Multidisciplinary Design of a micro-USV for Re-entry Operations

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Agenda

Introduction  USV System Models  Robust Multidisciplinary Design  Optimization Results  Conclusions
Motivations and Assumptions

Why USV?
- Unmanned Space Vehicles are seen as a test-bed for enabling technologies and as a carrier to deliver and return experiments to and from low-Earth orbit and upper atmosphere.
  - PRORA-USV designed by the Italian Aerospace Research Center (CIRA) // the Boeing X-37B Orbital Test Vehicle (OTV).

How small can we go?
- The goal of this study is to derive the technical specifications for a very small reentry vehicle.
- Assumed availability of last generation TPS based on ultra-high temperature ceramic (UHTC) materials.

The approach
- Multifidelity modeling of the USV aerodynamics.
- Model uncertainty included into the design and optimisation process.
- Robust design optimization by means of an incremental single process (ISP)
- Evolutionary-based optimization algorithm combining global and local search.
- Direct transcription method for optimal control problem for trajectory optimization.
USV System Models
The planform and the upper surfaces of the vehicle are parameterized by the length $l$, the width, $w$, a power law exponent $n$, the vehicle center line wedge angle, $\vartheta$, and the oblique shockwave inclination angle $\beta$. 
Aerodynamic Models

- Three different models are used to predict the aerodynamic characteristics of the vehicle.
  - A simplified analytical model.
  - A computational fluid dynamic (CFD) model based on a finite volume integration of Reynolds Averaged Navier-Stokes equations (RANS).
  - A surrogate model based on an ANN approximator used for trajectory optimization.

- No thermo chemistry is included in any of the models.

- Unmodelled components are introduced as uncertainties in the aerodynamic parameters.

- Design parameters are chosen to minimise the impact of the uncertain quantities.
Aerodynamic Models: Simplified analytical model

The analytic model gives the lift \( L \) and wave drag \( D_w \) as functions of the pressure on the upper, lower and base surfaces, \( P_u, P_l \) and \( P_b \):

\[
\begin{align*}
L &= S_b(P_b - P_l)\sin\alpha + S_p(P_b - P_l)\cos\alpha \\
D_w &= S_b(P_l - P_b)\cos\alpha + S_p(P_l - P_u)\sin\alpha
\end{align*}
\]

where \( S_p \) and \( S_b \) are the planform area and the area of the base.

The viscous drag \( D_v \) is given in analytical form, by using the reference temperature method:

\[
\begin{align*}
D_{v,\text{surf}} &= G_1wF(n)\left(\frac{l}{\cos\theta_{\text{surf}}}\right)^{G_2}
\end{align*}
\]

with \( F(n) = F_0 + F_1n + F_2n^2 + F_3n^3 \), and \( \theta_{\text{surf}} \) is the inclination angle for the considered surface (upper or lower surface).

The total drag is \( D = D_w + D_{v,u} + D_{v,l} \)

**Aerodynamic Models: CFD Model**

The Reynolds Averaged Navier-Stokes (RANS) solver Numeca is used to compute an improved solution when the analytical model could be applied and to compute a solution when the analytical model could not be applied (for super- and sub-sonic flight regimes).

The computational domain was discretized by a multi-block structured mesh, changed by internal scripting on the basis of design parameters, made by 13 blocks with near $1.2 \times 10^6$ total nodes.

Four different settings are implemented and used during the process:

- Fully Laminar Hypersonic for Mach > 6 and Reynolds number < $10^5$
- Fully turbulent Hypersonic for Mach > 6 and Reynolds number > $10^5$
- Fully Laminar Supersonic and Subsonic for Mach < 6 and Reynolds number < $10^5$
- Fully turbulent Supersonic and Subsonic for Mach < 6 and Reynolds number > $10^5$
- No transition model is considered
Surrogate CFD Model

- The surrogate model is a Multi Layer Perceptron (MLP) Artificial Neural Network (ANN) approximators with one hidden layer.

- The training process is based on a Bayesian regularization back-propagation, which limits any overfitting problem.

- The inputs to the ANN approximator are the 5 geometric parameters, the angle of attack, the speed, and the altitude.

- The outputs are the coefficient of lift, \( C_L \) and drag, \( C_D \).

- The networks are trained to reach a mean squared error of 5% on the normalized training output.
TPS and Thermal Model

- The thermal protection system (TPS) is assumed to be made of Zirconium Diboride (ZrB$_2$) UHTC.

<table>
<thead>
<tr>
<th>Properties</th>
<th>unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>density</td>
<td>6000 kg/m$^3$</td>
</tr>
<tr>
<td>specific heat</td>
<td>628 J Kg$^{-1}$ K$^{-1}$</td>
</tr>
<tr>
<td>thermal conductivity</td>
<td>66 W m$^{-1}$ K$^{-1}$</td>
</tr>
<tr>
<td>emissivity</td>
<td>0.8</td>
</tr>
</tbody>
</table>

- The whole nose cone is made of UHTC with thickness $L_{TPS}$. The rest of the vehicle is covered with a thin shell with a constant thickness of 0.002m.

- No radiative or convective dissipation on the back of the vehicle.
TPS and Thermal Model

- The convective heat flux

$$\dot{q}_{\text{conv}} = K_e \sqrt{\frac{\rho_{\infty}}{R_n}} V_{\infty}^3$$

where $K_e = 1.742 \times 10^{-4}$ (the heat flux is in W/m$^2$)

- The internal temperature ($T_{\text{int}}$) is computed by solving the following one-dimensional heat equation:

$$\frac{\partial^2 T}{\partial x^2} = \frac{c \rho_{TPS}}{k} \frac{\partial T}{\partial t}$$

with boundary conditions:

$$\dot{q}_{\text{conv}} - \varepsilon \sigma T_w^4 + k \frac{dT}{dx} \quad \text{at} \quad x = 0$$

$$k \frac{dT}{dx} = \varepsilon \sigma T_{\text{int}}^4 \quad x = L_{TPS}$$

where $c$ is the heat capacity, $\rho_{TPS}$ is the density of the TPS material, $k$ is the thermal conductivity, $\varepsilon$ is the material emissivity, and $\sigma$ is the Stephen-Bolzmann’s constant.
Mass Model

- The total mass of the USV is made of the structural mass \( m_{st} \), the mass of the TPS \( m_{TPS} \) and the mass of the payload (avionics and power system) \( m_{pl} \).

\[
m = m_{TPS} + m_{st} + m_{pl}
\]

- The mass of the TPS is made of the mass of the nose \( m_{\text{nose}} \) plus the mass of the thin skin covering the rest of the vehicle \( m_{\text{skin}} \).

- The structure of the vehicle is supposed to be made of titanium, with a density of 4000 kg/m\(^3\).

- The structural mass \( m_{st} \) can be obtained as \( m_{st} = \rho_{\text{body}} (2 S_p + S_b) d_{\text{body}} \) where \( d_{\text{body}} = 0.004 \) m is the thickness of the structure of the vehicle, seen as a shell.
The vehicle is considered to be a point mass, whose motion is governed by the following set of dynamic equations

\[
\begin{align*}
\dot{r} &= vsin\theta_p \\
\dot{\lambda} &= \frac{v\cos\theta_p \cos \xi}{r \cos \phi} \\
\dot{\phi} &= \frac{v \cos \theta_p \sin \xi}{r} \\
\dot{v} &= -\frac{D(\alpha)}{m} - g \sin \theta_p \\
\dot{\theta}_p &= \frac{L(\alpha)}{m v} \cos \gamma_v - \left( \frac{g}{v} - \frac{v}{r} \right) \cos \theta_p \\
\dot{\xi} &= \frac{L(\alpha)}{m v \cos \theta} \sin \gamma_v - \frac{v}{r} \cos \theta_p \cos \xi \tan \phi
\end{align*}
\]

where \( r \) is the norm of the position vector with respect to the center of the planet, \( \lambda \) is the longitude, \( \varphi \) the latitude, \( v \) the magnitude of the velocity, \( \theta_p \) is the flight path angle, \( \xi \) is the heading angle (azimuth of the velocity).

No out of plane maneuvers are considered, thus \( \gamma_v \) is kept equal to zero during the whole trajectory.
Dynamic Equations and Optimal Control Subproblem

- The angle of attack $\alpha$ is the control variable therefore for each geometry the following optimal control subproblem needs to be solved:

$$\min_{\alpha} \max_t \dot{q}$$

subject to dynamic equations and terminal conditions

\[
\begin{align*}
r(t = 0) &= r_0 \\
\lambda(t = 0) &= \lambda_0 \\
\phi(t = 0) &= \phi_0 \\
v(t = 0) &= v_0 \\
\theta_p(t = 0) &= \theta_0 \\
\xi(t = 0) &= \xi_0 \\
r(t = t_f) &\leq r_f \\
r(t = t_f) &\geq r_{min}
\end{align*}
\]

The re-entry time is free and no other terminal conditions are imposed as there is no specific requirement on the landing point.
Robust Multidisciplinary Design
General Approach

- Simultaneous optimization of the shape and trajectory control profile of the vehicle.

- Hybridization of an evolutionary multi-objective algorithm with a direct transcription method for optimal control problems:
  - the evolutionary part handles the shape parameters and the global optimization of the performance indexes, i.e. heat flux, thermal load and their variance.
  - the performance index of each individual in the population are the results of the optimal control profile coming from the solution of a nonlinear programming problem.

- The trajectory optimization based on the ANN output

- Multi-fidelity incremental approach to reduce the computational cost related to the training and updating of the ANN.
Uncertainty Model

- One can associate to the nominal value of lift $L_{\text{det}}$ and drag $D_{\text{det}}$ the uncertain quantities:

$$L_{\text{unc}} = L_{\text{det}} + \text{Err}(\alpha, v, H) \cdot CE(\alpha, v, H) \cdot L_{\text{det}}$$
$$D_{\text{unc}} = D_{\text{det}} + \text{Err}(\alpha, v, H) \cdot CE(\alpha, v, H) \cdot D_{\text{det}}$$

- $CE$ is a sampling hyper-surface which maps the angles of attack, speed and altitude into the interval $[-1, 1]$

- $\text{Err}$ is modeled here as a linear hyper-surface, function of $\alpha, v, H$
  - Values varies from 0.2, when angle of attack, speed and altitude are 0, to $\text{Err} = 0.8$, when the incidence is 20deg, the speed is $=8000\text{m/s}$ and the altitude is 100km.
Uncertainty Model

- Uncertain thermal conductivity, \( k \), and the specific heat, \( c \), can uniformly vary in the range \( 0.1 \) of the reference value.

- Given a nominal trajectory with an optimal control profile \( \alpha^* \), \( N_s \) varied \( L, D \) distributions and \( k, c \) values were generated and used to re-propagate the trajectory, maintaining the control profile constant, and re-compute heat flux and internal temperature.

3d Err function (not the actual one)  
3d CE function
Robust Design Optimization Under Uncertainty

- The mean, $E_q$ and $E_T$, and the variance, $\sigma_q^2$ and $\sigma_T^2$, of all the computed maximum heat flux and maximum internal temperatures were used as performance indexes.

- Based on this definition of the performance indexes, the robust design optimization under uncertainties can be formulated as follows:

$$\min_{d \in D}[E_q, E_T, \sigma_q^2, \sigma_T^2]$$

subject to the following constraints on the variance:

$$\sigma_q^2 \leq \bar{\sigma}_q^2; \sigma_T^2 \leq \bar{\sigma}_T^2$$

- The design vector $d$ is defined as $d = [l, w, n, \theta, R_r, L_{TPS}]$.
Multi-objective Algorithm

- The MOO problem was solved with a particular type of evolutionary algorithm which belongs to the sub-class of Estimation of Distribution Algorithms (EDAs).

- The specific EDA employed in this work is a multi-objective optimization algorithm for continuous problems that uses the Parzen method to build a probabilistic representation of Pareto optimal solutions, with multivariate dependencies among variables (Multi-Objective Parzen based Estimation of Distribution, MOPED).

- Non-dominated sorting and crowding operators are used to classify promising solutions in the objective space, while new individuals are obtained by sampling from the Parzen model.
Multi-objective Algorithm: \textit{Trajectory Optimization}

- Transcription with a Gauss pseudospectral method and with Finite Elements in Time on spectral basis. (The two approaches gave similar results therefore it was decided to omit from this paper the comparison between the two approaches on this particular problem).

- In both cases, the trajectory is decomposed in $n_e$ elements, each of which have $n_p$ collocation points.

- After transcription, the optimal control problem becomes the following general nonlinear programming problem:

subject to the nonlinear:

$$\min_{\alpha_s} \max_{t_s} \dot{q}_s$$

$$C(r_s, \lambda_s, v_s, \xi_s, \theta_s, \alpha_s, t_s) = 0$$

algebraic constraints:

$$\begin{cases}
  r(t = 0) = r_0 \\
  \lambda(t = 0) = \lambda_0 \\
  \phi(t = 0) = \phi_0 \\
  v(t = 0) = v_0 \\
  \theta_p(t = 0) = \theta_0 \\
  \xi(t = 0) = \xi_0 \\
  r(t = t_f) \leq r_f \\
  r(t = t_f) \geq r_{\text{min}}
\end{cases}$$

- Solution with Matlab \textit{fmincon} with interior point approach.
Evolutionary Control and Multi-fidelity Approach

- The MOO optimization algorithm MOPED is integrated with an external procedure that monitors the status of the approximated models.

At the end of each iteration (generation), the external procedure checks if an updated version of the approximated model is ready and available.
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In an asynchronous way, an additional external procedure manages the training and updating of the approximated model.
Update of the Surrogate Model

- At generation 0, a first ANN is trained using the lowest-fidelity model (fidelity level 0) and then passed to MOPED;

- The database $DB_{train}$ is initialized with both analytical and CFD model.

- At each subsequent generation:
  - Initialize counter $i_c = 0$;
  - While $i_c <= n_t$
    - (a) extracts from the population a sampled trajectory and extract $n_o$ operative points;
    - (b) for $i = 1$ to $n_o$
      - compute the minimum Euclidean distance $d_{sl,i} = \min_j ||S_{opt,i} - DB_{train,j}||$ where $j$ loops over all the points in the database (the rows of $DB_{train}$);
      - if $d_{sl,i} > d_{min,sl}$ then the point $S_{opt,i}$ is evaluated and immediately inserted into the database $DB_{train}$, and $i_c = i_c + 1$; all the solutions in the database that were computed with a lower fidelity model and have $d_{sl} < d_{min,ll}$ are discarded from future updates of the approximating model;
      - if $i_c = n_t$ interrupt loops

- Every $n_{gl}$ generations of the global optimizer, it increases the level of fidelity of the model.
Optimization Results
The design space for problem is defined by the following bounds on the design parameters:

- the nominal length \( l \in [0.9, 1.5] \text{m} \),
- the nominal width \( w \in [0.4, 0.9] \text{m} \),
- the exponent \( n \in [0.2, 0.7] \),
- the angle \( \Theta \in [6, 11.9] \text{deg} \),
- the radius of the nose \( R_n \in [0.0115 \, l, 0.026 \, l] \),
- the thickness of the TPS at the nose \( L_{TPS} \in [0.05, 0.15] \text{m} \).
The trajectories are discretized using 5 elements, with 7 nodes for the states, and 6 Gauss integration points.

The bounds on the variables of the trajectory optimization are:
- total time $T_{tot} \in [500, 6500]$s,
- angle of attack $\alpha \in [0, 20]$deg,
- radius $r \in [6.367 \times 10^6, 6.47 \times 10^6]$m,
- longitude $\lambda \in [-100, 20.9559]$deg,
- latitude $\varphi \in [-60, 68.0767]$deg,
- speed $v \in [10^2, 10^4]$m/s,
- path angle $\vartheta_p \in [-10, 10]$deg,
- heading angle $\xi \in [-225.7396, -55.7396]$deg.

The initial conditions are imposed as $x_0 = [R_E + 10^5, 20.9559, 68.0767, 7700, -0.63247, -145.7641]^T$ (where $R_E$ is the mean radius of the Earth)

Terminal conditions $r_f = R_E + 25$ km and $r_{\text{min}} = R_E + 15$ km.
Implementation

- The MOO process was carried out for 50 generations with a population of 60 individuals.

- The initial approximator (ANN) was built with 1000 calls to the analytic model, selected on a randomized Latin Hypercube of the inputs, plus additional 100 super- and subsonic CFD computations to allow the approximator to have an extended range of validity, without needing to extrapolate.

- The computation of the first database required nearly 700 hours of computational time, distributed on a cluster of 15 linux64 processors (2 days of effective time).

- The computations of the CFD solver were stopped when convergence was obtained on the aerodynamic forces.
Levels of Fidelity

- Level 0, from generation 0 to 10, mainly the analytical model is used to train the ANN. The CFD is used only when the regime is subsonic or subsonic.

- Level 1, which is considered from generation 10 to 20, CFD computations are introduced to improve trajectory points up to 50 km of altitude.

- Level 2, from generation 20 onwards, the altitude limit for the use of CFD computation is increased to 90 km.

- From level 0 to level 2 the calls to the CFD model increased up to 450, allocated in the promising region of the search space, while the analytical ones, used to build the ANN approximator, decreased to nearly 550.

- The characteristic parameters of the evolution control were set as follows: $n_t = n_o = 10$, $n_{gl} = 10$, for a total of 2 switches; $n_{gcyc} = 5$; $d_{min,sl} = 0.25$ (all the inputs are normalized to $[-1, 1]$); $d_{min,ll} = 0.5$ for the first 30 generations, and then is increased to 1.0.
Pareto Optimal Solutions

Mean internal temperature [K] vs. Mean heat flux [W/m²] vs. Sum of the variances

Points A, B, and C represent different solutions in the Pareto front.
Individual A minimizes the mean value of the maximum heat flux, while individual B is the most robust one, minimizing the sum of the variances.

The shape of individual A is the most common one and corresponds to a narrow and blunt body. The shape of individual B corresponds to a wider body.

A is 48 kg and B is 58 kg
L=1.15 m
A: w=0.562 m, B=0.787 m
Individual A, about 20% lighter than solution B, is able to follow a higher re-entry path in the critical part of the trajectory, limiting the heat loads.

On the other hand, solution A is more sensitive to changes in the aerodynamic model and in the characteristics of the thermal protection material.
The constraint on the final altitude and the bounds on the state variables strongly affect the optimal control law as well.

The vehicle passes through the critical part of the atmosphere with an angle of attack which is considerably larger than zero.

For a real application, it is likely that a blunt-body shape similar to solution A, would require an even higher value of the angle of attack; meaning that the stagnation point is not on the leading edge but more down-stream on the pressure side.
Trajectory

AOA = 0 deg

AOA = 20 deg

H = 73 km ; Mach = 15.4
Conclusions
The whole process was able to detect realistic optimal shapes, with a heating load at the nose that can be considered comparable to what is tolerate by last generation UHTC protection materials.

As expected, such a small vehicle cannot have sharp edges compared to the reduced and compact dimensions, and as a consequence can re-enter with an angle of attack which is considerably larger than zero.

The initial hypothesis that the maximum heating should be at the nose is over-conservative, and a correct prediction of the real heating should be obtained by models of higher fidelity, which combines medium- to high-fidelity aero-thermal dynamic computations.

Moreover, the analytical method resulted misleading, even if its use toward the end of the design process was minimized.

All these aspects will be considered in future works, together with a more careful tuning of the approximator and different shape models.
THANK YOU
Trajectory

Trajectory

\[ H = 73 \text{ km} ; \text{Mach} = 15.4 \]

\[ \text{AoA} = 0 \text{ deg} \quad \text{AoA} = 20 \text{ deg} \]