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Robust Operational Optimization of a Typical micro Gas Turbine

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Abstract

Due to their high total efficiency and flexibility, micro Gas Turbines (mGTs) offer great potential for use in small-scale distributed cogeneration applications. The economic success of this application; however, fully depends on the optimal usage of the system, which requires careful selection of the number and size of the units in the system and their specific operating strategy. This is only possible if the performance of each individual unit is known precisely. However, in real world operating conditions, the parameters determining the operation and performance of an mGT are only known with a certain uncertainty. Depending on the sensitivity of the model to these parameters, the uncertainties may have a strong negative effect on the performance of the mGT. These uncertainties should thus be taken into consideration by the designers in an early stage of the design process to achieve a so-called robust design. In this paper, we present the robust optimization of a typical mGT, the Turbec T100, operation. This optimization under uncertainties is based on a classical multi-objective optimization scheme linked with an uncertainty propagation technique. In this approach, a robust optimum is found, less sensitive to variations in design and operation parameters. The deterministic optimization results in a Pareto front for maximal electrical efficiency and power output, highlighting that the two objectives are conflicting. The impact of the uncertainties on the parameters is translated into a slight negative shift in this Pareto front. Finally, the most robust operation can be found at a power output of 106.5 kW_e, corresponding to a maximal efficiency of 30.6%.

Keywords: micro Gas Turbine; Deterministic Optimization; Uncertainty Quantification; Robust Design

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Nomenclature

CAF	Corrected Air Flow	RE	Renewable Energy
CoV	Coefficient of Variance	SM	Surge margin
mGT	micro Gas Turbine	SW	Stone Wall
NSPSO	Non-dominated Sorting Particle Swarm Optimizer	TIT	Turbine Inlet Temperature
PC	Polynomial Chaos	TOT	Turbine Outlet Temperature

1. Introduction

The massive deployment of Renewable Energy (RE) to reduce the CO_2 emissions of our energy production is putting some severe constraints on the electricity grid. Due to the highly fluctuating and unpredictable nature of the RE production from wind and solar, there is a growing need for flexibility of the power grid to keep demand and production balanced to avoid possible brown- or blackouts. Micro Gas Turbines (mGTs) in distributed power generation, typically in small-scale cogeneration applications, can provide such flexibility. However, due to their rather high capital investment costs (between 1500 and 2500 €/kW$_e$ [1]) and rather low electrical efficiency (30% for a typical 100 kW$_e$ unit), it is essential to optimize the thermodynamic performance (electrical power output and efficiency) to make the unit economically profitable.

In literature, several examples of the optimization of mGTs in co- or trigeneration applications can be found. Several examples of the different usage of mGTs as common electricity and heat source in these networks are available in literature. Pilavachi [2], Kaikko et al. [3], Katsigiannis and Papadopoulo [4], Nikpey et al. [5] and Caresana et al. [6] studied the use of mGTs in typical cogeneration applications for heat production. Alternative integrations, like Bruno et al., using an mGT as power source in combination with a desalination plant, which absorbs the generated heat [7] and Ho et al., studying the performance of an mGT CHP system with absorption chiller, where the heat is used to provide cooling [8], are other typical examples of studies on mGTs integrated in poly-generation networks. Next to the optimization of the unit itself, optimization of the grid, i.e. selection of the number of units and their nominal power, is also important, since it will influence strongly the yearly operation of the units (running hours and part/full load operation) [9,10].

When performing this optimization, especially when including thermo-economic calculations, typically, only the economic parameters (gas and electricity prices and possible subsidies or carbon saving reductions/taxes) are considered as variable, due to their very fluctuant nature. However, next to the variable economical parameters, in real-world operating conditions, the design and operating parameters determining the mGT and its performance are also subject to uncertainties. This will also influence the operation e.g. internal leakage between different components [11] or the uncertainty on the machining of the turbomachinery [12] having a severe impact on the cycle efficiency. Depending on the sensitivity of the performance to these parameters, the defined uncertainties may have a tremendous effect on the performance of the mGT. Deviations on this performance will impact both the network design and its operation, possibly leading to different economic results/conclusions.

It is thus essential for both designers and operators to consider these uncertainties when designing these units/grids and determining the operating strategy. This should finally lead to a design insensitive to these parameter variations: a so-called robust design. This implies that the impact of the variation of the different parameters needs to be calculated for all possible combinations. This is a quite challenging task, especially when the number of variables is high and/or when the computational model is costly to evaluate. Therefore, a more systematic approach is required. Several techniques exist to reduce the calculation time; however, to the knowledge of the authors, no such efforts have been applied on mGT operation.

In this paper, we present the robust optimization of a typical mGT operation. This optimization under uncertainties is based on a classical multi-objective deterministic approach; where no uncertainties are considered, which is linked with an uncertainty propagation technique, a non-intrusive Polynomial Chaos (PC) methodology. A numerical model of the Turbec T100 mGT is constructed in Aspen Plus and optimized, considering the uncertainties of both operational and design parameters. The objectives of the optimization are the maximization of the electrical performance (power output and efficiency) by changing the mGT rotational speed and the Turbine Outlet Temperature (TOT). The final aim of this paper is to obtain a robust design for the mGT operation. In the following section, we first present the mGT model, followed by the deterministic and robust optimization approaches. Finally, the results of the robust design are presented followed by some concluding remarks.

2. Simulation Approach

In this section, first the numerical model of the mGT, based on the Turbec T100, is presented. The Turbec T100 (now the Ansaldo Energia AE-T100) was selected since it is representative for the state-of-the-art of mGTs. Next, the used deterministic optimization approach and finally the robust optimization method are described and discussed.

2.1. Micro Gas Turbine (mGT) model

The Turbec T100 is a typical mGT, operating according the recuperated Brayton cycle principle (Figure 1). Indeed, given the typical low operating pressure of the system (3-5 bar), the compressed air leaving the variable speed radial compressor (1) is first preheated by the exhaust gases of the turbine in a recuperator (2) before entering the combustion chamber (3) to increase the cycle efficiency. In this combustion chamber, to achieve maximal efficiency, natural gas is burnt to increase the Turbine Inlet Temperature (TIT) to a maximum of 950°C. The hot gases expand in the turbine (4), delivering mechanical power to drive the compressor. The residual power is converted into electrical power by a variable speed generator (5). Finally, the remaining heat from the hot gases leaving the recuperator is partially recovered in a heat exchanger, the economizer (6), producing thermal power. In nominal operating conditions, the Turbec T100 produces 100 kW_e and 166 kW_{th} power at a total efficiency of 80% (30% electrical efficiency).

The used numerical Aspen Plus model of the mGT is an adapted model of the mGT [13], previously used to model humidification [14,15] and exhaust gas recirculation in the cycle [16] and is experimentally validated. For the robust optimization, presented in this paper, this mGT model was slightly adjusted. For the different components, the actual values given by the manufacturer have been used. For the compressor modelling, the actual map linking rotational speed with the air mass flow rate — expressed as Corrected Air Flow (CAF) —, pressure ratio and isentropic efficiency has been used (the maps are similar to the one presented in [6]). Although the recuperator combines, in reality, counter-flow exchange zones (interior of the component) with cross-flow zones (in- and outlet sections) [17], for this paper, the heat exchanger was modelled using a counter-flow model with corrected fixed heat transfer coefficient and area,

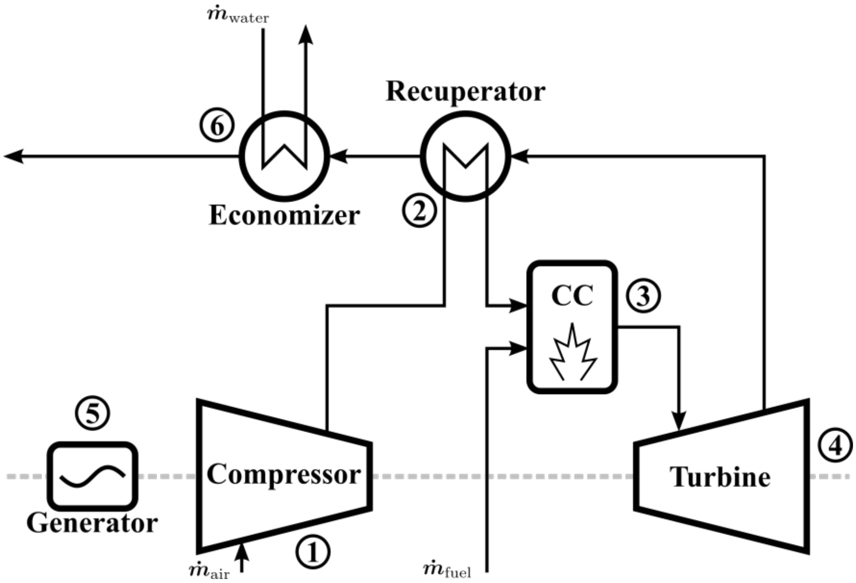

Figure 1: The Turbec T100 is a typical mGT operating according the recuperated Brayton cycle principle, consisting of a compressor (1), recuperator (2), combustion chamber (3), turbine (4), economizer (6) and generator (5).

Table 1: Nominal values and uncertainties of the operational parameters implemented in the Aspen Plus model of the mGT

Operational parameter	**Nominal Value**	**Uncertainty[3]**
Compressor inlet temperature	15°C	1°C
Compressor inlet pressure	1.013 bar	0.1%
Pressure ratio	Variable[1]	1%
Corrected Air Flow (CAF)	Variable[1]	1%
Compressor isentropic Efficiency	Variable[1]	1%
Recuperator surface	120 m²	1%
N_2 content of the fuel	10%	10%
Combustor heat loss	10 kW_{th}	1%
Turbine isentropic Efficiency	85%	1%
Turbine outlet pressure	1.050 bar	1%
Turbine choking constant	6.5 kg√K/sbar	1%
Leak flow 1	1%[2]	100%
Leak flow 2	1%[2]	100%
Leak flow 3	1%[2]	100%

[1]Pressure ratio, CAF and isentropic efficiency are determined based on the actual compressor maps and change according the rotational speed.

[2]The leak flow rate is defined as a percentage of the air flow rate entering the compressor.

[3]Presented uncertainties are relative values, except for the compressor inlet temperature (absolute uncertainty)

obtained based on data available in literature [17] and from experiments. A similar approach was used to model the pressure losses in this recuperator, linking heat exchanger surface with pressure loss. The combustion chamber was modelled using a Gibbs reactor, assuming complete combustion (100% combustion efficiency), given that the combustion takes place in lean conditions. In this combustion chamber, a given pressure loss (5%) and heat loss (10 kW_{th}) have been considered. As fuel, a mixture of methane (90%) and nitrogen (10%) was selected, which corresponds to a certain extend to the natural gas available to the test rig at the Vrije Universiteit Brussel [18]. To ensure Aspen converge each time, independent of the initial condition for the system air mass flow rate, to a physical solution, the turbine was not modelled using the actual maps. Alternatively, the component was assumed to be choked, considering a constant CAF of 6.5 kg√K/sbar, having a constant outlet pressure of 1.050 bar, an isentropic efficiency of 85% and a mechanical efficiency of 99% for all operating points. Previous simulations have validated this assumption of choked operation [13]. For the determination of the electrical power production and efficiency, a total conversion efficiency of 94% of the mechanical power of the shaft was assumed, combining the losses in the generator and the power electronics. To consider possible non-idealities of the mGT production process and aging of the machine, three leakage streams (from the compressor outlet to the recuperator cold side outlet, from the compressor outlet to the turbine inlet and from the recuperator cols side inlet to the recuperator hot side outlet) bypassing part of the cycle have been considered. Finally, concerning the thermal power production part of the mGT, the economizer is simulated as a cross-flow heat exchanger, again with given heat exchange coefficient and area. The different optional parameters entered in the Aspen Plus model are summarized in Table 1.

Like most mGTs, the Turbec T100 is a unit that operates at constant power output [19]. Rather than changing the amount of air entering the system or the TIT to control the power output, the rotational speed of the engine is adjusted. This allows to keep compressor efficiency high, even at part load operation. To ensure high electrical efficiency, the mGT operates at nominal and part-load operation at maximum TOT of around 645°C (material limit of the metal used for the recuperator) by controlling the fuel mass flow rate injected in the combustion chamber. In the Aspen model, both control loops are implemented as *Design Spec*, changing rotational speed for power control and fuel mass flow rate for TOT control. For the optimization presented in this case; however, the constant power operation was replaced by constant speed operation, which allowed more flexibility in the simulations (see following section).

Table 2: Design parameter space used for the optimization.

Design variables	Lower Limit	Upper Limit	Uncertainty
Rotational Speed	950 Hz	1250 Hz	0.01%
Turbine Outlet Temperature	560°C	645°C	1°C

2.2. Multi-Objective Deterministic Optimization

The first step of a robust optimization includes a deterministic optimization, not considering the uncertainties. For the robust optimization presented in this paper, the Non-dominated Sorting Particle Swarm Optimizer or NSPSO is used to handle the multiple objectives of the described test case [20]. The population in NSPSO consists of particles which can memorize their best solution found so far and communicate with other particles, in terms of the global best. The application of this optimization tool on the mGT operation has already been presented [21] and is briefly summarized here. For the optimization of the mGT operation, the TOT and the rotational speed are varied over their boundaries (Table 2), as would be done by the actual control system. Next to the design parameters, three constraints are also introduced: surge and stone limit and maximal TIT. The optimal solution should respect a minimal surge margin of 10%, should not cross the stone-wall and the TIT should not surpass the turbine material limit of 950°C. As objectives for the optimization, maximal electrical efficiency and power output were selected. The objective and constraints of the test case are thus defined as follows:

$$\max \quad \eta_{\mathrm{el}}, P_{\mathrm{el}}$$

$$\text{subject to:} \quad \mathrm{SM} \geq 10\%;\ \mathrm{SW} \geq 0\%;\ \mathrm{TIT} \leq 950°\mathrm{C}$$

where η_{el} and P_{el} are respectively the electrical efficiency and the electrical power output of the mGT, while SM and SW represent the Surge Margin and Stone Wall margin respectively.

2.3. Robust Optimization

The present uncertainty quantification module is based on a non-intrusive Polynomial Chaos (PC) methodology [22]. This approach for uncertainty quantification has been widely used for solving various non-deterministic systems [23–27]. Its main advantage compared to crude Monte Carlo technique is its faster convergence rate, i.e. the statistical moments are currently predicted with much fewer model evaluations. PC consists in expanding the output of interest (in our application electrical efficiency and power output) using multivariate orthogonal polynomials in the input variables. A regression-based approach is considered to compute the chaos coefficients. Once the chaos coefficients are known, the statistics of the system (mean, variance, higher order moments) can be derived from the expansion. A schematic overview of the approach is presented in Figure 2. For a more in-depth (mathematical) description of the approach including an application in Computational Fluid Dynamics, we refer to [22].

3. Results

The deterministic optimization results, as already presented in [21], in a clear Pareto front showing that the objectives are conflicting (Figure 3). The maximal power output of 137.9 kW_e is not reached at maximal efficiency of 30.6%, but at a lower efficiency of 28.6%. The maximal efficiency of 30.6%, in turn, corresponds to a power output of 111.8 kW_e. The efficiency values are slightly lower than the ones obtained in [21], which can be explained by the introduction of the different leakage streams. These streams lead to an extra loss in the cycle, negatively impacting the electrical performance. Finally, concerning the corresponding values of the control parameters, we can observe that the maximal efficiency is obtained at maximal TOT, while the maximal power output is achieved at maximal rotational speed. This is in line with previous results and the expectations. Indeed, the power output mainly depends on the air

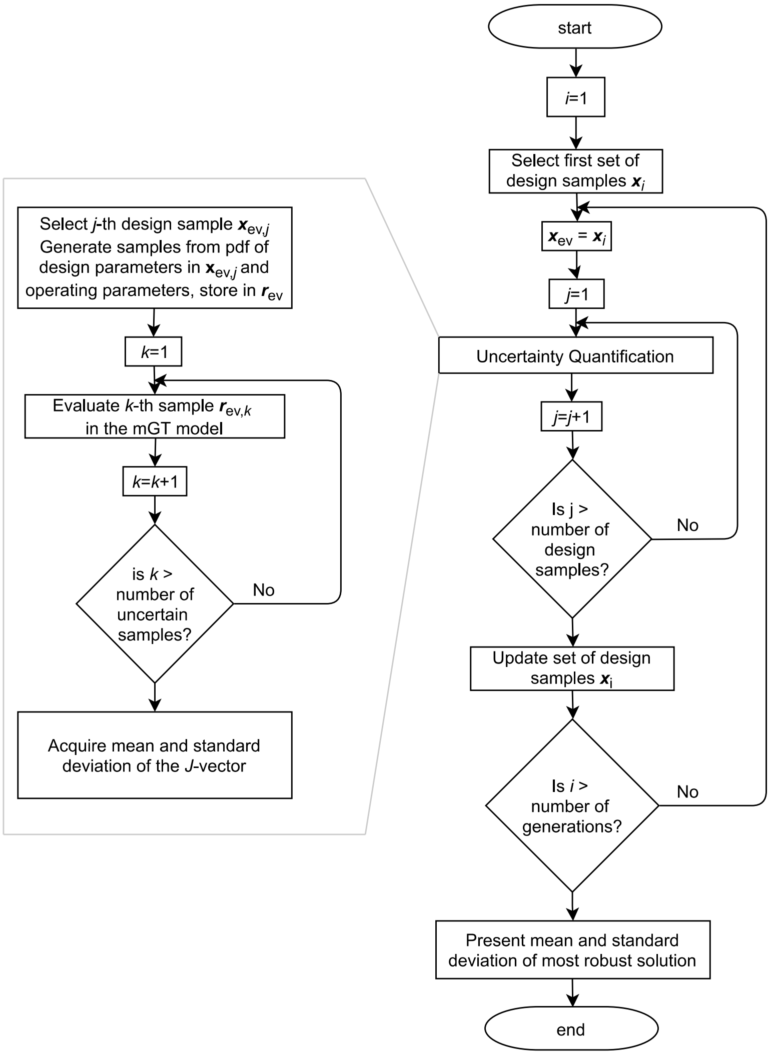

Figure 2: The schematic overview of the Robust Optimization procedure.

mass flow rate entering the cycle, which increases with increasing rotation speed. On the other hand, the efficiency of the cycle is mainly function of the TIT, which is directly linked with the TOT. The lower efficiency at maximal power output is a result of the lower compressor efficiency (the compressor enters a region with lower isentropic efficiency) and the lower TIT.

For the robust optimization process, again the aim was to obtain the inputs, TOT and n, which lead to the most/least robust results using PC. To reduce the total dimension of the problem, both objectives, being electrical power output (P_{el}) and electrical efficiency (η_{el}), are combined in a single result vector J, using following weight function:

$$J = \left(w_1 \frac{P_{\text{el}}}{P_{\text{el,0}}} + w_2 \frac{\eta_{\text{el}}}{\eta_{\text{el,0}}} \right) \tag{1}$$

with $w_1 = w_2 = 0.5$, $P_{\text{el,0}}$ equal to 96 kW$_\text{e}$ and $\eta_{\text{el,0}}$ 28.5%. The robust optimization aims to minimize both μ_J and σ_J/μ_J — which is equal to the Coefficient of Variance (CoV) —, still respecting the constraints on the surge margin

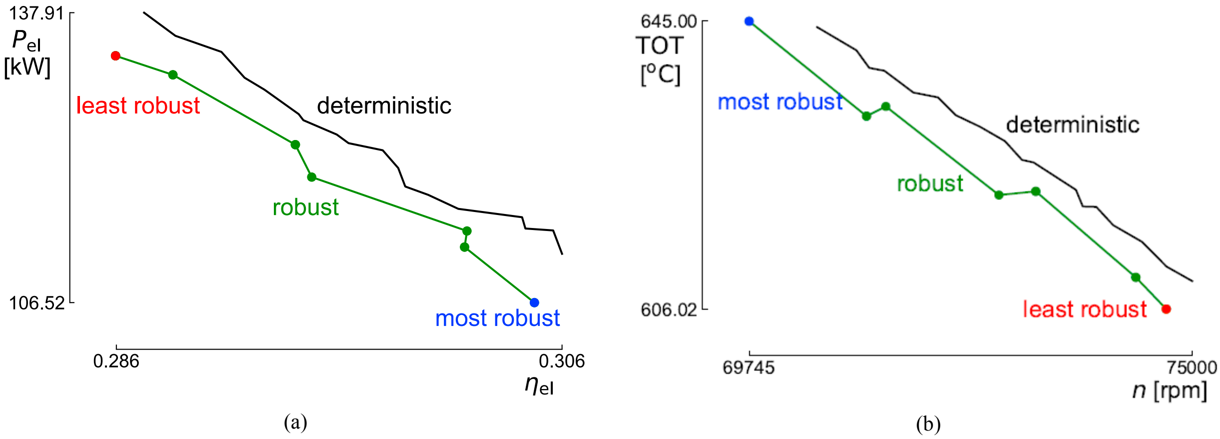

Figure 3: The Pareto front (a) with corresponding values of the design variables (b) — the rotational speed (n) and the Turbine Outlet Temperature (TOT) — indicates that both objectives, maximal electrical power output (P_{el}) and electrical efficiency (η_{el}), are conflicting for the deterministic optimization. Due to the consideration of the uncertainty of each constraint, the robust result is situated below the deterministic result. The most robust result is obtained by reducing the rotational speed while keeping TOT equal to the maximal value of 645°C (b), which corresponds to maximal electrical efficiency (a).

and stone wall and the TIT constraint, taking a margin of 3σ for each of the parameters into account. Indeed, not only the mean value of each parameter, but given the uncertainty on the input parameters, also the standard deviation on these constraints (surge margin, stone wall and TIT) need to be considered.

The robust optimization of the mGT operation leads to a Pareto front for the results vector J, showing that the CoV can be reduced from 1.25%, which is already relatively low, for the least robust solution to a value of 1.04% for the most robust solution (Figure 4). The rather low initial CoV can be explained by the small uncertainties of the operational and design parameters (Table 1 and Table 2). Additionally, this also indicates that the model is rather insensitive to variations in these parameters. Nevertheless, a reduction remains still necessary to ensure economical profitability under all circumstances. The input samples to achieve this Pareto front are also presented in Figure 3 (b), clearly indicating that the robustness of the mGT can be improved by reducing the rotational speed, while operating at the predefined TOT upper limit. Finally, when focusing on the final electrical power output and efficiency of the mGT (Figure 3 (a)), the results between the least and most robust solution are below the Pareto front of the deterministic results achieved before. This can be explained by the more severe constraints for the robust optimization, since they include an extra 3σ for all three parameters. Therefore, the robust results achieve lower performances, but

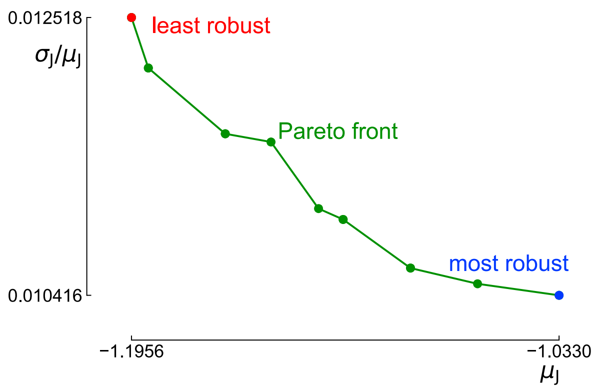

Figure 4: The Pareto front for minimization indicates that the CoV can be reduced from 1.25% to 1.04% when going from the least robust to the most robust solution.

ensure that the constraints will never be violated, keeping in mind the uncertainty on these constraints. Finally, the most robust operation is found at maximal TOT, corresponding to a maximal electrical efficiency of 30.4% and a corresponding power output of 106.5 kW_e.

4. Conclusion

In this paper, we presented the robust optimization of a typical mGT, the Turbec T100, operation. The aim was to achieve a final operating strategy, less sensitive to the variations of both design and operational parameters. This optimization under uncertainties is based on a classical multi-objective deterministic approach; where no uncertainties are considered, which is linked with an uncertainty propagation technique using non-intrusive PC methodology. A numerical model of the Turbec T100 mGT is constructed in Aspen Plus and optimized, considering the uncertainties of both operational and design parameters. The objectives of the optimization are the maximization of the electrical performance (power output and efficiency) by changing the mGT rotational speed and the TOT.

The deterministic optimization resulted in a clear Pareto front for both optimization parameters, highlighting that the two objectives are conflicting: maximal electrical efficiency cannot be reached at maximal power output. The impact of the uncertainties on the parameters is translated into a slight negative shift in optimal Pareto front, because of the additional margin on these constraints due to the uncertainties. Finally, the most robust operation could be found at maximal TOT of 645°C and a rotational speed of 67,745 rpm (below the upper limit), corresponding to a maximal electrical efficiency of 30.4% and an electrical power output of 106.5 kW_e.

5. References

[1] G. Pepermans, J. Driesen, D. Haeseldonckx, R. Belmans, W. D'haeseleer, Distributed generation: definition, benefits and issues, Energy Policy. 33 (2005) 787–798.

[2] P.A. Pilavachi, Mini- and micro-gas turbines for combined heat and power, Appl. Therm. Eng. 22 (2002) 2003–2014.

[3] J. Kaikko, J. Backman, Technical and economic performance analysis for a microturbine in combined heat and power generation, Energy. 32 (2007) 378–387. http://www.sciencedirect.com/science/article/B6V2S-4KV2RFH-2/2/2f097cac7012ee71feba335be67facea.

[4] P.A. Katsigiannis, D.P. Papadopoulos, A general technoeconomic and environmental procedure for assessment of small-scale cogeneration scheme installations: Application to a local industry operating in Thrace, Greece, using microturbines, Energy Convers. Manag. 46 (2005) 3150–3174.

[5] H. Nikpey, M. Assadi, P. Breuhaus, Development of an optimized artificial neural network model for combined heat and power micro gas turbines, Appl. Energy. 108 (2013) 137–148.

[6] F. Caresana, L. Pelagalli, G. Comodi, M. Renzi, Microturbogas cogeneration systems for distributed generation: Effects of ambient temperature on global performance and components' behavior, Appl. Energy. 124 (2014) 17–27.

[7] J.C. Bruno, V. Ortega-López, A. Coronas, Integration of absorption cooling systems into micro gas turbine trigeneration systems using biogas: Case study of a sewage treatment plant, Appl. Energy. 86 (2009) 837–847.

[8] J.C. Ho, K.J. Chua, S.K. Chou, Performance study of a microturbine system for cogeneration application, Renew. Energy. 29 (2004) 1121–1133.

[9] E. Carpaneto, G. Chicco, P. Mancarella, A. Russo, Cogeneration planning under uncertainty. Part II: Decision theory-based assessment of planning alternatives, Appl. Energy. 88 (2011) 1075–1083.

[10] E. Carpaneto, G. Chicco, P. Mancarella, A. Russo, Cogeneration planning under uncertainty: Part I: Multiple time frame approach, Appl. Energy. 88 (2011) 1059–1067.

[11] M.J. Kim, J.H. Kim, T.S. Kim, The effects of internal leakage on the performance of a micro gas turbine, Appl. Energy. 212 (2018) 175–184.

[12] S.S. Talebi, A.M. Tousi, The effects of compressor blade roughness on the steady state performance of micro-turbines, Appl. Therm. Eng. 115 (2017) 517–527.

[13] F. Delattin, S. Bram, S. Knoops, J. De Ruyck, Effects of steam injection on microturbine efficiency and performance, Energy. 33 (2008) 241–247. http://www.sciencedirect.com/science/article/B6V2S-4PYMWKT-3/2/fa1c1fd7a6a719668d25ca1a76c45b26.

[14] W. De Paepe, F. Delattin, S. Bram, J. De Ruyck, Steam injection experiments in a microturbine – A thermodynamic performance analysis, Appl. Energy. 97 (2012) 569–576.

[15] W. De Paepe, M. Montero Carrero, S. Bram, F. Contino, A. Parente, Waste heat recovery optimization in micro gas turbine applications using advanced humidified gas turbine cycle concepts, Appl. Energy. 207 (2017) 1–12.

[16] W. De Paepe, M. Montero Carrero, S. Giorgetti, A. Parente, S. Bram, F. Contino, Exhaust gas recirculation on humidified flexible micro gas turbines for carbon capture applications, ASME Turbo Expo 2016 Turbine Tech. Conf. Expo. (2016).
[17] G. Lagerstrom, M. Xie, High Performance and Cost Effective Recuperator for Micro-Gas Turbines, ASME Conf. Proc. (ASME Pap. GT2002-30402). (2002) 1003–1007. http://link.aip.org/link/abstract/ASMECP/v2002/i36061/p1003/s1.
[18] M. Montero Carrero, W. De Paepe, J. Magnusson, A. Parente, S. Bram, F. Contino, Experimental characterisation of a micro Humid Air Turbine: assessment of the thermodynamic performance, Appl. Therm. Eng. (n.d.).
[19] W. De Paepe, M. Montero Carrero, S. Bram, A. Parente, F. Contino, Towards higher micro Gas Turbine efficiency and flexibility --- Humidified mGTs: A Review, J. Eng. Gas Turbines Power. (2017).
[20] P. Tsirikoglou, S. Abraham, F. Contino, Ö. Ba?ci, J. Vierendeels, G. Ghorbaniasl, Comparison of metaheuristics algorithms on robust design optimization of a plain-fin-tube heat exchanger, in: 18th AIAA/ISSMO Multidiscip. Anal. Optim. Conf., American Institute of Aeronautics and Astronautics, 2017.
[21] W. De Paepe, S. Abraham, P. Tsirikoglou, F. Contino, A. Parente, G. Ghorbaniasl, Operational Optimization of a Typical micro Gas Turbine, in: Energy Procedia, 2017: pp. 1653–1660.
[22] O.P. Le Maitre, O.M. Knio, Spectral Expansion, in: Spectr. Methods Uncertain. Quantif., 2010: p. 29.
[23] S. Abraham, M. Raisee, G. Ghorbaniasl, F. Contino, C. Lacor, A robust and efficient stepwise regression method for building sparse polynomial chaos expansions, J. Comput. Phys. 332 (2017) 461–474.
[24] A.M. DeGennaro, C.W. Rowley, L. Martinelli, Uncertainty quantification for airfoil icing using polynomial chaos expansions, J. Aircr. (2015).
[25] N. Ricks, S. Abraham, F. Contino, G. Ghorbaniasl, Sensitivity Analysis and Uncertainty Quantification for the Ffowcs Williams-Hawkings Equation, in: 23rd AIAA/CEAS Aeroacoustics Conf., American Institute of Aeronautics and Astronautics, 2017.
[26] N. Ricks, S. Abraham, F. Contino, G. Ghorbaniasl, Uncertainty quantification for the aeroacoustics of rotating blades in the time domain, Appl. Acoust. 139 (2018) 57–68.
[27] S. Abraham, P. Tsirikoglou, J. Miranda, C. Lacor, F. Contino, G. Ghorbaniasl, Spectral representation of stochastic field data using sparse polynomial chaos expansions, J. Comput. Phys. 367 (2018) 109–120.