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# AI-driven Unmanned Aerial System Conceptual Design with Configuration Selection

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***Abstract*—This paper presents an intelligent conceptual design framework for the configuration selection of aerial vehicles. In this approach, the quantitative data is brought to the earliest stage of design utilizing AI-driven analysis models and it allows to choose the most suitable one among the possible configurations. Thanks to the design optimization cycle, the initial dimensions of the main components such as the wing, tail and fuselage are more accurately provided for later design activities. At the same time, the generated structure provides a more appropriate design point selection thanks to the feedback loop in design iteration. Thus, while reducing the design cost, a significant time advantage is also provided in the design process. The paper presents a generic use case based on a high-performance combat UAV design study to demonstrate the abilities of the proposed model.**

***Index Terms*—aircraft design, conceptual design, configuration selection, AI-driven parametric design, design optimization**

## I. Introduction

The aircraft design process is a quite long and costly process that takes almost a decade on average. Especially nowadays, it is not possible to develop different concept configurations and design iterations due to the situation caused by competition and limited budgets. That is why focusing on the right concept from the beginning is crucial. However, the human interaction level is remarkably decisive in the early phase of the design process (see Fig. 1). In the classical approach, rapid but low-level approaches such as historical data, semi-empirical methods, and figures of merit are preferred for configuration selection [1]. The widely available studies in the literature are mostly on detailed design optimization-sizing of a predetermined configuration [2]. In this study, we have developed an intelligent conceptual design algorithm that includes AI-driven surrogate models and optimization loops to bring numerical information to the early stage of the design process. Thanks to this algorithm, it is possible to compare the optimized configurations of different concepts at the initial stage and choose the most suitable one. Thus, by reducing human interaction, the selection of the concept configuration that meets the design requirements, the initial sizing, and the design iteration is automated with a toolset that is computationally fast and inexpensive and is also of a higher order than existing methods.

Considering the uncertainty and variability at the beginning of the design process, performing optimization can be computationally expensive [3]. To overcome this issue, in this paper we proposed artificial neural network-based surrogate models to predict aerodynamic performance and mass properties including the structural layout of aerial vehicle configurations.

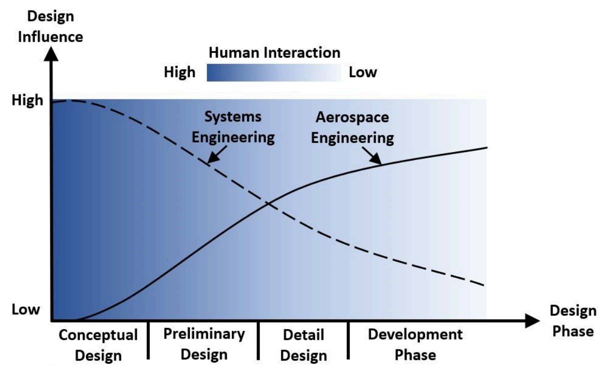


Fig. 1. Human interaction level in the design process

## II. Methodology

The intelligent conceptual design algorithm consists of three main parts: Design Point Calculation, Initial Sizing, and Optimization of Configurations. Each part is connected to the other one in an input-output relationship. Also, there is a main design iteration loop connected to whole process to obtain better designs. A general overview of the algorithm is given in Fig. 2.

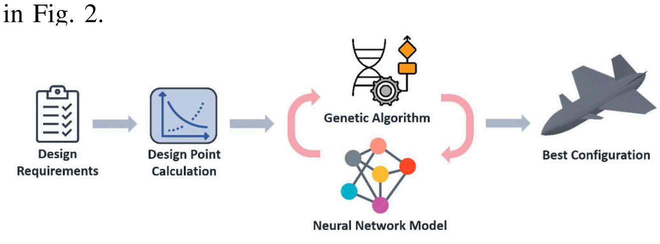


Fig. 2. General overview of the proposed framework.

### A. Design Point Calculation

In design point calculation, given performance requirements such as stall speed $(V_{\mathrm{s}})$, maximum speed $(V_{\max})$, maximum rate of climb $(\mathrm{ROC}_{\max})$, take-off run $(S_{\mathrm{TO}})$, ceiling $(h_{\mathrm{c}})$ are used to determine a feasible design space. For this, the flight performance equations are solved depending on wing loading and thrust loading and inequality constraints are generated. The relevant equations can be found in an aircraft design or flight performance book for jet or prop driven air vehicles. In order to drive this process, table-based aerodynamic and geometry parameters are used in the first design iteration. In the next steps, this information is obtained with AI-driven surrogate models using feedback loop.

### *B. Initial Sizing*

In initial sizing step, wing reference area and required thrust are determined by using the maximum take-off weight and the obtained design point data. In addition, initial length and cross section dimensions of fuselage are determined by using the selected engine and internal payload data.

$$S = W_{\text{mtow}} / \left(\frac{W}{S}\right), \quad T = W_{\text{mtow}} \cdot \left(\frac{T}{W}\right) \tag{1}$$

### *C. Optimization of Configurations*

In this layer, a genetic algorithm (GA) based optimization runs using AI-driven aerodynamic performance and structural mass prediction.

The performance of an aircraft is mainly related to geometry, flow direction, Reynolds number and Mach number. For the main performance parameters, lift ($C_L$) and drag coefficients ($C_D$), this relationship can be expressed as follows:

$$C_{L,D} = f_{aero}(Geometry, \alpha, \text{Re}, M) \tag{2}$$

The mass model includes the engine, avionics, payload, fuel, and structural weight. AI-based structural weight estimation is given as:

$$W = f_{structural}(Geometry, \alpha, \text{Re}, M) \tag{3}$$

In the GA approach, an initial set of designs is generated using design variables remaining within predetermined limits [4]. For each design, fitness values are calculated using the cost function, and a random subset is selected from the current design set for those that are better fits. Random operations are used to create new designs using the subset of selected designs.

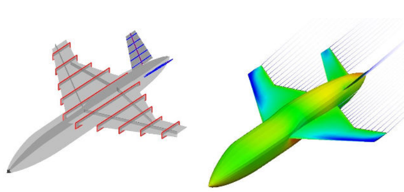

Fig. 3. Structural and aerodynamic models.

At the end of process each concepts are optimized for given objective function such as maximize efficiency while minimizing structural weight.

Fig. 4. Conventional, Lambda and Delta configuration concepts

## III. Application of the Model

In this section, a medium-size combat UAV is designed according to the given performance requirements using developed algorithm. Concept configurations of this UAV is given in Fig. 4.

The purpose of this optimization problem is to obtain a configuration with maximum efficiency that provides the required stability and aerodynamic conditions. The optimization problem can be defined as:

$$\underset{x}{\text{maximize}} \qquad f(x) = \frac{L}{D * W_{mtow}} \tag{4}$$

$$\text{subject to} \qquad 0.30 < C_L < 0.35 \tag{5}$$

$$C_{m_0} > 0, \quad C_{m_\alpha} < 0, \quad C_D < 0.03 \tag{6}$$

where $x$ includes the cruise angle of attack, wing aspect ratio, taper ratio and sweep angle.

After the optimization cycle, the performance of each concept configuration is compared in terms of fixed range and fixed payload requirements. As can be seen from Fig. 5, lambda configuration gives higher performance than conventional and delta configurations

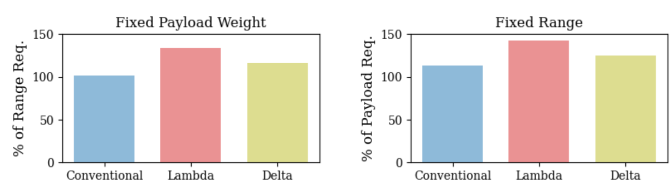


Fig. 5. Performance comparison of configurations

## IV. Conclusion

In this paper, an intelligent conceptual design algorithm is developed to bring numerical data to the early design process decreasing the human interaction level. The developed algorithm helps to select and do initial sizing of concept configuration. Using AI-driven algorithms this process significantly decreases computational time in the design process. Future work will combine other possible disciplines with existing algorithms.

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