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COMBUSTION PROCESS OPTIMIZATION USING EVOLUTIONARY ALGORITHM

Christian Oliver Paschereit[*], Bruno Schuermans, Dirk Büche[†]
ALSTOM (Switzerland) Ltd.
CH-5405 Baden
Switzerland

ABSTRACT

Flame stabilization in a swirl-stabilized combustor occurs in an aerodynamically generated recirculation region which is a result of vortex breakdown. The characteristics of the recirculating flow are dependent on the swirl number and on axial pressure gradients. Coupling to downstream pressure pulsations is also possible. Flame stability and emission formation depend on flow and mixing properties.

The mixing properties of the investigated burner can be influenced by the position and the amount of fuel injection into the burner. The fuel injection is controlled by two different setups using (a) 8 proportional valves to adjust the mass flow for each fuel injector individually or using (b) 16 digital valves to include or exclude fuel injectors along the distribution holes.

The objectives are the minimization of NO_x emissions and the reduction of pressure pulsations of the flame. These two objectives are conflicting, affecting the environment and the lifetime of the combustion chamber, respectively. A multi-objective evolutionary algorithm is applied to optimize the combustion process. Each optimization run results in an approximation of the Pareto front by a set of solutions of equal quality, each representing a different compromise between the conflicting objectives. One compromise solution is selected with NO_x emissions reduced by 30%, while mainaining the pulsation level of the given standard burner design.

Chemiluminescence pictures of this solution showed that a more uniform distribution of heat release in the recirculation zone was achieved. The results were confirmed in high pressure single burner tests. The suggested fuel injection pattern has been successfully implemented in engines with sufficient stability margins and good operational flexibility.

This paper shows the careful development process from lab scale tests to full scale pressurized tests.

1 INTRODUCTION

Modern design of low emission combustors is characterized by swirling air in the combustor's dome coupled with distributed fuel injection to maximize mixing. This design results in efficient combustion with extremely low emissions. The fuel distribution and mixing with the air stream play a critical role in the combustion process and in the performance of the system. Various flow dynamics processes control the mixing between fuel and air in diffusion flame configurations and the mixing between the fresh fuel/air mixture and hot combustion products and fresh air in premixed combustors. They include large-scale vortices that evolve in a separating shear layer downstream of a sudden expansion or bluff body flame holders, and swirling vortices that undergo vortex breakdown in swirl-stabilized combustors. Interaction between these vortices which are related to flow instabilities, acoustic resonant modes in the combustion chamber and the heat release process was shown to cause undesired thermoacoustic instabilities in combustors (Paschereit et. al, 1999).

The ALSTOM EV burner has the unique property of flame stabilization in free space near the burner outlet uti-

[*]Address all correspondence to this author (email: oliver.paschereit@power.alstom.com.)
[†]Also at: Institute of Computational Science, Swiss Federal Institute of Technology (ETH), CH-8001 Zürich, Switzerland

lizing the sudden breakdown of a swirling flow, called vortex breakdown. The swirler is of exceptionally simple design, consisting of two halves of a cone, which are shifted to form two air slots of constant width (Doebbeling et. al. 1999). Gaseous fuels are injected into the combustion air by means of fuel distribution tubes comprising two rows of small holes perpendicular to the inlet ports of the swirler. Complete mixing of fuel and air is obtained shortly after injection. During startup the EV burner is piloted by fuel supplied to a central fuel nozzle in the tip of the cone through a lance leading to a diffusion type flame.

The characteristics of combustion stabilization by vortex breakdown are controlled by the flow dynamics associated with this particular flow phenomenon. Vortex breakdown is defined as a flow instability that is characterized by the formation of an internal stagnation point on the vortex axis, followed by reversed flow (Leibovich, 1978). Upstream of the vortex breakdown location, the velocity profile is strongly jet-like with a peak velocity almost three times greater than the freestream velocity. Very close downstream of breakdown the flow in the core may completely stagnate and then transition to a wave-like flow. Downstream of breakdown turbulence increases, axial velocities are substantially lower and reverse flow is possible (Leibovich, 1978). Furthermore, the location of vortex breakdown is known to fluctuate in the flow direction (Gursul and Xie, 1998).

Two major factors play a role in the vortex breakdown phenomenon, the swirl ratio and the presence of an adverse pressure gradient (Leibovich, 1978; Dixon, 1978; Rusak and Lamb,1998). The sensitivity of vortex breakdown to pressure gradients can cause coupling between pressure perturbations in the combustion chamber and the heat release from the flame which is anchored at the recirculating region produced by the breakdown, thus forming a feedback loop that may lead to combustion instability and change in pollutants formation (Paschereit et al. 1998).

Beside the flow properties stability of the flame with respect to pulsations can be influenced by the fuel / air mixing profile (Paschereit et al. 1999). The optimum mixing is generally determined by the use of CFD and cold flow mixing experiments. Uniform mixing leading to low NO_x emissions is then verified in atmospheric and elevated combustion tests before prototype testing in the engine.

Automated optimization is an important aspect for reducing the development time. Technical product design optimization involves at least two aspects. First, the product design has to be described by a set of variables and second, evaluation tools are required for evaluation of the design properties. Finding a set of design variables, which fulfill various design specifications (objectives) is usually an iterative trial-and-error process. This process can either be performed by human designers or by automated optimization. Designers iterate, while trying to exploit their accumulated knowledge of the product in order to reduce the number of iterations to the maximal extent. In automated optimization, an optimization algorithm proposes new designs, which are automatically evaluated. Depending on the resulting objective values, the optimization algorithms proposes new designs until a certain termination criterion is fulfilled.

The main advantage of automated optimization is that the designer is unburden from the trial-and-error process by use of an optimization algorithm, requiring no human interaction. The designer can focus on the formulation of the design objectives and the analysis (post-processing) of the automated optimization result. In addition, automated optimization may lead to unexpected designs and thus to new design philosophies. Furthermore, automated optimization can be run 24h a day ass well as during weekends.

Applications often entail multiple objectives, which are conflicting. A solution to such an application is always a compromise between the different objectives. The set of best solutions is referred to the Pareto set of solutions (Pareto 1906). Starting from a Pareto solution, one objective can only be improved at the expense of at least one other objective. Traditional methods for handling multiple objectives consider the aggregation of all objectives in a single figure of merit. This can be performed by a weighted-sum of the objectives. The result of such an optimization run is always a single compromise solution and thus several optimization runs have to be performed, in order to obtain an approximation of the Pareto front.

Evolutionary or Genetic Algorithms are optimization algorithms, which apply the principles of evolution found in nature to the engineering problem of finding an optimal solution to a technical problem. They operate by evaluating a set of solutions (population), which is then modified by fitness based selection, recombination and mutation of the design variables. Evolutionary algorithms entail a key advantage in multi-objective optimization. The population-based search enables them to approximate the Pareto front in a single optimization run. While optimizing, different solutions in the population converge to different areas of the Pareto front.

Evolutionary or Genetic Algorithms are robustness to noise in the experimental setup and are capabable of handling discrete and continuous variables. An additional advantage is that both single single and multiple objectives can be optimised for. These algorithms do not require derivative information and incorporate random processes in the generation of new solutions. For the proposed mixing optimization, the variables are the fuel injection location and amount controlled by continuous or discrete valves.

2 EXPERIMENTAL SETUP

2.1 Atmospheric Combustion Facility

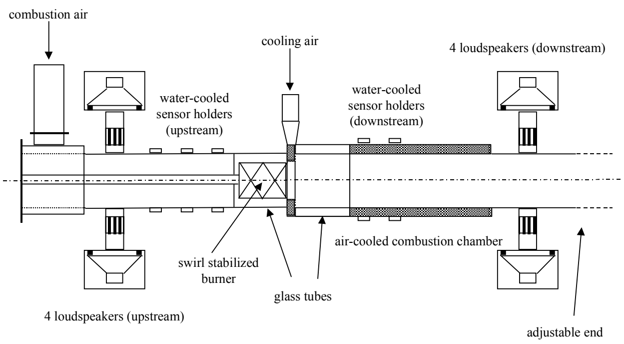

Figure 1. Schematic of the atmospheric test facility

The atmospheric combustion facility is shown in Fig. 1. The test rig consists of a plenum chamber upstream of a swirl-inducing burner and a combustion chamber downstream of the burner. The plenum chamber contains perforated plates to reduce the turbulence level of the flow. The circular combustion chamber consists of an air cooled double wall quartz glass to provide full visual access to the flame. The exhaust system is an air-cooled tube with the same cross-section as the combustion chamber to avoid acoustic reflections at area discontinuities. The acoustic boundary conditions of the exhaust system can be adjusted from almost anechoic (reflection coefficient $|r| < 0.15$) to open end reflection.

Pressure fluctuations were measured using Brüel & Kjær water-cooled microphones. The wall-mounted water-cooled 1/4" condenser microphones were placed at an axial distance of $x/D = 0.69$. The holders consisted of a small orifice ($d = 0.5$ mm) open to the combustion chamber. The microphone diaphragm was placed in a small cavity and was heat radiation protected. The resonance frequency of the holder was larger than $f_{res} > 20$ kHz. Using condenser microphones rather than piezoelectric pressure probes gave the advantage of highly accurate phase and amplitude data which is necessary for acoustic measurements. The frequency response of the microphones in probe holders were compared against standard B&K microphones and showed good agreement. To compare pressure pulsations in the different test configurations only one microphone was used placed at $x/D = 2.5$.

The operating conditions of the burner have been maintained by analyzing the exhaust gas composition using a physical gas analysis system. CO and CO_2 have been analyzed by using nondispersive infrared spectroscopy. The nitric oxides NO and NO_2, combined in NO_x have been detected with a chemiluminescence analyzer. The detection of the remaining O_2 in the exhaust gas was made utilizing the paramagnetic properties of oxygen in the analyzing device. Carbon and oxygen balances were continuously computed and agreement within 0.2% was assured.

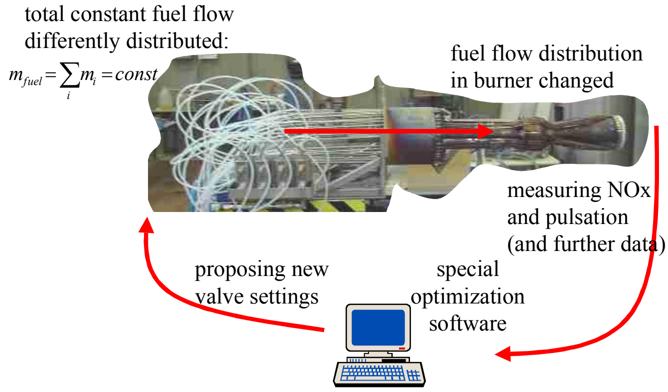

Figure 2. Sketch of the optimization process.

Gaseous fuels in the ALSTOM EV burner are injected into the combustion air by means of fuel distribution tubes comprising two rows of small holes perpendicular to the inlet ports of the swirler (Fig. 3). The fuel / air mixing profile at the flame location has an influence on the combustion propertie like emission generation and pulsations. The suggested design tool sugested here takes advantage of this behavior by actively optimizing the mixing profile to control pulsation and emission generation (Fig. 2). The adjustment of the fuel / air mixing profile in the burner was realized by controling the fuel flow through the injection holes along the distribution tubes as design variables of the setup. Instead of using the distribution tubes seperate supply tubes were added to the burner to deliver fuel to the individual injectors (Fig. 3). The fuel flow could be controlled by two different setups: (a) using proportional valves to adjust the mass flow for each fuel injector individually. (b) using digital valves to include or exclude fuel injectors along the distribution holes. The operating conditions were maintained by keeping the total fuel mass flow constant.

2.2 Elevated pressure combustion facility

The process of ALSTOM burner development and improvement includes combustion tests under elevated pres-

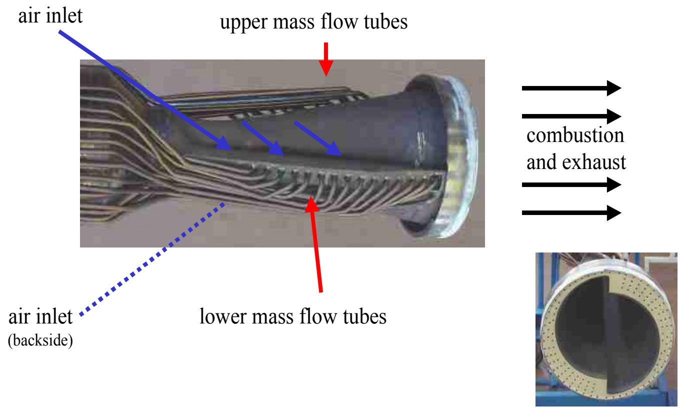

Figure 3. Sketch of the atmospheric combustion test-rig with a low-emission swirl stabilized burner. The fuel flow through the injection holes are the design variables of the setup. The NO_x emissions and the pulsation of the burner are the objectives to be minimized.

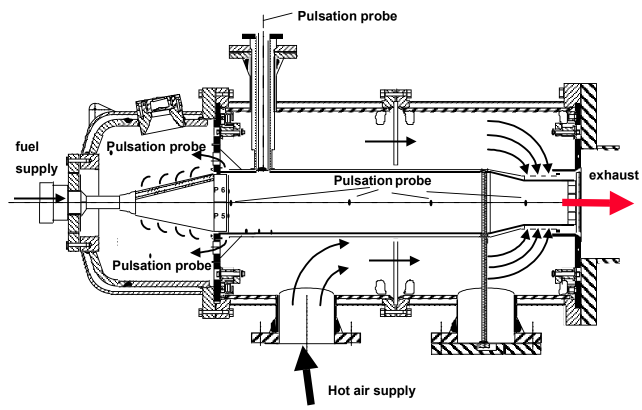

Figure 4. Schematic of the elevated pressure test facility

sure. The facility is shown in Fig. 4. It allows quick, cost effective and therefore extensive testing of single ALSTOM machine burners. The test rig consists of a plenum chamber upstream of the burner, two water cooled tubular pressure vessels and the rectangular chamber liner. The hot exhaust gases are quenched before the pressure reduction throttle and then discharged to the chimney. The operating conditions of the burner have been maintained as in the atmospheric test rig by analyzing the exhaust gas composition.

The combustor liner is convectively cooled to prevent contamination of actual burner emissions by introducing additional film cooling air into the combustor and to avoid introduction of unrelated acoustic damping effects. Direct optical observation of the flame is provided by a video system mounted downstream of the burner. In addition, optical observation of the mixing zone through the burner slots is possible by a video system mounted upstream of the burner in the plenum.

3 MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

3.1 Evolutionary Algorithms

Evolutionary Algorithms imitate the principles of natural evolution to find an optimal solution to a problem. Natural evolution is mainly driven by fitness-based selection and recombination/mutation of genetic information. In nature, individuals, which are well adapted to their environment (i. e., which are of high fitness), are more likely to survive the natural selection process by, e. g., pedators or limited food. They are likely to become parents and generate offspring by mating. The genetic information of the offspring is generated by sequences of the parents' genes and, in addition, include minor modifications due to reproduction error and some random mutation.

In an engineering environment, the genetic information are the design variables, which specify design properties. Evolutionary algorithms start by evaluating a set of solutions (population) with randomly chosen variable values. Then, the fitness of the solutions is computed as a function of the objectives of the design process. In average the solutions with the best fitness are choosen (fitness-based selection) as the parent population. A population of new solutions is created by combining and mutating the variables of the parent population. The fitness of the new solutions is evaluated and the previous steps are repeated until a termination criterion is reached.

Evolutionary algorithms continuously obtain an improvement of the objective function by exploiting progressively acquired information. These information can be used to accelerate the convergence e. g. by incorporating correlation information (Hansen and Ostermeier 2001) or by training self-organizing networks (Büche et al. 2002).

3.2 Multi-Objective Optimization Problem

Simultanous optimization of a set of conflicting objective functions is considered. Without loss of generality, we restrict to the minimization of 2 objectives, as it will occur in the combustion optimization. For conflicting objectives, there exists no best solution, but a set of best solutions, each representing the best compromises between the objectives.

The principle of dominance allows partial ordering of

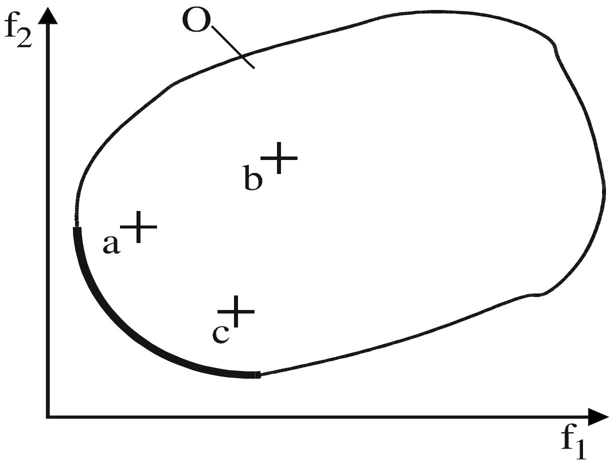

Figure 5. Illustration of the dominance principle a two-objective minimization problem. The solution a is dominating b, since a is superior in both objective values. a is indifferent to c, since each solution is superior in one objective. From the set of all feasible solutions O the set of Pareto solutions is marked by a bold line.

solutions as illustrated in Figure 5. A solution a is defined to *dominate* a solution b, if a is superior or equal in both objectives and at least superior in one objective. Two solutions a and c are *indifferent*, if neither solution is dominating the other one. In other words, in the mutual comparison a and c are each superior in one objective, while worse in the other objective. Without any weighing on the objectives, there is no preference between indifferent solutions. Among the set of all feasible solutions O, the complete set of nondominated solutions is referred to the Pareto set of solutions, after the work of the engineer and economist Vilfredo Pareto (Pareto 1906). This set represents the best solutions to a problem. In other words, starting from a Pareto solution, one objective can only be improved at the expense of at least one other objective.

Evolutionary algorithms are well suited candidates for multi-objective optimization, because of the ability to find an approximation of the whole Pareto front in a single optimization run. This is not possible with gradient-based optimization algorithms, which always converge toward a single point on the Pareto front. Various evolutionary algorithms for multi-objective optimization have been proposed and compared in literature (Zitzler and Thiele 1999) (Van Veldhuizen and Lamont 2000) (Coello Coello 1999).

3.3 Noise-tolerant Strength Pareto Evolutionary Algorithm

One of the most prominent multi-objective evolutionary algorithm is the the Strength Pareto Evolutionary Algorithm (SPEA) of (Zitzler and Thiele 1999). The algorithm consists of a fitness-based selection operator for multiple objectives and is described in the following. A key component of the algorithm is elitism, a technique of preserving always the best solutions obtained so far. Elitism ensures that the highest fitness in the population never decreases from one generation to the next and improves the convergence speed of the optimization algorithm (Laumanns et al. 2001). In multi-objective optimization, the fittest solutions are the nondominated solutions in the population. These solutions are always copied to the parent population of the next generation.

SPEA uses these nondominated solutions for the fitness assignment. First, the fitness of each nondominated solution is computed as the fraction of the population, which it dominates. Then, the fitness of the dominated solutions is computed as 1 plus the sum of the fitness of all nondominated solutions, by which it is dominated. This fitness assignment guarantees that the fitness of nondominated solutions is always lower than the fitness of the dominated solutions.

The fitness-based selection is a binary tournament. Always two solutions are taken from the population and then the solution with the lower fitness is selected as a parent of the next generation.

Noise is present in almost any application, especially if experiments are considered. In general we distinguish two types of noise. The first type is referred to as *experimental noise* and is a result of limited precision of the experimental setting and changing environmental conditions over the execution time period. This noise is present in every measurement. The second type addresses *outliers* and describes the rarely occurrence of some nonphysical results, due to, e. g., measurement failure.

Evolutionary algorithms are considered robust to noise. Empirical studies of Büche et al. (2002) demonstrate, however, that the robustness is limited, especially for multi-objective algorithms, which incorporate elitism. Elitism preserves the best solutions found so far in the optimization. This is especially critical if outliers occur. Then, the optimization process is in danger of getting misled by the outlier solutions.

Modifications for SPEA were proposed in Büche et al. (2002). These modifications show a negligible disadvantage for noise-free problems, but increase the performance in the presence of experimental noise and outliers. The resulting algorithm was defined as the Noise-tolerant Strength Pareto Evolutionary Algorithm (NT-SPEA). Three modifications were suggested for a noise-tolerant multi-objective algorithm:

1. *Domination dependent lifetime:* In contrast to elitism, which may preserve elite (nondominated) solutions for

an infinite time, a limited lifetime is assigned to each solution. Thus, a nondominated solution is just copied a limited number of times from one generation to the next. The lifetime of an solution is set to 4 generations, but is reduced, if a solution dominates a major part of the current set of nondominated solutions. This limits the impact of a solution and safeguards against outliers.
2. *Re-evaluation of solutions:* It is common to delete solutions with expired lifetime. In their work the nondominated solutions with expired lifetime are re-evaluated and added to the population. This enables good solutions to stay in the evolutionary process, but their objective values will change due to noise in the re-evaluation.
3. *Extended update of the archive:* The SPEA algorithm selects the nondominated solution always from the current population and the parent population. The update was extended to *all* solutions with non-expired lifetime. This hinders loss of information.

With these features NT-SPEA uses the advantage of elitism by preserving nondominated solutions, but it reduces the risk induced by outliers. For the combustion optimization the implementation of NT-SPEA algorithm of Büche et al. (2002) is chosen. The implementation includes also the recombination and mutation operator, which are based on Bäck and Schwefel (1993). However, the population size and number of parents is set to 15.

3.4 Encoding of the valves

The combustion process in the atmospheric test rig is controled by either a set of continuous or discrete valves, which detrmine the spatial distribution of the fuel in the burner. In the first case eight proportional valves were used to control the fuel mass flow to the different fuel injectors. Because the total mass flow is set constant, the 8 valves can be encoded by 7 real-valued variables as described by 2001 ().

In thethe second case, digital valves are used which represent binary switches, allowing the two states closed and open. As an operating constraint, at most 3 of the 16 valves are allowed to be closed. Thus, we use 3 discrete variables with integer values between 1 and 16 to describe the position of the closed valves. This allows to encode all solutions, which fulfill the constraint. All settings with 1, 2 or 3 closed valves can be obtained if 3, 2 or non of the variables are of equal, respectively. The setting with all valves open is the standard machine design, which was evaluated for reference.

Since permutating the variables does not lead to different solutions (e. g. setting the variables to $[1, 4, 7]$ is equivalent to $[7, 4, 1]$), the variables are always sorted in ascending order. Detecting permutations is important, since different permutations of the same solution should be deleted from the population as well as recombining differnt permutations should be avoided. The recombination and mutation operators of the proportional valves are chosen, except that here the obtained variable values have to be rounded.

4 BURNER OPTIMIZATION AT ATMOSPHERIC CONDITIONS

The extended Strength Pareto Evolutionary Algorithm was applied to a full size gas turbine burner at atmospheric conditions. The fuel distribution was either controlled by means of proportional valves or by digital valves (on/off-type). After convergence of the algorithm a Pareto front was obtained. Two extreme points on the Pareto front have been chosen for flame visualization by means of phase-locked chemiluminescence pictures.

4.1 Control by proportional valves

An optimization run is performed using NT-SPEA evaluating a total of 326 different burner settings within one working-day. All solutions are plotted in Fig. 6 in order to show the possible decrease in NO_x emissions and pulsations by the optimization compared to the given standard burner configuration and between the best and worst designs.
The given standard burner configuration is marked in the figure and represents a setting with equal mass flow through all valves. Some solutions found by the optimization process dominate the standard configuration, i.e. are superior in both objectives. Thus the optimization run is successful, delivering improved solutions for both objectives. The occurrence of a wide nondominated front underlines the conflict in minimizing both objectives and just (Pareto) compromise solutions can be found.

In the figure, the objectives are noisy. Thus, drawing just the nondominated front and picking one solution from the front is risky from the point of view, that an inferior solution is picked, which is nondominated due to the noise in its objective values. Picking an area close to the nondominated front increases the confidence in the front, especially if the valve settings are quite similar for the solutions in the area. A second reason for not drawing just the nondominated front is the possible shift of the front towards smaller objective values. The objectives contain noise and the selected nondominated solutions may “improve” due to noise, although there is not a physical, repeatable, solution.

In addition we are more interested in the valve settings than in the exact objective values, since the valve settings indicate the included physics.
Five areas along the nondominated front are picked and marked by boxes. For the solutions within the boxes, the

valve settings are displayed in Fig. 7. For better illustration, the settings are connected with a line and the dash-dotted line shows the standard burner configuration with equal mass flow through all valves. Within each box, the settings of the different solutions are in deed quite similar. 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. The fundamental mechanism corresponding to these settings is the fact that the increased mass flow through valves 1 and 2 leads to richer combustion in the center of the burner. The fuel-rich combustion zone stabilizes the combustion like a pilot flame, but increases the NO_x emissions. The lean zones are close to the middle of the burner at valves 5 and 6.
Box 5 indicates solutions with minimal NO_x emissions, but high pulsation. The mass flow through each valve is about equal, generating no rich combustion zones. Compared to the standard burner configuration, the small mass flow increase at valves 5 and 8 and decrease at 3 and 4 leads to lower NO_x emissions, while the pulsation is unchanged.

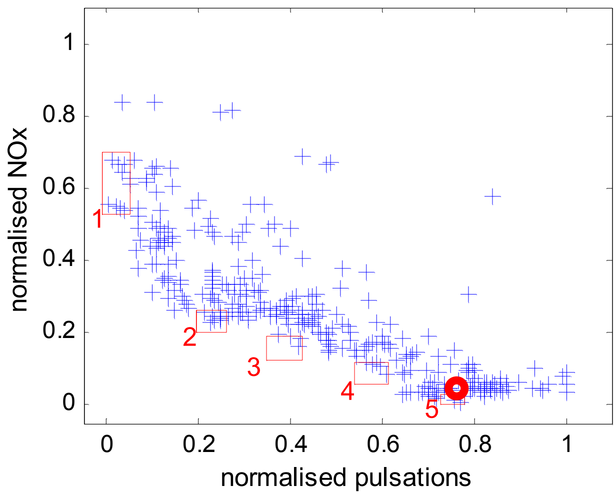

Figure 6. All measured solutions of the burner optimization run [plus symbol] and given standard burner configuration [circular symbol]. The 5 boxes mark the different areas along the nondominated front.

4.1.1 Statistical analysis One of the interesting features of the resulting nondominated 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 their 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 with the objective functions.

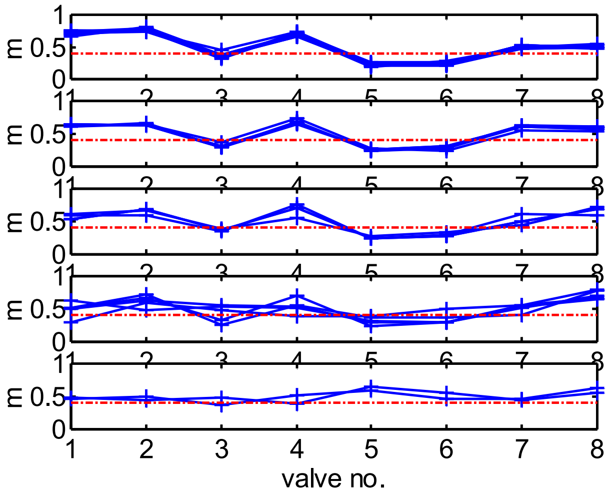

Figure 7. Mass flow $\dot{m}$ through the valves $V_{i,i=1,\ldots,8}$ for solutions along the nondominated front, marked by 5 boxes of Fig. 6.

The correlation coefficients $r_{V_i,\ NO_x}$ and $r_{V_i,\ pulsation}$ for the design variables and objectives are given in Fig. 8. Strong correlation can be observed between valves 1, 2, 5, 6 and the two-objective functions.

For all valves, the correlation coefficients have opposite signs for the two objectives. Therefore, changing the fuel injection in any of the valves improves always 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. For increasing the mass flow through valve 1 and 2, the emissions increase while the pulsation decreases. For valves 5 and 6, this is vice versa.
It has to be considered that these observations hold for the solutions obtained through an optimization process.

4.1.2 Convergence towards optimal designs
The convergence towards the optimal design is shown in Fig. 9. About 90 optimization loops per hour were possible limited only by the response time of the emission measurement and the pulsation averaging. The comparison between the optimised soultions and the initial solution (resulting from the careful development process including CFD, flow tests and combustion tests) indicates a possible 30% improvement in NO_x emisssions and a possible 20% pulsation reduction. Note that for the initial design, the valve stings are not the uniform fuel distribution like in box 5 (Fig.7), but more similar to box 3.

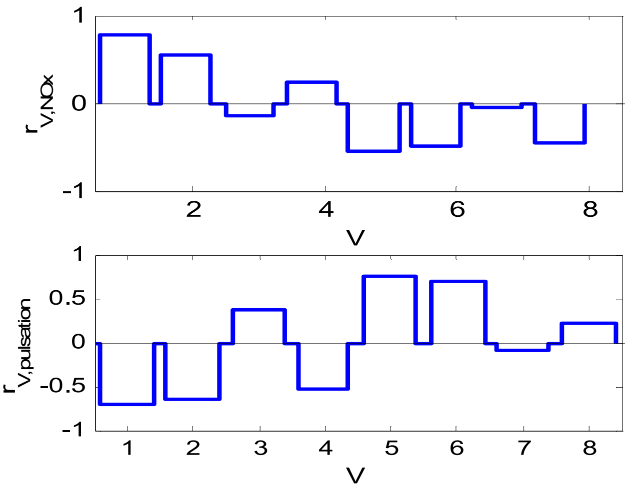

Figure 8. Correlation coefficient r between the mass flow through the valves $V_{i,i=1,\dots,8}$ and the objectives NO_x and pulsation.

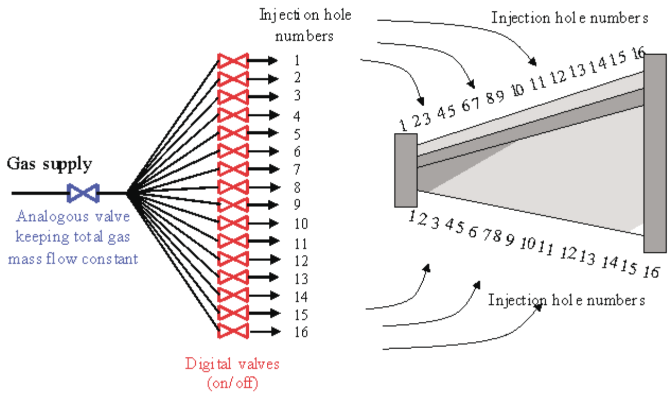

Figure 10. Schematic of the test rig using digital valves.

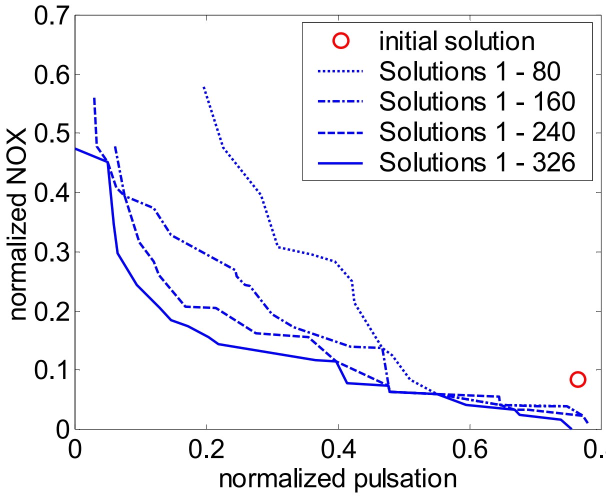

Figure 9. Convergence towards optimal design. Shown are the Pareto-optimal designs after 80, 160, 240 and 326 optimization loops. Convergence is not yet complete.

4.2 Control by digital valves

The tests using proportional valves gave valuable input for optimal fuel injector size and distribution. This information is used in the design of new burners. The simplicity of using one burner family in more than one gas turbine type and operating with different gas qualities may lead to the necessity to tune the burner for the different boundary conditions encountered. This can be done by different hole patterns or — more simple — by just closing injection holes out of the row of injectors along the distribution channel.

To assess the performance of the suggested control the following test was performed: instead of using proportional valves the test-rig was equipped with digital valves (Fig. 10). The results of the optimization run are displayed in Fig. 11 and show the possible decrease in NO_x emissions and pulsations when compared to the given standard burner configuration. The given standard burner configuration is marked in the figure and represents a setting with equal mass flow through all valves. Some solutions found by the optimization process dominate the standard configuration, i.e. are superior in both objectives. Thus the optimization run is successful, delivering improved solutions for both objectives.

The valve settings corresponding to the different objectives along the Pareto front are displayed in Fig. 12. Like in the tests using the proportional valves the results indicate that for low NO_x behavior the center has to be leaner (valves 1 and 2 at the tip of the closed). For low pulsations the center appears to be enriched (more valves are closed towards the exit of the cone).

The convergence towards the optimal design is shown in Fig. 13. About 60 optimization loops per hour were possible. The comparison against the initial solution resulting from the careful development process including CFD, flow tests and combustion tests indicates a possible 20% improvement in NO_x emisssions and a possible 30% pulsation reduction for the same burner.

The dependence of the Pareto front on flame temperature is shown in Fig. 14.

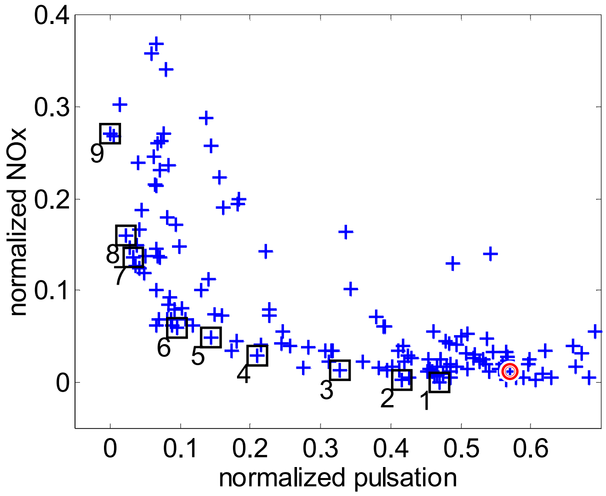

Figure 11. Optimization using digital valves. The numbered boxes correspond to the valve settings of figure 12.

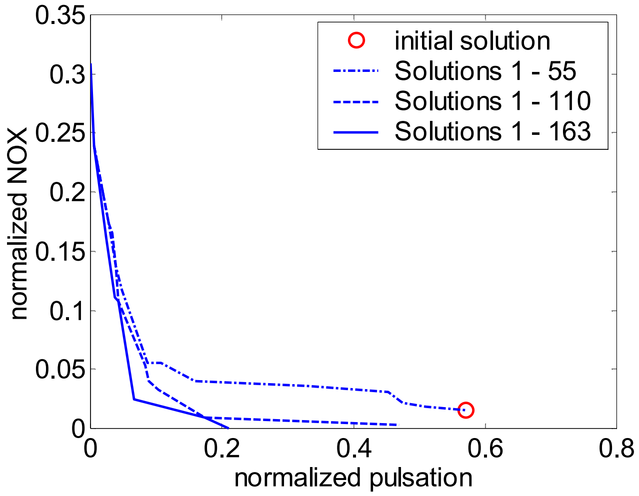

Figure 13. Convergence towards optimal design. Shown are the Pareto-optimal designs after 80, 160, 240 and 326 optimization loops. Convergence is not yet complete.

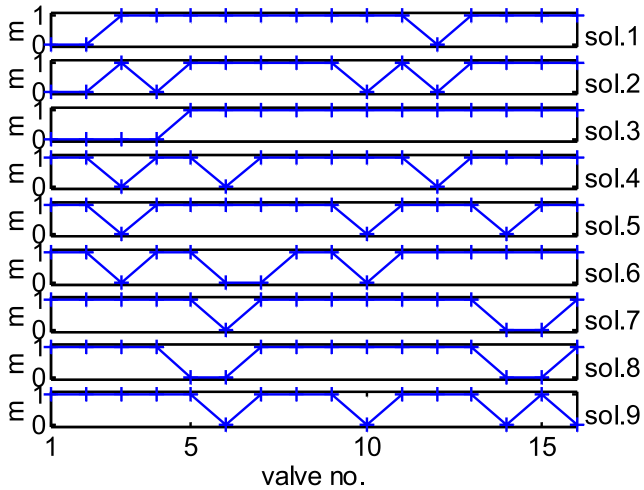

Figure 12. Optimization using digital valves: corresponding valve settings.

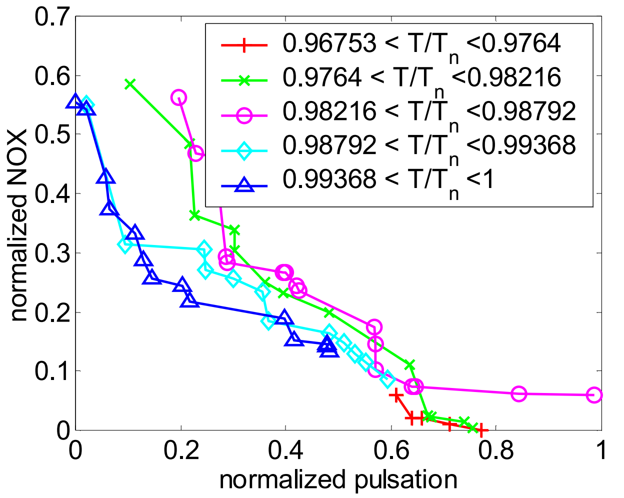

Figure 14. Pareto-optimal solutions (designs) dependent on flame temperature.

4.3 Visualization of the combustion process

The combustion process was visualized by taking phase locked images of the flame using an amplified (micro channel plate) CCD camera with an exposure time of $20\mu s$. The camera was triggered by either the pressure or OH signals which were band-pass filtered at the instability frequency and phase shifted. The images were filtered using a band-pass filtered with a low and high cutoff wavelength of 290 nm and 390 nm, respectively. The phase locked exposures were then averaged over 64 events. Two extreme cases, one with low NO_x emissions but with strong pulsation behavior, the other with low pulsations but high NO_x levels are displayed in Fig. 15.

5 PRESSURIZED COMBUSTION TESTS

The optimization was applied to an engine burner. The objective was to reduce emissions while keeping the pulsation level constant. Atmospheric tests of the optimized fuel injection showed reduction in NO_x (Fig. 16). The improvement was verified in pressurized combustion tests at engine conditions (Fig. 17).

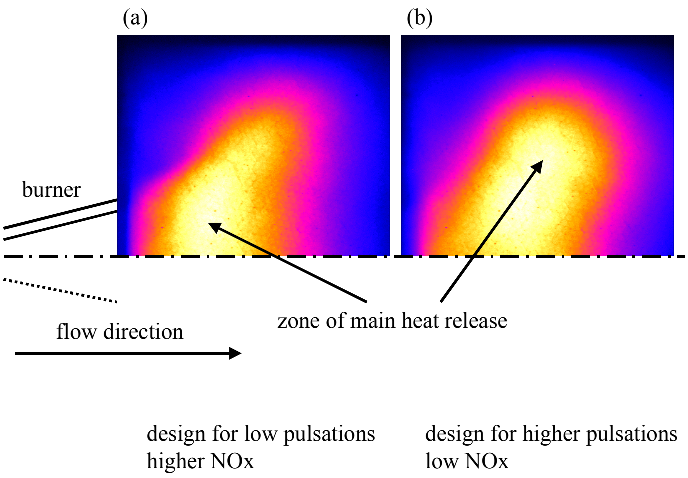

Figure 15. Flame visualization using OH chemiluminescence. Only the upper half of the symmetric flame is displayed. (a) flame shape for a low pulsation but higher NO_x design. (b) flame shape for low NO_x but higher pulsations.

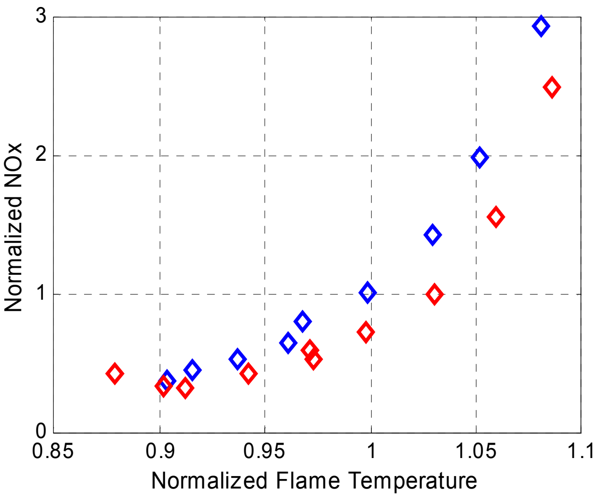

Figure 16. Combustion test at atmospheric conditions comparing the optimized burner against the baseline.

6 CONCLUSIONS

This paper describes an evolutionary algorithm applied to design optimization of premixed burners by changing the fuel to air mixing profile. The method was demonstrated in an atmospheric combustor and was verified in elevated pressure combustion tests. The objectives of design improvement were further reduction of pulsations and NO_x emissions. Other objectives like, e. g., lean extinction extension, can be introduced as well but were not part of the

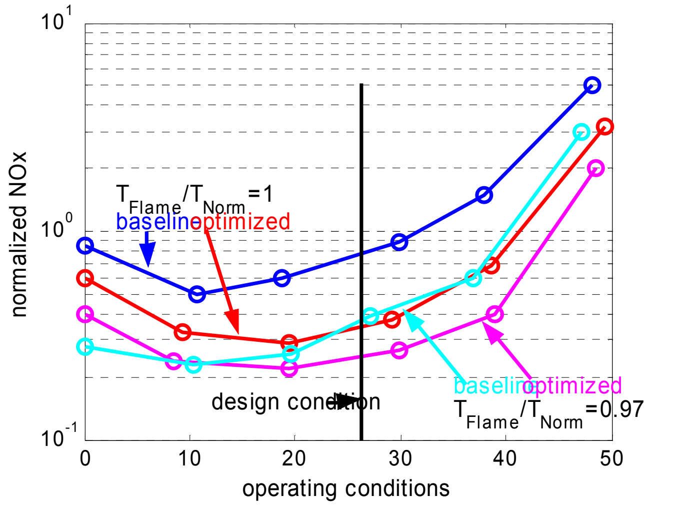

Figure 17. Combustion test at pressurized conditions comparing the optimized burner against the baseline.

tests presented here.

The method works as follows: a gas turbine burner is operated under steady state conditions. NO_x emissions and pulsations are continuously monitored. A special evolutionary algorithm suggests a new fuel / air distribution in the burner by controling the fuel flow to the injection holes within the burner. Control of fuel mass flow is accomplished by using either proportional valves or digital valves. The total fuel mass flow is kept constant. NO_x emissions and pulsations are measured and evaluated by the optimization software. New valve settings are again suggested by the software.

The evolutionary algorithm delivers in an automated fashion an approximation of the Pareto front for minimizing pulsations and emissions of an industrial burner in a single optimization run. This is a key advantage when compared to traditional point-to-point search methods and human designers, which would operate by searching one compromise solution at a time to build up the Pareto front.

For this purpose a novel noise-tolerant multi-objective evolutionary algorithm (NT-SPEA: Noise-Tolerant Strength Pareto Evolutionary Algorithm) is introduced with increased robustness for applications prone to noise and outliers. The algorithm takes advantage of the concepts of domination-dependent lifetime, the re-evaluation of non-dominated solutions and an extended update mechanism for the archive. The noise tolerant feature is important as the experimental data especially at short averaging times might exhibit scatter.

The optimization shows that $\approx 20-30\%$ reduction in pulsations and $\approx 20-30\%$ NO_x reduction is possible by maintaining emssions or pulsations respectively. The improvement is obtained by only fuel redistribution and without any changes of the burner flowfield. This allows for burner tuning for different operating conditions like, e. g., different gas quality.

Visualization of the flame shape was performed at the two extremes of the Pareto front — low NO_x and high pulsations and high NO_x and low pulsations. Not surprisingly, the low NO_x flame was leaner in the center and had maximum heat release at larger radial and axial location than the high NO_x flame. The more relevant cases, showing improvement in two objetives are settled in between these two extremes. For these cases, the advantages of the automated optimization become apparent, because the improvements are caused by subtle adjustments of the fuel distribution.

A burner optimized at atmospheric conditions by using the evolutionary process showed also under pressurized conditions the same improvement.

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