An evolutionary algorithm for multi-objective optimization of combustion processes

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1. Motivation and objectives

We study the optimization of the spatial distribution of fuel injection rates in a gas turbine burner. An automated procedure is implemented for the optimization. The procedure entails an evolutionary optimization algorithm and an automated interface for the modification of the parameters in the experimental setup for the fuel injection and for the post-processing.

The evolutionary algorithm is capable of handling multiple objectives in a Pareto setup and of efficiently accounting for noise in the objective function. The parameterization considers eight analogue valves for controlling the fuel distribution, and the evaluation tool is an experimental test-rig for a gas turbine burner. A measurement chamber and a microphone are used to analyze the emissions and the pulsation of the burner, respectively. These two values are taken as objectives for the evolutionary algorithm. The algorithm is shown to converge to a Pareto front and the analysis of the resulting parameters elucidates further relevant physical processes.

2. Accomplishments

2.1. *Evolutionary algorithms*

Evolutionary Algorithms (EAs) such as Genetic Algorithms and Evolution Strategies are biologically-inspired optimization algorithms, imitating the process of natural evolution, and are becoming important optimization tools for several real-world applications. They use a set of solutions (population) to converge to the optimal design(s). The population-based search allows easy parallelization, and information can be accumulated so as to generate accelerated algorithms. EAs are robust optimization methods. They do not require gradients of the objective function, they can handle noisy objective functions, and they may avoid premature convergence to local minima.

2.1.1. *Multi-objective evolutionary algorithms for noisy objectives*

Real-world applications, like product-design optimization, often imply multiple objectives. For example, the cost and the quality of products are two conflicting objectives, usually tackled by interdisciplinary design teams. Hence no single best solution exists, but a set of compromise solutions. The complete set of compromise solutions is referred to as the nondominated or Pareto set of solutions. They represent the best solutions to

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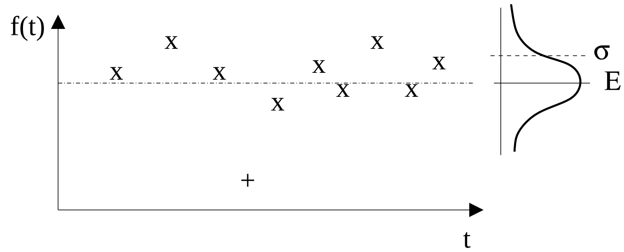

FIGURE 1. Illustration of noise and outliers in an experiment. For repeated measurements of the same operating point, the objective value f (marked by an $\times$) changes, governed by a normal distribution with mean E and standard deviation σ. An outlier solution is added to the figure and marked with a $+$.

the problem and are characterized by the definition that no other solution exists that is superior in all objectives.

The Strength Pareto Evolutionary Algorithm (SPEA) of Zitzler & Thiele (1999) is a well-established Pareto-optimization algorithm, which uses the dominance criterion for the fitness assignment and selection of solutions. Noise may change the dominance relation between different solutions. Dominated solutions may become nondominated and the selection may be missleaded. Noise is addressed in two recent publications of Teich (2001) and Hughes (2001), which adapt the Pareto ranking scheme of Goldberg (1989) by defining probabilities of dominance between noisy solutions. Both methods assume either a uniform or a normal distribution of the noise and can benefit from a priori knowledge of its magnitude.

In addition, a measurement may fail completely, producing outliers, i.e. arbitrary nonphysical results. This is illustrated in Fig. 1. SPEA is an elitistic algorithm, i.e. it keeps the best solutions found so far until superior successors are found. Elitism is critical for optimizing experimental setups. The optimization algorithm might get stuck in an outlier solution which dominates all present solutions. Thus we propose three modifications for an extended multi-objective algorithm to overcome the problem of noise and outliers:

(a) *domination dependent lifetime:* In contrast to elitism, which may preserve elitist (nondominated) solutions for an infinite time, a maximal lifetime κ is assigned to each individual. For evolution strategies, algorithms with implemented lifetime κ are referred to as (μ, κ, λ) algorithms (Bäck, Hoffmeister & Schwefel 1991). The novel approach is that the lifetime is variable and related to the dominance of a solution. The lifetime is shortened if the solution dominates a major part of the present nondominated solutions. This limits the impact of a solution.

(b) *re-evaluation of solutions:* In EAs, solutions with expired lifetime are usually deleted. In contrast, we re-evaluate all nondominated solutions whose lifetime has expired, and add them to the population. This enables good solutions to stay in the evolutionary process, but their objective values will change due to the noise in the re-evaluation.

(c) *extended update of the secondary population:* The SPEA algorithm updates the elitist solutions always with the current population. We propose to extend the update to *all* solutions with non-expired lifetime. This reduces loss of information.

2.1.2. *Performance comparison*

The performance of the *extended SPEA* is analyzed on a set of test functions. The extended algorithm is compared with the *standard SPEA* of Zitzler & Thiele (1999) and with a *non-elitistic SPEA*. The non-elitistic SPEA is obtained from the standard SPEA

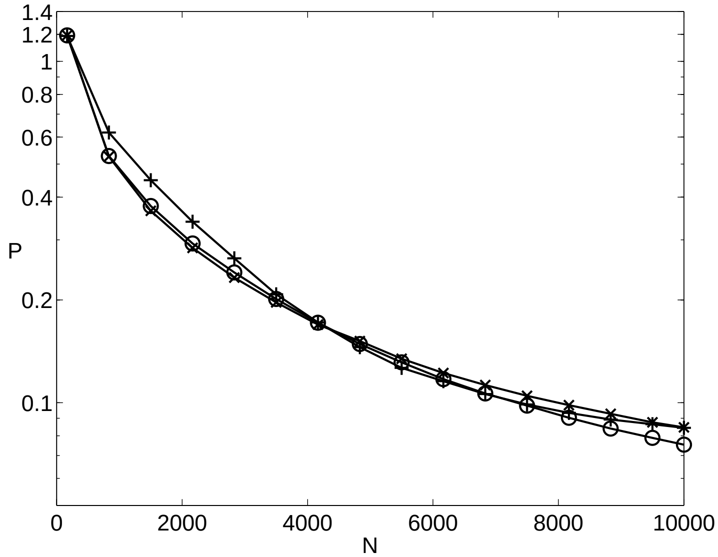

FIGURE 2. Convergence of the extended SPEA [circular symbol] on the noise-free test function 1, compared with the standard SPEA [cross symbol] and a non-elitistic SPEA [plus symbol]. The mean distance P of the present nondominated solutions to the analytical Pareto front is plotted over the number of function evaluations N.

by setting the lifetime of all individuals to one. Three test functions are considered. From Deb (1999), a two-objective minimization problem for an arbitrary number of real design variables $x_{i,\ i=1\ldots n}$ is chosen as the first test function:

$$f_1 = x_1$$
$$f_2 = \frac{1}{x_1}\left(1 + \sum_{i=2}^{n} x_i^2\right), \tag{2.1}$$

The number of design variables n is set to 7, and the design variables are bounded with $x_1 \in [0.5, 2]$ and $x_{i,\ i\neq 1} \in [-1, 1]$. The second test function is obtained by adding, to the first test function, normally distributed noise with zero mean and a standard deviation of 0.8. The third test function is identical to the first function except for generating outliers that replace the original solutions. With a probability of 1% per objective function, the objective value is divided by a factor of 10, hence producing an outlier with an improved value. The convergence of the extended, non-elitistic and standard SPEA algorithm is given for the three test functions in Figs. 2, 3 and 4. As a convergence measure, the mean distance P to of the present nondominated solutions to the analytical Pareto front is plotted over the number of function evaluations N. The comparison shows that the performance of the extended algorithm is equal to the standard algorithm if no noise occurs, but superior to the standard and non-elitistic algorithm if noise or outliers are involved.

2.2. *Atmospheric combustor test-rig*

Air entering a gas turbine flows through a compressor, then reacts with fuel in a combustion chamber, and is finally expanded in a turbine. The difference in power between the turbine output and the compressor input is the net power that can be used, say, to

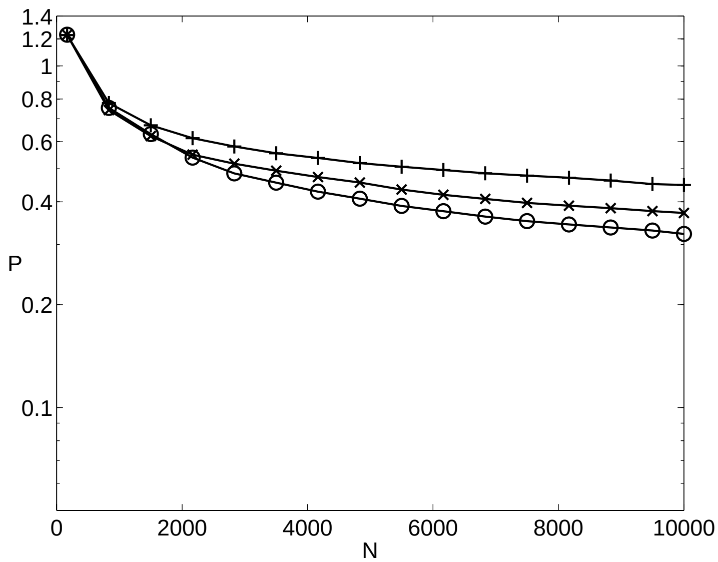

FIGURE 3. Convergence of the extended SPEA [circular symbol] on test function 2 with normal distributed noise, compared with the standard SPEA [cross symbol] and a non-elitist SPEA [plus symbol]. The mean distance P of the present nondominated solutions to the analytical Pareto front is plotted over the number of function evaluations N.

generate electricity. The combustion chambers of Alstom's larger gas turbines, e.g. GT24 and GT26, are annular around the turbine axis, with a set of burners aligned in the annulus. We consider the optimization of a single burner in an atmospheric test-rig as illustrated in Fig. 5. Preheated air enters through the plenum chamber and is mixed with fuel in the low-emission burner by swirl. The burner stabilizes the combustion flame in a predefined combustion area by a controlled vortex breakdown. The burned air leaves the test-rig through an exhaust. The burner exit temperature is about 1600 to $1700K$.
The fuel is natural gas or oil and enters though injection holes, which are uniformly distributed along the burner. The fuel mass flows through the injection holes are the design variables of the setup. The mass-flow distribution is controlled by 8 continuous valves. Each valve controls the mass flow through a set of adjacent injection holes along the burner axis. In order to keep the operating conditions constant, the total fuel mass flow is fixed, reducing the number of free design variables for the optimization from 8 to 7. The NO_x emissions and the pulsation of the burner are the two objectives to be minimized.

2.3. *Optimization results*

An optimization run is performed using the extended SPEA algorithm and evaluating a total of 326 different burner settings. All solutions are plotted in Fig. 6. The initial solution is marked in the figure, and represents a setting with equal mass flow through all valves. The solutions found by the optimization process dominate the initial solution, i.e. are superior in both objectives. The occurrence of a wide Pareto front underlines the conflict in minimizing both objectives and just (Pareto) compromise solutions can be found.
In the figure, boxes mark five different areas along the Pareto front. For the solutions within the boxes, the valve settings are printed in Fig. 7. For better illustration, the

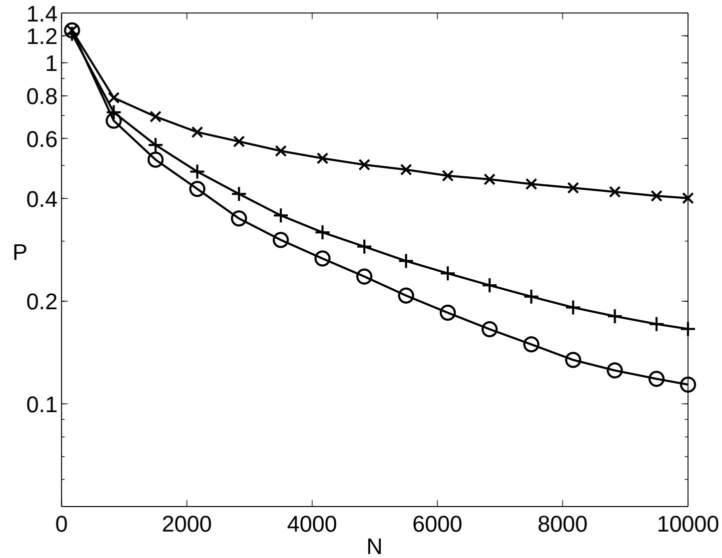

FIGURE 4. Convergence of the extended SPEA [circular symbol] on test function 3 with outliers, compared with the standard SPEA [cross symbol] and a non-elitistic SPEA [plus symbol]. The mean distance P of the present nondominated solutions to the analytical Pareto front is plotted over the number of function evaluations N.

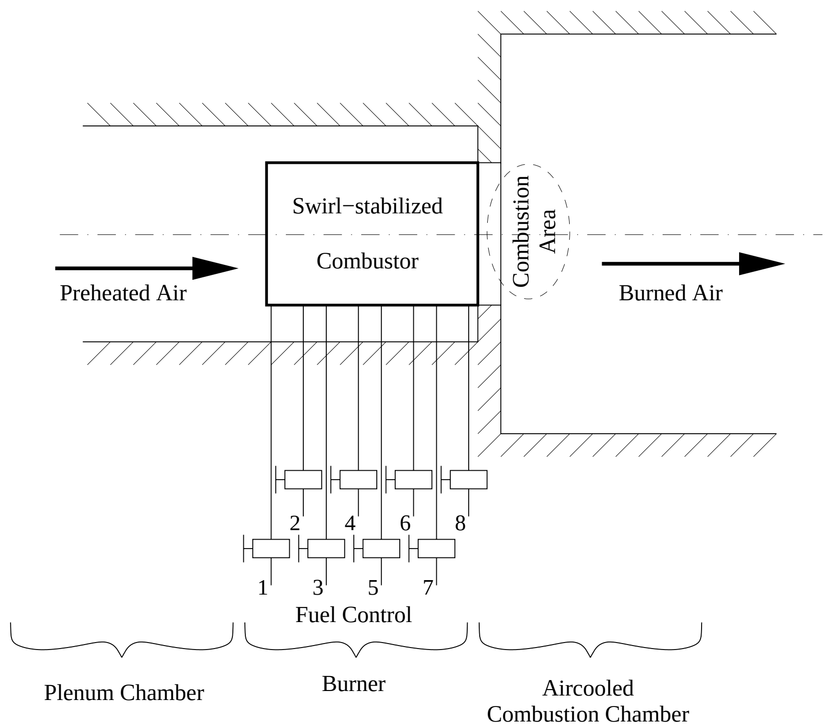

FIGURE 5. Sketch of the atmospheric combustion test rig with a low-emission swirl stabilized burner. The rates of fuel mass flow through the injection holes are the design variables of the setup. The NO_x emissions and the pulsation of the burner are the two objectives to be minimized.

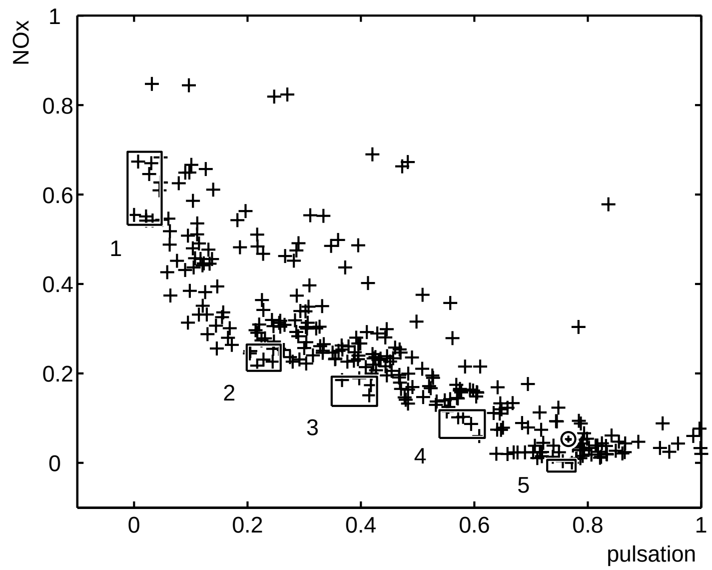

FIGURE 6. All measured solutions of the burner optimization run [plus symbol] and initial solution [circular symbol]. 5 boxes mark different areas along the Pareto front

settings are connected with a line.
Box 1 and 5 are at the extreme ends of the Pareto front. Box 1 represents Pareto solutions with high NO_x emissions, but low pulsation. The corresponding valve settings show an increased fuel mass flow at valves 1, 2 and 4, while the flow at valves 5 and 6 is reduced. (Refer to Fig. 5 for a sketch of the valve placement.) The basic physics behind these settings is that the increased mass flow through valves 1 and 2 leads to rich combustion in the center of the burner.

The rich combustion zone stabilizes the flame, but increases the NO_x emissions. The lean zones are in the middle of the burner, at valves 5 and 6.
Box 5 contains solutions with minimal NO_x emissions, but high pulsation. The mass flow through each valve is about the same, generating no rich combustion zones. Compared to the initial solution, the small mass flow increase at valves 5 and 8 leads to lower NO_x emissions, while the pulsation is unchanged.
This burner optimization follows a series of successful application of optimization tools in the field of turbomachinery design (Dornberger, Büche & Stoll 2000; Dornberger *et al.* 2000; Müller, Walther & Koumoutsakos 2001).

2.3.1. *Statistical analysis*

One of the interesting features of the resulting Pareto front is the almost linear change in valve settings along the front. At Box 1 five valves have either strongly increased or decreased mass flow and the amplitude is constantly decreasing from Box 1 to 5 until it reaches an almost equal mass flow for all valves in Box 5. This indicates simple dependencies of the valves on the objective functions. Fig. 8 contains a scatterplot for the valve settings and objective functions of all measured solutions. A scatterplot contains all possible 2D subspace plots for all design variables and objectives. The plot in column 9 and row 10 contains the objective space with the Pareto front. Most interesting are

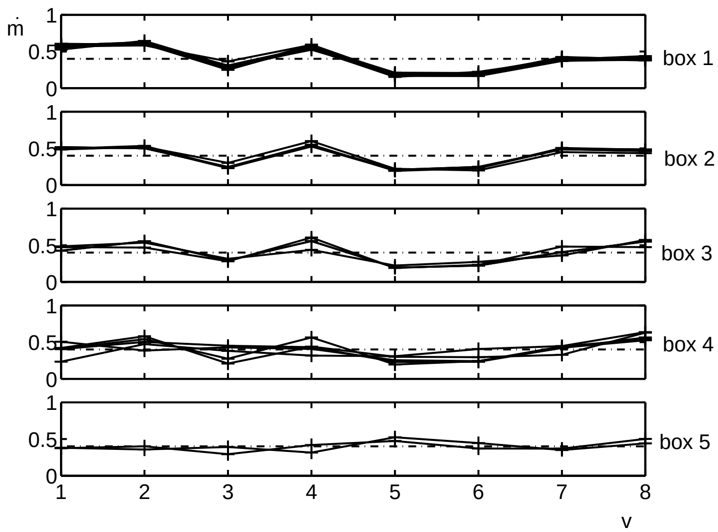

FIGURE 7. Mass flow $\dot{m}$ through the valves $V_{i,i=1...8}$ for solutions along the Pareto front, marked by 5 boxes of Fig. 6.

the last two rows, containing the correlation of the valves with the objective functions. For example, the horizontal and vertical axis of the plot in row 9, column 1 represent valve 1 and the NO_x emission, respectively. Strong correlation is expressed by narrow stripes at $\pm 45°$ to the axis. No correlation is implied by an axially symmetrical area of solutions. Strong correlation can be observed between valves 1, 2, 5, 6 and the two objective functions.

The correlation coefficients for the design variables and objectives are given in Fig. 9. They complement the results from the scatterplot. For all valves, the correlation coefficients have opposite signs for the two objectives. Therefore, changing the fuel injection in any of the valves always improves one objective while the other is worsened. Large coefficients indicate a strong correlation and occur between valves 1, 2, 5, 6 and the two objective functions. On increasing the mass flow through valve 1 and 2, the emissions increase while the pulsation decreases, and conversely for valves 5 and 6.

It has to be remembered that these observations hold for solutions obtained through an optimization process. The distribution of the solution in the scatterplot in Fig. 8 illustrates that they do not cover the whole design space. Hence, these solutions are not uniformly distributed in the design space and may not be representative.

2.3.2. *Noise analysis*

The extended SPEA algorithm that is used for burner optimization contains the special feature of re-evaluating solutions after their lifetime expires (Sec. 2.1.1). Among the 326 evaluated solutions, 40 were re-evaluated at least once by the optimizer. Comparing the difference in NO_x between a solution and the re-evaluated one, the maximal difference is about 8% of the objective range and the mean difference is 2%. For the pulsation, the maximal and mean differences are 13% and 4%, respectively. Thus the noise in the pulsation is more critical to the optimization. The large ratio of the maximal to the mean difference indicate the rare occurrence of outliers and the presence of noise in the objective measurement of all solutions.

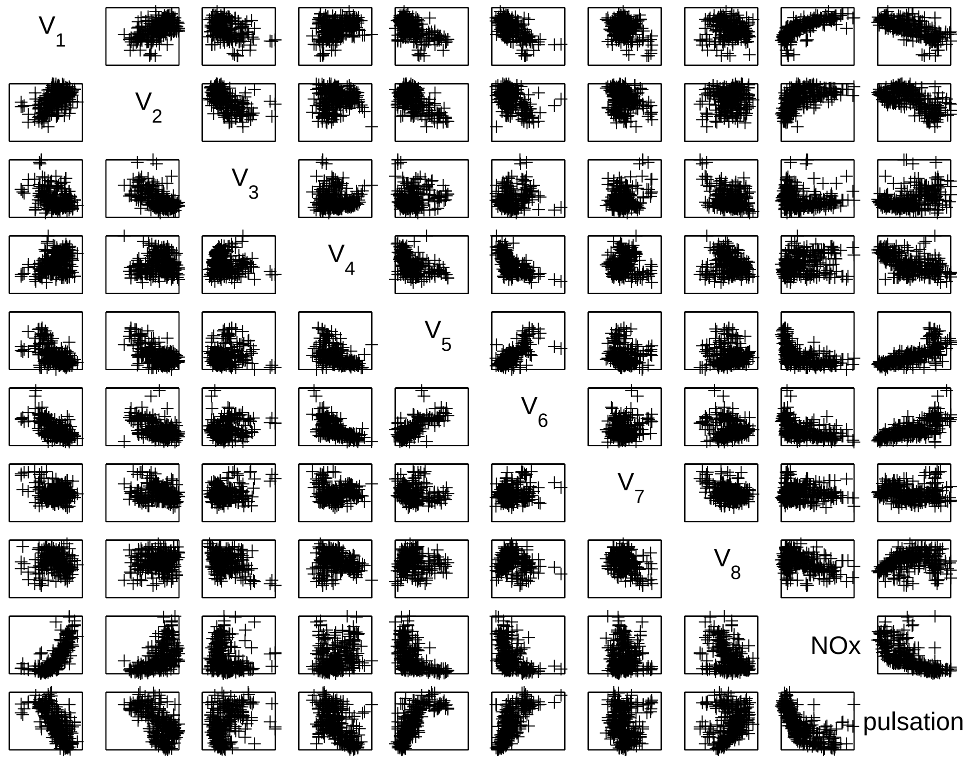

FIGURE 8. Scatterplot representing all possible combinations of 2D plots for the valves $V_{i,i=1\dots8}$ and the two objectives NO_x and pulsation.

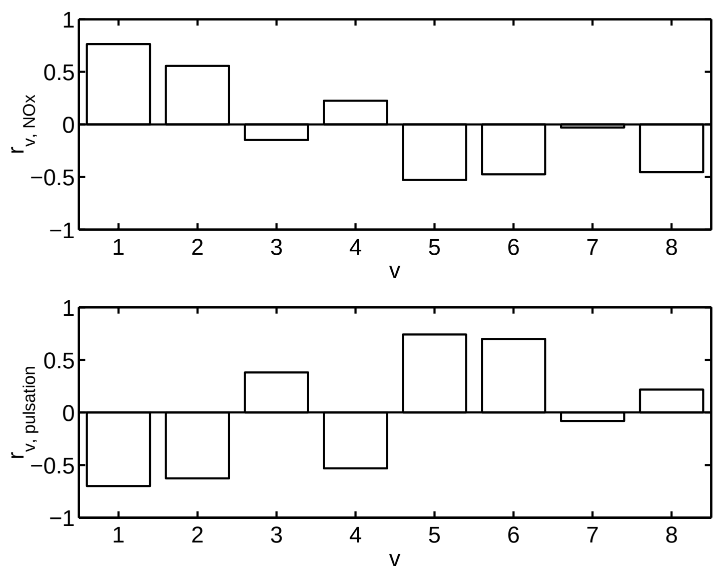

FIGURE 9. Correlation coefficient r between the mass flow through the 8 valves V and the two objectives NO_x and pulsation.

3. Conclusions

The present work demonstrates the capabilities of an automated optimization applied to the design process of gas turbine burners. The process, which includes an evolutionary algorithm, produces in an automated fashion an experimental Pareto front for minimizing pulsation and emissions of the burner. Automated optimization can be considered a supporting tool in a design process, complementing physical understanding as well as trial-and-error design. As a next step, the number of valves will be increased. This allows more flexibility in the fuel distribution and also allows non-axisymmetric distribution.

4. Acknowledgments

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