OPTIMIZATION ISSUES IN MODELING IPMC DEVICES

Claudia Bonomo[1], Gabriella Dellino[2], Luigi Fortuna[1], Pietro Giannone[1], Salvatore Graziani[1], Paolo Lino[3], Carlo Meloni[3], Alessandro Rizzo[3]

[1]Dipartimento di Ingegneria Elettrica Elettronica e dei Sistemi
Università degli Studi di Catania - Via Andrea Doria, 6, 95125 Catania, Italy
[2]Dipartimento di Matematica
Università degli Studi di Bari - Via E. Orabona 4, 70125 Bari, Italy
[3]Dipartimento di Elettrotecnica ed Elettronica
Politecnico di Bari - Via E. Orabona 4, 70125 Bari, Italy

gdellino@dm.uniba.it(Gabriella Dellino)

Abstract

The increasing pressure on the development time of new materials and devices has changed the modeling and design process over the years. In the past, they mainly consisted of experimentation and physical prototyping. Clearly, it is hard to incorporate changes in finished prototypes, while producing a variety of different prototypes at once may be very expensive. At this aim, computer simulation models such as circuit design models and continuous systems simulation models are widely used in engineering modeling, design and analysis. In this context, the search for a better understanding of complex systems calls for quantitative model development, and optimization tools and model fitting to observed data play an important role. In this framework, this paper deals with the optimization issues arising in the model calibration for a particular IPMC-based actuator in air. The considered formal model of the device is a nonlinear dynamical one, with lumped parameters, able to estimate the IPMC actuator absorbed current, together with the mechanical quantities of interest, which, in the case under study, are the free deflection and/or the blocked force. Two optimization problems have been formulated, focussing on different stages of the model parameters identification. The strategies adopted to solve the problems allow to achieve some promising — although preliminary — results.

Keywords: Model Identification, Simulation-Optimization, IPMC Devices, Multidisciplinary Design Optimization.

Presenting Author's Biography

Gabriella Dellino graduated cum laude in Computer Science Engineering at Politecnico di Bari, Italy, in 2005; since 2006 she starts a Ph.D. program in Applied Mathematics at University of Bari. She took part in research projects promoted by academic organizations and companies. Her main research interests include optimization models and methods, computer simulation methodologies, and Multidisciplinary Design Optimization. She is member of INFORMS society.

1 Introduction

Recently, computer simulation techniques such as circuit design models and continuous simulation models are widely used in engineering modeling, design and analysis. In this context, the search for a better understanding of complex systems calls for quantitative model development and within this process, simulation-optimization methods play an important role. The current quality of computer simulation tools has enabled the virtual prototyping of complex products and devices, a method adopted by many R&D groups. This has led to improved model quality and performance, and reduction of product development time and costs. Another benefit of employing simulation models is that operators can actually see cause and effect and track characteristics that cannot be physically measured. This approach has changed the traditional product development cycle making the physical test process a validation phase and reducing time to market and is much less labor intensive.

Still designers are confronted with the problem of finding settings for a number of model parameters that are optimal with respect to several simulated product or device characteristics. These characteristics may originate from different engineering domains suggesting a multidisciplinary approach. Since there are still many possible design variable settings and computer simulations are often time consuming, the crucial question becomes how to find the best possible setting with a minimum number of simulations. Usually in such a situation, experts use their intuition and experience. They carry out a number of simulation runs and choose the design that gives the best results. This intuitive approach can be considerably improved by using statistical methods and mathematical optimization techniques. Anyway, in this context, the problems differ from the standard optimization problems due to the not explicitly known specific functions, which may be present both in the objective and in the constraints.

In this paper the simulation-optimization issues arising in the model calibration for a particular IPMC-based actuator are addressed. The paper is organized as follows. Section 2 describes the models adopted for the considered device. In Section 3 the optimization problems and the adopted methods are illustrated. Section 4 describes the experimental setting and reports the computational results.

2 The electromechanical model of an IPMC actuator

The model adopted in this work is essentially based on that developed by co-authors in [1], for an IPMC-based actuator in air, in a mechanical configuration of a beam pinned at one end, which is also used to apply an electrical stimulus across its thickness. The model is a nonlinear dynamical one, with lumped parameters, able to estimate the IPMC actuator absorbed current, together with the mechanical quantities of interest, which, in the case of the pinned beam, are the free deflection and/or the blocked force.

Moreover, this is a cascaded two-stage model, in which the first stage models the nonlinear relation between the applied voltage and the absorbed current, and the second stage models the linear relation between the absorbed current and the free deflection and/or the blocked force. The explicit knowledge of the estimate of the absorbed current is of fundamental importance, as it is a key design factor which determines the power consumption in IPMC-based applications [2].

Finally, the model is developed through a *grey-box* approach, i.e. it is based on a set of equations able to reproduce the observed phenomena. The model parameters are identified by processing experimental data through suitable algorithms, which are generally based on optimization procedures. If the model parameters correspond to macroscopic properties of the system, the grey-box approach can be very useful in the design and simulation phase.

In past works, both *black-box* and *white-box* (also known as *first-principle*) models have been adopted to model IPMC transducers. In this work the grey-box approach is preferred, as black-box models must generally be re-designed for each different transducers, whereas white-box ones are generally either too complex for practical applications, or too simple for guaranteeing suitable predictions [3, 4, 5, 6, 7].

Let us examine in more detail the two stages of the model. For a comprehensive description of the model, refer to [1].

2.1 Electrical Stage

As stated above, the electrical stage of the model is able to establish the relation between the applied voltage, $v(t)$, and the absorbed current, $i(t)$. According to [1], this part of the model is described by a nonlinear equivalent circuit, illustrated in Fig. 1.

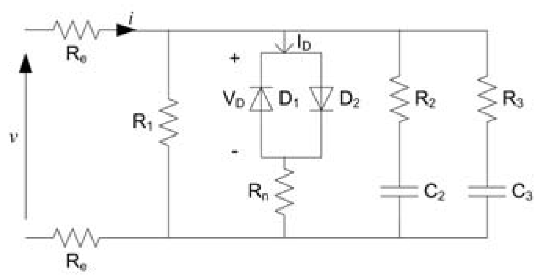

Fig. 1 Nonlinear equivalent circuit for the actuator's electrical stage

The equations describing the circuit behaviour can be easily written in the form of a second-order nonlinear ODE, as:

$$\begin{aligned} \dot{V}_{C2} &= \frac{V_D}{R_2 C_2} + \frac{R_n}{R_2 C_2} I_D - \frac{V_{C2}}{R_2 C_2} \\ \dot{V}_{C3} &= \frac{V_D}{R_3 C_3} + \frac{R_n}{R_3 C_3} I_D - \frac{V_{C3}}{R_3 C_3} \end{aligned} \tag{1}$$

As can be noted in Fig. 1, the nonlinearity is modelled by a diode antiparallel pair. Its behaviour can be described by exploiting and adapting the Shockley ideal diode equation. So, referring to the circuit in Fig. 1, we have:

$$
\begin{aligned}
I_{D1} &= I_{s_{nl}}\left(\exp\left(\frac{-V_D}{\gamma}\right)-1\right)\\
I_{D2} &= I_{s_{nl}}\left(\exp\left(\frac{V_D}{\gamma}\right)-1\right)\\
I_D &= I_{D1}+I_{D2} = 2I_{s_{nl}}\sinh\left(\frac{V_D}{\gamma}\right)
\end{aligned}
\tag{2}
$$

where $I_{s_{nl}}$ and γ are the equivalent inverse saturation current and the equivalent diode threshold, to be identified experimentally.

V_D is the solution of the nonlinear equation:

$$
\begin{aligned}
&\frac{v}{2R_e} - V_D\left(\frac{1}{2R_e}+\frac{1}{R_1}+\frac{1}{R_2}+\frac{1}{R_3}\right)+\\
&-2I_{s_{nl}}\sinh\left(\frac{V_D}{\gamma}\right)\left(\frac{R_n}{2R_e}+\frac{R_n}{R_1}+\frac{R_n}{R_2}+\frac{R_n}{R_3}+1\right)+\\
&+\frac{V_{C2}}{R_2}+\frac{V_{C3}}{R_3}=0
\end{aligned}
\tag{3}
$$

Finally, the current absorbed by the actuator is given by:

$$
i = \frac{v - V_D - R_n 2I_{s_{nl}}\sinh\left(\frac{V_D}{\gamma}\right)}{2R_e} \tag{4}
$$

The simulation of the electrical part of the model implies therefore the solution of Eq. (3) together with the ODEs (1). It appears clear that the simulation of the model for optimization/identification purposes can be time-consuming, therefore a metamodel assisted optimization approach will be used to cope with this issue.

In [1], the equivalent bulk resistance of the Nafion®, R_1, and the resistance associated with the observed nonlinear phenomena, R_n, as well as the terms $I_{s_{nl}}$ and γ were identified by analysis of experimental data. In the following, we will apply a Kriging metamodel approach in order to identify R_e, i.e. the resistance of the two electrodes, and the value of R_2,C_2,R_3,C_3 components, which are able to parallel the capacitive behaviour of the IPMC actuator.

2.2 Electromechanical Stage

As an electrical current flows into the actuator, a charge/water redistribution occurs, producing a mechanical reaction [8, 9, 10]. In particular, the currents flowing in the two capacitors C_2 and C_3 are responsible for the mechanical deformation of the membrane.

According to [1], the transfer function between the free deflection δ and the current flowing in the two capacitors ($I_C = I_{C1} + I_{C2}$) is given by:

$$
\frac{\delta}{I_C} = \frac{1}{s}\frac{3dL_s^2}{\eta\,(L_t+L_c)\,wt}\left(\frac{1}{1+s^2\dfrac{12L_t^4\rho}{\Gamma^4 Y t^2}}\right) \tag{5}
$$

and the transfer function between the blocking force F and the current I_C is

$$
\frac{F}{I_C} = \frac{1}{s}\frac{3Ydt^2}{\eta\,(L_t+L_c)\,4L_s} \tag{6}
$$

where s is the complex Laplace variable, and:

- L_c is the length of the clamped part of the IPMC;
- L_t is the free length of the IPMC;
- L_s is the length from the pinning point to the point to which the force is applied;
- w, t are the dimensions of the IPMC cross-section;
- Γ is a mechanical constant related to the first mode of oscillation of the clamped beam, its value is well known in the literature and is equal to 1.875;
- ρ is the IPMC density.

The role of the remaining terms in Eqs. (5-6) must now be clarified. d is a term which represents the electromechanical coupling, and can be computed by considering either the expression for the deflection or that for the blocked force. By considering the blocked force, we have:

$$
\frac{F}{v-2R_eI} = \frac{3dtwY}{4L_s} \approx \frac{F}{v} \tag{7}
$$

where the term $v - 2R_eI$ is the voltage actually applied to the capacitive branches, which is responsible for the mechanical conversions. Nevertheless, by neglecting the electrode resistance, it can be approximated with the applied voltage v. During the identification phase, the term d has been hypothesized as a second order transfer function with one zero and two poles, as shown in Eq. (8):

$$
d = K_d\,\frac{s+Z_d}{s^2+P_{1d}s+P_{2d}}\,. \tag{8}
$$

The frequency of the zero and the two poles can be fixed through an optimization process, which will be described in Sec. 3.4.2.

Y is the Young's modulus, which is constant for perfect elastic mediums. Nafion® can be rather assumed as a viscoelastic medium, so its Young's modulus has been assumed as a function of frequency, according to the GMH model [11, 12], as

$$
Y = Y_c\left(1+k\frac{s^2+2\zeta\omega s}{s^2+2\zeta\omega s+\omega^2}\right) \tag{9}
$$

where Y_c is the static Young's modulus, k is a real constant value, ζ is a damping coefficient, and ω a natural frequency. These parameters have to be identified through the optimization procedures, by exploiting experimental measurements.

η is an equivalent permittivity of the capacitive branches:

$$\eta = \frac{\epsilon_2}{1 + s\epsilon_2\rho_2} + \frac{\epsilon_3}{1 + s\epsilon_3\rho_3} \tag{10}$$

where ϵ_2 and ϵ_3 are the dielectric constants of the capacitors C_2 and C_3; ρ_2 and ρ_3 are the correspondent resistivities of the two branches.

3 Optimization issues in the model identification

The identification and the calibration of the model described in the previous section can be tackled adopting a simulation-optimization approach. The goal of the optimization problem is to minimize (maximize) a given set of functions of the design variables and responses, subject to a set of constraints. The functional relation between the design variables and the responses is not explicitly known and it is represented by a simulation model. For this reason, such kind of problem differs from a standard optimization problem, and classical solution methods become impractical when the simulation time is considerably high. They require too many time consuming function evaluations in the process of finding an optimum. Hence, depending on simulation time either classical optimization methods or special methods for simulation-optimization should be used. Aiming at reducing the high computational costs payed for running the simulation model, several approximation techniques (also called surrogates or metamodels) have been proposed in the literature. In this work we consider the use of Kriging surrogates, in the context of engineering design activities. The Kriging method provides exact interpolation (i.e., the predicted results at input combinations already observed are equal to the simulated results values at those inputs) and some recent research results showed such interpolation to be appealing in simulation-optimization engineering design approaches.

In numerical optimization schemes, metamodels are often used to obtain approximations of expensive objective functions. However, integrating metamodels in a computational optimization process based on classical, evolutionary or meta-heuristic optimizers is not straightforward and different model management issues emerge in order to coordinate optimization strategies and approximation efforts. In particular, the issue to find the trade-off between metamodel accuracy, computational efficiency, and solutions quality in a framework based on evolutionary optimization algorithms (EAs) is currently a research topic. At this aim, a Data Envelopment Analysis (DEA) approach is proposed in [13].

In the case under study, the simulation of the electromechanical stage model is much less time-consuming than that of the electrical stage, as the latter is purely linear. For this reason, a metamodel approach might not be needed. Nevertheless, the parameter identification and the related optimization procedure must be conducted simultaneously both on the relation between current and free deflection, and on that between current and blocked force. Moreover, better results are obtained if the objectives of the identification are set both on the time and on the frequency domain. This results in a multiobjective framework for the optimization procedure. Satisfactory results have already been obtained in [1] by linearly combining the objectives in a single objective functions. Nevertheless, this requires a thorough, sensible choice of suitable weighting constants of the partial objectives. This is the motivation for the implementation of an actual multiobjective optimization approach, which will be illustrated in the following of this section.

3.1 Optimization methods and algorithms

The optimization system we consider in this contribute can be classified as a simulation-based optimizer which is equipped with algorithms able to tackle both multi-objective and single-objective problems. Moreover, the framework adopts different metamodel assisted optimization schemes.
The framework has been developed in the MATLAB® environment, employing the Design and Analysis of Computer Experiments (DACE) Toolbox [14] for the construction of metamodels.
The system is composed of three main blocks, briefly described in what follows: the Design of Experiments (DOE) Tool allows studying the effects of multiple factors on design results; the Metamodel Constructor — based on the Kriging technique — provides useful tools to create a mathematical model approximating costly computational functions; the optimization algorithms are based on the MATLAB® Optimization Toolbox [15] and on the MATLAB® Genetic Algorithms and Direct Search Toolbox [16]; the Multiobjective Optimizer is mainly based on Deb's multiobjective algorithm NSGA-II (Non-Dominated Sorting Genetic Algorithm-II) [17] and it is able to solve constrained problems, by penalizing infeasible solutions. Moreover, an external solutions archive is available to save the non-dominated solutions found during the optimization.

3.2 Metamodel Management

The proposed implementation supports the use of successive approximation models of a costly fitness function and enables different strategies — usually referred to as metamodel management — to integrate and manage the metamodel in the iterative optimization process. A starting set of data samples (i.e. input/output descriptions of computer simulation experiments) is obtained through the Latin Hypercube Sampling (LHS) DOE technique, chosen because of its flexibility and easy construction [18]. These elements are given as inputs to computer simulation experiments; the computed outputs are used to construct a metamodel, based on the Kriging technique [19, 20] with the DACE Toolbox. To integrate the approximated model into an optimization process, many strategies can be adopted. The model management in the proposed framework can be performed by means of two main approaches: i) assuming the approximation model to be of high-fidelity and therefore, not using the original fitness function at all during the computation process; ii) adopting a dynamic update mechanism. The latter, in the case of evolutionary optimizers, can consist of either an individual-based or a generation-based evolution control [13].

3.3 Kriging Metamodels

In this subsection we briefly describe the characteristics of the Kriging metamodel adopted in our optimization framework to build and update the surrogates, referring to [20] for a detailed exposition of both theory and implementation of Kriging technique.
A Kriging model $y(\mathbf{x})$ can be seen as a combination of a global model and an additive localized approximation:

$$y(\mathbf{x}) = \sum_{i=1}^{p} \beta_i \, f_i(\mathbf{x}) + Z(\mathbf{x}) \; , \tag{11}$$

where $\mathbf{x} \in \mathbb{R}^n$ is a design variable, $f_i : \mathbb{R}^n \to \mathbb{R}$, $i = 1, \ldots, p$, are polynomial terms (typically of order 1 or 2, in many cases reduced to constants), the coefficients β_i, $i = 1, \ldots, p$, are regression parameters, and $Z(\mathbf{x})$ is a Gaussian random function with zero mean and non-zero variance representing a local deviation from the global regression model. The covariance of $Z(\mathbf{x})$ is expressed in terms of the correlation function between any two of the samples $\mathbf{x}^{(j)}$ and $\mathbf{x}^{(k)}$, with unknown parameters that need to be estimated by maximizing a likelihood function using numerical optimization techniques; the form of the correlation function $R(\theta, \mathbf{x}^{(j)}, \mathbf{x}^{(k)})$ can be chosen by the user among several models proposed in the literature.
One of the advantages of using Kriging models is that an estimation of the accuracy of the prediction can be obtained without much additional computational cost. However, the Kriging estimation of the fitness function value at untried points requires to perform matrix inversions, which may require high computational costs if the size of the problem is large. A performance evaluation of the adopted metamodel management schemes requires to consider different aspects of the entire optimization process. One measure, for example a specific error measure, may not give a complete picture of the overall performance. Thus, it is commonly necessary to look at several experimental inputs simultaneously, along with the multiple outputs they produce.

3.4 Optimization Problems Formulation

In this work two particular optimization problems are tackled: both of them require the objective functions to be evaluated by running simulations, even though in one case it is not an expensive task, as mentioned before.

3.4.1 Electrical stage

The first problem we consider deals with the model identification of the electrical circuit: in particular, it is necessary to identify the resistances and capacitances of the circuit, by solving a single-objective optimization problem. The vector of the decision variables is defined as $\mathbf{x} = (R_2, C_2, R_3, C_3, R_e)$. The objective to be minimized is a cost function, defined in terms of the error in the estimation of the absorbed current; the objective function is given by:

$$f_i = \sqrt{\sum\nolimits_k (i_k - \hat{i}_k)^2} \tag{12}$$

where i refers to the absorbed current — experimentally obtained by measurements — while $\hat{i}$ is the value estimated by numerically solving the differential equation describing the circuit dynamics; the sum is computed over the samples produced by the applied voltage.

In order to reduce the high computational costs required by running the simulations of the numerical solver of the differential equation, a Kriging metamodel has been used to assist the optimization process.

3.4.2 Electromechanical stage

The second problem concerns the identification of the parameters describing the piezoelectric coefficient d and the Young's modulus Y, i.e. gain, and zeros' and poles' frequency, as given by Eqs. (13-14):

$$d = x_1 \left(\frac{1}{s + x_2} + \frac{1}{s + x_3} \right) , \tag{13}$$

$$Y = x_7 \left(1 + x_4 \frac{s^2 + 2x_5 x_6 s}{s^2 + 2x_5 x_6 s + x_6^2} \right) , \tag{14}$$

where x_i, $i = 1, \ldots, 7$, represents the components of the vector of decision variables; refer to Eqs. (8-9) for the corresponding parameters.

A multi-objective optimization has been performed, by minimizing both the deformation error and the force error, evaluated as squared differences from some experimental values:

$$f_\delta = \sqrt{\sum\nolimits_k (\delta_k - \hat{\delta}_k)^2} \, , \tag{15}$$

$$f_F = \sqrt{\sum\nolimits_k (F_k - \hat{F}_k)^2} \, , \tag{16}$$

where δ and F are the free deflection and the blocking force experimentally obtained by some measurements, while $\hat{\delta}$ and $\hat{F}$ are the corresponding values estimated by the model. Notice that in this case running a simulation model is still required, but it is not necessary to approximate it by metamodels, since the computational effort is not too high.

4 Experimental Results

In the problem described in Sec. 3.4.1, the Kriging model has been built over an experimental design composed of 100 points, that have been sampled — by means of the Latin Hypercube Sampling technique — in the interval $[-10\%, +10\%]$ w.r.t. a nominal design element, $\bar{\mathbf{x}} = (127.91, 5.67 \cdot 10^{-5}, 183.02, 7.28 \cdot$

Tab. 1 Parameters setting for the Kriging model

Kriging Setting	
Correlation model	Anisotropic Gaussian
Regression function	Linear
Parameters optimization	MLE $\theta_0 = 10$, $[\theta_{lb}, \theta_{ub}] = [0.01, 20]$

$10^{-4}, 11.03)$. The setting used to build the metamodel is specified in Tab. 1.

As for the optimization, the *fmincon* function from the MATLAB® Optimization Toolbox has been used, performing a sequential quadratic programming (SQP) algorithm. This function allows to solve a constrained problem, by imposing box constraints over the vector of decision variables, asking it to stay in the aforementioned range. Note that the non-negativity constraint — that has been imposed too — is implicitely satisfied when the box constraints are. The maximum number of iterations has been fixed as a stopping criterion. The objective function to be optimized is the approximation value of the function described in Eq. (12), estimated on the Kriging metamodel, which is assumed to be sufficiently accurate and thus it is never updated during the entire process. The optimal solution is given by

$$\mathbf{x}^* = (117.75, 5.97{\cdot}10^{-5}, 183.88, 8.004{\cdot}10^{-4}, 12.135)\,;$$

the value of the objective function at $\mathbf{x}^*$, evaluated on the metamodel, is $\hat{f}_i(\mathbf{x}^*) = 0.31773$, with an estimated prediction error equal to $1.64 \cdot 10^{-7}$, in terms of the Mean Squared Error (MSE). Running the expensive simulation at the end of the optimization process, the value of the real objective function at the optimal solution is $f_i(\mathbf{x}^*) = 0.3179$.

To solve the problem described in Sec. 3.4.2, the algorithm adopted is NSGA-II and the setting used is sketched in Tab. 2.

Tab. 2 The setting for the Optimization Algorithm

Genetic Algorithm Setting		
Population	size = 50	
Archive	size = 500	
Selection operator	Stochastic Uniform	
Crossover operator	Scattered	probability = 0.7
Mutation operator	Gaussian	probability = 0.3
Stopping criterion	Max Computation time	3600 s

At the end of the optimization process — imposing the non-negativity constraint on the decision variables — 36 non-dominated points have been obtained after 67 generations. In Fig. 2 it is shown how the Pareto front evolves during the optimization.

By forcing the decision variables to stay in a range of $[-10\%, +10\%]$ w.r.t. a nominal design element, $\bar{\mathbf{x}} = (1.32 \cdot 10^{-7}, 0.253, 115.67, 74.67, 0.999, 93.75, 1.119 \cdot 10^7)$, 67 generations are produced, with a set of 52 non-dominated elements. The evolution of the Pareto front is depicted in Fig. 3.

In order to compare the obtained results with other strategies, we performed an optimization process by considering the two objectives independently from each other. Moreover, we considered an aggregation function — obtained as the sum of the two objectives — and tried to solve a single-objective optimization problem. In both the two cases, *fmincon* has been used to solve the optimization problems; as stopping criterion, the maximum number of iterations has been fixed to 150 for the first case and to 200 for the second case. By optimizing the deformation error only, the optimal solution is given by

$$\begin{aligned}\mathbf{x}^* &= (1.375 \cdot 10^{-7}, 38.64, 155.53, 82.8,\\ &\quad 5.032, 189.23, 1.12 \cdot 10^7)\end{aligned}$$

and the corresponding objective values are $f_\delta(\mathbf{x}^*) = 56.534$ and $f_F(\mathbf{x}^*) = 333.9638$. By optimizing the force error only, the optimal solution is

$$\begin{aligned}\mathbf{x}^* &= (1.317 \cdot 10^{-7}, 0.253, 155.67, 74.651,\\ &\quad 0.999, 93.754, 1.12 \cdot 10^7)\end{aligned}$$

and the corresponding objective values are $f_\delta(\mathbf{x}^*) = 87.9252$ and $f_F(\mathbf{x}^*) = 5.9897$. By optimizing the sum of the two objectives, the optimal solution is

$$\begin{aligned}\mathbf{x}^* &= (1.32 \cdot 10^{-7}, 0.253, 155.67, 74.683,\\ &\quad 0.999, 93.75, 1.119 \cdot 10^7)\end{aligned}$$

and the values of the two components of the objective function are $f_\delta(\mathbf{x}^*) = 87.891$ and $f_F(\mathbf{x}^*) = 6.0004$; the corresponding point is shown in Fig. 2.

The results are slightly different if we add the box constraints on the decision variables, as shown in what follows. By optimizing the deformation error only, the optimal solution is given by

$$\begin{aligned}\mathbf{x}^* &= (1.38 \cdot 10^{-7}, 0.278, 155.7, 77.193,\\ &\quad 1.099, 92.95, 1.119 \cdot 10^7)\end{aligned}$$

and the corresponding objective values are $f_\delta(\mathbf{x}^*) = 87.012$ and $f_F(\mathbf{x}^*) = 15.78$. By optimizing the force error only, the optimal solution is

$$\begin{aligned}\mathbf{x}^* &= (1.32 \cdot 10^{-7}, 0.253, 155.65, 74.612,\\ &\quad 0.999, 93.78, 1.119 \cdot 10^7)\end{aligned}$$

and the corresponding objective values are $f_\delta(\mathbf{x}^*) = 87.943$ and $f_F(\mathbf{x}^*) = 5.988$. By optimizing the sum of the two objectives, the optimal solution is

$$\begin{aligned}\mathbf{x}^* &= (1.32 \cdot 10^{-7}, 0.254, 155.71, 74.783,\\ &\quad 1.003, 93.73, 1.119 \cdot 10^7)\end{aligned}$$

and the values of the two components of the objective function are $f_\delta(\mathbf{x}^*) = 87.802$ and $f_F(\mathbf{x}^*) = 6.0686$; the corresponding point is shown in Fig. 3.

Some tests conducted on the optimization problem in the electrical stage confirm that integrating a metamodel into the optimization process allows saving computation time: in fact, fixing the number of iterations computed by *fmincon*, we noticed that the optimization

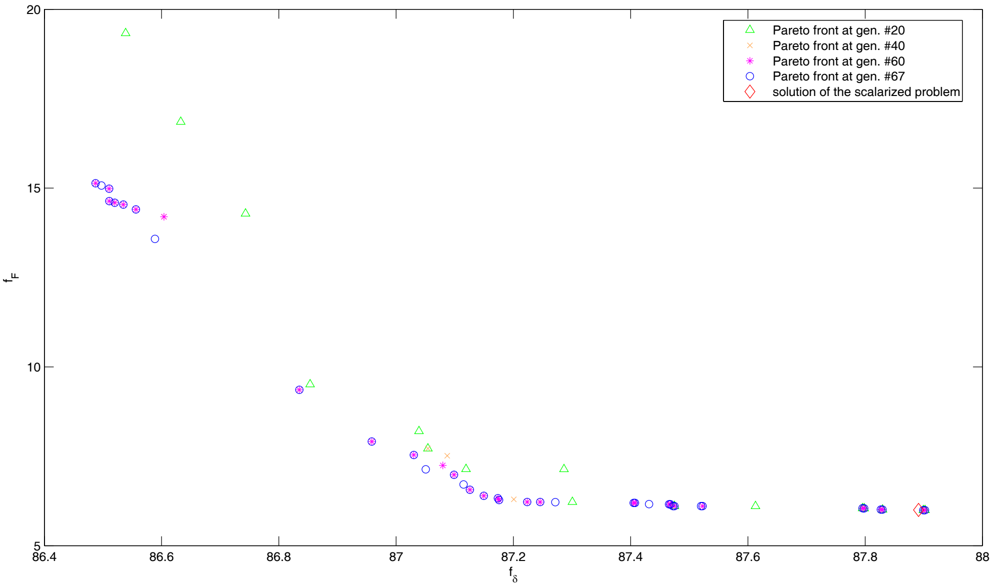

Fig. 2 Non-dominated Pareto Front during the evolutionary optimization process and solution of the scalarized problem (without box constraints on the decision variables)

using the expensive simulation requires more than one hour for each iteration; the evaluations on the metamodel, instead, require about 0.1 seconds. Moreover, the assessment of the quality of the approximations given by the metamodel confirms the validity of the overall optimization process. On the other hand, the analysis of the computation efforts confirms that it is less profitable to use metamodels in the optimization process for the electromechanical stage. This appears evident comparing the time required by a single run in the two cases: in the first problem it is almost 4 minutes, while in the second problem it is 2.5 seconds.

As for the optimization problem in the electromechanical stage, the best point found by *fmincon* is $(56.534, 5.9897)$, when the box constraints are not included, and $(87.012, 5.988)$, when the box constraints are also taken into account. Clearly, in both cases, when optimizing the two objectives indipendently from each other, the value of the other function may be even very far from the optimal solution. Instead, the solution obtained through the optimization of an aggregate function may be non-dominated w.r.t. the solutions found by NSGA-II, belonging to the same Pareto front. However, the multi-objective optimization model is able to identify a set of non-dominated points — instead of a single point — and it is possible to conduct further analyses on these solutions in order to select the most promising ones. This requires the application of some additional design criteria and constitutes a topic for further researches. The three approaches proposed in this work to solve the electromechanical identification problem do not have to be considered as alternative to one another; indeed, it could be useful to combine them such that the solutions found by the single objective models and the scalarized one could be used to initialize the multi-objective algorithm.

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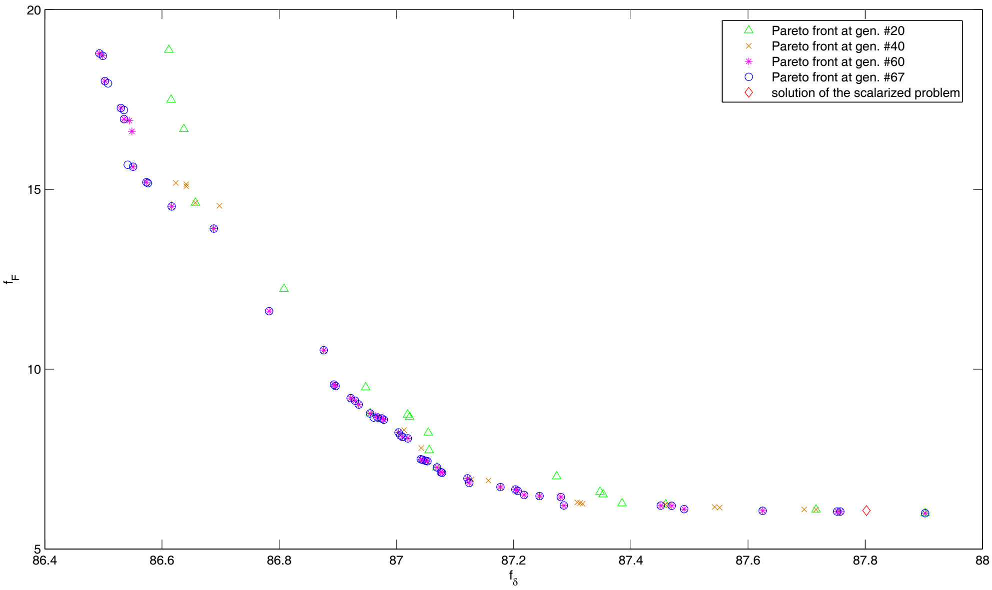

Fig. 3 Non-dominated Pareto Front during the evolutionary optimization process and solution of the scalarized problem (with box constraints on the decision variables)

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