Manipulation of a BFS flow by surface plasma discharge:
open and closed-loop control

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Primary objective of MARS EU project

The MARS project focuses on the effects of a number of active flow control devices on periodic Reynolds stresses of turbulent shear flows.

Two fundamentals flow configurations

- Backward Facing Step
- Airfoil NACA0015

- Separated turbulent shear layer from a fixed sharp edge
- Periodic unsteady flows
- Massive or partial flow separation
- Periodicity of the dynamic components
Properties of flow downstream of a BFS

A simple geometry but a complex flow

- Several instability wavelengths
- Many periodic organizations
- Two recirculating zones
- Vortical and flapping motions
- 3D organization of flow structures

Objective:
Reduce the reattachment location by optimal forcing

An ideal test case for flow control

R. Geisler (DLR) and N. Benard (PPRIME)
Model used in this study

- Step height: 30 mm
- Freestream velocity: 15.6 m/s
- Turbulent intensity: 0.8%
- Reynolds number $Re_h$: 30000
- Boundary layer thickness: 13 mm
- Momentum thickness: 1.3 mm

Sketch of the model installed in the test section

Wind-tunnel used for the study

Velocity profiles at the step corner (LDV)
Metrology applied to quantify the reattachment point

Wall pressure taps mounted on the bottom wall of the BFS

32 unsteady pressure sensors (up to 400 Hz)

- 42 pressure taps separated by 0.15h
- 32 unsteady pressure sensors with 400Hz bandwidth
- Simultaneous acquisition on PXI hardware with LabVIEW based program
- Plasma discharge piloted by the PXI
Actuators used in this study

A- Non-thermal plasma actuator driven by ac frequency

Electrode arrangement on the BFS model

- Electrode arrangement for electric wind production in positive x direction
- 3-mm thick dielectric (PMMA)
- AC frequency maintains at 2 kHz
- Maximum electrical power consumption of 0.4 W/cm
- Maximum local induced flow velocity of 3 m/s
Actuators used in this study

B- Electrical signal and design variables of the problem

The electrical signal has three design variables:

- $x_1$: Voltage amplitude (V, in kV); $V \in \mathbb{N}$, $12 \leq V \leq 21$
- $x_2$: Burst Frequency ($f_{bm}$, in Hz); $f_{bm} \in \mathbb{N}$, $10 \leq f_{bm} \leq 300$
- $x_3$: Duty Cycle (DC, in %); $DC \in \mathbb{N}$, $5 \leq DC \leq 95$

- Similar velocity profiles with frequency $f_{bm}$
- Flow perturbation imparted at the frequency $f_{bm}$
Objective functions

Two objectives functions are defined:

\[ X_R(\mathbf{x}) \quad \text{the mean flow reattachment location, where } \mathbf{x} \text{ is the vector containing the three design variables of the DBD plasma actuator.} \]

\[ \sum_{i=1}^{32} P_i'(\mathbf{x}) \quad \text{the sum of the wall pressure fluctuations, where } \mathbf{x} \text{ is the vector containing the three design variables of the DBD plasma actuator.} \]

Typical distribution of pressure fluctuations for \( U_0=15 \text{ m/s} \)
Part 1
Optimization by open-loop
Results – Parametric study on Xr

A- Influence of the design variable $f_{bm}$

- Large Xr reduction (-20%) when flow forced at $f_{BM}=125$ Hz
- Many local maxima or minima

Position of the reattachment location according to the superimposed periodic fluctuation frequency
Results – Parametric study on $P'$

A- Influence of the design variable $f_{bm}$

- Large increase in $P'$ (+105%) when flow forced at $f_{BM} \sim 65$ Hz
- A single maxima

![Graph showing Strouhal number vs. Frequency (Hz)](image)

Position of the integrated pressure fluctuations according to the superimposed periodic fluctuation frequency
Results – Parametric study on $X_R$ and $P'$

At the two best frequencies, local maxima and minima for varying duty-cycle

Reattachment and pressure fluctuations vs duty-cycle
Results – Parametric study on $X_R$ and $P'$

- ‘Linear’ reduction in $X_R$ for increasing voltage amplitude
- Saturation of the plasma actuator at $V>21$ kV

Reattachment and pressure fluctuations vs voltage amplitude
Part 2
Optimization by closed-loop: multi-input genetic algorithm
In Evolutionary computation, optimisation algorithms evaluate and classify the value of objective functions between several different candidates in order to detect best to worst performance.

A multi-criteria optimization problem can be formulated as follows:

Maximise/Minimise

\[ f_i(x), i = 1, \ldots, N_f \]

The solution can be a set of non-dominated solution well known as the Pareto optimal front.

Solutions are compared to other solutions using the concept of Pareto dominance.

Genetic algorithms can find global extremum even in complex functions with many local maxima or minima.

The single-objective case corresponds to a number of objective functions \( N_f \) equal to 1.
Presentation of the MOGA code

- Robust Multi-objective Optimization Platform (RMOP) developed at CIMNE
- Solve multi-objective problems using the hybridized techniques that combine Pareto-game, Nash-games and hierarchical optimization
- Here, only single-objective functions are solved with real encoding

![Diagram of MOGA process]

- Selection of best individuals (ranking by tournament)
- Mutation (probability of 0.3)
- Crossover (probability of 0.9)
- Evaluation (takes 15s per individual)
- Fitness function
- Population (10 individuals)

Time criterion 45’
Validation of the MOGA code with inverse problem

A- Inverse problem: Validation on $X_R$

Problem 1: A single objective problem to recover a prescribed reattachment length $X_R$. This prescribed value is 4.55h, the minimal reattachment obtained by open-loop

$$f(x_1, x_2, x_3) = f_e(x_1, x_2, x_3) - f_p(x_1, x_2, x_3)$$

- The values $f(x_1, x_2, x_3)$ will be the reattachment length in Problem (1)
- The values $f_p(x_1, x_2, x_3)$ and $f_e(x_1, x_2, x_3)$ are the prescribed value and the evaluated value for the objective functions

- The evaluation of $f_e(x_1, x_2, x_3)$ takes 5s for converged value +10s to avoid actuator on and off transient regimes

$x_1$: Voltage amplitude (V, in kV); $V \in \mathbb{N}, 12 \leq V \leq 21$
$x_2$: Burst Frequency ($f_{bm}$, in Hz); $f_{bm} \in \mathbb{N}, 10 \leq f_{bm} \leq 300$
$x_3$: Duty Cycle (DC, in %); $DC \in \mathbb{N}, 5 \leq DC \leq 95$
Validation of the MOGA code with inverse problem

A- Inverse problem: Validation on $X_R$

Evaluations of the individuals of generations #1, #4, #8 and #12.
A- Inverse problem: Validation on $X_R$

Convergence history for problem (1): matching the reattachment length

| Voltage (kV) | Frequency (Hz) | Duty-cycle (%) | $X_R$  
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<tr>
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<tbody>
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<td>20</td>
<td>125</td>
<td>50-70</td>
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Results by open-loop

| Voltage (kV) | Frequency (Hz) | Duty-cycle (%) | $X_R$  
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Results by closed-loop (MOGA)

- Fast convergence (~100 evaluations)
- Validation of the experimental-numerical MOGA methodology
Optimization by MOGA code

A- Optimization of $X_R$

The optimization problem is defined as:

\[ \text{Minimize } f_o(\vec{x}) = \min[X_R(\vec{x})] \]

where $\vec{x}$ is the vector containing the three design variables of the DBD plasma actuator.

The optimization problem is defined as a single-objective minimization problem

Voltage amplitude ($V$, in kV); $V \in \mathbb{N}, 12 \leq V \leq 21$
Burst Frequency ($f_{bm}$, in Hz); $f_{bm} \in \mathbb{N}, 10 \leq f_{bm} \leq 300$
Duty-Cycle (DC, in %); $DC \in \mathbb{N}, 5 \leq DC \leq 95$
Optimization by MOGA code

A- Optimization of $X_R$

Experimental evaluation of the individuals of the $n^{th}$ generation
Optimization by MOGA code

A- Optimization of $X_R$

Experimental evaluation of the individuals of the $n^{th}$ generation
Optimization by MOGA code

A- Optimization of $X_R$

**Convergence history for reattachment length optimization**

**Evaluation of the individuals from the last generation**

<table>
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- Fast convergence (~30 evaluations)
- Good agreement with open-loop results
- No more improvement can be expected for this objective function
Optimization by MOGA code

A- Optimization of $P'$

The optimization problem is defined as:

Maximize

$$f_o(\vec{x}) = \max[P'(\vec{x})]$$

where $\vec{x}$ is the vector containing the three design variables of the DBD plasma actuator.

The optimization problem is defined as a single-objective minimization problem

Voltage amplitude ($V$, in kV); $V \in \mathbb{N}, 12 \leq V \leq 21$

Burst Frequency ($f_{bm}$, in Hz); $f_{bm} \in \mathbb{N}, 10 \leq f_{bm} \leq 300$

Duty-Cycle (DC, in %); $DC \in \mathbb{N}, 5 \leq DC \leq 95$
Optimization by MOGA code

A- Optimization of P’

Experimental evaluation of the individuals of the nth generation
Optimization by MOGA code

A- Optimization of P’

Convergence history for P’ optimization

Evaluation of the individuals from the last generation

Results by open-loop

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<tr>
<td>20</td>
<td>65</td>
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Results by closed-loop (MOGA)

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<td>58</td>
<td>58</td>
<td>2.34</td>
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- Lower convergence (~120 evaluations)
- Good agreement with open-loop results
- Improvement of +3% for this objective function
Conclusion

Merits and benefits of MOGA approach

- Experimental optimization is an innovative approach.
- Coupling between the Plasma/Sensors and the optimizer, enabling a fast estimator of the candidate operating conditions of the actuator.
- No need for approximative and time consuming plasma modeling.
- Results are relevant; inverse problem analysis demonstrated the reliability of the process. The single-objective optimization converges successfully.
- New control scenario can emerge for MOGA optimization.

Perspectives

- Time-resolved PIV results for the optimized configurations have to be analyzed.
- Multi-objectives optimization, including the in-time electrical power consumption, is under investigation.
- Further work is under consideration due to the good expectations this work produced.
Questions?