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Macro-scale Reconfigurable Unmanned Aerial Vehicles for Civilian Offshore Applications

Souma Chowdhury[1], Victor Maldonado[2], Weiyang Tong[3], and Achille Messac[4]

[1]Mechanical and Aerospace Engineering, Syracuse University, Syracuse, USA, sochowdh@syr.edu
[2]Mechanical Engineering, Texas Tech University, Lubbock, USA, victor.maldonado@ttu.edu
[3]Mechanical and Aerospace Engineering, Syracuse University, Syracuse, USA, wtong@syr.edu
[4]Mechanical and Aerospace Engineering, Syracuse University, Syracuse, USA, messac@syr.edu

Abstract
The benefit of an optimization framework that can assist to optimally reconfigure a family of UAVs for distinct flight requirements is readily evident; collectively they could capture a wide segment/niches of the Civilian UAV market. As an aircraft manufacturer, one would seek industries and customers that can utilize the "reconfiguration" capability of a UAV family for different aerial tasks, which offers a clear cost advantage over acquiring separate UAVs dedicated to specific type of missions. This paper exploits the Comprehensive Product Platform Planning (CP^3) framework to design such a family of three reconfigurable twin-boom UAVs for offshore applications. The performance of the UAVs, expressed in terms of their fuel economy, is maximized in this process, while the cost of the UAV family is minimized. The majority of the cost savings come from the sharing of the UAV modules across different UAV variants. It is observed that, among the best tradeoff UAV families, the individual UAVs are most likely to share the horizontal tail and tail booms, and are least likely to share the wing. The best tradeoff UAV family designs provide a remarkable 26% reduction in cost for a 6% compromise in performance. The significant degree of commonality (module sharing) observed among these Pareto designs provide clear evidence towards the benefits of applying modular platform planning methods in the civilian UAV industry.

Keywords: Multi-Objective MINLP, Optimization, Product Family, Reconfigurable, Unmanned Aerial Vehicle (UAV).

1 Introduction

Sophisticated and expensive systems such an UAVs, which are also required to perform different types of operations (missions), can uniquely benefit from the flexibility to be "readily reconfigurable". Modular product platform planning concepts provide a unique opportunity to design such reconfigurable systems, thereby providing additional cost savings to the manufacturer and the user, on top of the typical overhead savings generally attributed to product family design (PFD). In this context, macro-scale reconfiguration refers to *reassembly of a set of modules prior to a mission/operation*. This reassembly creates a system that is optimally suited to the mission at hand, where the mapping between mission categories and optimal configurations are defined by the PFD process.

The Comprehensive Product Platform Planning (CP^3) method, extended to modular product families, was recently applied by the authors to design a family of three "twin-boom" UAVs for civilian applications with three distinct combinations of payload capacity and endurance [1]. The performance of each UAV, expressed in terms of "endurance/fuel consumption", was maximized, while also maximizing the overall commonality among the three UAVs. The optimized platform designs were an evolution from the scaling baseline designs developed by RenAir LLC [2], as shown in Fig. 1. This paper further extends the CP^3 framework to design a family of three reconfigurable twin-boom UAVs, where the net cost of the UAVs are minimized (while maximizing their performances). The cost reductions come from overall weight reductions as well as from sharing of parts through reconfigurability. An example of an industry where such an UAV family is pragmatic is the offshore petroleum industry, specifically deep-water platforms. In this context, we quantitatively address the following important questions: What are the cost and mission execution benefits (or trade-offs) of a macro-scale reconfigurable UAV family compared to a set individual UAVs suited to different applications?

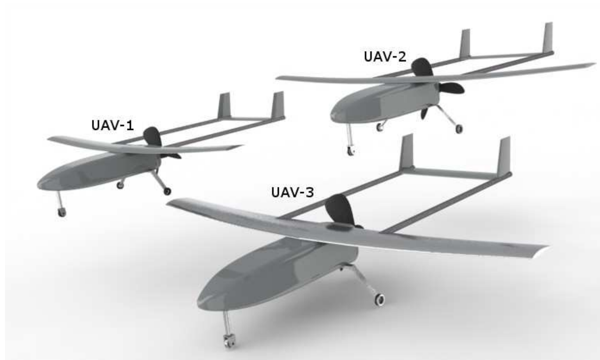


Figure 1: A scale-based family of twin-boom UAVs (courtesy of RenAir LLC)

1.1 Overview of Modular Product Family Design

In a module-based product family, distinct modules are added or substituted (on a common platform) to develop different products [3, 4]. A popular example of a modular product family is the series of Sony Walkmans [5, 6], whereas a standard example of a scalable product family is Boeing's 777 aircraft series [7]. In addition to the advantages derived from the increased scope of platform planning, modular product architecture also provides benefits such as easier transportation, easier replacement of products, potential for reconfigurability, and effective evolution of product generations. However, modular product families generally present significant challenges to the design process owing to factors such as: (i) module-interdependency, (ii) possibility of inclusion/exclusion/substitution of modules, and (iii) definition of each module in terms of multiple variables thereby requiring simultaneous evolution during platform-planning becomes.

One of the popular approaches to module-based product family design conceptually divides the process into the following three levels (i) Architectural level: to establish a system structure and its variations, (ii) Configuration level: to establish standard configuration(s), and its variations of products and modules, and (iii) Instantiation level: to develop a practical product family through variable quantification and combinatorial selection of the modules. The assumptions involved in these two classes may lead to sub-optimal module-based product families. Very few optimization approaches exist to solve Class 3 type optimization problems, such as developed by . Several well known methods exist in modular PFD, such as presented by Stone et al. [8], Dahmus et al. [9], Guo et al. [10], Fujita et al. [11, 12], Jose et al. [13], Kalligeros et al. [14], Rai et al. [15], Saron et al. [16], and Yu et al. [17]. A detailed description of these methods is not within the scope of this paper, since the focus of this paper is on introducing and exploring the benefits of optimal modular platforms for macro-scale reconfigurable UAVs.

1.2 Product Family Concepts in Aircraft Design

Product family methodologies in aircraft design are employed by some aircraft manufacturers to design a series of multi-mission capable aircraft with superior performance at a lower cost. Unlike the application of multidisciplinary design optimization (MDO) techniques to optimize a single aircraft for a specific mission, product family aircraft designs are optimized with a certain degree of commonality while interchanging key components in order to satisfy a wide range of mission requirements. Historically, this has been accomplished though derivatives or variants of the baseline aircraft. For example, the original Boeing 737-100 which first flew in 1967 has evolved (through 11 major design variants in 39 years) in order to increase passenger capacity, fuel efficiency, and flight range. However, despite the steady increase in performance, the Boeing 737 series continues to operate primarily domestic routes. The goal of modern product family methods is to design aircraft with a significant variation in performance in order to serve multiple market segments, i.e. domestic and transatlantic routes. Such a motivation is discussed in the study by [18] to design a family of two blended-wing-body (BWB) aircraft with a capacity of 272 and 475 passengers with built-in commonality. Other noteworthy investigations includes the use of decomposition-based methods [19] and genetic algorithm techniques [20] for aircraft family design.

In recent years, the academic community has seen an explosive growth in research towards unmanned aerial vehicles (UAVs) fueled by sharp sales projections from a nascent Civilian UAV market. The industry now seeks to develop unmanned aircraft for a wide range of applications and mission profiles.

This presents a unique opportunity to utilize product family methods to design a modular UAV family that simultaneously meets the needs of diverse customer requirements while reducing the design, fabrication, and transportation costs to the manufacturer. A methodology for the design of a two-UAV family operating under aerial fire-fighting in the vicinity of the Greek islands and maritime surveillance off the coast of Norway is described by Freeman et al. [21]. However, although the applications are different, both missions require long endurance monitoring with similar camera payloads. In the current paper, we consider a family of three UAVs designed to fulfill missions with distinct endurance and payload/ weight requirements. Moreover, it becomes more profitable to both the manufacturer and the consumers (or end-users) when the UAV family is designed for industries where the same end-user can take advantage of the modular design and utilize all three UAV configurations.

2 Modular Product Platform Planning of UAVs

2.1 Comprehensive Product Platform Planning (CP^3): Overview

The Comprehensive Product Platform Planning (CP^3) framework, introduced by Chowdhury et al. [22], seeks to coherently address a wide range of problem scenarios. The CP^3 framework presents a generalized mathematical model of the platform planning process based on the formulation of a commonality matrix. This model yields a *mixed-integer nonlinear programming* (MINLP) problem with a large number of binary variables. Originally, Chowdhury et al. [22] developed and implemented a Platform Segregating Mapping Function (PSMF) method to convert the MINLP problem into a less expensive continuous optimization problem, and the approximated problem was solved using conventional Particle Swarm Optimization (PSO). A reduction of the high-dimensional MINLP problem into a more tractable MINLP problem was later developed [23], and the reduced problem was solved using a mixed-discrete PSO algorithm [24].

The commonality matrix in the original CP^3 method, as well as in other similar commonality formulations [25], do not readily represent the platform-plan for modular products, where each module comprises *multiple* design variables. In their latest work, Chowdhury et al. [1] modified the commonality matrix definition for application to modular families. Subsequently, the commonality constraint, which ensures feasible product platform plans, is also modified to enable effective sharing of multivariate modules among product variants. Importantly, the scaling attributes of the original CP^3 model are favorably retained, which is unique in the PFD literature. Important features of the new modular CP^3 model include:

1. This model facilitates sharing of entire multivariate modules among product variants.
2. Modules are allowed to be included or excluded, based on allowed physical product configurations.
3. If necessary (from a practical manufacturing standpoint), individual design variables within particular modules are allowed to be independently shared or scaled, without necessitating the entire module to be shared or scaled correspondingly.
4. This model enables simultaneous identification of platforming modules and determination of the optimal module attributes (design variable quantification), during the product family optimization process.

The allowed physical combinations of modules is however assumed to be known, based on the product architecture; this assumption is generally valid for commercial products. Detailed mathematical description of the modular CP^3 model can be found in the paper by Chowdhury et al. [1].

2.2 UAV Family Optimization

2.2.1 Application of UAV Family

The Civilian UAV market has emerged in great part due to strong military investment in the development of UAVs, which subsequently fueled interest in utilizing this technology for commercial aerial applications. UAVs offer a unique set of attractive features, most notably long-endurance and high-risk mission acceptance, which is often prohibitive for manned aircraft to perform. The biggest hindrance to the burgeoning market is the integration of Civilian UAVs into the national airspace system (NAS), currently slated until 2015. However, this hasn't prevented the UAV community from identifying a whole host of aerial applications ranging from Environmental/Scientific survey to Search and Rescue missions. A NASA report summarized the key barriers that need to be overcome for UAVs to become viable, cost-effective, and regulated alternatives to current technologies [26]. Some of these barriers are: (i) affordability (price and customization), (ii) capacity for payload flexibility, and (iii) multi-mission capability. The development of robust platforms for modular and/or reconfigurable UAVs can offer a powerful solution to these particular challenges.

With this vision, we pursue the design of a family of three modular UAVs with the following applications and mission classes:

1. **Transportation of Commercial Goods**. Low Endurance: 4 hrs, High Payload: 20 lb
2. **Environmental Survey**. High Endurance: 24 hrs, Medium Payload: 7 lb
3. **Search/Surveillance**. Medium Endurance: 16 hrs, Low Payload: 3 lb

These mission capabilities are defined in the context of the offshore Petroleum industry. In such platforms located tens of miles from shore, the supply of goods during the planning and operational stages is a regular occurrence. While normally supplied by ships, UAVs may be able to rapidly and cost-effectively transport small cargo during routine and emergency situations. Environmental surveying is an important factor to consider prior to and after securing oil platforms on-site. In this capacity, UAVs can aid in studying the ecological effects of the platform (e.g., marine life) utilizing video cameras and hyperspectral image sensors. Finally, safety is of prime concern and a topic which came to the national spotlight following the explosion of the BP *Deepwater Horizon* platform off the coast of Louisiana on April 21, 2010. Subsequently, it became the worst oil spill in U.S. history. To help prevent such accidents from happening again, medium endurance UAVs are envisioned to be deployed as preventative safety measures for surveillance and remote detection of oil leaks in the platform infrastructure. Alternatively, the same UAV can be utilized for post-disaster relief efforts by searching for survivors and assessing the damage.

2.2.2 Optimization Formulation

In this paper, we apply CP^3 to design a family of 3 UAVs with different endurance and payload capacity specifications, as given in the previous section. For this application, all the UAV variants comprise the same physical set of modules. A block diagram, illustrating the modules, the module attributes (physical variables), the operational variables, the constants or specifications, and the performance outputs of the *UAV performance model*, is shown in Fig. 2.

It can be seen from Fig. 2 that each UAV is comprised of 6 modules: (1) wing, (2) fuselage or pod, (3) vertical tails, (4) horizontal tail, (5) booms, and (6) fuel tank. The modules comprise a total of 14 physical design variables (or module attributes), as seen from Fig. 2. In addition, the aircraft *cruise velocity* is treated as an operational variable, which does not participate in platform planning. The variable limits can be found in the paper by Chowdhury et al. [1]. The allowed airfoil types are integer coded, where the wing is allowed to use 7 different non-symmetric airfoils (Eppler and NACA types) and the tails are allowed to use 2 different symmetric NACA airfoils, typical of small-medium sized unmanned aircraft. It is important to note that although *payload* is a performance attribute in practice, it is an input for the *UAV performance model* $-$ the payload specification is used to calculate the initial and final weights of the UAV.

Since all three UAVs comprise the same type of physical modules, the diagonal elements of the *commonality matrix* or the *module-inclusion variables* are known a priori, i.e., $\lambda_i^{kk} = 1, \quad \forall\ i, k$. The optimization problem can be formulated as follows:

$$
\begin{array}{l}
\text{Max}\ \ f_p\left(X, Y\right) \\
\text{Max}\ \ f_c\left(Z\right) \\
\text{subject to} \\
\qquad g_j\left(X, Y\right) \leq 0, \qquad j = 1, 2, ..., p \\
\qquad h_{cc}\left(X, Z\right) = 0 \\
\text{where} \\
\qquad X = \left[\begin{array}{ccccccccc} X_1^1 & \cdots & X_1^3 & \cdots & X_i^1 & \cdots & X_i^3 & \cdots X_6^1 & \cdots & X_6^3 \end{array}\right]^T \\
\qquad Y = U_\infty \\
\qquad Z = \left[z_1\ \cdots\ z_i\ \cdots\ z_6\right]; \quad z_i \in \{0, 1, 2, 4, 7\} \\
\qquad k, l = 1, 2, 3; \qquad i = 1, 2, \ldots, 6
\end{array}
\tag{1}
$$

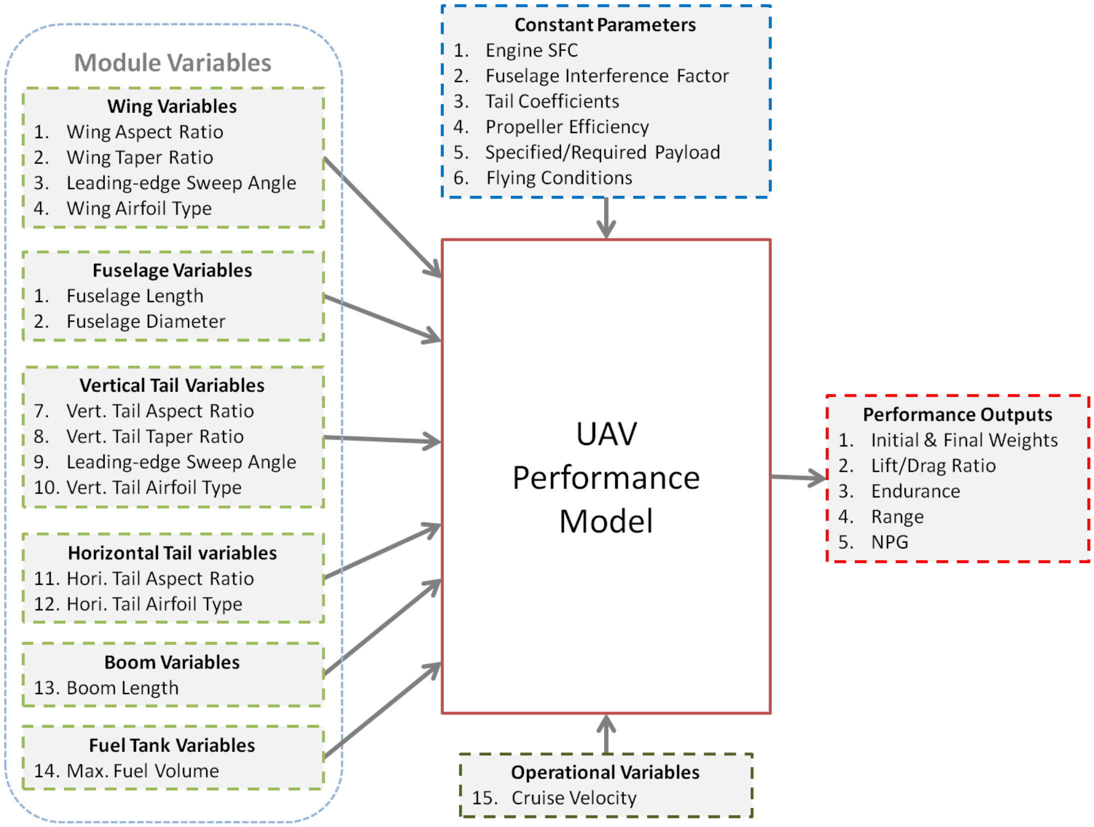


Figure 2: A block diagram of the inputs and outputs of the UAV performance model

where f_p is the aggregate performance and f_c is the net cost of the UAV family (described in next section). In Eq. 1, the design vector X includes the 14 module attributes/variables of the three UAVs in the same order as listed in Fig. 2; the superscript indicates the UAV variant and the subscript represents the module. The vector U_∞ represents the cruise velocities of the UAVs. In this case, all 6 modules are included in all 3 UAVs, all $\lambda_i^{kk} = 1$; the ensuing allowed values for the *integer commonality variables* (z_i) for this 3-UAV family is shown in Eq. 1. The inequality constraints (g_j) include four primary physical design constraints that address (i) conflicts between fuel volume and fuselage size, (ii) conflicts between wing root chord and fuselage size, (iii) satisfaction of the required endurances, and (iv) avoidance of aircraft stalling. The variable bounds are also formulated as inequality constraints. The equality constraint, h_{cc}, represents the *commonality constraint*, which is the pivotal component of the CP^3 model; this constraint ensures compatibility between the *product platform plan* and the *physical design of each product*

The performance objective is given by the scaled average of the *range per unit fuel-consumption* of the 3 UAVs:

$$f_p = \frac{1}{3 \times MPG_{AS}} \sum_{k=1}^{3} MPG_i \tag{2}$$

where MPG_{AS} is the approximate *range per unit fuel-consumption* of the Aerosonde UAV, which is equal to 1350 miles/gallon [27]; and MPG_i is the *range per unit fuel-consumption* of the i^{th} UAV variant.

2.2.3 UAV Family Cost Model

The purpose of cost modeling is to estimate the cost of a UAV development program or the cost of an individual UAV. Typically a life-cycle cost modeling approach is employed, which consists of development, manufacturing, and operations costs. However, at the platform planning stage, UAV cost models are based on simplified system parameters known within the conceptual design framework. This includes variables such as the UAV's structure weight, engine thrust, intended mission and payload.

In this investigation, we wish to quantify the cost of optimized UAV configurations with varying degrees of commonality relative to individual UAVs with no shared modules. The cost model developed here considers the weight of the module attributed to the manufacturing material, in this case carbon fiber composite (except for the fuel tank) and the hardware associated with each module (i.e. landing gear for the fuselage and linkages). The fabrication material considered is the aerospace grade 12K Biaxial carbon fiber with a weight of 0.0778 lb/ft^2. The hardware weight component is approximated as relatively low fraction (10% to 20%) of the composites material weight of each module, which is a reasonable assumption. Finally, the module cost is calculated by applying an empty weight cost metric of $1,500 per pound as suggested by the OSD UAV Roadmap [28] for modern UAVs. This figure includes the electronics, communications, and propulsion subsystems that are integrated into the modules and make up the empty weight of the UAV. Expressions for the cost of each module are given as follows, in terms of original aircraft design parameters:

- Wing: $C_W = \$1,500\,[0.317S_W + 0.15\,(0.317S_W)]$, where S_W is the wing area
- Fuselage: $C_F = \$1,500\,\left[0.176L_F d_F^2 + 0.2\left(0.176L_F d_F^2\right)\right]$, where L_F and d_F are the fuselage length and fuselage maximum diameter
- Vertical Tails: $C_{VT} = \$1,500\,[0.317S_{VT} + 0.10\,(0.317S_{VT})]$, where S_{VT} is the vertical tail area
- Horizontal Tail: $C_{HT} = \$1,500\,[0.158S_{HT} + 0.10\,(0.158S_{HT})]$, where S_{HT} is the horizontal tail area
- Tail Booms: $C_{HT} = \$1,500\,[0.0916L_B]$, where L_B is the tail boom length
- Fuel Tank: $C_{HT} = \$90F$, where F is the fuel tank size in Liters

The cost of each UAV configuration is an aggregate sum of the six module costs, i.e, $C_{UAV} = C_W + C_F + C_{VT} + C_{HT} + C_B + C_{FT}$. Notice that this model does not account for the payload or sensor cost, which depends on the mission and user requirements and furthermore cannot be correlated to any degree of accuracy to its weight. The net cost of the three UAV variants solely optimized for individual performance [1] is treated as the reference cost. The cost objective, f_c, is expressed in the normalized form, where the cost of the candidate UAV families are divided by reference cost, i.e., $f_c = \left(C_{UAV}^1 + C_{UAV}^2 + C_{UAV}^3\right)/3$.

3 Optimized Family of UAVs: Results and Discussion

The current UAV family optimization problem involves a total of (i) 45 *physical design variables* including 36 continuous and 9 discrete variables and (ii) 6 *integer commonality variables*. The Non-Dominated Sorting Genetic Algorithm (NSGA-II) [29] is used to solve this *multi-objective MINLP* problem. A population size of 250 particles is used in this case study, and the optimization is allowed to run for a maximum of 500,000 function evaluations. The equality constraint h_{cc} (*commonality constraint*) in the optimization (Eq. 1) is relaxed by a tolerance of $\epsilon = 1.0e-06$, and converted to an inequality constraint, as is common for constraint handling in heuristic algorithms: i.e., $h_{cc} - \epsilon \leq 0$. The Pareto solutions obtained are shown in Fig. 3.

It is observed from Fig. 3 that all the *best tradeoff UAV families*(Pareto solutions) have a lower cost than the net cost of the three individually optimized UAV variants (optimized for performance). At the same time, the *best tradeoff UAV families* also provide better performance (fuel economy) than the Aerosonde UAV. The overall Pareto is observed to be highly non-convex, thereby justifying the use of a powerful heuristic solver. Across the Pareto, the UAV-family performance changes from 1.07 to 1.13, a 6% increase; the UAV-family cost changes from 0.70 to 0.44, a 26% decrease with respect to the reference cost. Chowdhury et al. [1] estimated the maximum aggregate performance of the individually optimized UAVs to be 1.16 times of that of the Aerosonde. Therefore, CP^3 offers promising cost savings for a relatively small compromise of the UAV performances.

It is important to note that the cost savings in this case are mainly attributed to (i) material reductions and (ii) reconfigurability or reduction in the overall number of parts required to create the three different UAVs (lower than 3×6 parts). In practice, additional commonality-based cost savings are expected owing to (i) reduced manufacturing overhead, (ii) reduced transportation costs, and (ii) more streamlined design evolution (based on standard platforms). These Pareto results thus highlight the immense potential of applying product platform planning concepts to design efficient, affordable, and multi-mission-capable families of civilian UAVs.

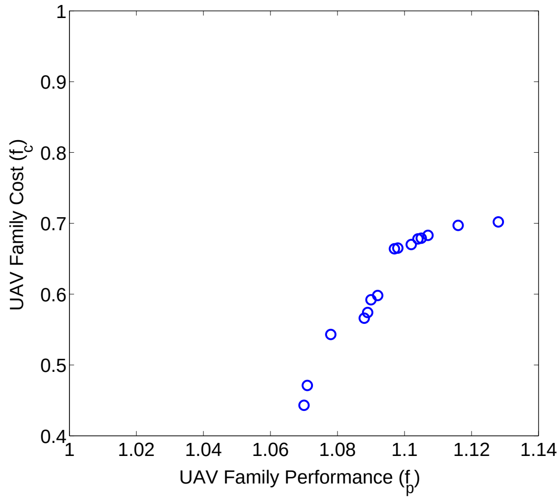
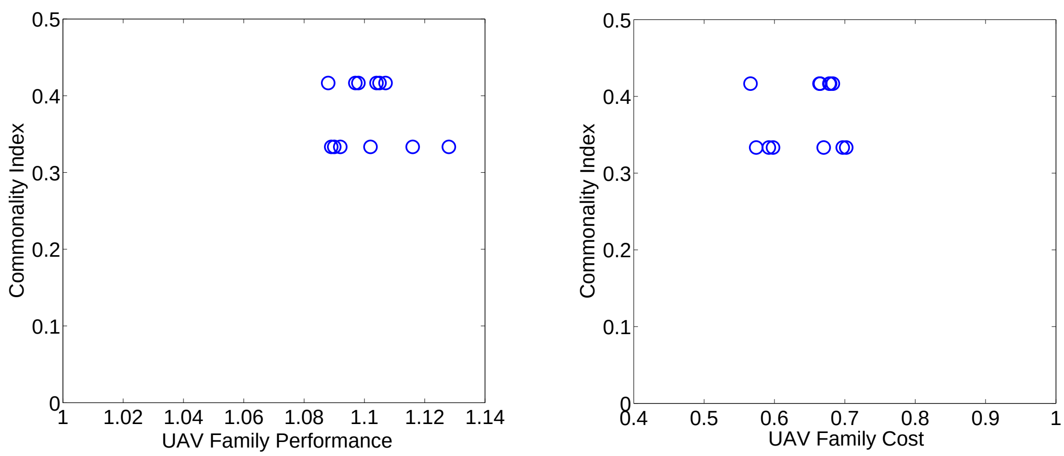


Figure 3: Pareto obtained for the UAV family designed by CP^3

Figures 4(a) and 4(b) show the level of commonality (in terms of the *commonality index*) in the Pareto solutions. It is observed from these figures that the *best tradeoff UAV families* fall into two levels of commonality. When UAV-family performance and *commonality index* were maximized by Chowdhury et al. [1] (without any cost considerations), the *commonality index* varied from 0 to 0.5 across the Pareto solutions. Interestingly, the current explorations show that when cost is taken into consideration, the Pareto solutions are pushed towards higher degree of commonality (0.33 to 0.42).

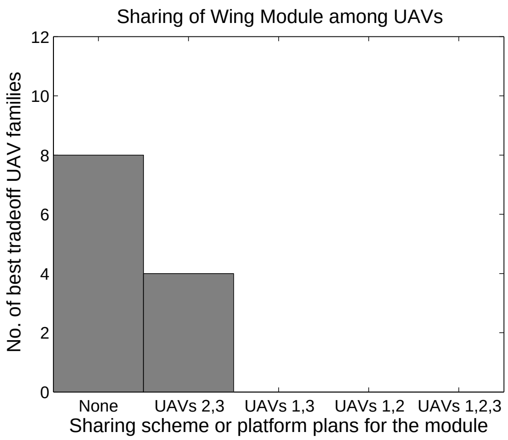


(a) *Commonality index (CI) vs. cost of the Pareto solutions*

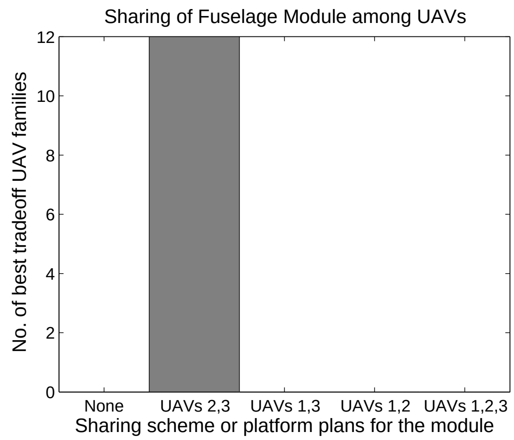
(b) *Commonality index (CI) vs. Performance of the Pareto solutions*

Figure 4: Commonality Indices of the best tradeoff UAV families

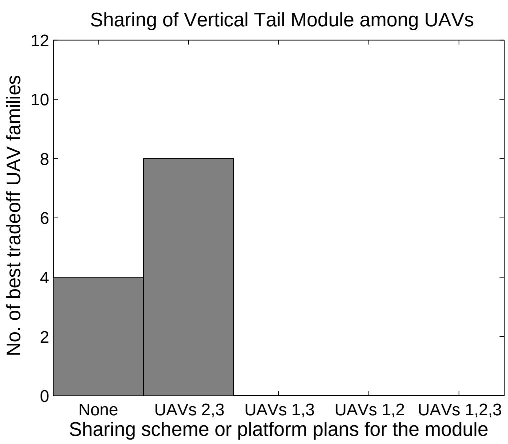
To provide further insights into the degree of commonality or module sharing adopted by the *best tradeoff UAV families*, we illustrate how many of the Pareto solutions fall into the different platform schemes. The histograms in Figs. 5(a) to 5(f) provide these illustrations, with respect to each of the 6 UAV modules. The five different "*platform plans*" or "*module sharing schemes*" possible in this case are: the module is (i) not shared by any UAV, (ii) shared by UAVs 2 and 3, (iii) shared by UAVs 1 and 3, (iv) shared by UAVs 1 and 2, and (v) shared by all three UAVs. The platform plans in Figs. 5(a) to 5(f) appear in this same order. It is observed that the wing is least likely to be shared (Fig. 5(a)), and the horizontal tail and booms are most likely to be shared (Figs. 5(d) and 5(e)). It is also observed that UAVs 2 and 3 are in general most likely to share the different modules.



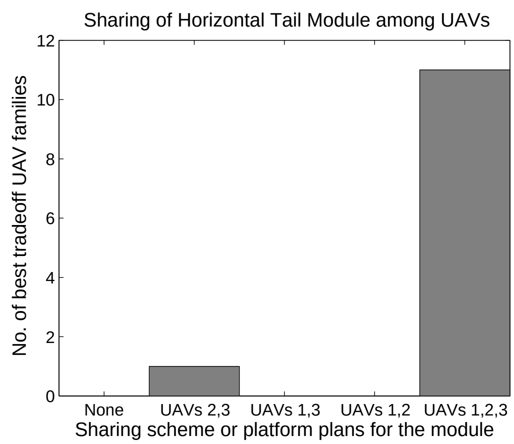
(a) Platform plans for the wing module



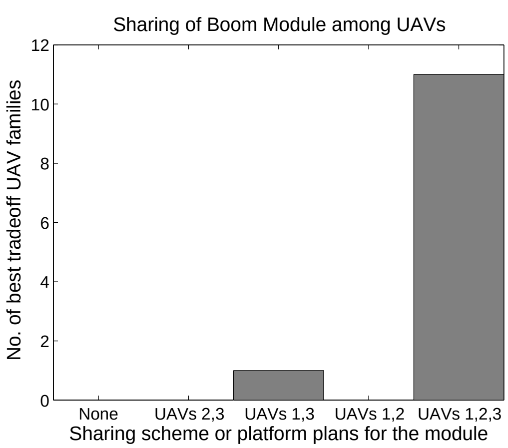
(b) Platform plans for the fuselage module



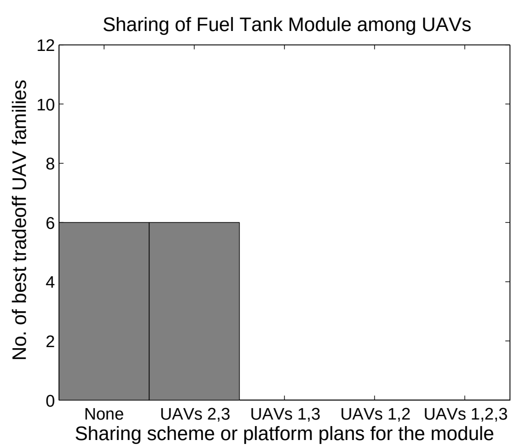
(c) Platform plans for the vertical tail module



(d) Platform plans for the horizontal tail module



(e) Platform plans for the boom module



(f) Platform plans for the fuel tank module

Figure 5: No of Pareto solutions under different possible platform plans

4 Concluding Remarks

In this paper, modular product family design concepts were applied to design multi-mission-capable families of civilian Unmanned Aerial Vehicles (UAVs). These UAVs share certain modules that are developed around common platforms, which allows the individual UAVs to be reconfigured for unique missions. The *modular design* and the *common module platforms* provide cost savings both to the manufacturer and the end-user, and is also expected to provide more streamlined product-line evolution.

The modular UAV platform planning was performed using the recently developed Comprehensive Product Platform Planning (CP^3) method, which leverages the helpful characteristics of both scale-based and module-based platform planning. The CP^3 method was applied to design a family of three UAVs with different endurance and payload specifications. These UAVs are intended for different applications in the offshore petroleum industry. Optimization of the UAV family was performed to maximize the average fuel economy while minimizing the cost of UAV family. Across the *best tradeoff UAV families* obtained through CP^3, a 26% reduction in cost could be accomplished for a 6% compromise in performance. The *best tradeoff UAV families* were also observed to adopt relatively high degrees of commonality, where the horizontal tail and the tail boom modules were shared the most among the UAV variants. These promising results illustrate the immense potential of developing effective module-based platforms for civilian UAV applications by leveraging modular product family design methods.

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