PHM-Based Multi-UAV Task Assignment

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Abstract — **This paper is relating to the application of Integrated Vehicle Health Management (IVHM) concepts based on Prognostics and Health Monitoring (PHM) techniques to Multi-UAV systems. Considering UAV as a mission critical system, it is expected and required to accomplish its operational objectives with minimal unscheduled interruptions. So that, it does make sense for UAV to take advantage of those techniques as enablers for the readiness of multi-UAV. The main goal of this paper is to apply information from a PHM system to support decision making through an IVHM framework. PHM system information, in this case, comprises UAV remaining useful life (RUL) estimations. UAV RUL is computed by means of a fault tree analysis that it is fed by a distribution function from a probability density function relating time and failure probability for each UAV critical components. The IVHM framework, in this case, it is the task assignment based on UAV health condition (RUL information) using the Receding Horizon Task Assignment (RHTA) algorithm. The study case was developed considering a team of electrical small UAVs and pitch control system was chosen as the critical system.**

Keywords—Prognostics, Health Management, Task Assignment, Unmanned Aerial Vehicle.

I. INTRODUCTION

Developments in Prognostics and Health Monitoring (PHM) technology within the aeronautical sector have been of value for aircraft operators, MRO (Maintenance, Repair and Overhaul) service providers, aircraft manufacturers and OEMs (Original Equipment Manufacturers) to achieve important competitive advantages such as reduction in operational cost and increase in fleet reliability [1].

The main goal of PHM is to estimate the remaining useful life (RUL) and the health state of components and systems. For this purpose, *a priori* probability distributions and actual measurements are used to assess health state and predict impending failures of on-board equipment. The literature on PHM solutions for aeronautical components comprises a wide range of applications, such as the monitoring of valves [2], pumps [3], engines [4] and electronic devices [5].

Methods for decision support using RUL information have also been reported in the PHM literature. Previous investigations, such as [6] and [7], presented examples of decision support methods that use PHM information to improve maintenance planning. In [1], the authors present an inventory optimization method based on RUL information. An algorithm to assign a group of Unmanned Aerial Vehicle (UAVs) to accomplish a set of missions considering PHM information is presented in [8]. However, those works focused on the RUL of single components separately, without considering that those components are part of a complex system composed by multiple interacting components.

In order to optimize the recommendations made by the decision support algorithms, system architecture must be taken into account. Due to the redundancies in system architectures, system functionality may still be retained after the loss of a single component. This information must be considered by the decision support algorithm.

A possible solution for this problem is the design of a system level RUL (S-RUL) distribution. In this approach, decision support algorithms do not deal with a set of component-level RUL distributions. Instead, the S-RUL provides information related to the time when the whole system will stop working (i.e. when the combined failures of individual components will lead to a system failure). In [9], the authors proposed a method for obtaining the S-RUL distribution on the basis of component level RULs and a Fault Tree representation of the system architecture.

This work presents a task assignment algorithm that considers health monitoring information in a system level. The proposed algorithm is used to assign a group of UAVs to a set of weighted tasks.

The remaining of this paper is organized as follows. Section II describes basic concepts of IVHM and PHM. Section III discusses the fault tree as a tool to represent interactions and redundancies in system architecture and the cut sets representation. Section IV revises the S-RUL estimation procedure introduced in [9]. Section V introduces the task assignment problem. Section VI presents the PHM-based task assignment algorithm. Section VII delineates the case study

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scenario. Section VIII summarizes the results. Finally, some conclusions and directions for further research are given in Section IX presents paper conclusions.

II. IVHM and PHM Principles

IVHM is the unified capability of systems to assess the current or future state of the system health and integrate that picture of system health within a framework of available resources and operational demand.

PHM can be defined as the ability of assessing the health state, predicting impending failures and forecasting the expected RUL of a component or system based on a set of measurements collected from the aircraft systems [10]. It comprises a set of techniques, which use analysis of measurements to assess the health condition and predict impending failures of monitored equipment or system.

The main goal of a PHM system is to estimate the health state of the monitored equipment and forecast when a failure is expected to occur [11]. In order to accomplish this task, it is necessary to collect a set of data from the aircraft. The dataset that will be recorded is defined on the basis of the type of equipment to be monitored (hydraulic, electronic, mechanic, etc.) and the failure modes that are intended to be covered by the PHM system. A health monitoring algorithm must be developed for each monitored equipment. Each algorithm processes the relevant data and generates a degradation index that indicates how degraded the monitored equipment is.

In many cases it is possible to establish a threshold that defines the system failure. When the failure threshold is known, it is possible to extrapolate the curve generated by the evolution of the degradation index over time and estimate a time interval in which the failure is likely to occur [12], [13]. This estimation is usually represented as a probability density function, as illustrated in **Figure 1**. There is always a confidence level associated with the predicted time interval.

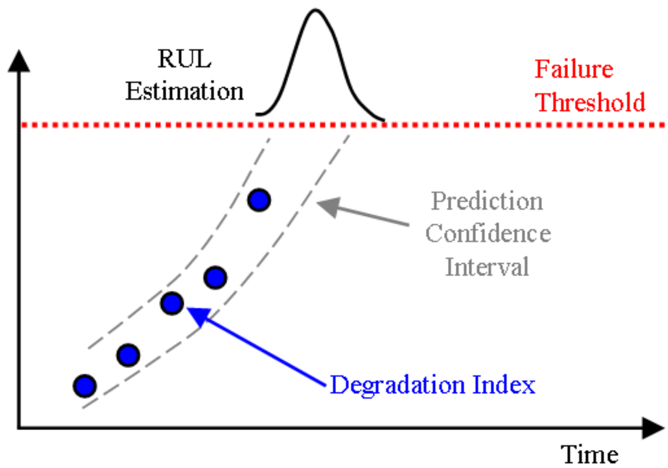

Figure 1. Degradation index evolution and remaining useful life estimation

III. Fault Tree Analysis

Fault Tree Analysis (FTA) is a failure analysis technique that, due to its ease of use and effectiveness in discovering and representing the interaction of component failures in a system, it was widely adopted since the seventies in industries such as nuclear power generation, aviation and automotive. A detailed description of the application of FTA on aircraft systems safety assessment can be found in [14].

During the FTA process, graphical diagrams called "fault trees" are produced in order to investigate what are the possible causes for an undesired and unsafe system state, called the "top event". Fault trees represent sequences of events that may lead to the unsafe top event. These sequences usually start from faults originated in system components, which combine with other component faults in order to cause failures that will propagate through the system.

The basic elements of a fault tree diagram are an undesired top event, intermediate events and basic events. Intermediate events represent failures propagated through the system and can be represented as logical combinations of basic events and other intermediate events, most commonly using the AND and the OR logical operators. Other operators are allowed in fault tree analysis but they are not relevant for the purpose of the present work. Basic events are events that are not further developed in the fault tree and are usually used for representing component faults. It is possible to attribute a probability of occurrence to each of the basic events in a given operating scenario. If the probabilities of all the basic events are known, it is possible to calculate the probability of the top event. **Figure 2** shows an example of a simple fault tree.

Assuming that all basic events are independent, a convenient form of calculating the top event probability is by transforming the fault tree into its union of cut sets form. A cut set is a combination of basic events that leads to the occurrence of the top event. In the union of cut sets form, all combinations that lead to the top event are explicitly shown below an OR logical gate. **Figure 3** shows the same fault tree as in **Figure 2** represented in its union of cut sets form.

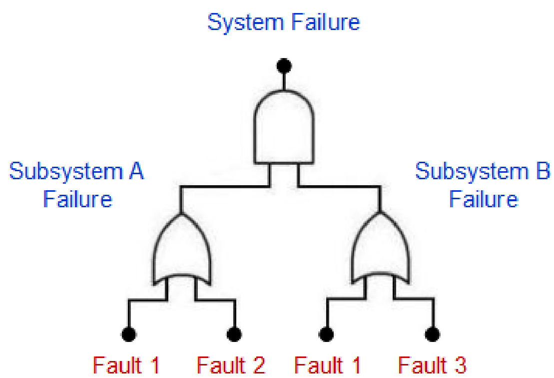

Figure 2. Fault tree example

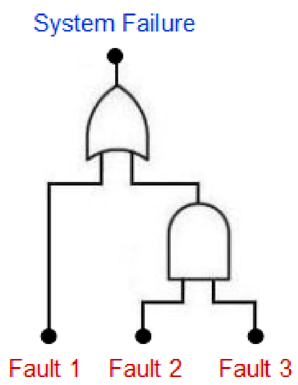

Figure 3. Cut sets representation

Each input of the top OR gate is by itself a sufficient cause for the top event. The probability of the top event can then be obtained by calculating the union probability of all cut sets. On the other hand, if the basic events are mutually independent, the probability of each cut set can be obtained by calculating the joint probability of the events that compose the cut set. If all the basic events are mutually independent, the joint probability of a cut set is just the product of all its basic events.

IV. System Level RUL Estimation

The S-RUL can be obtained by using the system architecture represented by the system fault tree and the RUL distributions for each component. The procedure to calculate the S-RUL is summarized in **Figure 4** [9].

In the first step it is necessary to obtain the fault tree that represents the system under study. This information is commonly available for aircraft since fault trees are widely used in safety analysis.

Based on the fault trees, it is possible to obtain the minimal cut sets list representation. In this representation, the probabilities of each cut set and of the top event can be calculated as (1) and (2) respectively.

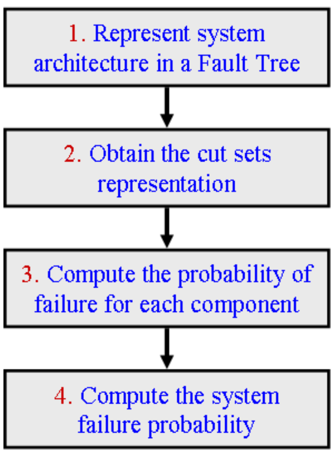

Figure 4. S-RUL calculation procedure (adapted from [9])

$$P(c_i) = P(e_1 \cap e_2 ... \cap e_n) = \prod_{j=1}^{n} P(e_j) \tag{1}$$

$$P(Top) = P(c_1 \cup c_2 ... \cup c_n) \tag{2}$$

where $P(c_i)$ denotes the probability of the i-th cut set, $P(e_j)$ denotes the probability of an event e_j, n is the number of events in a cut set and $P(Top)$ is the probability of the top event.

At step 3, the probabilities of failure for all components are calculated using the RUL predictions for each component.

Using the probabilities thus obtained and the cut set representation, it is possible to calculate the probability of a system failure to occur during the missions using the expressions presented in (1) and (2). This is done in step 4. Steps 3 and 4 are repeated for each mission.

V. Task Assignment Problem Definition

The high level mission planning system depends on task assignment and trajectory planning to achieve sorties overall goals. A common strategy is to solve task assignment problem first and after that trajectories are designed to accomplish those assignments.

A task is defined as a tuple (w_i, p_i), where w_i is the location of task i and p_i is the priority (or value) of task i. There is a set of n vehicles $V = \{v_1, ..., v_n\}$ that can be located at a common base x_{base} or at different initial locations, each with first-order dynamics and maximum speed $v_{\max}$. Besides, there is a set W of tasks that have not been visited by a vehicle. Formally, the task assignment problem consists in computing a mapping $T : V \rightarrow W$, which assigns a task for each vehicle to visit. So that, the goal is to compute the map T, *which minimizes the total,* weighted service time over all the tasks:

$$\min_{T} \sum_{(w_i, p_i) \in W} p_i t_i \tag{3}$$

where t_i is the wait time before task i is performed by a vehicle.

The task assignment solution proposed in the section VI is a slightly modification of RHTA algorithm [15], that has as assumption the existence of a PHM system capable of predicting critical components probability of failure.

VI. PHM-Based RHTA Algorithm

Given the set of waypoints W and the shortest distances $D(i,j)$ between waypoints i and j, it enumerates all possible waypoints sequences (permutations), or petals, P_{vj} up to a specified length n_c, it means that each UAV would cover a path with at most n_c waypoints. Additionally, the cost of each petal is estimated in equation (4):

$$S_{vp} = \sum \lambda^{T_{di}} s_{wd} \tag{4}$$

where T_{di} is the time between waypoints visits, s_{wd} are the waypoints values (priority), and λ is a time discount factor. Given the values of all the petals S_{vp}, RHTA solves an optimization problem to assign the optimal petal (an ordered subset of waypoints) for each UAV:

$$\max J = \sum_{v=1}^{N_v}\sum_{p=1}^{N_{vp}} S_{vp} x_{vp} \tag{5}$$

$$s.t \qquad \sum_{v=1}^{N_v}\sum_{p=1}^{N_{vp}} A_{vpi} x_{vp} \le 1, \qquad x_{vp} \in \{0,1\} \tag{6}$$

$$\sum_{p=1}^{N_{vp}} x_{vp} = 1, \quad \forall v \in \{1,\ldots,N_v\} \tag{7}$$

In this paper, the RHTA algorithm was extended to integrate the probability of failure in objective function. That extension includes an estimate of each vehicle's probability of failure, which was achieved redefining the estimation of the cost of each petal, which is redefined as:

$$S_{vp} = \sum \frac{1}{T_{di}} (1 - D_v) s_{wd} \tag{8}$$

which is subject to the same restrictions – equations (6) to (7). Such restrictions grant that for each iteration one UAV is assigned to one and only one task.

D_v represent UAVs team failure probability given by S-RUL procedure [9], as stated in the section IV, which include failure probability in RHTA, that still takes into account the total mission time minimization and waypoints priorities.

In [8], authors also did modified RHTA in order to embed health information, by means of adding restriction to the length of possible sequences of waypoint. It was accomplished reducing the vehicle operational radius every time a failure occurrence came into play.

In this article approach, it was assumed that probability of failure is known in advance; so that, mission planning could take advantage of this to proceed task assignment, getting a part from this process those vehicle with unacceptable probability of failure, as a preventive action based on safety margins.

VII. Case Study

In this case study, the PHM-Based RHTA algorithm presented in the previous section is used in a simulation considering 5 UAVs, 15 waypoint, $n_c = 3$, λ = 0.5, $v_{\max} = 10$ m/s and waypoints/tasks priorities determined such as $w_1 < w_2 < \ldots < w_{15}$. **Figure 5** shows UAVs initial location and waypoints positions.

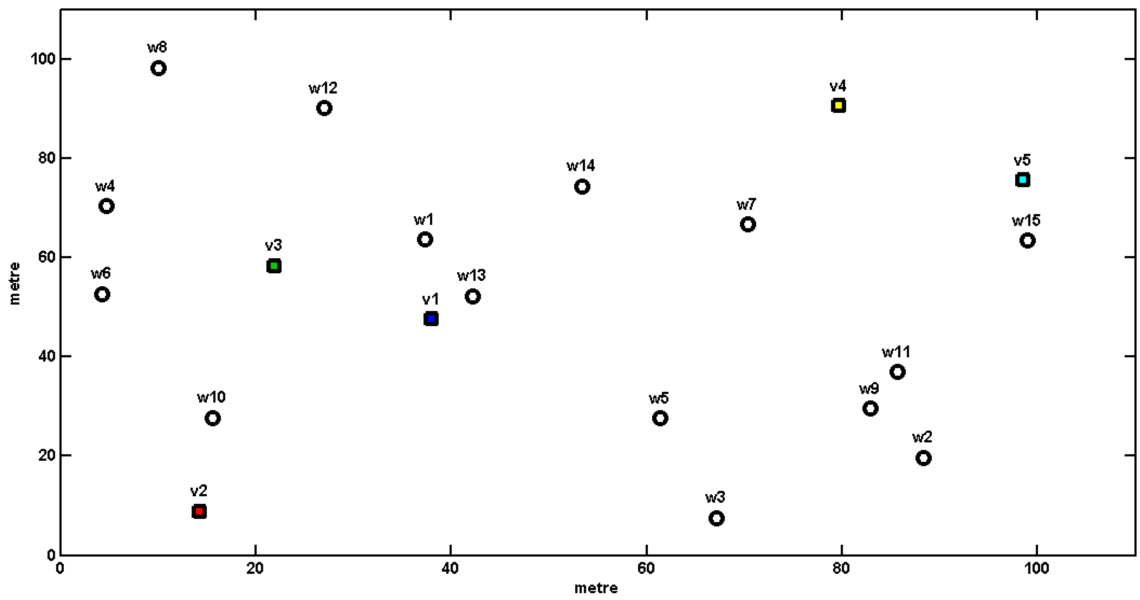

Figure 5. UAVs initial locations and tasks initial positions.

For this case study, it was selected a pitch control system fault tree from [16]. That one is presented in **Figure 6**. The top event is loss of pitch control that is a catastrophic event.

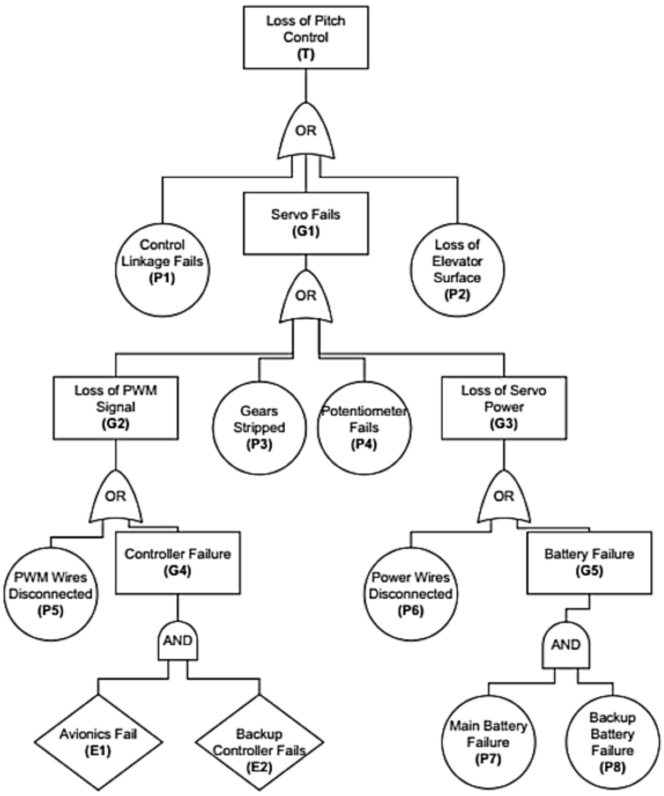

Figure 6. Loss of pitch control fault tree (Source: [16])

So that, probability of failure given by a PHM systems for each of those critical components necessary for the regular operation of pitch control system are presented in TABLE I. , for the UAV 1.

TABLE I. FAILURE PROBABILITIES FOR UAV 1

Failure Probabilities	
Basic Event	***Probability of Failure During Mission***
P1	13.1%
P2	2.1%
P3	3.3%
P4	8.1%
P5	5.3%
P6	1.6%
P7	17.0%
P8	9.8%
E1	1.5%
E2	28.0%
S-RUL	31.0%

After that, from the data in TABLE I. relating to UAV 1 pitch control system critical components and applying S-RUL methodology, in the end, the system probability of failure, called here S-RUL, is computed as follows:

$$P_{S-RUL} = 1 - \left[(1-P_1)\cdot(1-P_2)\cdot(1-P_3)\cdot(1-P_4)\cdot \right. \\ \left. \cdot(1-P_5)\cdot(1-P_6)\cdot(1-(P_7\cdot P_8))\cdot(1-(E_1\cdot E_2))\right] \quad (9)$$

TABLE II. summarizes the probability of failure for the UAV swarm. For each UAV, it was performed the same process used to determine the failure probability of UAV 1.

TABLE II. FAILURE PROBABILITIES FOR ALL UAVS

Failure Probabilities	
UAV	***Probability of Failure During Mission***
UAV1	31.0%
UAV2	13.1%
UAV3	8.2%
UAV4	25.4%
UAV5	18.6%

After that, the values in TABLE II. are input into PHM-base RHTA algorithm as D_v vector. In order to simulate this scenario and perform the BIP (Binary Integer Programming) optimization in RHTA algorithm, MATLAB [17] and CPLEX [18] were deployed to generate the result in section VIII.

VIII. SIMULATION RESULTS

In **Figure 7** and TABLE III. , result is summarized for task assignment considering total mission time and task priority.

For the first iteration all the UAV moved ahead to the most valuable tasks and the closest too.

So, during the second iteration UAV v_1 is the closest vehicle to task w_1, but it takes w_5 that worth 5 times more and relating to task w_7 it is almost the same distance; although, probably RHTA algorithm was not able to find a sequence involving tasks w_7 and w_{13} that minimizes mission time. UAV v_2 and v_3 was assigned respectively to w_6 and w_8, the closest valuable task from each one. UAV v_4 and v_5 also were assigned to the closest valuable task from each one, respectively to w_7 and w_{11}. Moreover, they took over advantage locations, considering the next tasks features.

In the third iteration, there are almost low priority tasks remaining; so, the decision was made based mainly on the distance, in order to minimize the mission time.

TABLE III. MISSION TIME FOR EACH UAV WITHOUT S-RUL

UAV	***Mission Time (seconds)***
UAV1	5.8
UAV2	6.4
UAV3	9.5
UAV4	10.0
UAV5	4.4

Figure 8 and TABLE IV. present the result for task assignment considering total mission time, task priority and S-RUL information.

UAV v_5 keeps the same assignment did in the result of **Figure 7**, which means this sequence still satisfies mission time and priority, even though the new information of probability of failure that decrements the chance of mission success.

UAV v_1 has the highest probability of failure in the swarm, so that, in order to compensate this, PHM-based RHTA assigned it to a set of waypoint with higher value and almost the same total distance relating to the previous assignment in **Figure 7**.

UAV v_2 has one of the lowest probabilities of failure and it was assigned to a longer path than the previous one; cause the time is higher; but chance of succeeding is higher too.

UAV v_3 took advantage of the highest chance of succeeding among all UAVs and it combined a shorter path than the previous assignment to maximize mission profit.

And UAV v_4 was assigned to low priority task, considering the higher degradation and that there was not a path to compensate such probability of failure discount.

TABLE IV. MISSION TIME FOR EACH UAV WITH S-RUL

UAV	***Mission Time (seconds)***
UAV1	6.1
UAV2	8.6
UAV3	6.4
UAV4	12.5
UAV5	4.4

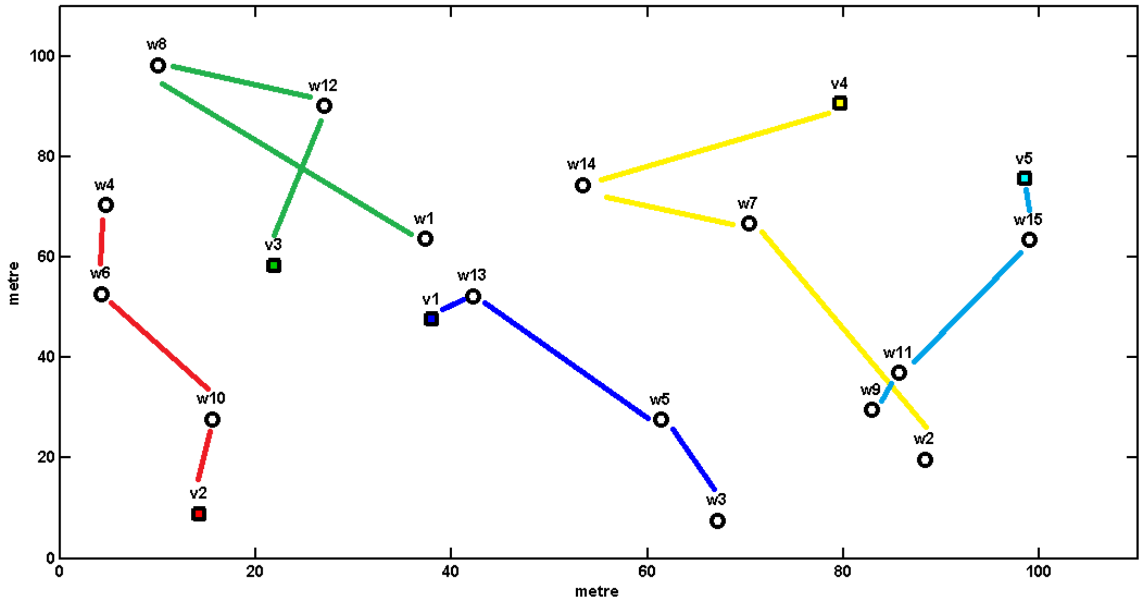

Figure 7. Result considering mission time and task priority

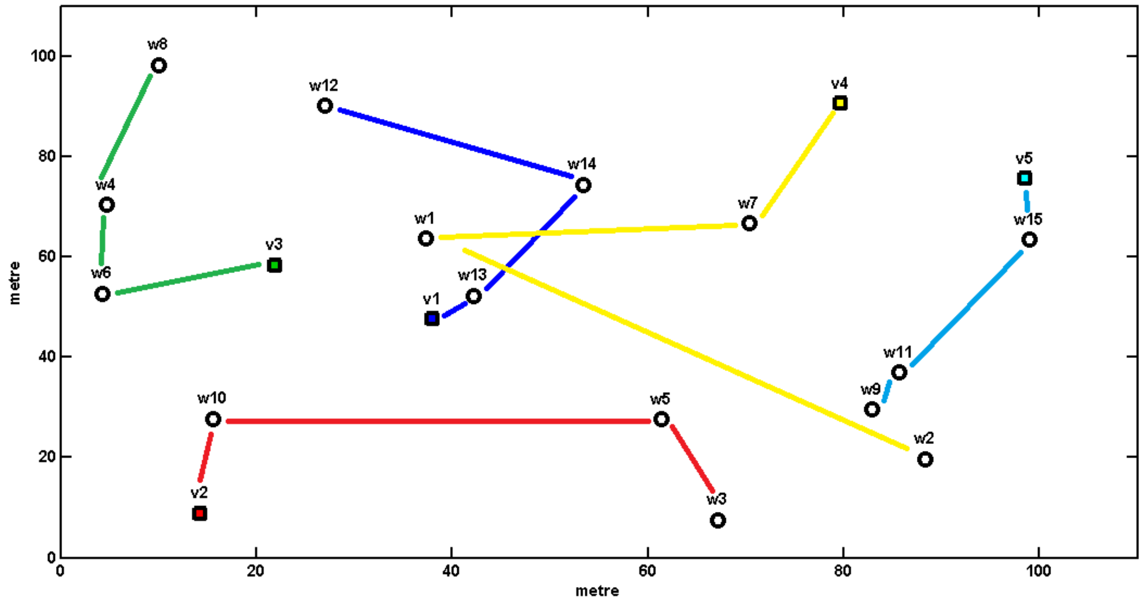

Figure 8. Result considering mission time, task priority and probability of failure

IX. CONCLUSIONS

This paper introduced a modified version of RHTA algorithm, named PHM-based RHTA algorithm, in order to include system probability of failure into task assignment. Additionally, it also introduced how to apply S-RUL methodology to accomplish that.

At first glance, PHM-based RHTA results did not look reasonable such as v_3 and v_4 assigned to task with half of the importance in the first iteration of PHM-based algorithm. However, when observing the big picture in the end of assignment process; trade off as healthier vehicle taking a longer path and more degraded vehicle getting high value and shortest task to compensate the higher probability of failure made sense.

It is important to point out PHM-based RHTA, as the original version, assigns tasks to UAVs looking forward to the possible final path into each iteration. So that, assignments also take into account the influence of the current assignment to the remaining possible path.

Future work could investigate PHM-based task assignment for long haul mission and how the algorithm behave when probability of failure changes during the mission.

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