Evolutionary optimization for flow experiments

By Ivo F. Sbalzarini†, Lester K. Su and Petros Koumoutsakos†‡

1. Motivation and objective

Despite the ever increasing power of digital computers and numerical algorithms, experiments are still the ultimate test for physical reality. However, in a design cycle they are usually conducted in later stages in order to test the configurations that have been selected by theoretical or computational studies. The reasons are usually the expense associated with experiments as well as the lack of automation. For parameter optimization, the latter drawback can be alleviated by implementing evolution strategies for the optimization cycle.

Evolution Strategies (ES) were initially developed for experiments four decades ago (see e.g. Box (1957) or Schwefel (1977)). In the absence of computers, they were implemented by hand using paper, pencil, and the throwing of a dice to simulate random numbers. Early studies have shown that ES cover the whole search space, and that is what makes them better suited for experimental purposes than grid search methods (Box & Wilson (1951)). Today's ES are based on random mutations rather than the pattern based variations of their ancestors (Schwefel (1977), Rechenberg (1994)). This makes them more efficient, and they have proven to be a very powerful tool in computational optimum seeking. Moreover, they are highly portable since every optimization problem that can be formulated as a vector of parameters being sought in order to maximize (or minimize) one or several quantities (called *cost function* or *fitness function*) can be addressed by Evolution Strategies. Due to the fact that many experiments belong to this class of problems, it has been the objective of this work to implement and develop suitable evolutionary algorithms for the automation of optimization in experiments.

Inexpensive general purpose digital computers, hardware interfaces such as A/D converters, and suitable control software have made it possible for a computer to take the place of the experimenter for routine tasks and repeating measurement cycles. Evolution Strategies communicate the methodical selection of parameters to the control software of the experimental device using an interface and they could ultimately control the course of the experiment on a higher level, just as a human experimenter would do.

This paper is organized as follows: Section 2 of this paper gives a short introduction to Evolution Strategies in general as well as to the specific Evolution Strategy used for this work. Section 3 describes the basic set-up of an automatic experiment and gives detailed information about the communication interface that has been developed. Section 4 discusses some of the main problems and issues of using evolution to control optimization in experiments and introduces variance analysis. Section 5 shows how this methodology has been applied to the problem of finding optimal parameters to control high Reynolds number round air jets, and Section 6 presents results obtained from the experiments.

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2. Evolution strategies

The fundamental concept of ES is the imitation of the natural process of biological evolution. The problem to be solved is described using a certain number of *parameters* (design variables). One then creates a group of $\lambda(>0)$ different parameter vectors and considers it as a *population of individuals*. The quantity λ is called the *population size*. The quality of a certain vector of parameters (i.e. an *individual* in the population) is expressed in terms of a scalar valued *fitness function* (objective function). Depending on whether one wants to minimize or maximize the objective function, individuals (i.e. parameter vectors) with lower or greater fitness are considered better, respectively. The algorithm then proceeds to choose the $\mu, (\mu < \lambda)$ best individuals out of the population to become the parents of the next generation (natural *selection*, survival of the fittest). Therefore, μ denotes the *number of parents*. The smaller μ that is chosen compared to λ, the higher the *selection pressure* will be. Out of the μ individuals chosen to be parents for the next generation, one then creates a new population of λ offspring $\mathbf{x}_i^{g+1}$ by applying *mutation* (c.f. Fogel (1997)) on the parents $\mathbf{x}_j^g$ as follows:

$$\mathbf{x}_i^{g+1} = \mathbf{x}_j^g + \mathcal{N}(0, \Sigma) \quad , i = 1, \ldots, \lambda \quad , j \in \{1, \ldots, \mu\} \tag{2.1}$$

where $\mathcal{N}(0, \Sigma)$ denotes a vector of jointly distributed Gaussian random numbers with zero mean and covariance matrix Σ. The standard deviations (i.e. the square roots of the diagonal elements σ_i^2 of Σ) of the additive random numbers determine "how far away from its parent a child will be on the average" and are called *step sizes* of the mutation. Now, the first iteration is completed and the algorithm loops back to the evaluation of the fitness function for the new individuals. Several different techniques for adaptation and control of the mutation step size have been developed (see e.g. Bäck (1997a), Bäck (1997b), Bäck (1993), Hansen & Ostermeier (1996) or Hansen & Ostermeier (1997)).

2.1. *The (1+1)-ES*

For this work, one of the simplest and yet powerful evolution strategies has been employed: the "one plus one evolution strategy", denoted by (1+1)-ES. In this strategy, both the number of parents and the population size (i.e. number of offspring) are set to one: $\mu = \lambda = 1$. Mutation is accomplished by adding a vector of uncorrelated Gaussian random numbers, i.e. $\Sigma = diag(\sigma_i^2)$. Step size adaptation has been performed according to Rechenberg's 1/5-rule: if less than 20% of the past generations are successful (i.e. offspring better than parent), then decrease the step size for the next generation; if more than 20% are successful, then increase the step size in order to accelerate convergence. This adaptation is done every $N \cdot L_R$ generations where N is the number of parameters (i.e. dimension of search space) and L_R is a constant, usually equal to one. Selection is done out of the set union of parent and offspring, i.e. the better one of the two is chosen to become the parent of the next generation.

3. Subsystems of an automatic experiment

Our automated optimization experiment as driven by evolution consists of the following functional blocks: the experimental hardware set-up, hardware computer interfaces such as D/A and A/D converters, a general purpose digital computer, a data acquisition and control software, an evolution strategy code, and a communication interface between the ES code and the acquisition/control software. We will not discuss experimental hardware,

File	Format	Usage/Meaning
evo.in	NF16.9 \n F16.9	actual parameters, fitness value
evo.out	N[F16.9 \n]	parameter values to be tested
flag	I1.1	measurement status
Nstart	I3.3	index shift for restart
abort	I1.1	global execution control

Table 1. Interface ASCII files.

digital computers, or hardware interfaces in this paper, but will focus on the software needed.

3.1. *Data acquisition and control software*

This piece of software provides the only connection of the ES code to the real, physical world. It can be viewed as a replacement for the eyes and hands of the experimenter. For this work, National Instrument's LabView 5.1† running on a Microsoft Windows 98 PC has been used. It was set up to control the whole experiment in its sequential course and collect all the measurement data needed.

3.2. *Evolution Strategy code*

The evolution algorithm may be viewed as a simple replacement for the strategy of the experimenter. It looks at measurement readings and decides where to go next in order to eventually achieve the optimum it is looking for. For this work, a restartable (1+1)-ES has been implemented in Fortran with a communication subroutine connecting it to LabView.

3.3. *Communication interface*

The evolution code and LabView are assumed to be running on the same computer in a multitasking mode that allows them to be executed concurrently. To ensure portability across computing platforms, a simple file interface has been chosen to handle all communication. Both LabView and the ES code write and read shared files to exchange information or monitor flag files for the sake of synchronization. The interface consists of the files shown in table 1. The format column indicates the numeric format of each ASCII file in Fortran notation where N is the number of parameters, \n means a newline character, and N[F16.9 \n] indicates N numbers separated by newline characters.

The control flow proceeds as follows:

1. ES code starts, initializes its parameters or reads a restart file, writes a zero in the files "flag" and "abort", writes the current generation number to "Nstart", and creates the first (or next if a restart) parameter vector to be tested.

2. LabView starts, initializes and reads "Nstart" to determine the current generation number. For all output of LabView, Nstart will be added to the value of its loop counter to get the correct generation number.

3. LabView monitors the file "flag" every t seconds. It sits idle as long as the file contains a zero.

† http://www.ni.com/labview/

4. ES deletes the old “evo.in” file.
5. ES writes the current parameter vector to be evaluated in “evo.out”.
6. ES writes a one in “flag” to tell LabView to start.
7. ES test for the existence of “evo.in” in fixed time intervals.
8. LabView starts the experiment using actual values as close to the parameter values as possible (i.e. next discrete digital level).
9. When the measurement is completed, LabView calculates the fitness value and writes the actual parameters as well as the fitness value to “evo.in”. It also checks the file “abort” and terminates if it contains a nonzero value. Otherwise, LabView loops back to step 3.
10. ES detects existence of “evo.in”.
11. ES writes a zero in “flag” to set LabView on hold.
12. ES starts reading “evo.in”. If an error occurs because LabView has not yet finished writing the file, the ES code will step back and try again later. It reads the actual parameters (overwriting its internal representation of the parameter vector) and the fitness value for this population member.
13. ES checks “abort” file. If it contains a nonzero value, execution is terminated. If the next generation is the last one, ES writes a one in “abort” to halt LabView and itself after the next evaluation.
14. ES writes the current information to a restart file, performs selection based on the latest fitness values, and creates a new population before looping back to step 4.

Since LabView will not overwrite any files without prompting the user for permission, the ES code has to make sure that all files are deleted before LabView overwrites them. Otherwise, LabView will display a message box and wait for user action, which is in contradiction to the goal of having automated experiments. A second point to consider is that LabView is very strict regarding file formats and separator characters. That is why all file I/O in Fortran has to be done using explicit, fixed format specifiers instead of list directed output. The same format specifiers have to be used in LabView. Moreover, numbers that are passed to LabView need to be separated by a well defined delimiting character. This ultimately means that they need to be on separate lines using the newline character as a delimiter because Fortran will pad and number to the right length using spaces. If the numbers were on the same line, there would be an unknown amount of spaces between each of them and, therefore, no well defined delimiter, since LabView is sensitive to the number of spaces.

4. Main problems and issues

Applying evolution to experiments means coping with additional effects that are usually not present in computation. They can roughly be divided into effects caused by measurement uncertainties (or errors), digital signal quantification, and uncontrollable environmental influences. The following subsections discuss each of these causes in turn and proposes some solutions.

4.1. *Measurement uncertainties*

During selection, the ES code determines the population member with the highest (or lowest) fitness value, and it assumes that the differences in fitness between different individuals are entirely caused by the differences in their parameters, i.e. a better fitness value corresponds to better parameters. However, if the fitness is determined in measurements and the difference between two fitness values is less or equal to the measurement uncertainty, it could possibly be that the "better" individual only has a better fitness value due to measurement errors and not due to its parameter set, which could actually be worse than others. This can mislead the ES since it relies on information that is no more than an artifact of the experimental procedure. To avoid this problem, mutation step sizes must always be larger then any uncertainty in order to get changes in the objective function that are larger then the general measurement noise. This poses a lower limit to the convergence of the Evolution Strategy and an additional constraint to the method of step size adaptation to ensure that step sizes are always significant. ES using recombination (Booker, Fogel, Whitley & Angeline (1997)) are more robust against distorted selection and should, therefore, be favored for experimental purposes. Other strategies to cope with this problem could include a cutoff coefficient, which forces the ES to select variances larger than this cutoff. If the distance between two individuals in objective space is less than the cutoff value, the ES should not take the "better" of them as a parent for the next generation but rather the mean of them.

4.2. *Digital quantification*

Digital hardware is capable of producing or measuring signals only in discrete steps. For certain hardware such as on-board waveform generators, these steps can be as large as 0.5%, depending on the buffer size of the device. For a wave form generator, this could mean that frequencies around 1000Hz can only be varied in steps of 5Hz. This means that parameter vectors differing less than one such discrete step will cause the same physical output to be produced and are, therefore, actually identical. Besides adding another lower limit for the mutation step size of the ES, this quantification also calls for some feedback mechanism to "tell" the ES what values have actually been produced instead of the parameter vector it requested. The ES should then take these physical values to replace its internal representation of the parameter vector in order to be consistent with the fitness value that has been caused by the physical values. This calls for a certain robustness of the ES against unpredictable changes in the parameter vectors. Problems can occur in ES that have some sort of "memory" to keep track of the evolution path in order to improve their convergence (e.g. the CMA-ES by Hansen & Ostermeier (1996)).

4.3. *Uncontrollable environmental factors*

Every experiment is affected by various uncontrollable external factors, such as ambient temperature or pressure, electro-magnetic fields, sunlight, etc. Since these factors can not be controlled by the ES, one has to make sure that they do not affect the fitness function. In other words, the same parameter vector should (within experimental accuracy) always produce the same fitness value regardless of changes in any environmental quantity. The easiest way to achieve this is to determine the most important environmental factors (impact analysis) and normalize the fitness function accordingly.

5. Application to jet control

We consider the application of an evolutionary optimization procedure to the problem of control of high Reynolds number jet flows. These flows have been the subject of several experimental works, and they have been chosen because it is a quite well known, old (Leconte (1958)) issue where lots of reference works in conventional experiments (e.g. Lepicovski, Ahuja & Salikuddin (1984), Lepicovski & Ahuja (1985), Lee & Reynolds (1985), Parekh, Reynolds & Mungal (1987), Lepicovski, Ahuja, Brown, Salikuddin & Morris (1988), Parekh, Leonard & Reynolds (1988) and Juvet & Reynolds (1993)) as well as computational studies (e.g. Urbin, Brun & Metais (1997) and Freund & Moin (1998)) have been done. Evolution Strategies have been successfully applied to numerical simulations at lower Reynolds numbers (Koumoutsakos, Freund & Parekh (1998), Müller, Milano & Koumoutsakos (1999) and Koumoutsakos, Freund & Parekh (2001)), involving methods with step size adaptation developed by Hansen & Ostermeier (1997).

5.1. *Basic experimental set-up*

The experimental set-up consists of a vertical jet of warm (about 35°C) air exiting from a straight nozzle (inner diameter $D = 20mm$). The surrounding air was air-conditioned to about 20°C. Temperature profiles were measured on a straight path from the center of the jet outward using a type K thermocouple connected to a Fluke thermocouple adaptor. The thermocouple was moved across the jet $d = 122.2$mm ($d/D = 6.11$) above the nozzle exit. The jet was acoustically excited using 5 loudspeakers. 4 of them were used to create a helical excitation of certain frequency, amplitude, and phase, and one was used to create an axial excitation. Detailed descriptions of the set-up and the hardware can be found in Parekh, Reynolds & Mungal (1987), Parekh, Leonard & Reynolds (1988) and Juvet & Reynolds (1993). The inputs of the amplifiers driving the speakers were connected to the outputs of D/A converters (National Instruments BNC-2090 DAQ board for the two helical channels and Data Translation 2D16A board for the axial channel), which in turn were connected to a computer. The temperature sensor was mounted on an arm and moved across the jet by a step motor controlled by the computer. Temperature readings at each point were digitized using the National Instruments BNC-2090 DAC and fed to the computer. Temperatures were measured at certain distances from the center of the jet, collecting 3000 samples per point at a sampling rate of 500Hz.

5.2. *Excitation*

The jet was acoustically excited using two different modes: helical and axial. The helical excitation was done by four speakers, regularly arranged around the centerline of the jet at angles of 90°. Their sound was fed into the jet right before the exit nozzle using wave guides. The excitation signal was sinusoidal, and the phase corresponded to the geometrical set-up, i.e. one speaker was fed a sine wave, the one to its right a cosine wave, the one opposite of it a negative sine wave, and the one to its left a negative cosine wave. Therefore, the phase between adjacent speakers was 90° in normal operation mode. However, this phase could be shifted by adding some value. Opposite speakers were always 180° out of phase regardless of the phase shift between adjacent ones. The two pairs of opposite speakers (i.e. the ones fed with a sine wave and the ones fed with a cosine wave) were connected to two different channels of the same power amplifier (Kenwood Stereo Power Amplifier Basic M2A). Phase reversal for opposite speakers was done by simply changing the polarity of the wires. The amplifier was adjusted to a gain of 60, which corresponds to a maximal output amplitude of $16V_{RMS}$.

The axial excitation was done by a single loudspeaker sitting in the bottom of the jet column. It was connected to the output of a second power amplifier (Kenwood Stereo Power Amplifier Basic M1 and Kenwood C1 preamplifier) and fed with a simple sine wave of specific frequency. The amplifier was adjusted to a gain of 30, which also corresponds to a maximal output amplitude of $16V_{RMS}$.

All 5 speakers were 120 Watt compression drivers of type JBL 2485J. Their frequency range is 300Hz to 3000Hz, and they are designed to be used in large systems such as those found in stadiums. The amplitudes and frequencies for both modes as well as the phase shift of the helical excitation were controlled by the computer.

5.3. *Parameters*

The parameters to be optimized were:

- frequency of helical excitation (f_h) in Hertz
- frequency of axial excitation (f_a) in Hertz
- amplitude of helical excitation (A_h) in Volts
- amplitude of axial excitation (A_a) in Volts
- phase shift of helical excitation (φ) in radians

The parameters were subject to the following constraints defining the boundaries of the search space: both frequencies have to be between 300Hz and 3000Hz (band limit of the speakers), both amplitudes have to be between $0V_{RMS}$ and $16V_{RMS}$ (amplifier power limitation), and the phase shift is between 0 and π (periodicity).

5.4. *Fitness function*

Since the goal was to maximize the spreading of the jet, the fitness function was chosen to be proportional to the discrete variance of the normalized temperature profile, normalized to the number of measurement points, i.e.:

$$F = \frac{100}{N} \sum_{i=1}^{N} \left(\frac{T_i}{T_{max}} - \mu_T \right)^2 \tag{5.1}$$

where T_i is the physical temperature at the i-th measurement point, N is the number of measurement points per profile, T_{max} is the peak value of the profile:

$$T_{max} = \max_i T_i \tag{5.2}$$

and μ_T is the mean of the normalized temperature profile:

$$\mu_T = \frac{1}{N} \sum_{i=1}^{N} \frac{T_i}{T_{max}} \tag{5.3}$$

5.5. *Variance analysis*

As mentioned in Section 4.1, the changes in fitness due to parameter changes have to be significantly larger than the ones due to measurement noise. To see whether a certain experiment can be treated by evolution using a given fitness function, a small variance analysis should be performed. One simply measures the fitness values at certain fixed points in parameter space several times to get an estimate of mean and variance at these points. If the error bars for two parameter sets do not overlap, evolution strategies will be able to distinguish between them and use this information to converge towards the better point. Variance analysis for the jet has been done for the parameter sets listed in table 2. For all sets, the phase of the helical excitation has been fixed at 0 and the amplitudes have been fixed to their maximal values of $16V_{RMS}$. 5 temperature profiles have been taken for each set under varying environmental conditions (i.e. ambient temperature and jet temperature) on different days, and the fitness values for all profiles have been calculated according to Section 5.4. Each profile consisted of 8 measurement points at $0, 5, 10, 15, 20, 30, 40$, and 50mm distance from the center of the jet. All runs were performed at $Re_D = 10^5$, which corresponds to an exit velocity of about $77\frac{m}{s}$. The "strong blooming condition" was found by Juvet & Reynolds (1993) as a condition

Set nr.	Meaning of point	Helical [Hz]	Axial [Hz]
1	Natural jet, no excitation	0	0
2	Lower boundary of search domain	300	300
3	"Strong blooming condition"	896	2060
4	Random starting point for ES	1000	1800
5	Best point of ES run 1	777	1773
6	Upper boundary of search domain	3000	3000

TABLE 2. Parameter sets for variance analysis.

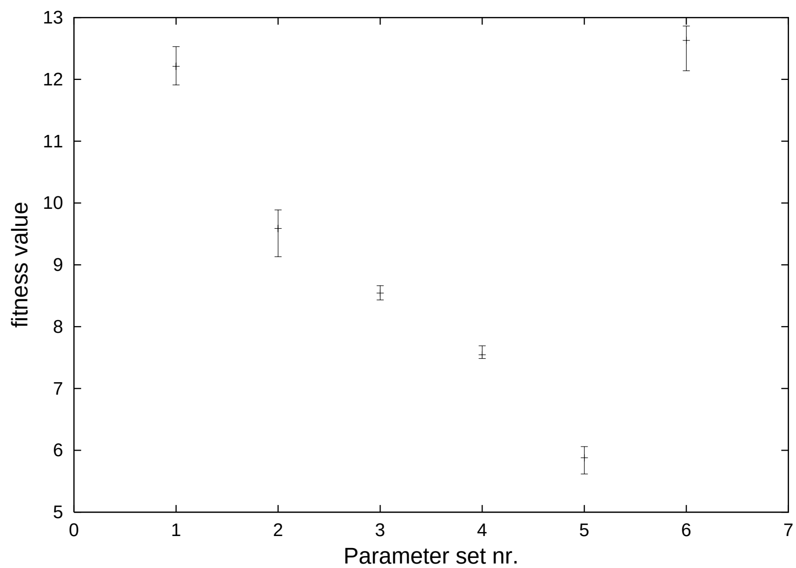

FIGURE 1. Variance analysis for the jet. See table 2 for parameter values.

which gives very high spreading. The best point of the ES run was taken from the (1+1) optimization of both frequencies (see Section 6.1).

The bar plot in Fig. 1 shows mean and span for all measurements of each parameter set. It can be seen that the bars generally do not overlap except for the natural jet and the upper domain boundary. Moreover, the variation due to measurement uncertainties seems to be small enough to allow evolution with an accuracy of at least one unit in fitness value. This implies that if the difference in fitness of two parameter vectors is more than one, it can be considered a significant difference, and one parameter set is clearly better then the other. It can also be seen that there must exist a (at least local) minimum in the search space chosen since there are points between the domain boundaries that have lower fitness values than the boundaries themselves.

6. Results for the jet

Several runs under different conditions were performed for the jet. The amplitudes have been fixed to their maximal value for all runs since higher amplitudes always cause higher spreading and, therefore, they should simply be as high as possible (Müller, Milano & Koumoutsakos (1999)). In the first run presented here, both frequencies have been varied independently; the phase shift was fixed at 0 and the evolution started from a random point. In the second run, the frequency ratio has been optimized starting from the "strong blooming condition" found by Juvet & Reynolds (1993). Finally, in the third run, both frequencies and the phase have been varied independently, starting from the same point as the first run. The results are presented in the following subsections.

6.1. *Run 1: Two frequencies at* $Re = 102000$

Both frequencies were optimized using a (1+1)-ES as described in Section 2.1, while the amplitudes were fixed at their maximum of $A_a = 16V_{RMS}$ and $A_h = 16V_{RMS}$. The phase shift has been fixed at 0, which means that adjacent speakers were 90° out of phase (c.f. Section 5.2). The initial step sizes for the ES were 50Hz for both frequencies, and step size adaptation was done every 20 generations. The temperature was measured at 8 points at distances of $0, 5, 10, 15, 20, 30, 40$, and 50mm from the center of the jet (i.e. at $l/D = 0, 0.25, 0.5, 0.75, 1, 1.5, 2, 2.5$). We collected 3000 samples at each point at a sampling rate of 500Hz, which corresponds to a sampling time of 6 seconds. Statistical analysis showed that this sampling time is sufficient to get a stable mean within 1%. The stagnation pressure in the jet right before the exit was fixed at 15 inches of water over ambient pressure, which translates into an exit velocity of about $78\frac{m}{s}$ (by isentropic calculation). The Reynolds number based on the inner diameter of the exit nozzle was $Re_D = 102000$ for this run. The starting values for the parameters were: helical frequency $f_h = 1000$Hz and axial frequency $f_a = 1800$Hz, which corresponds to Strouhal numbers (based on the inner diameter of the exit nozzle) of $St_h = 0.26$ and $St_a = 0.46$, respectively. The initial fitness value at this point was 6.8. The ambient temperature was between 21°C and 22°C during the whole period of measurement, and the temperature of the jet was between 35°C and 38°C at the exit nozzle. The ES was run for 100 generations.

Figure 2 shows the fitness values of all the individuals that have been created by the ES. The best parameter vector has been found at generation 48 as $f_h = 777$Hz ($St_h = 0.20$), $f_a = 1773$Hz ($St_a = 0.45$) and had a fitness value of 3.4, which is half of the fitness value at the starting point. Since the change in fitness was clearly larger than one, it can be considered a *significant* (c.f. Section 5.5) improvement. Figure 3 shows the temperature profiles (normalized to the peak temperature) for initial and best parameters as well as for the natural jet without any excitation. The profiles got clearly flatter, which implies a higher spreading of the jet. The results found by the ES are supported by computational results of Freund & Moin (1998) that strong flapping of the jet appears for $St_h = 0.2$. The same has been observed in experiments by Parekh, Kibens, Glezer, Wiltse & Smith (1996). Moreover, a large amplification of signals was observed by Parekh, Kibens, Glezer, Wiltse & Smith (1996) and Parekh, Leonard & Reynolds (1988) for $St_a \approx 0.4$. The same Strouhal numbers have also been found in the first attempt to find optimal actuation parameters for compressible jets with numerical simulations and ES by Koumoutsakos, Freund & Parekh (1998). This suggests that ES work well on experiments and that they have found reasonable parameters in this case.

6.2. *Run 2: Frequency ratio at* $Re = 95000$

In this run, the frequency ration was optimized while the frequency of the axial excitation has been fixed at 2060Hz ($St_a = 0.56$). Both amplitudes were fixed at their maximal values of $16V_{RMS}$ each. and the phase shift was again fixed at 0. The helical frequency was varied by the (1+1)-ES starting from 896Hz ($St_h = 0.24$) with an initial step size of

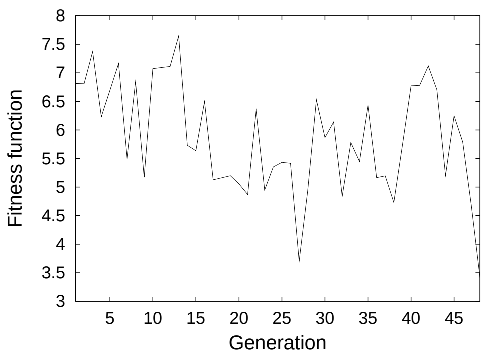

FIGURE 2. Path of (1+1)-ES

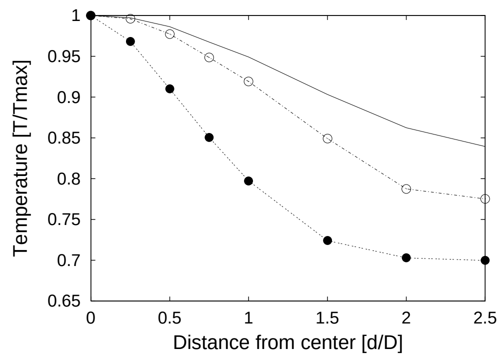

FIGURE 3. Normalized temperature profiles of natural jet (—•—), initial condition for ES (—∘ —) and best result of ES (———).

50Hz. Step size adaptation was performed every 10 generations. The temperature profiles were measured in exactly the same way and at exactly the same positions as in the first run. The stagnation pressure in the jet right before the exit was fixed at 13.2 inches of water over ambient pressure, which corresponds to an exit velocity of about $73.6\frac{m}{s}$ (isentropic calculation) and a Reynolds number of $Re = 95000$. The starting values for this run correspond to a frequency ratio of 2.3, which is clearly within the range for blooming (Lee & Reynolds (1985)). They are identical to the parameters of the "strong blooming condition" that have been found by Juvet & Reynolds (1993) as a condition of very high spreading. They also fixed the axial frequency to 2060Hz and run at the same Reynolds number. The only differences between their measurements and the present work are that they used a shrouded jet (which should not have any influence on the position of the optimum, however) and hot-wire velocity measurements instead of temperature measurements. The initial fitness value for the strong blooming point was found to be 8.3. The ambient temperature fluctuated between 21°C and 25°C; the temperature of the jet was between 35°C and 38°C at the exit nozzle. The ES was run for 100 generations.

Figure 4 shows the fitness values of all the individuals that have been created by the ES. The best parameter vector has been found at generation 25 as $f_h = 791Hz$ $(St_h = 0.21)$, which corresponds to a frequency ratio of 2.6 and a fitness value of 4.5. Compared to the initial fitness value of 8.3, this is again a significant improvement. Figure 5 shows the temperature profiles (normalized to the peak temperature) for initial (strong blooming) and best parameters as well as for the natural jet without any excitation. Even compared to the "strong blooming condition", the evolution has achieved a significant improvement.

6.3. *Run 3: Two frequencies and phase at* $Re = 102000$

In a third run, both frequencies plus the phase shift between adjacent speakers of the helical excitation have been varied independently. Again, the amplitudes were fixed at their maximal value of $16V_{RMS}$ each. Frequencies and phase were varied by the (1+1)-ES starting at the same point as in the first run, i.e. $f_h = 1000$Hz $(St_h = 0.26)$, $f_a = 1800$Hz $(St_a = 0.46)$, and $\varphi = 0$, with an initial step size of 50Hz for both frequencies and 0.1rad for the phase shift. Step size adaptation was done every 30 generations. The temperature profiles were measured in exactly the same way and at exactly the same positions as in the previous two runs. The jet exit velocity was the same as in run 1, i.e. this run was done at $Re = 102000$ as well. The initial fitness value was 6.9, which is (within

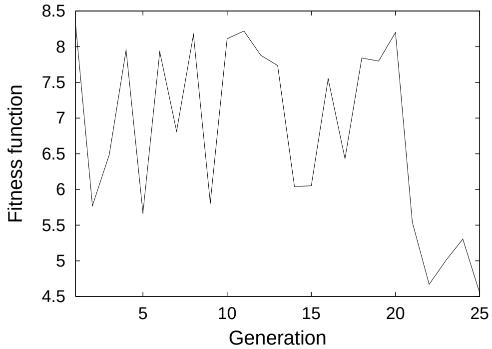

FIGURE 4. Path of (1+1)-ES

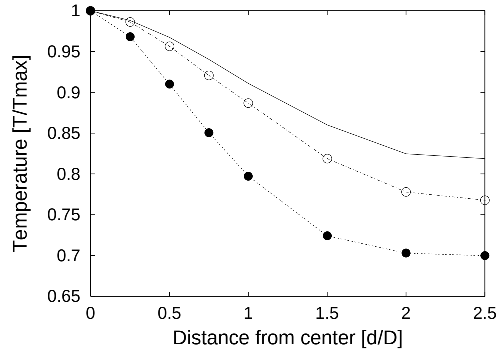

FIGURE 5. Normalized temperature profiles of natural jet (—●—), strong blooming condition (—○—) and best result of ES (——).

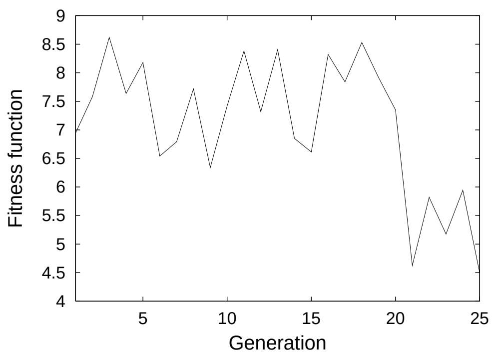

FIGURE 6. Path of (1+1)-ES

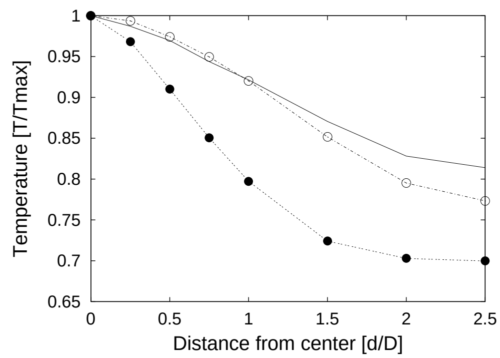

FIGURE 7. Normalized temperature profiles of natural jet (—●—), initial condition for ES (—○—) and best result of ES (——).

given experimental accuracy) the same as in run 1. The ambient temperature fluctuated between 21°C and 23°C; the temperature of the jet was between 35°C and 38°C at the exit nozzle. The ES was run for 100 generations.

Figure 6 shows the fitness values of all the individuals that have been created by the ES. The best parameter vector has been found at generation 25 as $f_h = 952$Hz ($St_h = 0.24$), $f_a = 1645$Hz ($St_a = 0.42$), $\varphi = -0.488$rad (28°), which corresponds to a fitness value of 4.5. Figure 7 shows the temperature profiles (normalized to the peak temperature) for initial and best parameters as well as for the natural jet without any excitation.

7. Conclusions and future work

We have shown that Evolution Strategies can successfully be applied to the optimization of control parameters in experimental set-ups. The results found by these strategies demonstrate that they can successfully complement human expertise. Some key issues of the implementation of evolution algorithms in an experimental set-up have been identified and addressed. However, further work is needed in this area in order to improve certain properties of ES for experiments. Such work should include the application of different ES in order to compare their performance. Above all, ES with recombination, time averaging, or self-adaptation of step sizes should be tested for better robustness against measurement errors and parameter changes. As far as the jet experiment is concerned, different fitness functions and their influence on the optimum found should be investigated. Runs at different Reynolds numbers and with different numbers of measurement points per profile should be performed in order to test whether the fitness function and the location of the optimum are independent of them or not. In summary, we believe that, with today's hardware and software technologies, evolutionary algorithms offer a strong candidate for the automation of optimization and design cycles in realistic set-ups.

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