TSP, there is one important difference: in this case agents need to explore a mesh forming an optimised route without having to visit every single contained node, unlike the TSP where agents have to visit the entire search space ending up at the point they started from. For this reason, a new algorithm was developed, namely *3D ACOHARN*, loosely based on the ACS. *3D ACOHARN* is able to connect a source subsystem to one or more subsystems (sinks), creating optimal topologies within the available inner satellite space. Ants are able to trace interfering objects within the search space, avoiding collision or routing through prohibited areas within the satellite volume. Due to the large size of the search space, colony populations must be larger ($\geq 20 ants$) than a typical TSP colony [2]. In order to improve the optimisation process speed without compromising the solution quality a new iteration termination criterion is imposed, namely m_{term}. The iteration termination criterion

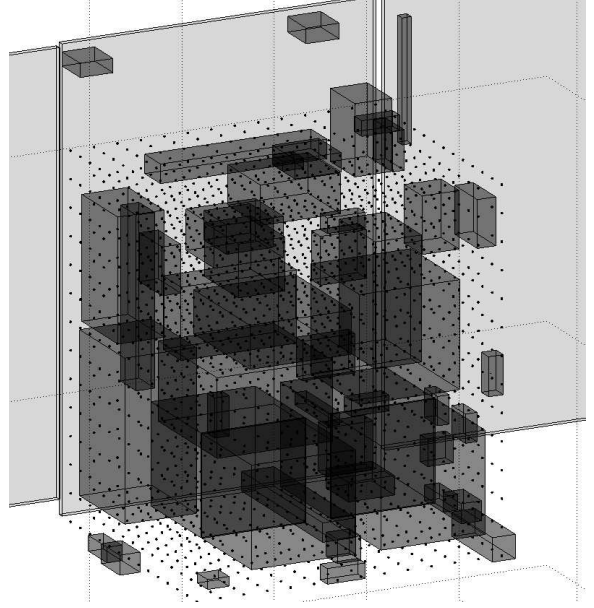
Figure 1: Discretised inner space of satellite.Nodes intersecting the prisms are eliminated

is defined as the maximum number of ants allowed to reach the sink before the iteration is terminated, and it is defined as $m_{term} = d * m$, with m being the number of ants per colony and d being a tuning parameter ≥ 0.4. Once m_{term} is reached, the entire colony of ants returns back to the source and the algorithm proceeds to the next step. Furthermore a maximum iterations threshold, I_{last}, can be set dynamically, depending on the improvement rate of the optimisation process. Once the improvement rate slows down significantly, which implies that the solution has reached a satisfactory optimality level, the I_{last} is met, terminating the optimisation cycle. The number of ants allowed to reach the sink m_{term} along with the iteration threshold, I_{last}, allow the designer to control the quality and speed per optimisation cycle. The following algorithm (Algorithm 2) describes the procedure followed for conducting a full harness optimisation cycle.

Initially the algorithm sets values for specific parameters. The ants start circulating the search space, exploring possible optimal pathways. Once the iteration termination criterion, m_{term}, is met, pathways' lengths are measured, the shortest pathway, T^+, is enhanced with pheromone and all ants start a new search for more solutions. This iterative procedure continues until the optimisation termination criterion, I_{last}, is met, resulting in acquiring the optimal path. If I_{last} becomes equal to I_{max}, the optimisation cycle is forced to end. A more detailed

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Algorithm 2 3D ACOHARN algorithm

Set values for $m, \alpha, \beta, \gamma, m_{term}, I_{last}, n_{Col}, I_{max}$
Calculate τ_0 using Eq. (6)
Define candidate list $J_i \ \ \forall i \in [search\ space]$
Set initial values for ρ_{ad}, ξ_{ad}
while I_{last} not met **do**
    Place ants on source
    for k = 1:m **do**
        while m_{term} not met **do**
            Calculate $\eta_{ij}, \eta_{lE}, \eta_{\Delta T}, \tau_{lj}\ with\ l \in J_i^k$
            Decide next j^k
            Perform a local pheromone update on edge ij
            Once m_{term} is met, break
        end while
    end for
    Calculate the length of all tours T^k
    Find T^+
    Perform a global pheromone update on T^+ using Eq. (5)
    Update ρ_{ad}, ξ_{ad} using Eqs. (14) and (15)
    if $I_{last} = I_{max}$ **then**
        End optimisation
    end if
end while

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description of the steps included in Algorithm 2 is found below.

1. Set values for the number of ants per colony, m, pheromone influence parameter, α, heuristics influence parameter, β, bundling heuristic influence parameter, γ, iteration termination condition, m_{term}, optimisation termination criterion, I_{last}, number of colonies per optimisation cycle, n_{Col}, definite optimisation termination criterion I_{max} used whenever I_{last} is not met.

2. Calculate the initial pheromone level of the search space, τ_0,

$$\tau_0 = (L^{SE})^{-1} \qquad (6)$$

where L^{SE} is the straight-line euclidean distance between the source and sink nodes. The reason for setting τ_0 according to Eq. (6) is to avoid suboptimal solutions or an ineffective pheromone level. Suboptimal solutions can occur when the τ_0 is too low, leading to a biased exploration of the area around the initial ant tours thus trapping the ants around inferior quality search zones. On the other hand τ_0 can prove to be ineffective if its level is too

high, leading ants to perform less efficient optimisation iterations until the pheromone level is lowered due to evaporation. Once the τ_0 level is reduced, the pheromone deposited by the best-so-far ants can start to influence the exploration of the following colonies.

3. Define the candidate list of every node in the search space, J_i, with $i \in [search\ space]$.

4. Initiate the global pheromone evaporation rate parameter, ρ_{ad} and local pheromone evaporation rate parameter, ξ_{ad}

5. While the optimisation termination criterion, I_{last}, is not met

6. Place all ants on source subsystem

7. For all the ants of the colony, m

8. While the iteration termination criterion, m_{term}, is not met

9. Calculate the heuristic of edge ij, η_{ij}, as previously stated in Algorithm 1, step 7. The heuristic of edge lE, η_{lE} is the eucledian distance between each node l contained in the candidate list J_i^k of node i and the sink node E i.e the finishing point of each ant's tour, indicating the proximity of the J_i^k to the sink.

$$\eta_{lE} = (L^{lE})^{-1} \qquad (7)$$

where L^{lE} is the euclidean distance between every node $l \in J_i^k$ and the sink node E. The bundling heuristic, $\eta_{\Delta T}$ is the distance between node i and the neighbouring cables' nodes. This heuristic is used for producing a bundling effect between neighbouring cables.

$$\eta_{\Delta Tl} = (\gamma \cdot L^{\Delta Tl})^{-1} \qquad (8)$$

where $L^{\Delta Tl}$ is the euclidean distance between all nodes $l \in J_i^k$ and all nodes $T \in C^{closer}$ comprising the closest neighbouring cable (C^{closer}). γ is a positive weight parameter influencing the significance of $L^{\Delta Tl}$ Bundling cables is considered important with respect to EMI (Electro-Magnetic Interference) constraints. Cables may act as antennas or conduits for radiated or conducted EMI respectively. Furthermore, routing topologies usually accommodate practical considerations such as the subsystem's physical location or easily reachable paths during integration. This makes it difficult to quantify the EMI environment associated to the satellite

harness. One way of controlling the harness induced EMI is to separate cabling according to its voltage, frequency and susceptibility class. This is achieved by bundling same-class cables together according to cabling specifications and requirements [7].

10. Define the next ant step, j^k, using a variant of the probabilistic part of the *pseudo-random proportional rule*

$$p_{ij} = \frac{[\tau_{ij}]^\alpha \cdot ([\eta_{loc}]^{(\beta+1)} + [\eta_{glob}]^\beta)}{\sum_{l \in J_i^k} [\tau_{il}]^\alpha \cdot ([\eta_{locl}]^{(\beta+1)} + [\eta_{globl}]^\beta)} \quad (9)$$

where τ_{ij} is the pheromone level of edge ij chosen according to the probability p_{ij}^k, α and β are positive weight parameters, $\eta_{loc} = \eta_{ij}$ and $\eta_{glob} = \eta_{\Delta Ti}$ based on Eq. (8). Likewise τ_{il} is the pheromone level of edge il, $\eta_{locl} = \eta_{il}$ and $\eta_{globl} = \eta_{\Delta Tl}$ based on Eq. (8).

The next node is selected using *stochastic sampling* also known as *roulette wheel selection method*. Utilising a weighted sample selection process, each ant chooses its next step accordingly. Higher probabilities within the probability distribution p_{il}^k acquire a bigger weight, corresponding to a larger area on the roulette wheel. This leads to a biased selection favouring the choice of nodes corresponding to higher probabilities within the distribution p_{il}^k.

11. Perform a local pheromone update on edge ij after each ant move.

$$\tau_{ij}(t) \leftarrow (1 - \xi_{ad}) \cdot \tau_{ij}(t) + \xi_{ad} \cdot \tau_0(t) \quad (10)$$

where i, j are the nodes comprising edge ij that was just visited by ant k, ξ_{ad} is the adaptive local pheromone evaporation rate parameter, τ_0 is the initial pheromone trail value occurring from Eq. (6)

12. Once the m_{term} criterion is met, the specified number of ants has reached the sink therefore ants are put on a halt.

13. All the ants' tour eucledian length L is calculated

14. The shortest tour length signifies the best-so-far tour T^+

15. A global pheromone update is performed on T^+

$$\tau_{ij}(t) \leftarrow (1 - \rho_{ad}) \cdot \tau_{ij}(t) + \rho_{ad} \cdot \Delta\tau_{ij}(t) \quad (11)$$

where ij are the edges comprising T^+, ρ_{ad} is the adaptable global pheromone evaporation rate parameter deriving from Eq. (14) and

$$\Delta\tau ij(t) = (L^+)^{-1}$$

with L^+ being the length of T^+

16. The local pheromone evaporation parameter ξ_{ad} and the global pheromone evaporation parameter ρ_{ad} are adapted in three steps, depending on the maturity of the optimisation process [8].

Initially a *similarity search* is conducted between all tours performed by a single colony based on Eq. (12), searching for the intersection between the current tour and the best-so-far tour.

$$S_{Tk}^{T^+} = |T_k \cap T^+| \quad (12)$$

where T_k is the tour performed by ant k while T^+ is the best-so-far path i.e the shortest length path.

Furthermore, the *average tour similarity* (ats) index is computed and normalised ($\overline{ats}$) according to Eq. (13)

$$ats = \frac{1}{m} \sum_{k=1}^{m} S_{Tk}^{T^+}$$
$$\overline{ats} = n^{-1} \cdot ats \quad (13)$$

where m is the number of ants contained in the colony, n originally represents the total number of nodes included in the search space. Since visiting all nodes included in the search space is not a requirement in the *3D ACOHARN* case, n is the number of nodes contained in the global best path T^+.

Finally, the adaptive global pheromone evaporation rate ρ_{ad} is calculated using Eq. (14) based on the fact that initially pheromone deposition on shorter paths is higher, in order to attract more ants. As the optimisation matures, pheromone deposition on shorter paths gradually decreases in order to avoid trapping the ants in local optima.

$$\rho_{ad} = A_\rho \cdot \overline{ats} + B_\rho \quad (14)$$

where A_ρ and B_ρ are tweaking parameters used for keeping the value of ρ_{ad} within a proper interval.

Likewise, the adaptive local pheromone evaporation rate ξ_{ad} is calculated using Eq. (15)

based on the fact that initially ρ_{ad} is high in order to attract more ants therefore ξ_{ad} remains low in order not to weaken or cancel the global pheromone trails' effect. As the optimisation matures, ξ_{ad} becomes higher in order to avoid local optima.

$$\xi_{ad} = A_\xi \cdot \overline{ats} + B_\xi \qquad (15)$$

where A_ξ and B_ξ are tweaking parameters used for keeping the value of ξ_{ad} within a proper interval.

17. If the optimisation termination criterion value, I_{last}, becomes equal to the definite optimisation criterion value, I_{max}, end the optimisation cycle.

3   TEST CASE

The implemented algorithm has been applied to a small satellite inspired by the European Student Earth Orbiter (ESEO) [9]. Utilising a small satellite as the test case, the *3D ACOHARN* can be tested on a mission scenario with specific requirements and constraints. ESEO is a student satellite supported by the European Space Agency (ESA) Education Office. Build exclusively by university students coordinated by their academic advisors, ESEO aims at educating the future European space engineering workforce by providing hands on experience to the students involved. In order to demonstrate the validity of the approach, the harness problem has been simplified, and only three cables have been considered. This allows to assess the performance of the code, without needing an excessive amount of computation time, which is not affordable during the test phase.
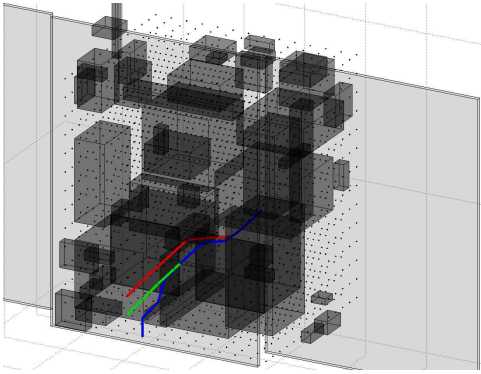

Figure 2: Example of automated optimised harness topology using three cables

Due to the sparsity of the mesh, sometimes cables appear not to connect to the corresponding sink subsystems.

4   RESULTS

The *3D ACOHARN* was used in three different implementations of the optimisation problem. Initially, a length only approach was used. Utilising the length local η_{ij}, $\eta_{\Delta T}$, and global heuristics η_{lE} respectively, tests were conducted both with and without the use of *local pheromone updating*. Two bundling approaches were also used, one leading to loose bundling and another leading to absolute bundling. Loose bundling was achieved automatically utilising the bundling local heuristic occurring from Eq. (8) whereas forced bundling was achieved by setting one waypoint between the source and sink situated at approximately 2/3 of the straight line distance from the source, forcing ants to pass by this node while searching for the optimal solution. When using length based heuristics only, figures 3 and 4 as well as the *Length* section of Tables 1 and 2 show that there is a negligible difference between utilising a local pheromone update and omitting that step. Since local pheromone updating can be computationally intensive, it is hereby shown that it is possible to omit the local pheromone update when performing length-only optimisation.
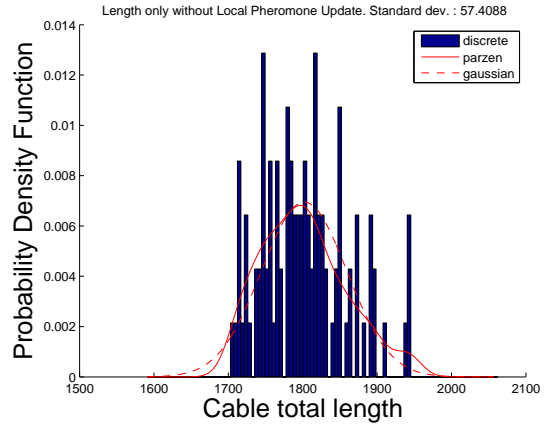

Figure 3: Probability density function vs total cable length for the length only without local pheromone update case

While utilising the loose bundling heuristics, figures 5 and 6 as well as the *Loose* section of Tables 1 and 2 show that, in this particular case only, there is an important difference between using a *local pheromone update* and omitting this
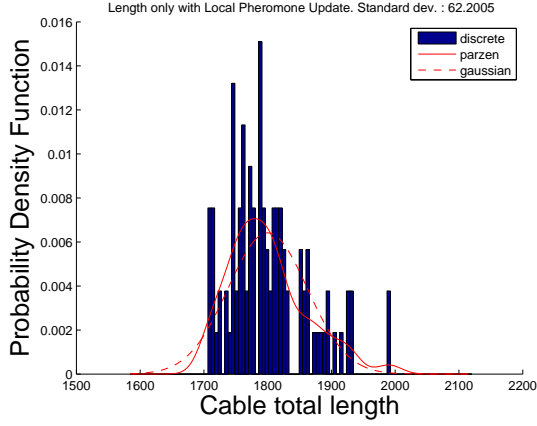
Figure 4: Probability density function vs total cable length for the length only with local pheromone update case
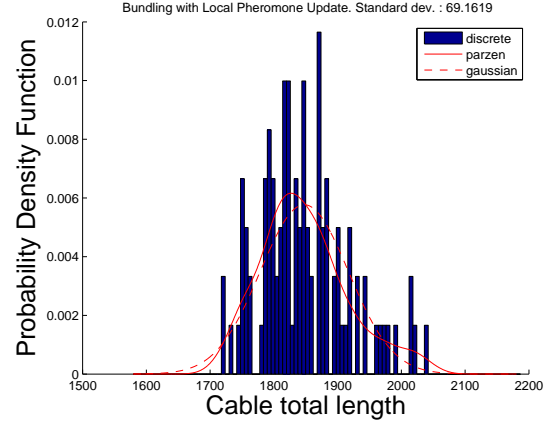

Figure 6: Probability density function vs total cable length for the loose bundling case with local pheromone update case

step. This change can be accredited to the fact that the bundling heuristic is affecting ants' exploration. Without the existence of a local pheromone update, preventing ants to follow common paths during the exploration process, ants are strongly driven by the bundling heuristic. Hence, performing a biased search around the vicinity of neighbouring cables. This results in containing the ants to an area of the mesh situated around the neighbouring cables, thereby preventing them from exploring other areas.

of Tables 1 and 2 as well as figures 7 and 8. The reason for that being that all cables are forced to be bundled at a specific waypoint, and the length of the loose cabling branching out of the bundle ending point is negligible with respect to the bundle length itself. Therefore, applying a local pheromone update or not makes practically no difference, since there is no need to take measures against ants stagnating. The physical distance between the bundle and the sink is small enough to prevent ants from creating suboptimal solutions due to stagnation.
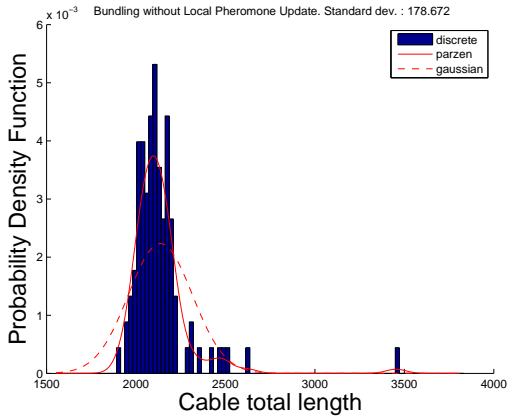

Figure 5: Probability density function vs total cable length for the loose bundling without local pheromone update case
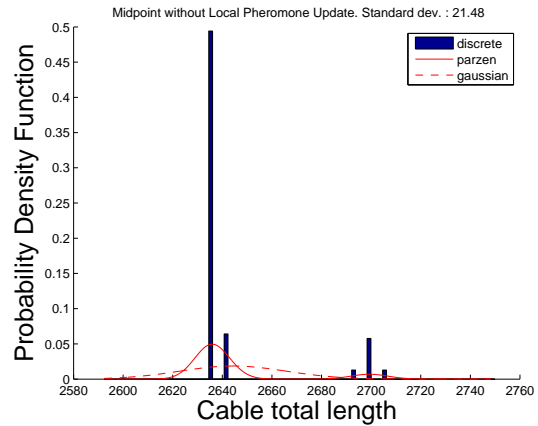

Figure 7: Probability density function vs total cable length for the forced bundling without local pheromone update case

When applying the forced bundling heuristic, it is expected that results will present almost no difference between utilising local pheromone updating and omitting this step, as seen in the *Forced* section

Overall, while bundling is a requirement for keeping EMI within an acceptable level [7], both bundling cases applied show that the total cable length tends to be bigger as seen in Table. 1.
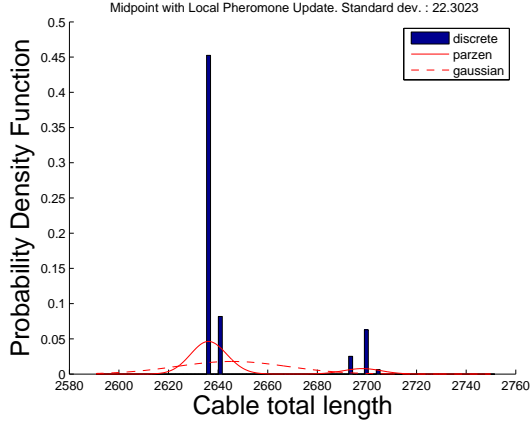
8

Figure 8: Probability density function vs total cable length for the forced bundling with local pheromone update case

From the probability density function included in the figures above, it can be seen that in many cases the results do not present a Gaussian distribution, thus analysing the results using classical statistical measures such as the mean and standard deviation cannot provide complete information.

Table 1: Mean total cable length for all three test cases using a sample of 100 runs: Length only heuristic *(Length)*, loose bundling *(Loose)*, forced bundling *(Forced)*.

Total cable length [mm]	Length	Loose	Forced
local pheromone	1800	1847	2645
no local pheromone	1802	2136	2644

Table 2: Mean maximum distance between cables for all three test cases using a sample of 100 runs. Length only heuristic *(Length)*, loose bundling *(Loose)*, forced bundling *(Forced)*.

Max.cable distance [mm]	Length	Loose	Forced
local pheromone	150.42	137.62	72.22
no local pheromone	150.60	229.83	72.17

Depending on the case (local pheromone update, no local pheromone update), the search space (sparse 3D mesh, dense 3D mesh) and the type of heuristics used (length related heuristics, bundling related heuristics), the algorithm performance can vary significantly. Overall, omitting the local pheromone update step greatly speeds up the optimisation cycle as seen in Table 3 without affecting the result quality in most cases. Nevertheless, the quality of results in the loose bundling case when

omitting the local pheromone update step is significantly inferior. This is an interesting phenomenon that will be further investigated.

Table 3: Mean total time for all three test cases using a sample of 100 runs. Length only heuristic *(Length)*, loose bundling *(Loose)*, forced bundling *(Forced)*.

Mean total time [min]	Length	Loose	Forced
local pheromone	27.74	77.03	5.48
no local pheromone	0.64	93.84	0.25

5   CONCLUSION

A novel approach to satellite harness design is presented here. A modified Ant Colony algorithm is used to optimise the path followed by the cables, within a discretised internal space of the satellite. Different strategies have been adopted and results show that the code is effective to optimise cable routing both considering only the length as well as the bundling of cables. Performed tests are also able to highlight the impact of the internal pheromone heuristics on considered problems.

The obtained tool has a broad spectrum of applications, with automated satellite harness optimisation being only one of them. Utilising the same concept, the tool can be applied to a variety of routing problems such as building/vehicle pipe routing, vehicle harness routing and others.

Future improvements of this work include a further investigation of the bundling local pheromone versus no local pheromone behaviour, the implementation of more constraints, further enhancing the quality of the optimised solution such as avoiding the area around EMI susceptible systems e.g spacecraft computers. Furthermore, performing tests with more cables simulating a real full harness design project as well as routing signal cables with respect to EMI design regulations [10] will be performed.

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