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*Research Article*

# INVESTIGATION ON THE PERFORMANCE OF META-HEURISTICS FOR SOLVING SINGLE OBJECTIVE CONCEPTUAL DESIGN OF A CONVENTIONAL FIXED WING UNMANNED AERIAL VEHICLE

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**ABSTRACT:**
*In this work, conceptual design optimisation of a conventional fixed wing unmanned aerial vehicle (UAV) is performed through metaheuristics. Five optimisation objective functions including take-off gross weight ($W_G$), take off distance ($S_{TO}$), endurance ($E$), lift coefficient ($C_{L,c}$) and drag coefficient at cruising ($C_{D,c}$) are scalarised into a single-objective optimisation problem subject to aircraft flight mission, performance, and stability constraints. Aerodynamic and stability analyses are executed by a vortex lattice method (VLM) while aircraft component weights and aircraft performance are estimated by empirical equations. Six state-of-the-art of single-objective meta-heuristics (MH) including Equilibrium Optimizer (EO), Evolution Strategies algorithm (ES), Moth-Flame Optimization Algorithm (MFO), Marine Predators Algorithm (MPA), Slime Mould Algorithm (SMA), and Salp Swarm Algorithm (SSA) are employed to solve the problem while their search performance are statistically investigated based on the Friedman test. The results obtained shown that the best and second-best optimiser are EO and MFA, respectively. Based on this study, the optimal result which can be chosen for further design stages (preliminary and detail design) is revealed.*

**Keywords:** *Comparative study, Aircraft conceptual design, Metaheuristics, Aircraft performance*

## 1. INTRODUCTION

The optimisation methods have been continuously developed and employed to solve real-world problems in many areas including aircraft conceptual design. Optimum designs with better performance such as longer endurance and less fuel consumption need to be carried out to compete in aircraft industry. Generally, an aircraft design process can be divided into three phases including conceptual, preliminary, and detailed design. The optimisation methods are commonly employed to solve the conceptual design problem since the calculations of objective and constrained functions in this phase are much less time-consuming compared to the other phases. The goals of the conceptual design optimisation are usually posed to minimise take-off weight, maximise endurance, and/or maximize lift to drag ratio under flight conditions, stability, and control. This phase mainly adopts the historical data method to define the aircraft configuration and the empirical equation is used to predict weight and flight quality.

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In the conceptual design process, the weight estimation of the aircraft can be done by the empirical method obtained from the historical data of the aircraft while aerodynamic and stability analyses can be estimated by means of a medium-fidelity method such as the vortex lattice method (VLM) or a high-fidelity method such as computational fluid dynamics (CFD). The VLM and CFD methods have pros and cons in speed and accuracy. The VLM is much less time-consuming while the CFD is much more accurate [1, 2]. According to the aerodynamic validation data [3], the aerodynamic coefficients obtained from VLM are close to the results obtained from CFD and wind tunnel experiment at low speed when the angle of attack is less than the stall angle. As a result, VLM is arguably the most popular method applied for an aircraft conceptual design optimisation due to a vast amount of function evaluations required in the optimisation process. In addition, there are several freeware or open source for the VLM method that has been developed and easy to access and apply such as Athena Lattice Vortex (AVL) [4], Tornado Vortex Lattice Method, XFLR5 [5], SUAVE [6] and OpenVSP [7].

Nowadays, there is numerous research which investigated the optimisation with aircraft conceptual design [8-10], however, most of them employed the outdated optimisation algorithms such as a genetic algorithm (GA) [11, 12], particle swarm optimization (PSO)[13] or differential evolution (DE)[14]. Moreover, the aforementioned studies considered the conceptual design of conventional transport aircraft [15, 16] or general aviation aircraft [17, 18]. Over the last decade, numerous MHs have been developed for various real-engineering applications due to their derivative-free advantage [19-22], however, most of them have yet to be implemented with the aircraft conceptual design. From the no free lunch theory, there is no MH that can be efficient for all kinds of problem. So, when the new design problem is introduced, the best algorithm for solving it should be found out. It should be noted that gradient based methods which are faster than MHs are struggling when solving aircraft design because the gradient of the objective functions and constraints are not easy to compute.

In this regard, this paper aims to address the gap of two research fields, conceptual design of UAV and applications of MHs. Several existing MHs are used to solve the conceptual design optimisation problem of UAV. Five objective functions including minimising take-off gross weight, take off distance and drag coefficient, and maximising endurance and lift coefficient are considered. The five objective functions are then converted into single objective optimisation problem using the weighted sum technique. The state-of-the-art MHs used to tackle the single objective design problem are: Equilibrium Optimizer (EO)[23], Evolution Strategies algorithm (ES)[24], Moth-Flame Optimization Algorithm (MFO)[25], Marine Predators Algorithm (MPA)[26], Slime Mould Algorithm (SMA)[27], Salp Swarm Algorithm (SSA)[28]. The comparative results obtained from the six optimisers will be discussed.

## 2. AIRCRAFT CONCEPTUAL DESIGN OPTIMISATION PROBLEM

In this study, conventional UAV is designed to complete the aircraft flight mission as shown in Fig. 1. The flight starts with warming up, then, the aircraft will take-off through the runway with maximum thrust. After that, it will climb to the cruise altitude for cruising at a trim condition. This is the longest part of the flight. When the mission is completed, it will fly back landing at the starting point. The aircraft design requirement, flight conditions and payload weight are detailed in Table 1. The model of the conventional UAV generated by OpenVSP is illustrated in Fig. 2.

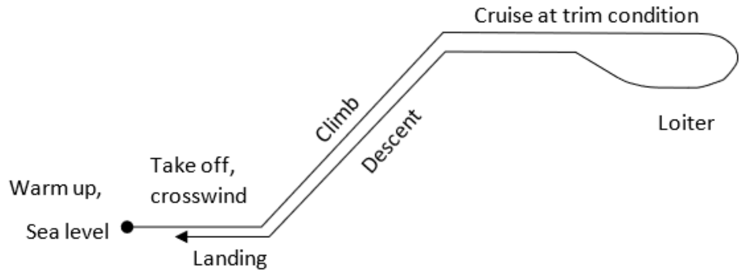


**Fig. 1.** Aircraft flight mission

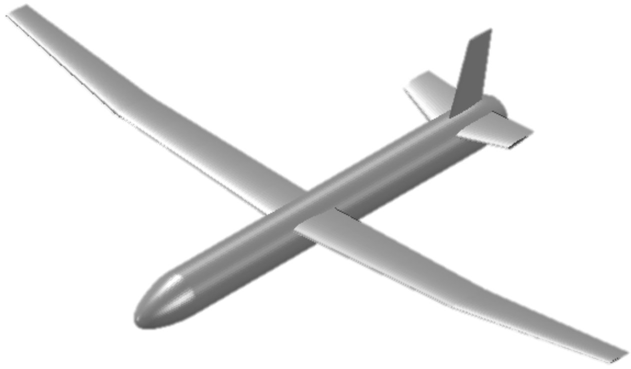

**Fig. 2.** Isometric view of a conventional UAV.

**Table 1:** Aircraft design requirements.

| Metric for requirements | Values or limits |
|---|---|
| Take-off altitude | Sea level |
| Endurance ($E$) | > 24 hr |
| Take off distance ($S_{TO}$) | < 500 m |
| Landing distance ($S_{LD}$) | < 500 m |
| Maximum velocity ($V_{max}$) | 42 m/s |
| Crosswind velocity | 10 knots. |
| Payload weight ($W_{payload}$) | 300 kg |

*2.1 Formulation of the aircraft conceptual design optimisation problem*

In this study, the optimisation problem has five objective functions ($f$) that are take-off gross weight ($W_G$), take off distance ($S_{TO}$), endurance ($E$), lift coefficient ($C_{L,c}$) and drag coefficient at cruising ($C_{D,c}$). The five objective functions are scalarised to a single objective function which can be expressed as follows:

$$\min_{\mathbf{x}} \mathbf{f}(\mathbf{x}) = n_{W_G} + n_{S_{TO}} + n_{C_{D,c}} - n_E - n_{C_{L,c}} \tag{1}$$

**subject to**

$$\boldsymbol{g}(\mathbf{x}) \leq 0$$
$$\mathbf{x}^L \leq \mathbf{x} \leq \mathbf{x}^U$$

where $\{n_{W_G}, n_{S_{TO}}, n_{C_{D,c}}, n_E, n_{C_{L,c}}\}$ are the normalised function values of take-off gross weight, take off distance**,** endurance**,** lift coefficient and drag coefficient at cruising. Each function is normalised based on maximum and minimum values. Latin hypercube sampling (LHS) is used to generate 100,000 sampling points of design variables. Then, the objective and constraints functions of the sampling points are calculated while feasible solutions are sorted to find the boundary of the objective function values as shown in Table 2.

**Table 2:** boundary of feasible objective function value.

| Objective functions | Minimum of feasible objective function value | Maximum of feasible objective function value |
|---|---|---|
| Take-off weight (kg.) | 801.0788 | 1004.5099 |
| Take off distance (m) | 244.4206 | 499.9335 |
| Endurance (hr.) | 24.0004 | 51.2975 |
| Lift coefficient at cruise | 0.6286 | 1.9727 |
| Drag coefficient at cruise | 0.007386 | 0.08848 |

The vector **x** is a set of design variables detailed in Table 3 while the details of the UAV design variables are illustrated in Fig. 3. The $x_1$-$x_{13}$ are used to form the wing shape which has two sections of taper wing. $x_{14}$-$x_{18}$ and $x_{19}$-$x_{21}$ are used to generate horizontal and vertical tails, respectively while $x_{22}$-$x_{23}$ are the details of a fuel system. The rest design variables are detailed in the table. It should be noted that the $x_{13}$ and $x_{25}$ are discrete design variables. The vector $\boldsymbol{g}$ is a set of design constraints shown in Table 4. The constraints $g_1$-$g_5$ are aircraft design requirements while $g_6$-$g_7$ and $g_{11}$-$g_{18}$ are static stability and dynamic stability constraints, respectively. The constraints $g_6$-$g_7$ are control deflection constraints while the rest are angle of attack constraints. To deal with the design constraints, an exterior penalty function is used. The exterior penalty parameters ($r$) is set to be 1000.

**Table 3:** List of design variables.

| No. | Design Variables | Description | Lower limit | Upper limit |
|---|---|---|---|---|
| 1 | $S_w$ | Wing surface area (m$^2$) | 10 | 16 |
| 2 | $r_{b,w}$ | Wingspan section ratio | 0.8 | 1.3 |
| 3 | $AR_w$ | Wing aspect ratio | 13 | 18 |
| 4 | $\lambda_{w,1}$ | Wing taper ratio of section 1 | 0.8 | 1 |
| 5 | $\lambda_{w,2}$ | Wing taper ratio of section 2 | 0.6 | 0.8 |
| 6 | $\Lambda_{LE,w,1}$ | Leading edge wing sweep angle of section 1 (°) | 0 | 5 |
| 7 | $\Lambda_{LE,w,2}$ | Leading edge wing sweep angle of section 2 (°) | 5 | 15 |
| 8 | $\Gamma_{w,1}$ | Wing dihedral of section 1 (°) | 0 | 3 |
| 9 | $\Gamma_{w,2}$ | Wing dihedral of section 2 (°) | 3 | 5 |
| 10 | $i_{w,1}$ | Wing incidence (°) | 0 | 3 |
| 11 | $x_{tranx,w}$ | Wing translational position on *x* axis (m) | 0.25 | 0.45 |
| 12 | $x_{tranz,w}$ | Wing translational position on *z* axis (m) | 0 | 0.3 |
| 13 | $t_{af,w}$ | Airfoil profile: 1. E423,<br>2. NACA4412, 3.CH10SM | 1 | 3 |
| 14 | $AR_h$ | Horizontal tail aspect ratio | 3 | 5 |
| 15 | $S_h$ | Horizontal tail surface area (m$^2$) | 3 | 5 |
| 16 | $\lambda_h$ | Horizontal tail taper ratio | 0.6 | 1 |
| 17 | $i_h$ | Horizontal tail incidence (°) | -10 | -3 |
| 18 | $\Gamma_h$ | Horizontal tail dihedral (°) | 0 | 5 |
| 19 | $AR_v$ | Vertical tail aspect ratio | 2 | 4 |
| 20 | $S_v$ | Vertical tail surface area (m$^2$) | 2.5 | 3.5 |
| 21 | $\lambda_v$ | Vertical tail taper ratio | 0.5 | 0.7 |
| 22 | $V_{ftank}$ | Fuel tank volume (m$^3$) | 0.1 | 0.3 |
| 23 | $x_{ftank}$ | X-position of centre of gravity of fuel tank (m) | 2.5 | 4.5 |
| 24 | $\alpha_{cr}$ | Angle of attack at cruise (°) | 0 | 4 |
| 25 | $t_{en}$ | Engine type: 1. ROTAX 912 UL/A/F,<br>2. ROTAX 912 ULS/S,<br>3. ROTAX 914 UL/F | 1 | 3 |
| 26 | $A_{cr,mean}$ | Flight Altitude at cruise (m) | 3000 | 4500 |

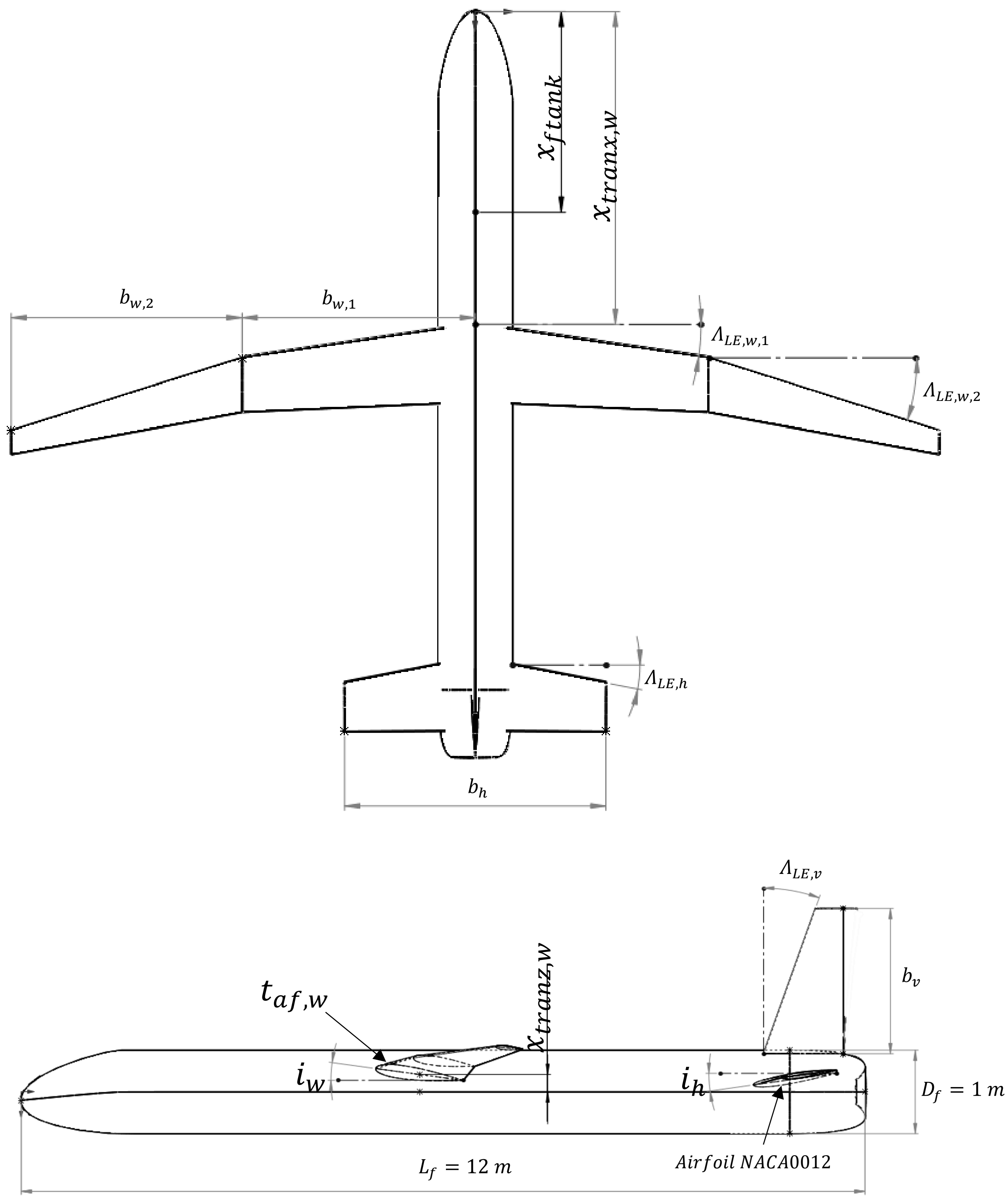


**Fig. 3.** Some design variables of the UAV.

**Table 4:** List of constraints.

| No. | Constraint | Description | Lower limit | Upper limit |
|---|---|---|---|---|
| 1 | $E$ | Endurance (hr.) | > 24 | |
| 2 | $S_T$ | Take off distance (m) | | < 500 |
| 3 | $R$ | Range (km) | > 3000 | |
| 4 | $S_L$ | Landing distance (m) | | < 300 |
| 5 | $V_{max}$ | Maximum velocity (m/s) | 42 | |
| 6 | $C_{m_\alpha}$ | Coefficient of the pitching moment versus angle of attack | < 0 | |
| 7 | $C_{n_\beta}$ | Coefficient of the yawing moment versus side slip angle | | > 0 |
| 8 | $\alpha$ | Maximum angle of attack (°) | | < 7 |
| 9 | $\delta_{e,max}$ | Maximum deflection of the elevator (°) | -20 | 20 |
| 10 | $\delta_{r,max}$ | Maximum deflection of the rudder (°) | -30 | 30 |
| 11 | $f_{sp}$ | Short period frequency (rad/s) | > 1 | |
| 12 | $\omega_{sp}$ | Short period damping ratio | 0.3 | |
| 13 | $f_{ph}$ | Phugoid frequency (rad/s) | 0.2 | 1 |
| 14 | $\omega_{ph}$ | Phugoid damping ratio | 0.05 | 0.8 |
| 15 | $f_{dr}$ | Dutch roll frequency (rad/s) | > 1 | |
| 16 | $\omega_{dr}$ | Dutch roll damping ratio | 0.08 | 0.7 |
| 17 | $T_{spi}$ | Spiral time constant (s) | >1 | |
| 18 | $T_{roll}$ | Rolling time constant (s) | 0.01 | 1 |

### *2.2 Aircraft analysis method*

An aircraft analysis method consists of three modules for objective function calculation: (I) weight and mass properties, (II) aerodynamic and stability execution, (III) performance analysis.

### *2.2.1 Weight and mass estimation*

To estimate the aircraft weight, there are several empirical equations that can be used, for example, the Raymer and USAF method which are suitable for general aviation aircraft (GA). The Kroo, Kundu and Torenbeek methods are appropriated for design of light transport aircraft while the Jay Gundlach method is developed for manned sailplanes. In this work, the new equation for UAV weight estimation proposed by [29] is used. The centre of gravity of each component is computed based on [30] while the moment of inertia is also calculated based on the same reference for using in stability analysis.

### *2.2.2 Aerodynamic and stability analyses*

In this work, the VLM method is used for the aerodynamic and stability analyses. The Athena Vortex lattice program (AVL) which is open-source software is employed. The results obtain from AVL include lift coefficient, drag coefficient, static stability and control deflections at each stage, as well as state space matrices for longitudinal and directional/lateral motions at cruise. Five flight conditions including taking-off, climbing, cruising, descending and landing are simulated based on two-dimension planes flight simulation, which are detailed as follows:

1. Take-off phase: in this phase, maximum thrust with fifteen-degree of flap are applied until passing the obstacle. The take-off crosswind is set to be 10 knot. This value is considered to ensure that the rudder deflection does not exceeding the design constraint.
2. Climbing phase: The angle of attack at climbing is set to be 4 degrees with maximum thrust. The elevators are used to trim the aircraft about lateral axis.
3. Cruising phase: this phase is the longest of the flight mission. The angle of attack at cruise is set as a design variable of this problem. The elevator is also used to trim the aircraft about the lateral axis in this phase. The equilibrium force in the longitudinal and vertical axis of the aircraft are computed to estimate the minimum thrust and minimum specific fuel consumption (SFC) that maintain the altitude of the aircraft.
4. Descending phase: this phase is aimed at decreasing altitude to ground level.
5. Landing phase: using drag force from flap deflection and friction from brake.

### *2.2.3 Performance analysis*

The real engine data such as engine power, rotational speed of an engine, and specific fuel consumption combined with aerodynamic coefficient at each stage are employed for evaluating the flight performance such as flight endurance, range, maximum velocity and take-off distance by simulating of two-dimension flight.

## 3. NUMERICAL EXPERIMENT

The flowchart of aircraft conceptual design optimisation is shown in Fig. 4. The workflow is separated into two sides. The left side is an optimisation procedure while the right side is the evaluation of objective and constraint functions.

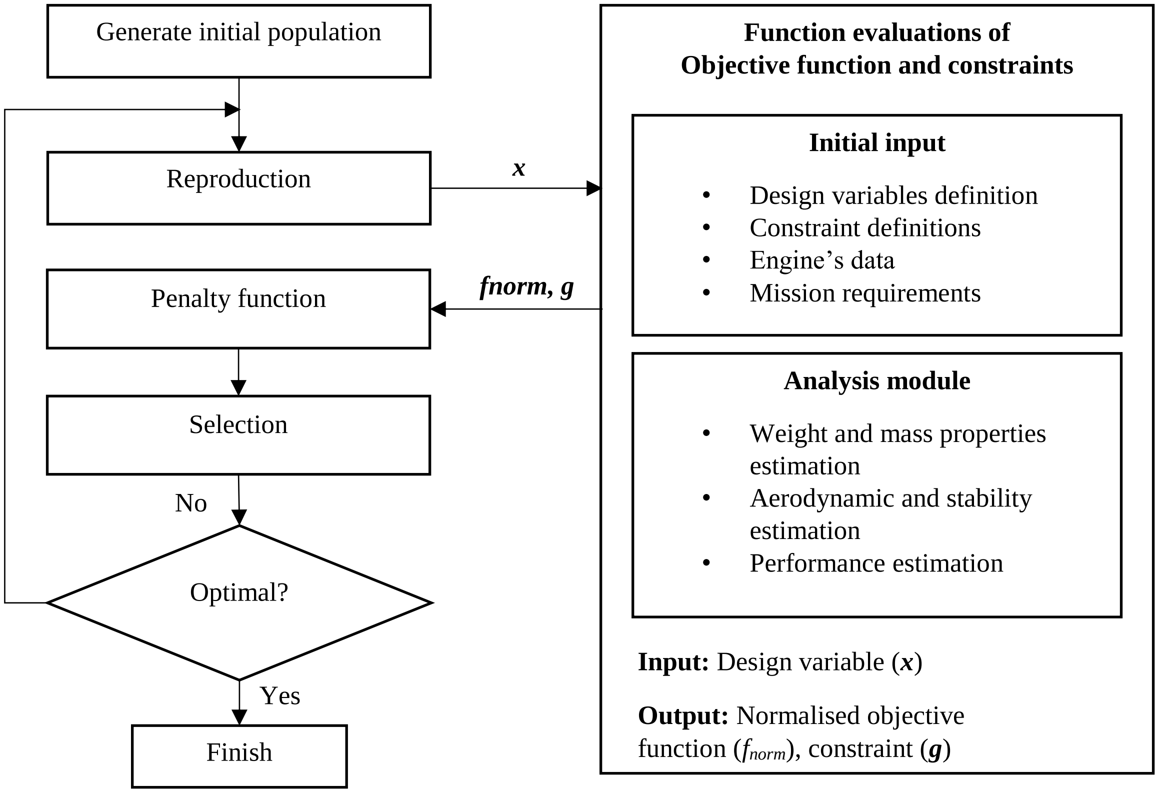


**Fig. 4.** Flowchart of aircraft design methodology

In this study, six meta-heuristic algorithms including EO, ES, MFO, MPA, SMA and SSA, are used to solve the proposed UAV conceptual optimisation design problem. The MHs used in this study and their optimisation parameter setting are detailed as follows:

- Equilibrium Optimizer (EO): Generation Probability (GP) equal 0.5 and $a_1$ and $a_2$ are equal to 2 and 1 respectively.
- Evolution Strategies algorithm (ES): Number of points in the tournament selection is 3.
- Moth-Flame Optimization Algorithm (MFO): The shape of the logarithmic spiral (b) is set to be 1.
- Marine Predators Algorithm (MPA): Fish Aggregating Devices (FADs) is 0.5 and P = 0.5 is a constant number.
- Slime Mould Algorithm (SMA): All of control parameters are iteratively adapted.
- Salp Swarm Algorithm (SSA): All of control parameters are iteratively adapted.

Each optimiser is used to solved the design problem for 10 optimisation runs for comparative the performance of the algorithms. The number iterations and population size are set to be 200 and 50 respectively.

## 4. Results and Discussion

After performing 10 optimisation runs on solving the proposed UAV conceptual design problem by using 6 MHs, the results are reported in Table 5. From the table, the mean, minimum, maximum and standard deviation (STD) of objective function values are used for measuring the search convergence rate and consistency performances. The lower mean value the better search convergence while the lower STD the better search consistency. In addition, the statistically significant test at 95% level based on the Friedman test is also used to rank the various MHs. The lower Friedman score means the better MH. From the table, EO is the best performer based on mean, min, max, STD and Friedman test values while MFO and MPA are the second-best and third-best respectively.

**Table 5:** Comparison of objective function values based on Freidman test.

| MHs | Mean | Min | Max | STD | Friedman test |
|---|---|---|---|---|---|
| EO | -0.3592 | -0.3656 | -0.3285 | 0.0111 | 1.4 |
| ES | -0.2773 | -0.3449 | -0.0170 | 0.0959 | 4.6 |
| MFO | -0.3509 | -0.3645 | -0.2925 | 0.0222 | 2.3 |
| MPA | -0.3336 | -0.3601 | -0.2982 | 0.0187 | 2.9 |
| SMA | -0.3201 | -0.3569 | -0.2758 | 0.0284 | 4.0 |
| SSA | -0.1690 | -0.2821 | 0.1272 | 0.1460 | 5.8 |

Figure 5 shows the search history of the six optimisers which displays the plot of mean objective function values (from 10 runs) versus iteration numbers. Based on the figure, it is seen that EO has the best convergence from the start to end of the search process. The EO reaches the optimum after about 60 iterations. The SMA and MFO perform well as with EO at early iterations, however, SMA gets stuck in local minima in later iterations while MFO can get close to EO after about 120 iterations.

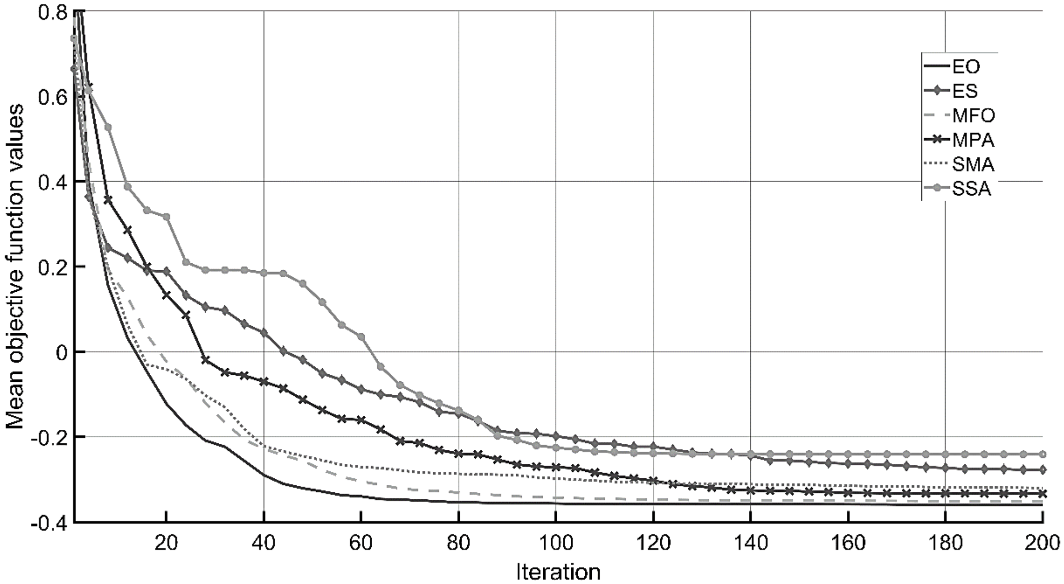


**Fig. 5.** Mean objective function value versus iteration

Tables 6, 7 and 8 show the objective functions, design variables and constraints of best solution obtained by EO, respectively, while the three-dimensional view of the optimal result is illustrated in Fig. 6. Table 6 show the trade-off between the five objective functions i.e., minimising the take-off distance leading to the increasing of drag coefficient at cruise due to the requirement of increasing wing surface area. Also, minimising take-off weight leads to the reducing of flight endurance due to the reducing of fuel volume. However, this study successfully shows the applications of single objective MHs for solving many-objective optimisation of UAV conceptual design. Within a single run, an optimum point, which optimises several objective functions can be obtained while weighting coefficient can be added to the proposed optimisation problem for further design in order to fulfil the design requirements.

**Table 6:** Objective function of selected result

| Objective functions | Normalised values of objective functions | True values of objective functions |
|---|---|---|
| Take-off weight (kg.) | 0.1286 | 827.2361 |
| Take off distance (m) | 0.0267 | 237.5947 |
| Endurance (hr.) | 0.2086 | 29.6935 |
| Lift coefficient at cruise | 0.6500 | 1.5022 |
| Drag coefficient at cruise | 0.3910 | 0.0391 |

**Table 7:** Design variables of the selected solution

| Design variables | Optimal solution |
|---|---|
| Wing surface area ($m^2$) | 15.9774 |
| Wing span section ratio | 0.8018 |
| Wing aspect ratio | 17.9985 |
| Wing taper ratio of section 1 | 0.8000 |
| Wing taper ratio of section 2 | 0.6001 |
| Leading edge wing sweep angle of section 1 (°) | 1.7772 |
| Leading edge wing sweep angle of section 2 (°) | 9.1685 |
| Wing dihedral of section 1 (°) | 2.9804 |
| Wing dihedral of section 2 (°) | 4.9974 |
| Wing incidence (°) | 3.0000 |
| Wing translate position on $x$ axis (m) | 4.7868 |
| Wing translate position on $z$ axis (m) | 0.2997 |
| Type of wing airfoil section | CH10SM |
| Horizontal tail aspect ratio | 3.0136 |
| Horizontal tail surface area ($m^2$) | 3.0008 |
| Horizontal tail taper ratio | 0.6129 |
| Horizontal tail incidence (°) | -3.0481 |
| Horizontal tail dihedral (°) | 4.8180 |
| Vertical tail aspect ratio | 2.5071 |
| Vertical tail surface area ($m^2$) | 1.5000 |
| Vertical tail taper ratio | 0.6960 |
| Flight Altitude at cruise (m) | 4237.5106 |
| Centre of gravity of fuel tank (m) | 3.3198 |
| Angle of attack at cruise (°) | 0.0002 |
| Engine type | ROTAX 914 UL/F |
| Fuel volume ($m^3$) | 0.1764 |

**Table 8:** Constraints of the selected solution

| Constraints | Optimal solution |
|---|---|
| Endurance (hr.) | 29.6935 |
| Take off distance (m) | 237.5947 |
| Range (km) | 3001.1721 |
| Landing distance (m) | 154.4730 |
| Maximum velocity (m/s) | 45.10 |
| Coefficient of the pitching moment versus angle of attack | -0.8886 |
| Coefficient of the yawing moment versus side slip angle | 0.002333 |
| Maximum angle of attack (°) | 3.0002 |
| Maximum deflection of the elevator (°) | 10.3935 |
| Maximum deflection of the rudder (°) | 1.3694 |
| Short period frequency (rad/s) | 1.0000 |
| Short period damping ratio | 0.7381 |
| Phugoid frequency (rad/s) | 0.3768 |
| Phugoid damping ratio | 0.06635 |
| Dutch roll frequency (rad/s) | 1.1151 |
| Dutch roll damping ratio | 0.5219 |
| Spiral time constant (s) | 45.7150 |
| Rolling time constant (s) | 0.2535 |

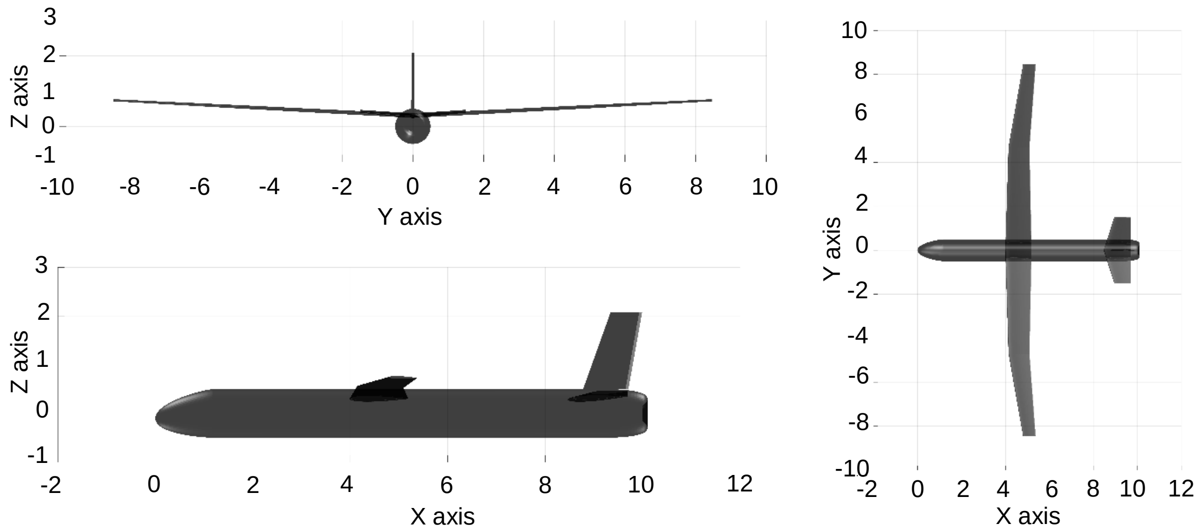


**Fig. 6.** Three views of optimal result

## 5. Conclusions

In this work, the conceptual design optimisation of a conventional type UAV based on MHs is successfully presented. Five design objective functions including take-off gross weight, take-off distance**,** flight endurance**,** lift coefficient and drag coefficient at cruising are normalised and scalarised into a single-objective optimisation problem subject to aircraft flight mission, performance and stability constraints. Six established MHs are implemented to solve the proposed UAV conceptual design problem. The comparative results show that the best performer is EO while the runner-up is MPO. The best solution obtained by EO is illustrated. Within a single run, an optimum point which optimise several objective functions can be obtained while weighting coefficient can be added to the proposed optimisation problem for further design in order to meet the design requirements.

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## References

[1] Bravo-Mosquera, P.D., Cerón-Muñoz, H.D., Díaz-Vázquez, G. and Martini Catalano, F. Conceptual design and CFD analysis of a new prototype of agricultural aircraft, Aerospace Science and Technology, Vol. 80, 2018, pp. 156-176.

[2] Panagiotou, P., Kaparos, P., Salpingidou, C. and Yakinthos, K. Aerodynamic design of a MALE UAV, Aerospace Science and Technology, Vol. 50, 2016, pp. 127-138.

[3] Bravo-Mosquera, P.D., Botero-Bolivar, L., Acevedo-Giraldo, D. and Cerón-Muñoz, H.D. Aerodynamic design analysis of a UAV for superficial research of volcanic environments, Aerospace Science and Technology, Vol. 70, 2017, pp. 600-614.

[4] Budziak, K. Aerodynamic analysis with Athena Vortex Lattice (AVL), 2015, Hamburg university of applied sciences, Hamburg.

[5] Deperrois, A. XFLR5: Analysis of foils and wings operating at low Reynolds numbers, URL: http://www.xflr5.tech/xflr5.htm, accessed on 29/09/2021.

[6] Stanford Aerospace Design Lab, Stanford University, United States. SUAVE: Aerospace conceptual design environment, URL: https://suave.stanford.edu/, accessed on 29/09/2021.

[7] NASA. OpenVSP: NASA open source parametric geometry, URL: https://blog.adafruit.com/2012/01/16/openvsp-nasa-open-source-parametric-geometry/, accessed on 29/09/2021.

[8] Oh, T.H. Conceptual design of small unmanned aerial vehicle with proton exchange membrane fuel cell system for long endurance mission, Energy Conversion and Management, Vol. 176, 2018, pp. 349-356.
[9] Mohammad Zadeh, P. and Sayadi, M. An efficient aerodynamic shape optimization of blended wing body UAV using multi-fidelity models, Chinese Journal of Aeronautics, Vol. 31(6), 2018, pp. 1165-1180.
[10] Singh, V., Sharma, S.K. and Vaibhav, S. Transport aircraft conceptual design optimization using real coded genetic algorithm, International Journal of Aerospace Engineering, Vol. 2016, 2016, Article number: 2813541.
[11] Sastry, K., Goldberg, D. and Kendall, G. Genetic algorithms, In: Burke, E.K. and Kendall, G., Eds. Search methodologies: Introductory tutorials in optimization and decision support techniques, 2005, Springer, Boston, pp. 97-125.
[12] Deb, K., Agrawal, S., Pratap, A. and Meyarivan, T. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II BT, paper presented in the Parallel problem solving from nature PPSN VI, 2000, Paris, France.
[13] Kennedy, J. and Eberhart, R. Particle swarm optimization, paper presented in the Proceedings of ICNN'95 - International Conference on Neural Networks, 1995, Perth, Australia.
[14] Storn, R. and Price, K. Differential evolution - A simple and efficient heuristic for global optimization over continuous spaces, Journal of Global Optimization, Vol. 11, 1997, pp. 341-359.
[15] Leifsson, L., Ko, A., Mason, W.H., Schetz, J.A., Grossman, B. and Haftka, R.T. Multidisciplinary design optimization of blended-wing-body transport aircraft with distributed propulsion, Aerospace Science and Technology, Vol. 25(1), 2013, pp. 16-28.
[16] Wroblewski, G.E. and Ansell, P.J. Mission analysis and emissions for conventional and hybrid-electric commercial transport aircraft, Journal of Aircraft, Vol. 56(3), 2019, pp. 1200-1213.
[17] Riboldi, C.E.D., Gualdoni, F. and Trainelli, L. Preliminary weight sizing of light pure-electric and hybrid-electric aircraft, Transportation Research Procedia, Vol. 29, 2018, pp. 376-389.
[18] Silva, H.L., Resende, G.J., Neto, R.M.C., Carvalho, A.R.D., Gil, A.A., Cruz, M.A.A., et al. A multidisciplinary design optimization for conceptual design of hybrid-electric aircraft, Structural and Multidisciplinary Optimization, Vol. 64, 2021, pp. 3505-3526.
[19] Panagant, N. and Bureerat, S. Truss topology, shape and sizing optimization by fully stressed design based on hybrid grey wolf optimization and adaptive differential evolution, Engineering Optimization, Vol. 50(10), 2018, pp. 1645-1661.
[20] Marques, J., Cunha, M. and Savić, D. Many-objective optimization model for the flexible design of water distribution networks, Journal of Environmental Management, Vol. 226, 2018, pp. 308-319.
[21] Patel, V., Savsani, V. and Mudgal, A. Many-objective thermodynamic optimization of Stirling heat engine, Energy, Vol. 125, 2017, pp. 629-642.
[22] Zhang, B., Zhu, J., Xiang, G. and Gao, L. Design of nanofluid-cooled heat sink using topology optimization, Chinese Journal of Aeronautics, Vol. 34(2), 2020, pp. 301-317.
[23] Faramarzi, A., Heidarinejad, M., Stephens, B. and Mirjalili, S. Equilibrium optimizer: A novel optimization algorithm, Knowledge-Based Systems, Vol. 191, 2020, Article number: 105190.
[24] Beyer, H.G. and Schwefel, H.P. Evolution strategies - A comprehensive introduction, Natural Computing, Vol. 1, 2002, pp. 3-52.
[25] Mirjalili, S. Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm, Knowledge-Based Systems, Vol. 89, 2015, pp. 228-249.
[26] Faramarzi, A., Heidarinejad, M., Mirjalili, S. and Gandomi, A.H. Marine predators algorithm: A nature-inspired metaheuristic, Expert Systems with Applications, Vol. 152, 2020, Article number: 113377.
[27] Li, S., Chen, H., Wang, M., Heidari, A.A. and Mirjalili, S. Slime mould algorithm: A new method for stochastic optimization, Future Generation Computer Systems, Vol. 111, 2020, pp. 300-323.
[28] Mirjalili, S., Gandomi, A.H., Mirjalili, S.Z., Saremi, S., Faris, H. and Mirjalili, S.M. Salp swarm algorithm: A bio-inspired optimizer for engineering design problems, Advances in Engineering Software, Vol. 114, 2017, pp. 163-191.
[29] Essari, A. Estimation of component design weights in conceptual design phase for tactical UAVs, Dissertation, 2015, University of Belgrade, Belgrade.
[30] Sadraey, M. Aircraft performance analysis, 2009, VDM Verlag Dr. Müller, Saarbrücken.