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The Price of a Safe Flight: Risk Cost Based Path Planning

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***Abstract*—A risk aware UAS path planning methodology is proposed using monetary value as the sole cost metric. A third party ground risk model is used to generate a non-uniform costmap for a modified A* heuristic search. The Value of a Prevented Fatality provides a basis to convert fatality risk to monetary value terms as a Human Value at Risk (HVaR) measure. Additional operating and UAS Capital Value at Risk (CVaR) costs are modelled to provide a holistic monetary cost model for path cost minimisation. A number of future cost variants are investigated based upon prior work for a realistic urban-rural mix logistics case study in Southern England. Results show increasingly risk averse paths with decreasing future UAS operating costs.**

***Index Terms*—uas safety, ground risk, path planning, value of a statistical life**

I. Introduction

A considerable number of use cases for uncrewed aircraft systems (UAS) are focused around logistics, be it medical cargoes [1] or last mile services such as food delivery or general package shipping [2]. The logistics use cases commonly involve operating in and around urban areas, as this is where the majority of the probable consumers are located. UAS have two main modes of operation: Visual Line of Sight (VLOS) or Beyond Visual Line of Sight (BVLOS), the former requires that the remote pilot always maintains visual contact with the aircraft and commonly abide by altitude restrictions (depending upon local regulations). The latter allows the aircraft to operate at greater distances relying upon higher integrity communication methods to maintain contact with the operator(s). As the rules of VLOS are too restrictive to feasibly operate logistics operations under, BVLOS presents a path forward to a potential future where multiple aircraft can be overseen by a single operator.

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Such a future would rely upon the increasing automation of UAS flights, including the ability to autonomously navigate to given locations in a safe and expeditious manner. Unfortunately, “safe” and “expeditious” are commonly at odds with each other, particularly in urban areas. As the reliability of UAS is not yet proven or certified, unlike conventional aircraft [3], operational mitigations to the third party risks posed by UAS must remain in place in order to avoid causing harm to persons being overflown. Whilst qualitative risk assessment are commonplace within UAS Operating Safety Cases (OSCs) in the UK, they are prone to subjectivity and are inclined to result in relative rankings of hazards compared to other hazards. Fortunately objective, quantitative methods are seeing increased interest [4], [5]. Such quantitative risk analysis methods can be leveraged for the purposes of path planning routes which are quantifiable safe when compared to a Target Level of Safety (TLS). This provides the assurance to operators and regulators that the proposed operation aims to reduce its third party risk exposure as low as reasonably practicable (ALARP). ALARP is a common goal across many safety-critical industries such as aviation and nuclear [6], [7]; and is implicit in many other decisions taken across all industries.

ALARP is an idealistic goal, however, unfortunately very little in life is entirely risk-free therefore it is also likely to be an unattainable goal, though this does not mean it is an unworthy target to strive towards. Numerous other safety-critical industries face similar dilemmas with many utilising quantifiable valuations of life [8]–[10] as a benchmark for their operations.

This work proposes the use of quantitative valuations of life in the analysis of third party risk posed by UAS. A significant motivation behind this is to allow the comparison of all UAS operation costs on an equal footing, using dimensionally identical values. This eliminates the requirement for semi-arbitrary weightings to be introduced, particularly between risk and other more tangible costs of the operation. We further demonstrate an application of this concept to a modified optimal path planning problem [11] where all the path costs are calculated in terms of monetary value.

This paper is structured as follows: Section II reviews relevant past works including the use of valuations of life in other academic fields and industries; Section III describes the methods used including an overview of the risk model and modifications made to the path planning algorithm; Section IV presents the results of applying the proposed algorithm to a logistics case study in Southern England with projections for future UAS operating costs then discusses the potential further uses of the proposed method and their implications to UAS operations going forward and Section V draws conclusions and suggests future avenues of exploration.

II. Past Work

UAS have the potential to pose a wide range of hazards to third parties, generally within the vicinity of overflight. This is a particularly important issue in urban environments, where certain use cases such as package delivery or even medical logistics make the avoidance of urban areas unavoidable. There is, therefore, a need to characterise the risk posed by overflying certain areas within the urban environment.

Past work has sought to derive quantified boundaries that define the "acceptable" level of risk; this generally lies in the region of 1×10^{-7} fatalities per flight hour [12] with 1×10^{-7} fatalities per flight hour also being commonly used as a Target Level of Safety (TLS) [13]. Risk quantification methods are therefore able to use these thresholds as either constraints or minimisation objectives. Since utilising the TLS as a constraint could make certain use cases impossible, due to the inability to avoid urban environments, a minimisation approach is used.

The non-uniform costmap optimal path planning problem has significant research with a wide range of methods being applied from sampling based approaches [14], genetic algorithms [15] and stochastic approaches [16] to graph search methods [17], such as that proposed here.

Applications to risk aware path planning feature a similar diversity in approaches [18]. Feyzabadi et al. [19] model simulated indoor factory environments using a Constrained Markov Decision Process. This presents challenges in terms of computational complexity, especially for larger costmaps, such as that used here. The authors mitigate this through the use of hierarchical approaches, but this comes at the cost of sub optimal path selection.

Primatesta et al. [20] use a sampling based approach for near-optimal path planning on ground risk maps. The authors focus on the intra-urban case, therefore use smaller risk maps. A post optimisation smoothing procedure is also used to make the paths more feasible on the smaller scale used. An advantage of the sampling based approach is making the generation of a configuration space graph unnecessary; this is valuable in real time and Simultaneous Localisation and Mapping (SLAM) path planning. The downside is the lack of optimality in the paths. In this case, the risk map needs to be generated beforehand regardless, therefore there is little advantage to using sampling methods in this work.

The use of a value of a statistical life (VSOL) is a common method for performing safety critical cost benefit analysis. There are a number of differing measures which are interrelated such as VSOL, Value of a Prevented Fatality (VPF) and Judgement Value (J-Value). The nature of the measures can at times be controversial and it is common for wide range to exist on the actual values [21], as well as vary significantly between countries and jurisdictions [22]. Many different factors can affect the VSOL measures, such as age, potential future earnings and cohort effects [23]. The J-Value [24] is of particular research interest as it aims to account for a wider range of factors than VPF, however is significantly more complex and has yet to gain widespread use [25].

This work focuses on the UK and uses the VPF method, as this is standardised across the transportation industry in the UK, amongst other industries. Additionally, it is potentially beneficial to have the ability to compare with other transport modes as these are ultimately what UAS have to compete with and will be benchmarked against in terms of safety. The authors have already conducted work into relative safety between UAS and vans [26].

III. Methods

The proposed method depends upon the existence of a quantitative UAS risk analysis model that is able to generate risk maps. Risk maps represent the probability of a UAS causing a fatality if it were to be flown at the physical positions that correspond to the represented locations in the risk map. The nature of the risk map is not limited to two dimensions, (i.e., representing the same height above ground), however, it is more easily visualised in that form.

The risk map is utilised as a non-uniform costmap by the proposed path planning method. The risk model used in this work is one previously developed by the authors [4]. This risk model accounts for spatiotemporal changes within the population distribution to produce risk maps that are specific to the aircraft and the types of descent modes it may enter (based upon parameterised models) as well as the time of day and the altitude of flight. It is also available as an open source tool [27]. Further detail on the risk model is available from [4], but is omitted here for brevity.

For the case study demonstration, a hybrid VTOL logistics UAS was modelled with the parameters shown in Table I. This UAS was selected as it is representative of the UAS being used for current logistics trials. It has a maximum payload of 5 kg and a cruise speed of 40 m/s. For the case study presented here, the aircraft is modelled as fully laden and operating at its design cruise speed. Additionally, it is modelled as operating at 120 m above ground level, as this is a common vertical boundary for UAS operations in the UK.

TABLE I
RISK MODEL PARAMETERS OF THE AIRCRAFT USED FROM [4]

Parameter	Value
Mass [kg]	17
Length [m]	1.63
Width [m]	2.22
Horizontal Airspeed [m/s]	31
Frontal Area [m^2]	0.5
Ballistic Descent Drag Coefficient	0.8
Glide Airspeed [m/s]	21
Glide Ratio	11
Event Probability [h^{-1}]	5x10^{-3}

The proposed path planning algorithm is a modified version of the common A* heuristic search. Our modifications account for the non-uniform costmap and cost functions return the path cost as monetary values rather than entirely motion-based quantities.

The path costs can be divided into the canonical categories: fixed and marginal. The fixed costs are trivially handled by applying them to the found path after reconstruction from the graph. Marginal costs are calculated to every node that is explored by the search. The marginal costs include the vehicle operating costs, as derived in [28] for a similar platform; Human Value at Risk (HVaR); and Capital Value at Risk (CVaR). The hierarchy of costs is shown in Figure III.

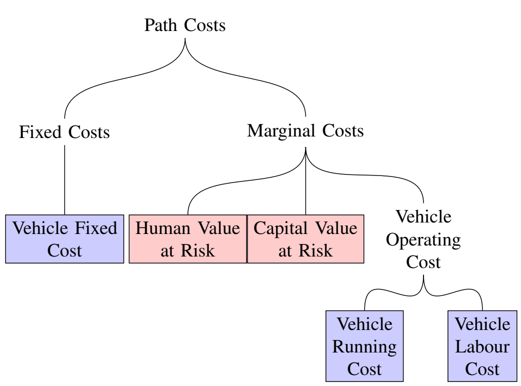

Fig. 1. Hierarchy of path costs. ● represents the costs actually incurred by the operation. ● represents the probabilistic costs calculated by the value at risk.

Three price points were explored in this study, whereby (i) "current" regulations and costs were assumed; (ii) hypothetical "future" costs were assumed, with greater automation; and (iii) a critical price point was assumed, as identified by Oakey et al. [28], where UAS are noted to be advantageous over existing modes in a medical logistics system with respect to cost (18.5% of current levels, "tipping point").

The vehicle fixed costs, $\mathrm{FC_{veh}}$, consisted of the assumed insurance and traffic management (UTM) fees per day. Similarly, the vehicle running cost between nodes n and m, $\mathrm{MC_{veh}}(n,m)$, were derived from the cost of the UAS platform components on a per flight-hour basis, in line with the concept of an approved maintenance programme where parts are replaced based on accrued flight time [29], [30]. The platform was discounted in the 'Future' scenario, with a linearly decreasing discount from 3% to 0% in 0.1% increments, compounded over 30 years, resulting in a cost multiplier of 62.58% of present day levels.

The labour cost accounted for the personnel requirements for conducting the operation itself. In the 'Current' scenario, 2× safety pilots and 2× loaders/technicians were assumed, in addition to a mission commander, whilst only the mission commander and 1× loader/technician featured in the 'Future' scenario.

The marginal cost for a given node pair is found through the time taken to traverse between those nodes, then pro-rated against the hourly cost; this is repeated piecewise along the path. The future labour costs were divided by an expected operator to UAS ratio of 1:20, as suggested in [31]. Table II outlines the figures that were found using the multi-modal transport model, presented in [28].

TABLE II
UAS OPERATING COSTS FROM [28] THAT ARE USED AS THE BASIS OF INCURRED PATH COSTS.

Cost	Current	Future (∼43% of Current)	Tipping Point (18.5% of Current)
Labour (£/h)	£175.64	(£31.44/20=) £1.52	(£32.49/20=) £1.62
Veh. Running (£/h)	£32.40	£20.33	£5.99
Veh. Daily (£/veh./day)	£8.99	£8.99	£1.66

The CVaR, VaR_C, is found using the nominal value of the UAS in addition with the reasonable assumption that should the UAS cause a human fatality on the ground, it is almost certain the UAS itself will also be beyond economic repair; therefore the entire value of the UAS, $\mathrm{CV_{UAS}}$, is considered to be at risk. CVaR is a function of the aircraft probability of loss of control, P_{LoC}, and the flight time, t_f, given by Equation 1

$$\mathrm{VaR}_C = P_{\mathrm{LoC}} \cdot t_f \cdot \mathrm{CV_{UAS}} \tag{1}$$

Finally HVaR, VaR_H, is found using the Value of a Prevented Fatality, VPF. This is a reasonable statistic to use in this context, as its use here results in lower ground risk paths that probabilistically work to prevent fatalities when compared to potentially higher risk, more direct paths. The VPF, most recently for 2022, is set by the UK government (HM Treasury) to be £2,308,000 [32]. This value is adjusted upwards with economic conditions and is most recently maintained by the UK Rail Safety and Standards Board (RSSB) [33]. The HVaR is given by Equation 2 for a path with N nodes and risk map R.

$$\mathrm{VaR}_H = \sum_{i=0}^{N} \mathrm{VPF} \cdot R(x_i, y_i) \tag{2}$$

The basic A* algorithm is omitted here for brevity with only the modifications to the cost functions given. The cost function accounts for both the CVaR and HVaR and is given by Equation 3 for the i-th node. In order to account for the fixed costs, the start node cost is modified, given by Equation 4.

$$g(n_i) = \mathrm{VaR}_H(n_i) + \mathrm{VaR}_C(n_{i-1}, n_i) + \mathrm{MC}_{\mathrm{veh}}(n_{i-1}, n) + g(n_{i-1}) \tag{3}$$

$$g(n_0) = \mathrm{FC}_{\mathrm{veh}} \tag{4}$$

The heuristic function is required to be both admissible and consistent for optimality. Here, this is achieved relaxing the cost function in Equation 3 and discounting the contribution of the HVaR. Due to the probabilistic nature of the risk maps generated, the cost map therefore asymptotically approaches but does not equal zero [4], this is expressed in Equation 5.

$$\forall x, y(R(x, y) > 0) \therefore \forall n(\mathrm{VaR}_H > 0) \tag{5}$$

The heuristic function is therefore simply the marginal vehicle cost between the nodes, given by Equation 6.

$$h(n, m) = \mathrm{MC}_{\mathrm{veh}}(n, m) \tag{6}$$

IV. Results

A realistic case study is used to demonstrate the proposed methods. The area is a mixture of urban and rural settings on the Southern coast of the UK, shown in Figure 2. The urban areas are evident in the generated riskmap, shown overlaid with the generated paths in Figure 3. The origin and destination of the paths is held fixed for all variants and are chosen such that the direct path between them results in overflight of the a large number of urban areas (shown in Figure 3); this enables the proposed methods to demonstrate optimisation behaviour in an explicit manner.

Each of the cost variants from [28] was modelled using the proposed methods, the paths are displayed visually on the non-uniform costmap used (that is the risk map) in Figure 3, the incurred fatality risk level along each of the paths is shown in Figure 4 and statistics on the path costs and motion are detailed in Table III.

The constituent parts of the path costs are shown in Figure 5 with the proportion of each path's cost that is probabilistically obtained through combining the VaRs with the corresponding probabilities. The future operating costs of UAS are expected to decrease, through factors such as fewer safety pilots and the ability for a single operator to oversee many UAS. This is in stark contrast to the majority of current operations where multiple operators and safety pilots can be involved in operating a single UAS in larger scale operations. Whilst the operating costs are projected to decrease, the probabilistic costs as a result of VaR remain approximately the same, therefore their proportion of the total path costs increases. The same is true for the direct path cases which are shown as a comparative benchmark for each of the cost variants.

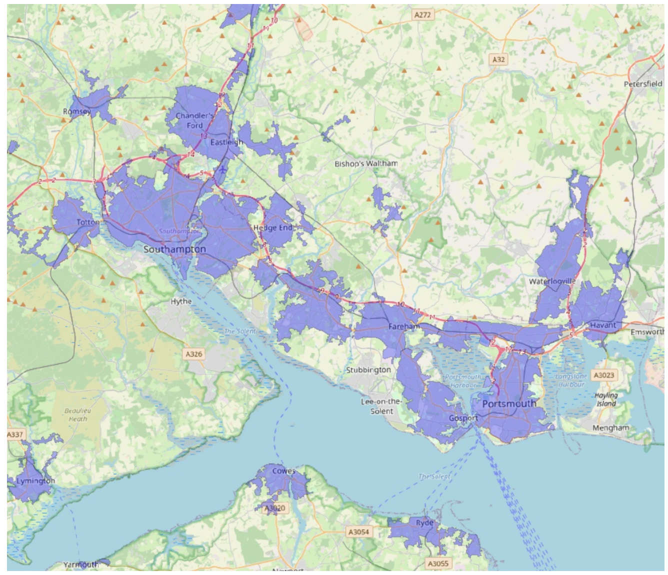

Fig. 2. Map of case study area. ● represents areas that are identified as "urban" based upon a 2011 UK census.

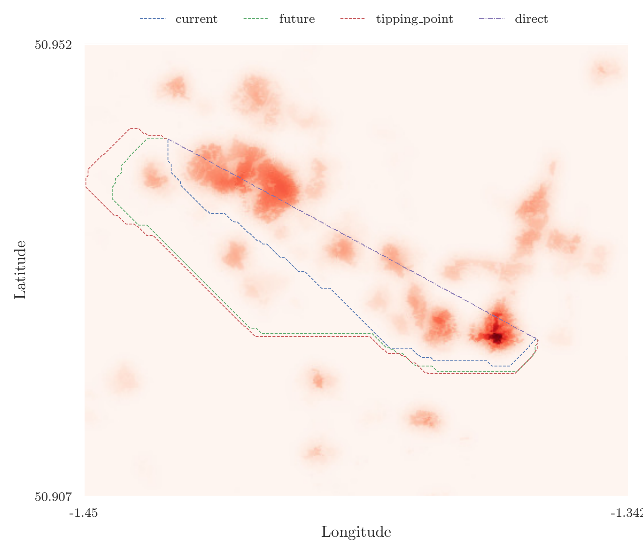

Fig. 3. Variant Paths plotted on risk map.

This result is logical, as if it becomes cheaper to operate the UAS for a greater amount of time, then the cost of a

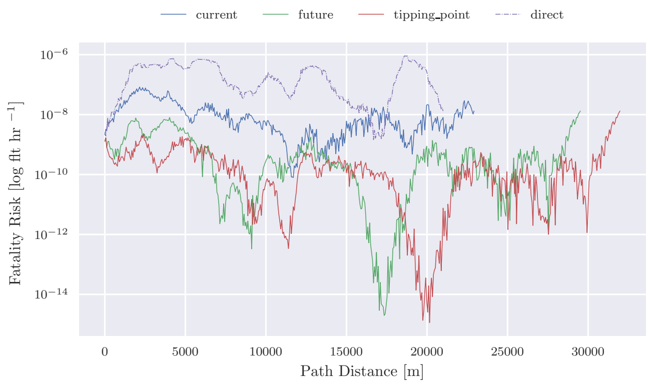

Fig. 4. Fatality Risk measure along each of the paths generated. Direct paths are provided as comparisons to the path generated by the proposed method.

TABLE III
VARIANT PATH STATISTICS.

Variant	Cost [£]			Distance	Time
	Incurred	VaR_H	VaR_C	[m]	Enroute [s]
current	67.15	11.22	13.98	28174.24	1006.22
direct_current	58.32	199.54	11.85	23894.77	853.38
future	16.59	1.13	17.35	34973.06	1249.04
direct_future	14.18	199.54	11.85	23894.77	853.38
tipping_point	4.56	0.50	19.02	38352.61	1369.74
direct_tipping_point	3.47	199.54	11.85	23894.77	853.38

"detour" around urban areas to decrease the risk of the path comes at a smaller operating cost impact. It should be noted that the probability of Loss of Control, P_{LoC} is held fixed for all cost variants, therefore this is likely a worst case as UAS are expected to become more reliable. Additionally, the P_{LoC} is assumed to be constant over the course of a flight. The VPF is adjusted upwards on an approximately annual basis and accounts for prevailing economic conditions. This means that the HVaR should maintain its "real" value and improved reliability should contribute to lower HVaR routings. Placing a quantitative figure on the future reliability of UAS is a notoriously difficult exercise [3], as there is very little in the way of large scale evidence to basis such assertions upon, as in other more established industries such as automotive. Generally, more expensive UAS would be expected to be more reliable, however pose a larger CVaR.

Despite the increasing risk aversion, Figure 5 shows the decreasing overall path costs for future cost variants. This is primarily a result of a significant reduction in the operating costs, by definition of the cost variants. Whilst the probabilistic costs are indeed small in absolute terms for a single trip, it should be noted that this is the cost for a single path in one direction. This becomes a significant amount for large scale operations, which are almost certainly required for commercial viability of an endeavour. For example, to operate a return UAS sortie three times per day for one year assuming the future variant presented in this work would give a Human Value at Risk exposure of £436,993 if using a direct path and only £2,475 if using the path planning methodology proposed here. This is a reduction, cumulatively over a year, in Human Value at Risk exposure of £434,517 or 99.4% of the direct path risk exposure. Such values are far from insignificant and most rational enterprises would do well to minimise their risk exposure in such a manner.

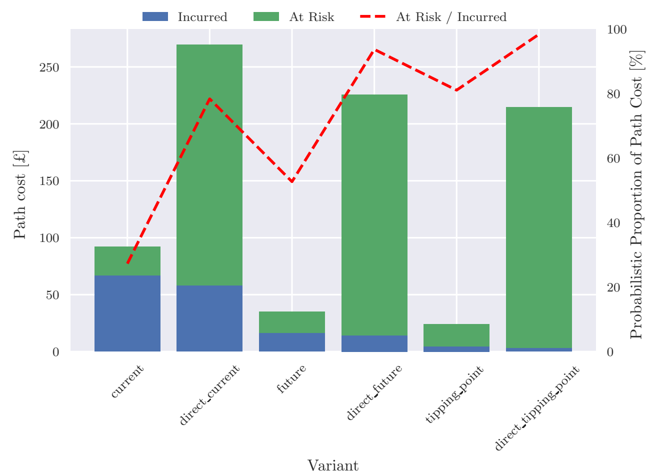

Fig. 5. Monetary path costs for different cost variants. Trend line shows the ratio of the "At Risk" costs increasing into future scenarios, even in the direct path case.

V. Conclusion

In conclusion, the proposed path planning methodology provides a unified cost basis on which to objectively and quantitatively assess the true cost of UAS operations through a common dimensional; monetary value. This negates the need for arbitrary weightings or Pareto analysis between dimensionally incompatible costs, of which risk is a notable such quantity. The concept of Value at Risk (VaR) is extended to include Human and Capital Value at Risk (HVaR and CVaR respectively) to account both for the cost of causing a fatality as well as the loss of the UAS in such a scenario.

A modified A* implementation is created to generate cost-optimal paths based upon a risk map generated through a third party ground risk model, previously developed by the authors [4]. Prior multi-modal logistics work by the authors [28] is used to model current and future UAS operating cost variants, where UAS are able to remain cost competitive against other transport modes. Paths are generated using the proposed method for each of these cases and compared against both the direct path for that cost variant and past and future variants.

The results for a realistic urban-rural mix case study in Southern England show that decreasing UAS operating costs increase the risk aversion of the generated paths. This is due to the probabilistic (HVaR and CVaR) costs becoming a larger proportion of the total path costs, therefore the proposed algorithm is given higher incentive to minimise such costs.

A. Future Work

Future work includes more use case specific specialization of the model to account for the differing payloads carried on different sorties. Additionally, medical use cases present further challenges through the potential for operations to increase the life expectancy of patients, however it should be noted the number of payloads this is true for is very narrow, e.g., the majority of medicines have sufficient shelf lives to make this unnecessary [1], [28], [34]. This could also be true for other UAS payloads, however the benefit of the deliveries becomes more difficult to quantify.

The use of alternative valuations can also be explored, such as the Quality Adjusted Life Year (QALY), which is commonly used to give a more holistic view on the benefits provided by medical interventions accounting for the expected quality of life. Relative measures such as the J-Value, could also provide more specificity for individual cases, rather than the generalised approach presented here.

A notable and potentially significant cost that is not modelled in this work is that of (infra) structure damage as a result of the loss of control of the aircraft. This is particularly important in built up urban areas. It is considerably difficult to quantify the value of such structures on a large enough scale to be able to model in the same manner as presented here.

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