Multi-Objective Design Optimization of Piezoelectric Energy Harvesting System for UAVs

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Energy harvesting in UAVs

- Energy harvesting from ambient energy sources, such as various **sources of vibrations** has become a practical alternative to conventional power sources
- We examine the possibility of embedding piezoceramics in wing spars of Unmanned Aerial Devices (UAVs)

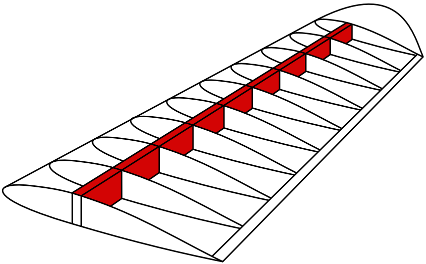
A weather drone (UAV)

The multi-objective nature of the problem

- The aim is to keep the UAV's fly-ability intact, while contributing extra energy to the UAV
- Modification: aluminum wing spar $\Rightarrow$ generator wing spar
- Constraint: upper limit on mass addition
- Two objectives:
  1. $\uparrow$ output power of the generator spar
  2. $\downarrow$ mass of the structure
- A Finite Element Model was developed
- 3 multi-objective algorithms were exercised

The structure

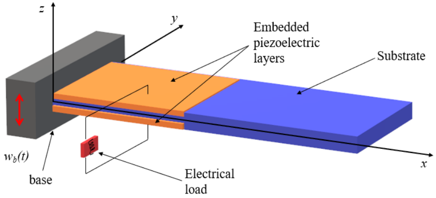
- The structure consists of a host metal plate



A wing spar

The structure

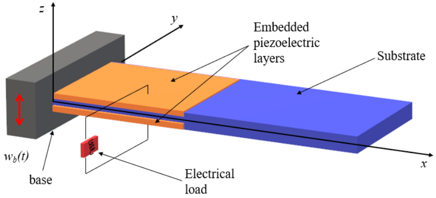
- The structure consists of a host metal plate with piezoelectric layers embedded on its top and bottom surfaces (bi-morph)



Piezoelectric harvester

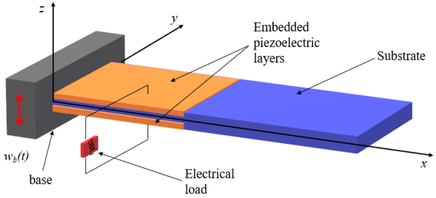
The structure

- The structure consists of a host metal plate with piezoelectric layers embedded on its top and bottom surfaces (bi-morph)
- The piezoelectric layers are poled through the z-direction and are covered by continuous electrodes with negligible thickness



The structure

- The structure consists of a host metal plate with piezoelectric layers embedded on its top and bottom surfaces (bi-morph)
- The piezoelectric layers are poled through the z-direction and are covered by continuous electrodes with negligible thickness
- The electrodes of the top and bottom (identical) piezoelectric layers are connected to an external resistance R



Problem formulation

- The FEM formulation is based on **laminated plate theory** combined with the **first-order shear deformation theory (FSDT)** for which each piezoelectric layer has one additional electrical degree of freedom.
- This work extends the following work: C. De Marqui Jr, A. Erturk, D.J. Inman, "An electromechanical finite element model for piezoelectric energy harvester plates", Journal of Sound and Vibration 327 (2009), 9–25

The governing piezoaeroelastic equations for the generator wing are:

$$\begin{aligned} [M]\left\{\ddot{d}\right\} + [C]\left\{\dot{d}\right\} + [K]\{d\} + [\Theta]\,v &= \{m^*\}\ddot{w}_b \\ -[\Theta]^T\left\{\dot{d}\right\} + C_p\dot{v} + \frac{v}{R} &= 0 \end{aligned}$$

where
d is the vector of mechanical coordinates,
$[M]$ is the mass matrix,
$[K]$ is the stiffness,
$[C]$ is the mechanical damping matrix,
C_p is the effective capacitance,
$[\Theta]$ is the effective electromechanical coupling vector,
$\{m^*\}$ is an effective mass,
R is the load resistance,
v is the voltage across the load

Problem formulation

- Some part of the aluminum material (Al 2024-T3) is replaced by the piezoceramic material (PZT-5A)
- L^* is the % of spar's length that PZT covers
- $h^* =$ is the % of spar's height that PZT covers
- f_1 is the generated power (negated)
- f_2 is the added mass (%)

$$\begin{array}{lll} min & F(L^*, h^*, R) \equiv (f_1, f_2) & \\ s.t. & 0 \leq L^* \leq 1.0 & \\ & 0 \leq h^* \leq 0.5 & \\ & 1 \leq R \leq 600 & (k\Omega) \\ & f_2 \leq 0.3267 & \end{array}$$

Fly-ability constraint

The added mass due to the piezoelectric layers **should not exceed 10%** of the mass of the original aluminum plate.
Mass densities:
PZT-5A $\rightarrow 7800 kg/m^3$
Al 2024-T3 $\rightarrow 2750 kg/m^3$

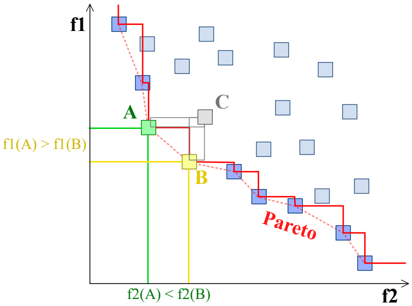
Multi-objective optimality

- 3 state of the art multi-objective algorithms are tested against the constrained optimization problem: NSGA-II, NSGA-III, GDE3
- All 3 algorithms:
  - retain a population of solutions that evolve over generations
  - produce a front of Pareto optimal solutions
- We examine how good are the solutions produced, employing suitable metrics

Pareto front - non dominated solutions

The concept of dominance:

- x_1 dominates x_2 if
  - x_1 is no worse than x_2 in all objectives
  - x_1 is strictly better that x_2 in at least one objective
- Pareto front: set of Pareto optimal solutions (those that are not dominated by any other solutions)



Example of a Pareto front min(f1, f2)

NSGA-II (2002)

- The 2 goals of the **Non-dominated Sorting Genetic Algorithm II** are:
  - Find solutions as close as possible to the Pareto optimal front
  - Find solutions as diverse as possible in the obtained non dominated front

```
Procedure NSGA-II
  Input: N', g, f_k(X) ▷ N' members evolved g generations to solve f_k(X)
Initialize Population P';
Generate random population - size N';
Evaluate Objectives Values;
Assign Rank (level) based on Pareto - sort;
Generate Child Population;
   Binary Tournament Selection;
   Recombination and Mutation;
for i = 1 to g do
    for each Parent and Child in Population do
        Assign Rank (level) based on Pareto - sort;
        Generate sets of nondominated solutions;
        Determine Crowding distance;
        Loop (inside) by adding solutions to next generation starting from
        the first front until N' individuals;
    end
    Select points on the lower front with high crowding distance;
    Create next generation;
      Binary Tournament Selection;
      Recombination and Mutation;
end
```

Pseudo code[1] for NSGA-II

[1] Matnei Filho, R. A., & Vergilio, S. R. (2016). A multi-objective test data generation approach for mutation testing of feature models. Journal of Software Engineering Research and Development, 4(1), 1-29

NSGA-III (2014)

- **NSGA-III** extends NSGA-II. In NSGA-III:
  - A set of reference points is determined before generating the initial population
  - The reference point set serves to guide the evolution into creating a uniform Pareto front in the objective space

Algorithm 1 Generation t of NSGA-III procedure

Input: H structured reference points Z^s or supplied aspiration points Z^a, parent population P_t

Output: P_{t+1}

```
S_t = ∅, i = 1
Q_t = Recombination+Mutation(P_t)
R_t = P_t ∪ Q_t
(F_1, F_2, ...) = Non-dominated-sort(R_t)
repeat
    S_t = S_t ∪ F_i and i = i + 1
until |S_t| ≥ N
Last front to be included: F_l = F_i
if |S_t| = N then
    P_{t+1} = S_t, break
else
    P_{t+1} = ∪_{j=1}^{l-1} F_j
    Points to be chosen from F_l: K = N − |P_{t+1}|
    Normalize objectives and create reference set Z^r:
    Normalize(f^n, S_t, Z^r, Z^s, Z^a)
    Associate each member s of S_t with a reference point:
    [π(s), d(s)] =Associate(S_t, Z^r)   % π(s): closest
    reference point, d: distance between s and π(s)
    Compute niche count of reference point j ∈ Z^r: ρ_j =
    Σ_{s∈S_t/F_l} ((π(s) = j) ? 1 : 0)
    Choose K members one at a time from F_l to construct
    P_{t+1}: Niching(K, ρ_j, π, d, Z^r, F_l, P_{t+1})
end if
```

Pseudo-code for NSGA-III[1]

[1] Deb, K., & Jain, H. (2014). An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints. IEEE Transactions on Evolutionary Computation, 18(4) 577-601

GDE3 (2005)

- GDE3 (**Generalized Differential Evolution 3**) is based in the common DE, but is also able to solve optimization problems with multiple constraints and objectives. In GDE3:
  - Decisions are based on the objective values, and crowdedness while ensuring feasibility
  - The algorithm is less reliant on the selection of control parameters

Algorithm 5 GDE3

Initialise the population $\mathbf{P}$ of size N with randomly generated solutions and evaluate their fitness;
while Termination condition is not met **do**
  Initialise empty offspring population with size $2N$;
  for $i = 1 : N$ **do**
    Randomly select three distinct parent solutions $\mathbf{x^{r1}}, \mathbf{x^{r2}}, \mathbf{x^{r3}}$ and a random variable index j_{rand};
    {Apply mutation}
    $\mathbf{u} = \mathbf{x^{r3}} + F\left(\mathbf{x^{r1}} - \mathbf{x^{r2}}\right)$ with F scale factor [1];
    {Apply binomial crossover [1]}
    for $j = 1 : d$ **do**
      if $rand[0,1) < CR$ OR $j = j_{rand}$ (CR crossover rate) **then**
        $u^i_j = u^i_j$;
      else
        $u^i_j = x^i_j$;
      end if
    end for
    Evaluate the fitness $f_1(\mathbf{u}), f_2(\mathbf{u}), \dots f_k(\mathbf{u})$;
    if the child solution $\mathbf{u}$ and the solution $\mathbf{x^i}$ of the parent population are indifferent to each other **then**
      Add both solutions to offspring population;
    else if $\mathbf{x^i} \prec \mathbf{u}$ **then**
      Add solution $\mathbf{x^i}$ to offspring population;
    else
      Add child solution $\mathbf{u}$ to offspring population;
    end if
  end for
  Sort the offspring population as in Algorithm 3;
  Choose the best N solutions for the next generation;
end while

Pseudo-code[1] for GDE3

[1] Rostami, S., Neri, F., & Gyaurski, K. (2020). On algorithmic descriptions and software implementations for multi-objective optimisation: A comparative study. SN Computer Science, 1(5), 1-23

Hardware and software used

- MATLAB 2018b on Windows 10
- BIMK / PlatEMO[1] (Evolutionary multi-objective optimization platform)
- pfevaluator[2] python package for performance metrics
- OAPackage[3] python package for identification of Pareto optimal solutions

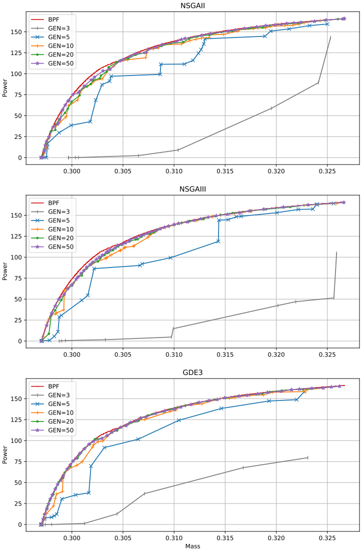
Hardware

Intel Core i9 7960X @2.8GHz GPU, 64GB DDR4 RAM
Population = 50, generations = 50 $\approx$ 2500 seconds runtime

[1] https://github.com/BIMK/PlatEMO
[2] https://pypi.org/project/pfevaluator/
[3] https://pypi.org/project/OApackage/

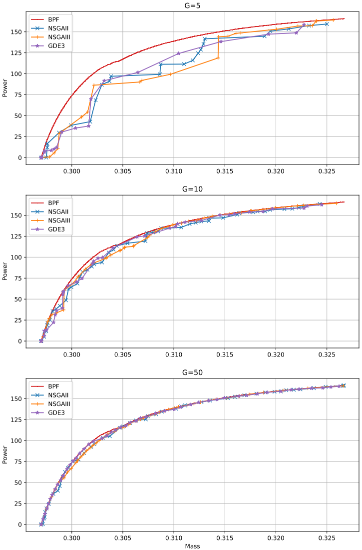
Evolution of the Pareto front

1. A Base Pareto Front was generated based on collected results of several runs
2. Around 20^{th} generation convergence occurs (population=50)
3. GDE3 has a small lead



Pareto fronts proximity to BPF

Proximity to the Base Pareto Front (BPF) for generations 5, 10 and 50
The red line is the approximated optimal Pareto front aka BPF



Metrics

Table: Performance metrics for NSGA-II, NSGA-III and GDE3 (population=50, generations=50)

		GD	IGD	MPFE	MS	HV
NSGA-II	Mean	0.0348	0.0806	4.6917	**0.9980**	**26545.1330**
	SD	0.0044	0.0055	0.7847	0.0052	33.2109
	Best	0.0291	0.0895	3.5325	*1.0000*	*26577.9370*
NSGA-III	Mean	**0.0299**	**0.1013**	9.0326	0.9970	26506.6338
	SD	0.0031	0.0016	0.7498	0.0048	56.0942
	Best	*0.0226*	*0.1042*	7.7758	*1.0000*	26564.4818
GDE3	Mean	0.0363	0.0648	**3.3602**	0.9940	26489.0978
	SD	0.0035	0.0030	0.4547	0.0072	54.3403
	Best	0.0297	0.0703	*2.7993*	*1.0000*	26577.5045

1. GD = Generational Distance (favor ↓ values)
2. IGD = Inverted Generational Distance (favor ↑ values)
3. MPFE = Maximum Pareto Front Error (favor ↓ values)
4. MS = Maximum Spread (favor ↑ values)
5. HV = Hyper Volume (favor ↑ values)

Selected solutions

Table: Some "good" non-dominated solutions

Power ($\frac{mW}{g^2}$)	Mass	L* (%)	H* (%)	R ($k\Omega$)	Algorithm
165.71184	0.32666	0.24316	0.11184	139.61471	NSGA-II
165.57695	0.32656	0.22207	0.12203	160.53703	NSGA-III
165.27248	0.32619	0.20690	0.12934	190.74535	GDE3

Conclusions

- The production of electrical energy from sources available within the environment of UAVs is of vital importance
- The mass of structures used in aerospace applications is a crucial factor for the design
- A multi-objective problem has been studied in order to achieve an optimal design of a wing spar generator with embedded piezoceramics
- 3 state-of-the-art multi-objective algorithms (NSGA-II, NSGA-III and GDE3) have been carried out to optimize the geometric dimensions (length and thickness) and the load resistance for maximum power output and minimum mass added by the embedded piezoceramics
- The results show that the solutions achieved closely resemble a constructed reference Pareto optimal front by all 3 algorithms (no clear winner)
- Better results are reported than ones found in the bibliography

Thank You!
Questions?