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THE USE OF A GENETIC ALGORITHM TO DETERMINE THE OPTIMAL OPERATING CONDITIONS FOR A LOW-TEMPERATURE ORC SYSTEM

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Abstract. Organic Rankine Cycle (ORC) devices are systems that implement the basic Rankine cycle, but use an organic medium instead of water. These devices can use low-temperature heat, but it should be remembered that the achievable efficiency decreases as the source temperature decreases. Previous publications have shown that maximizing capacity, rather than efficiency, is the main goal of the ORC system. This can be achieved by establishing the correct operating conditions, while ensuring the correct mass flow of the working medium to each component. For instance, the expander must reach the required rotational speed. This work focuses on using genetic algorithms to determine optimal operating conditions and maximize capacity. A genetic algorithm was developed for a newly built ORC device, enabling determination of optimal operating conditions. The results were implemented in the device driver and validated experimentally, confirming that genetic algorithms can easily achieve the desired effect.

Keywords: ORC, energy efficiency, genetic algorithm, R600a, process optimization.

JEL Classification: Q42, Q55.

Introduction

The work and efficiency of devices based on Organic Rankine Cycles (ORCs) are dependent on several factors. These are: the temperature of the heat source, the temperature of the cooling source, possible mass streams of these sources, the type of working medium used, the efficiency of the heat exchangers used, the efficiency of the expansion machine, the efficiency of the generator and the efficiency of the pumps (Kajurek et al., 2019; Hasanzadeh et al., 2023; Rusowicz et al., 2019a; Rusowicz et al., 2019b). The idea of the operation of installations based on ORC cycles is reduced to the operation of the Rankine steam cycle (Figure 1), with the difference that the working medium is not water (as in a typical power plant), but organic or inorganic compounds characterized by a low boiling point (Lecompte et al., 2015; Lion et al., 2017). Water, despite many advantages, which include: high heat of phase change, high value of specific heat in the liquid phase, chemical stability in a wide temperature range, low viscosity, non-toxicity, non-flammability or availability, also has one particular disadvantage – high normal temperature boiling point, equal to 100 °C, which eliminates its practical use in low-temperature systems. The concept of low-temperature means that the upper heat source can have a temperature of 80–300 °C, which directly translates into the efficiency of the system (Mikielewicz & Mikielewicz, 2010; Laskowski et al., 2021; Lei et al., 2022). The efficiency of the system at the level of 5–10% means that the investment cost is very high due to the huge size of the heat exchangers compared to the amount of energy produced in the generator (Yu et al., 2021). Very similar situation can be meet for trigeneration and Phase Change Material (PCM) systems with low temperature heat source (Rusowicz & Ruciński, 2011; Grzebielec & Rusowicz, 2013; Łapka et al., 2020; Rolka et al., 2021).

The cycle shown in Figure 1 is implemented as follows. The waste heat is supplied to the evaporator of the ORC system, causing the concentration of the working medium to change from liquid to gas (line 3-4-5). Then, the gas of the working medium goes to the expansion machine, which cooperates with the electric generator. The gas flowing through the expansion machine loses pressure (line 5-6). Subsequently, the working gas flows into the regenerator exchanger, giving off heat – it cools down (line 6-7). Next, the working medium flows into the condenser (cooled by

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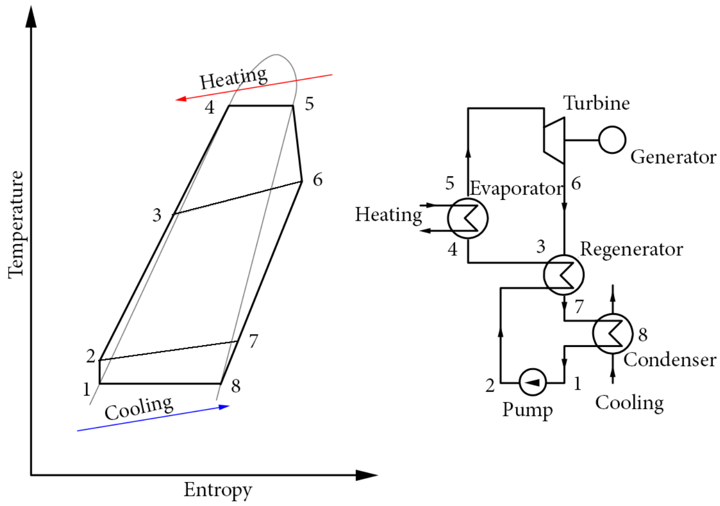

Figure 1. General principle of ORC system

water or air), where it undergoes a phase transformation and from the gas phase to the liquid phase (line 7-8-1). The process medium in the liquid phase flows to the pump, where its pressure increases from point 1 to point 2. Then, in the liquid phase, it flows through the regenerator, where it is heated from point 2 to point 3. Heated, it goes to the evaporator – thus closing the circuit.

In the literature, descriptions can be found of other cycles that can also utilise low temperature heat sources different from the one presented in Figure 1. They are:

– Cascading ORC;
– Supercritical Organic Rankine Cycle (SORC);
– Kalina Cycle;
– Trilateral Flash Cycle (TFC);
– Partially Evaporated Cycle (PEC).

The ORC device in the form of a cascade consists of two or more ORC cycles – each contains working medium with a different boiling point (Yu et al., 2022). The general principle of operation is that the heat from the condensation of the lower boiling working medium is used to vaporize the lower boiling working medium. Each part contains its pump and its expansion machine (Li et al., 2021). The cascade cycle is another step towards increasing the unit thermal efficiency of the whole cycle. Cascading ORC is a more flexible approach that involves using multiple stages of turbines with different working mediums and operating conditions. This allows for more fine-tuned optimization of the system to the specific heat source, resulting in increased efficiency and improved performance. Cascading ORC also offers greater flexibility in terms of the range of heat sources it can utilize. With the ability to use different working mediums and operating conditions, Cascading ORC can be adapted to a wider range of low-grade heat sources, such as waste heat from industrial processes, geothermal sources, or solar thermal collectors.

In a Supercritical Organic Rankine Cycle (SORC), the working medium is heated to a temperature and pressure above its critical point, where it becomes a supercritical medium with unique thermodynamic properties (Xu et al., 2020). The main benefit of using supercritical cycles is the ability to maintain a constant temperature difference between the heat source and the working medium in the heat exchanger. This allows to reduce exergy losses. And for a finite mass flow of the upper source, it allows to obtain larger capacity, because at the end of the process the heat source can reach a temperature close to the ambient temperature (Schifflechner et al., 2020). Due to the specific (high) operating parameters of the working medium, in the design of the cycle, it is required to use appropriate solutions resistant to high pressures and temperatures (for example, the use of centrifugal pumps due to high pressures or the use of heat exchangers with proper walls thickness).

The Kalina cycle is another special type of thermodynamic cycle, next to the ORC, used for the utilization of low-temperature heat sources, which is usually operated with the process medium ammonia-water (Zhang & Li, 2022). The cycle begins by heating up the ammonia-water mixture in the heat source, where the ammonia evaporates at a lower temperature than water. This means that more of the ammonia is vaporized. The vaporized ammonia-water mixture is then separated into two streams based on the ammonia concentration. The higher concentration stream goes to a high-pressure turbine. The ammonia-water mixture expands through the turbines, producing mechanical work that can be used to generate electricity. In the next step both streams are mixed in condenser, where it releases its heat to the cooling medium, which could be air or water. The condensed mixture is then pumped back to the boiler to repeat the cycle. Ammonia is used as the working medium in a Kalina cycle because of its favorable thermodynamic properties. Ammonia has a relatively low boiling point and a high latent heat of vaporization, which means that it can absorb a large amount of heat when it evaporates, and release that heat when it condenses. This makes it an efficient working medium for power generation (Akimoto et al., 2021).

A special case of an ORC is the Trilateral Flash Cycle (TFC). The difference between the classic ORC and TFC is that in the latter there is no classic phase change. The working medium is heated to the boiling point and then expanded in a two-phase expander. In such a cycle, there is practically no evaporator, because there is no evaporation process, as is the case of the standard ORC. The advantage of such a solution is the increased efficiency of heat exchange between the heat sources and the medium (due to operating all the time in the liquid region, the heat capacity of the medium does not change), which minimizes exergy losses (Rijpkema et al., 2017). Due to the fact that the expansion process takes place with the use of a two-phase mixture, the system requires the use of non-standard expansion machine solutions (e.g., Pelton turbine, where the medium is fed to the blades through a de Laval nozzle).

A modification of the above-mentioned TFC is the Partially Evaporated Cycle (PEC). As the name suggests, in this cycle the working medium is partially evaporated by the heat source. The assumption behind it is to maintain a compromise between the classic ORC and TFC. This cycle utilizes a larger heat source and a smaller amount of working medium compared to the standard ORC (Dawo et al., 2023).

All the above-mentioned variations on ORCs, with the exception of the Kalina cycle, are characterized by better efficiency when it is possible to significantly increase the temperature of the heat source. In the implemented project, the temperature of the heat source could be reduced by a maximum of 20 K, so it was decided to implement a regular ORC. The Kalina cycle in this research was rejected due to the toxicity of ammonia.

1. Methodology

The issue to be solved is to determine the correct operating parameters of the ORC system, depending on the variable parameters obtained on the cooling and heating sources. At the same time, remembering that in order to get the right voltage on the electric generator – and for this purpose, a rotational speed of 3000 rpm is required. To solve this issue there will be used genetic algorithm – it works in different way that neural network (Foresee & Hagan, 1997; Świrski & Milewski, 2009; Milewski & Świrski, 2009, 2011; Milewski et al., 2012; Torkan et al., 2022; Min et al., 2022).

1.1. Input data

The input parameters for the algorithm have been defined as follows:

$T_{in,HS}$ – temperature at the inlet to the evaporator of the upper heat source,

$T_{in,CS}$ – temperature at the inlet to the condenser of the cooling source.

1.2. Constant values

As constant values there were used:

$c_{p,HS}$ – specific heat of the heat source medium,

$c_{p,CS}$ – specific heat of the cooling source medium,

k_{evap} – heat transfer coefficient for the evaporator,

k_{cond} – heat transfer coefficient for the condenser,

A_{evap} – heat transfer area in the evaporator,

A_{cond} – heat transfer area in the condenser.

1.3. Optimized parameter

The constant volumetric flow $\dot{V}_{exp}$ through the expander was selected as the optimized parameter. As was mentioned the proper value should be 3000 rpm.

2. Genetic algorithm structure

For the genetic algorithm, individuals with chromosomes consisting of two genes were created.

$$Ind = f\left(p_{evap}, \dot{m}_{HS}\right), \tag{1}$$

where p_{evap} is process medium evaporation pressure, $\dot{m}_{HS}$ – heat source mass flow. For each individual, a set of thermodynamic data was calculated using input parameters and the CoolProp library for the Python programming language.

2.1. Individuals' reproduction

The correlation number 2 was used to calculate the finest probability of reproduction:

$$FP = \frac{Fi}{\sum_{i=1}^{i=n} Fi}, \tag{2}$$

where FP – finest probability, F_i – deviation from the expected value. Then, according to the rules adopted in genetic algorithms, it was randomly selected whether the individual will have children or not. The closer to the set value, the greater the probability of reproduction.

2.2. Crossing individuals

The selection of parents was randomized within the birth pool of individuals from the previous generation. Prevented having children drawn with themselves. As part of the built algorithm, a slightly non-standard solution for crossing was used, namely, the children of individuals were not created by combining half of the genes, but by determining the average value for the genes transferred by the parents. The same number of individuals were predicted in each generation.

2.3. Mutations

Within the proposed algorithm, mutations were also performed non-standard. In the first step, the mutation level was determined by experiment. It was determined at what percentage of mutations the result converges. The gene describing the flow of the medium in the upper heat source was mutated according to the following equation:

$$\dot{m}_{HS} = \dot{m}_{HS} \pm \left(0.2 \times random() \times \dot{m}_{HS}\right), \qquad (3)$$

on the other hand, the gene describing the pressure in the evaporator p_{evap} [Pa] was mutated (if present) according to the following equation:

$$p_{evap} = p_{evap} \pm \left(0.9 \times random(\ ) \times 1\,000\,000\right), \qquad (4)$$

where for the Python programming language, the random () function returns a value between 0 and 1.

3. Algorithm validation

One of the main issues for genetic algorithms is determining whether the algorithm performed correctly and "predictably". This is due to the fact that for:

- different numbers of individuals,
- different number of generations,
- different mutation levels
- the result may be different. At this stage of the project, these three parameters should be set so that the final results are convergent.

3.1. Determination of the number of individuals

The Figure 2 shows the results of convergence for different population sizes, for mutations at the level of 5% and the number of generations at the level of 200.

The conducted analysis shows that the results for 200 individuals are completely satisfactory. For too few individuals (20, 40, 60) in generation the average deviation from the expected value changes strongly between successive generations – which means that stable results are not achieved. In addition, the average value obtained is higher

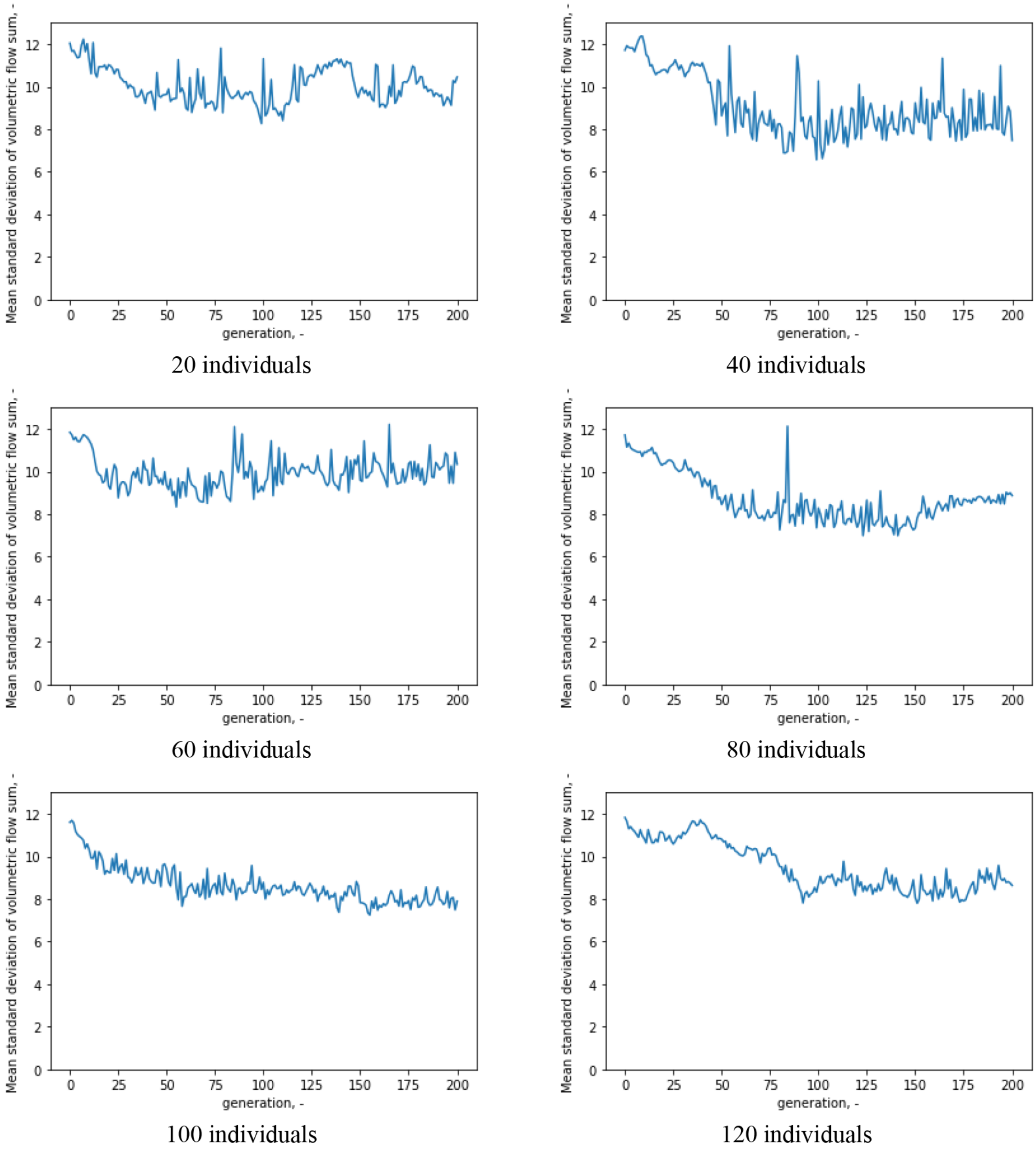

Figure 2. *To be continued*

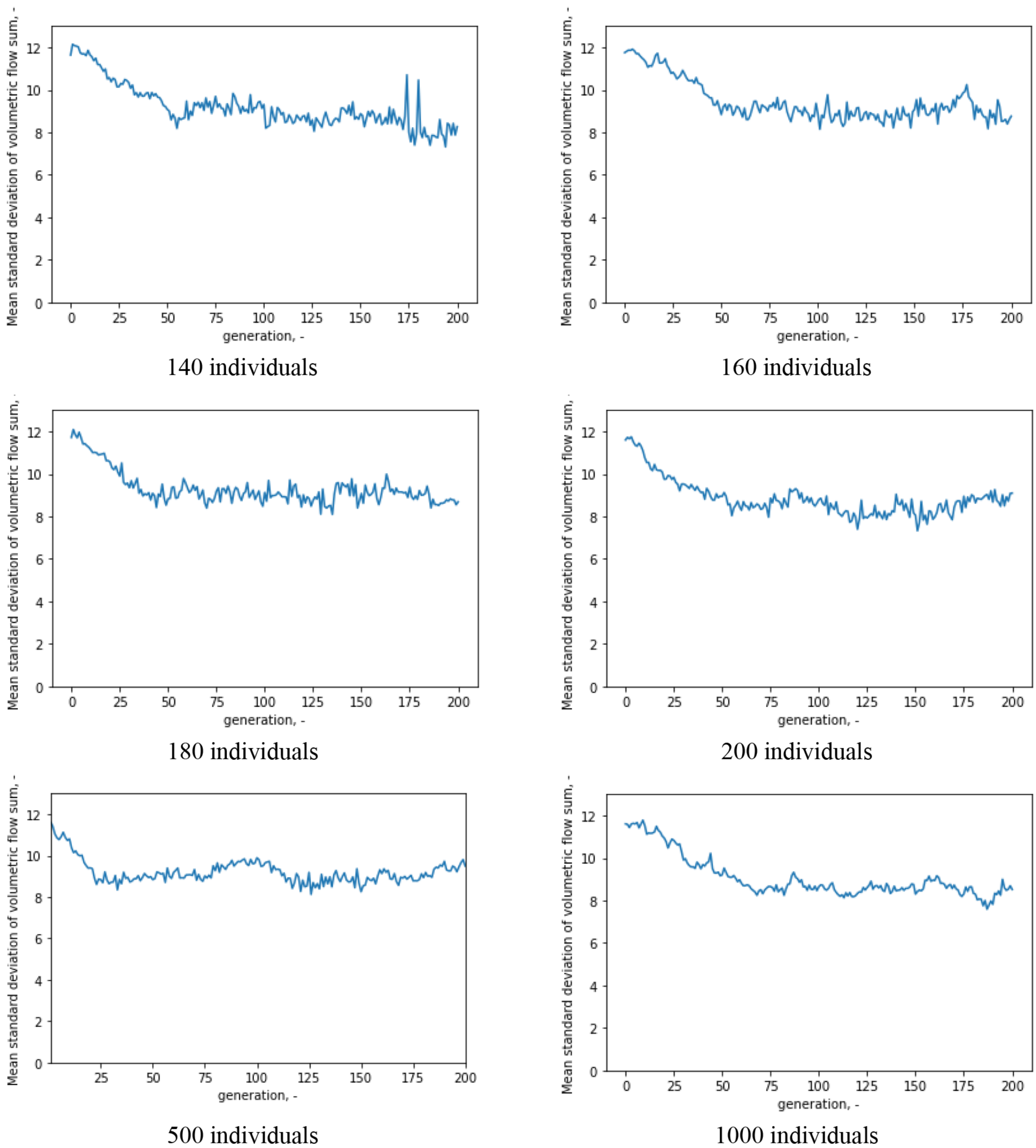

Figure 2. Determination of individuals amount in one generation

than for cases where we have more individuals. With a larger number of individuals, the average deviation is reproducible (the shape of line is very similar). However, with too many individuals (500, 1000), the differences between successive generations are getting smaller, which means that the mutation mechanism stops working. 200 individuals were defined as the last acceptable smoothing value of the obtained calculation results.

3.2. Determination of the number of generations

The Figure 3 shows the results for different number of generations, for 200 individuals in every generation and mutations at the level of 5%.

The results presented in Figure 3 show that the number 200 is the appropriate value for generations. For 200 generations, as the first number, it was noticed that the average deviation tends asymptotically to a constant value. For smaller numbers of generations, also at the end of modelling, a similar deviation value was obtained in the last calculation step. However, it was not possible to clearly determine whether this value would increase or decrease in the next generation. By increasing the number of generations from 200 to 500 the results were reproducible. Above the value of 500 there were often cases (as in the last graph Figure 3) that the results were unrealistic.

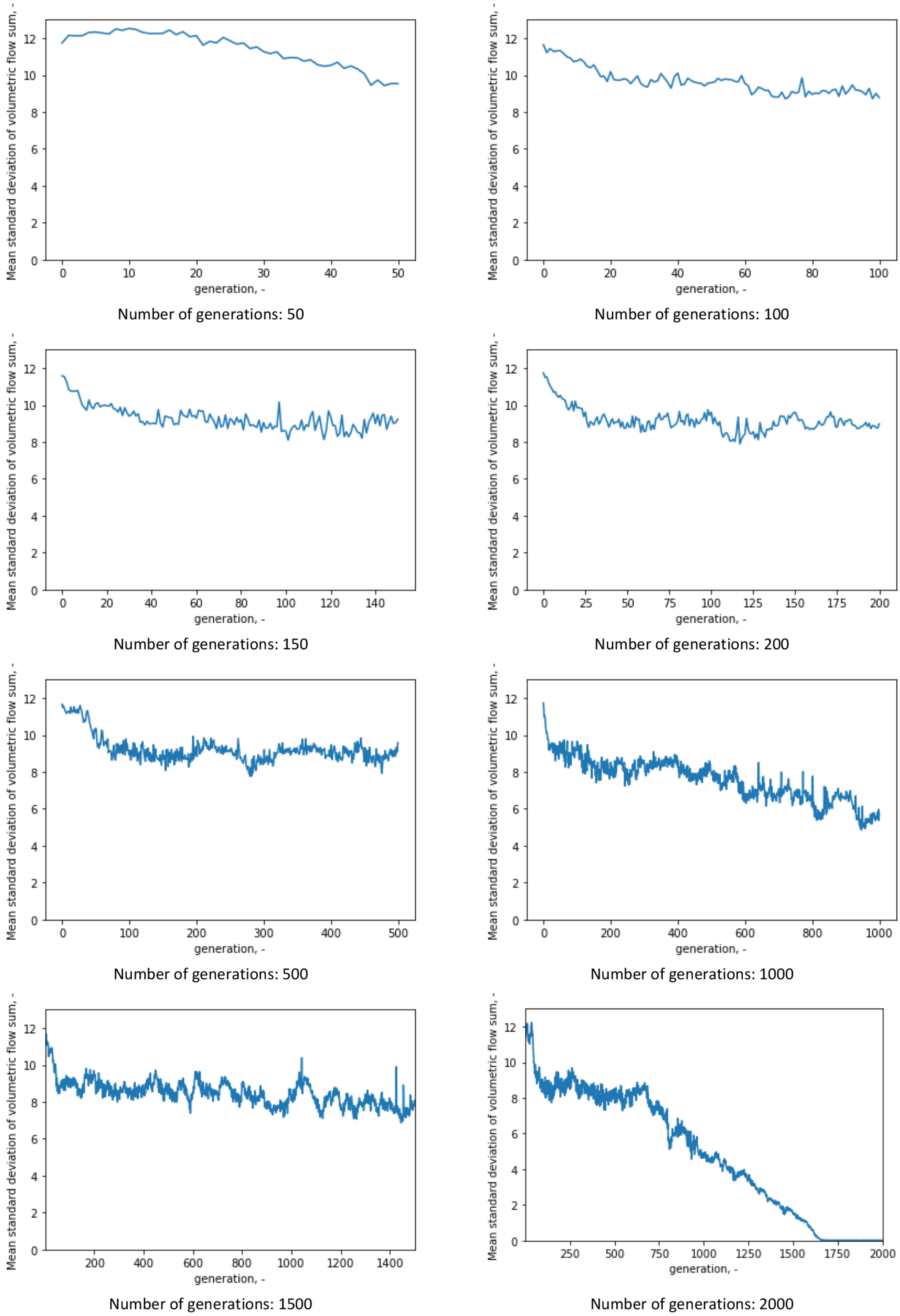

Figure 3. Determination of generations number

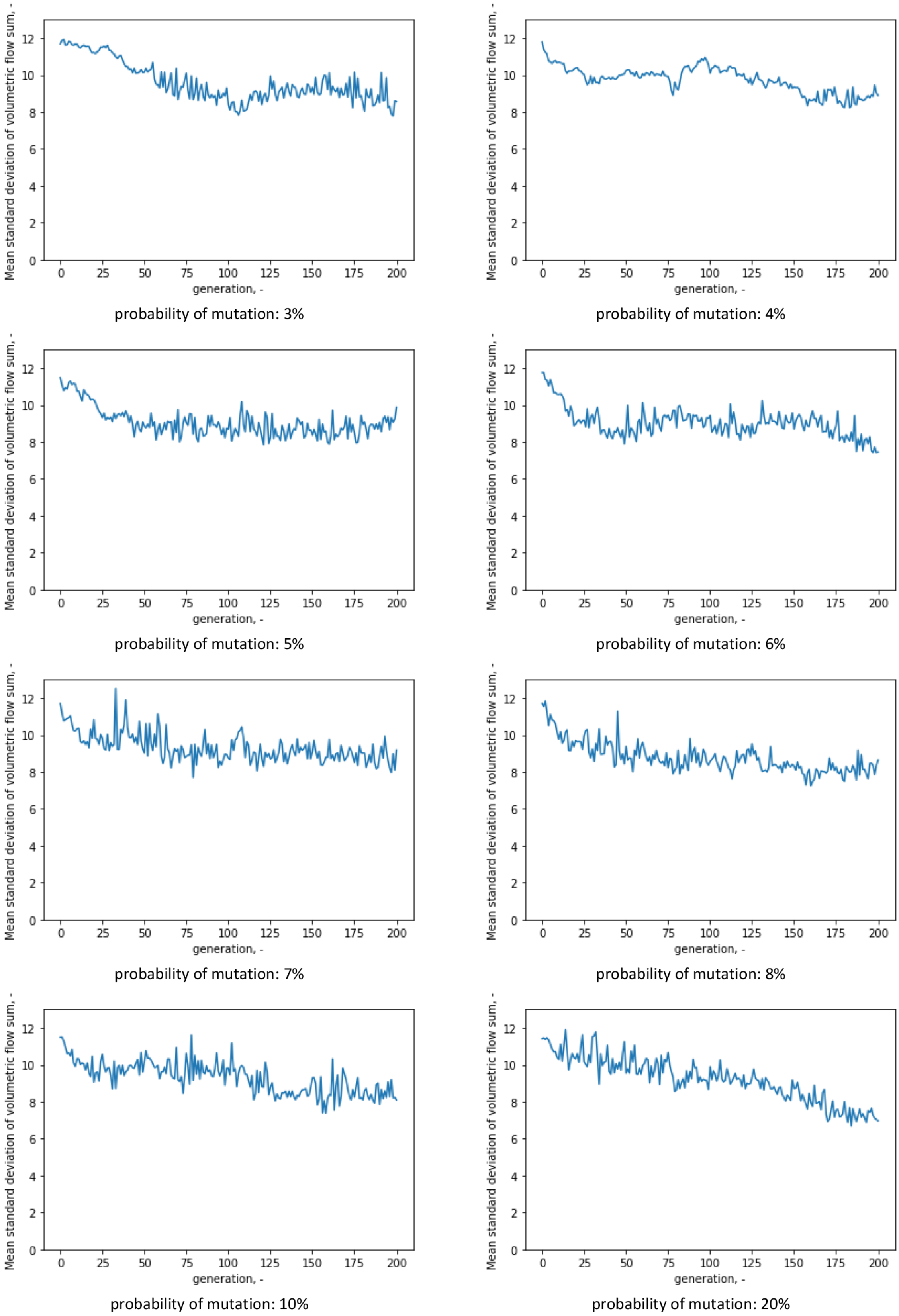

Figure 4. Determination of mutation level

3.3. Determination of the mutation level

The Figure 4 shows how the level of mutation affects the convergence of results. 200 generations and 200 individuals in each generation (according to previously calculated values) were used.

The presented results of the analysis show that increasing the range of mutations allows to reach equilibrium faster, while after exceeding a certain value, the results can either be unchanged or change in a completely different direction. It was decided to assume a mutation level of 5% of the entire generation for the analysis. The criterion for choosing this value was the speed of reaching a relatively unchanged value in subsequent generations. Both for a lower level of mutations and for larger ones, unstable results or convergence were obtained after a longer time (i.e., in later generations).

4. Results implementation

The values of the number of individuals in a generation, the number of generations and the degree of mutation specified in the previous chapter allow to determine the values of parameters that determine the actual optimal parameters of the device's operation (Figure 5).

According to Figure 5. There was obtained optimal evaporation pressure at level 14.25 bar(g) for R600a as a process medium, and $\dot{m}_{HS}$ equal to 2.8 kg/s.

5. Experimental results

As the part of the project, a test stand was built. The stand allows for the measurement of temperature and pressure at all characteristic points of the cycle. The scheme of the stand is presented in the Figure 6, while its view is presented in the Figure 7.

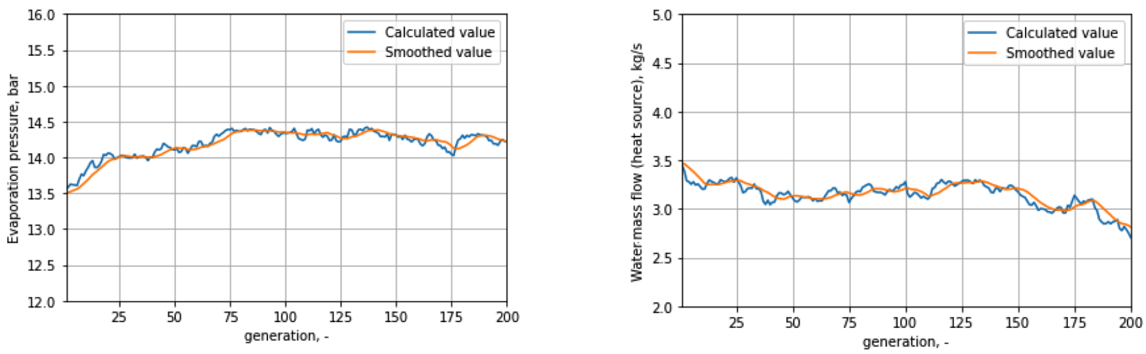

Figure 5. Average evaporation pressure (left side) and upper heat source mass flow (right side)

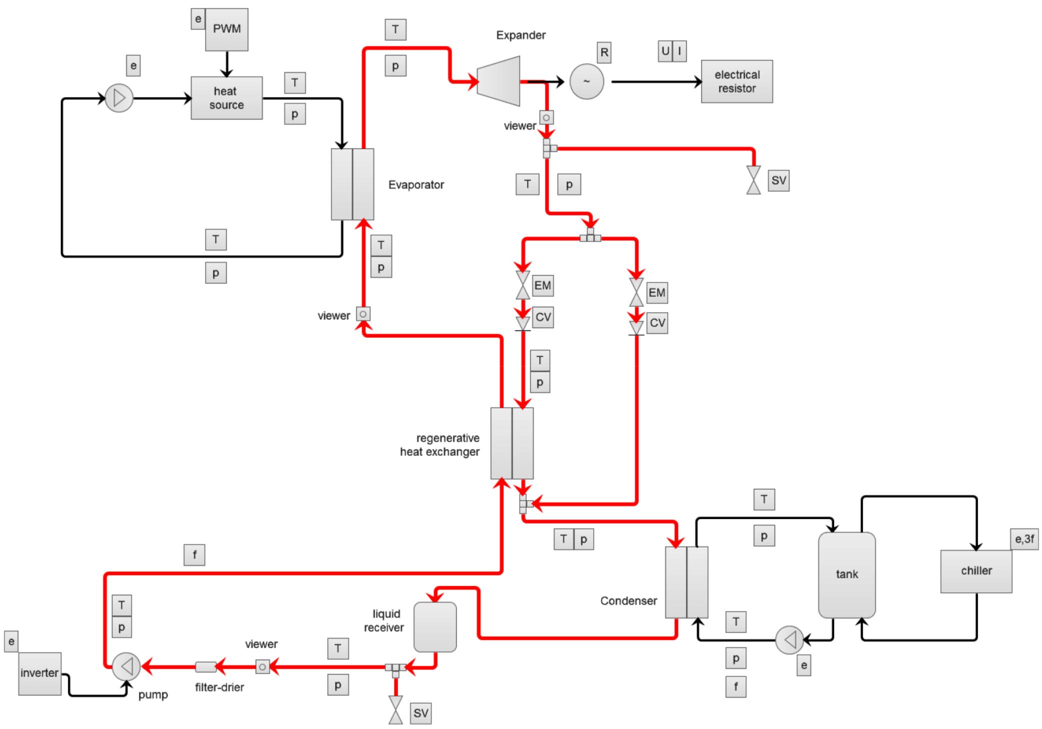

Figure 6. Experimental stand (T – temperature meter, pressure meter, e – electricity meter, f – flow meter, U – voltage meter, I – current meter; EM – electromagnetic valve, CV – check valve, SV – service valve)

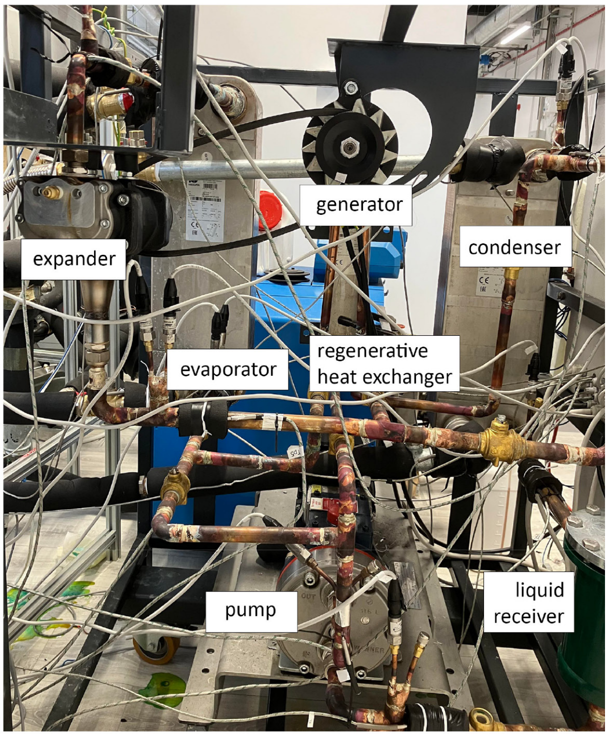

Figure 7. Experimental stand view

The test bench consists of a condenser (plate heat exchanger) connected to the cooling system, an evaporator (plate heat exchanger) connected to the heating system, an expansion machine in the form of a screw expander, and a regenerative heat exchanger (also plate heat exchanger). An open-type screw compressor was used as the expander – after checking its ability to work in the expansion mode. A pulley was mounted on the expander shaft, which allowed the energy to be transferred from expander to the electricity generator (Figure 7). The generator load was regulated by changing the electrical resistance in the electrical circuit shown in Figure 6. Changing the load allows to study the operating characteristics of the generator.

The stand allows to:

- cooler inlet temperature control;
- control of the stream flowing through the cooler;
- inlet temperature control in the heat source;
- control of the stream flowing through the heat source;
- control of the flow of the working medium;
- work with and without the regenerator;
- measurement of pressure and temperature at all characteristic points of cycle;
- changing the electrical load on the generator.

The results obtained in modelling part of project (Figure 5) were implemented in the laboratory device. According to the results of the algorithm, it was established:

- evaporating pressure,
- heat source medium flow through the evaporator.

Figure 8 presents a comparison of the device operation results for the original settings, which were determined to achieve maximum capacity on the generator, with the results obtained after introducing changes resulting from the applied genetic algorithm. The maximum capacity of the generator was first calculated in previous work to determine the evaporation pressure required to achieve a level of 10 bar(g). As a result of these changes, a significant increase in the efficiency of the isentropic expander was observed, which directly affects the capacity obtained at the expander.

Conclusions

As a result of analyzing and implementing the results in a real ORC device, it was possible to improve the device's operation by maximizing the isentropic expander efficiency from 36% to 45%. However, it is important to note that when using genetic algorithms, the analysis should be performed multiple times to ensure reproducibility of the results. For this purpose, the main part of the analysis was determining the optimal number of individuals in each generation and the appropriate mutation level. The results obtained were repeatable, leading to changes in the ORC system's operating parameters. Previous analysis had suggested that energy generation would be maximized at a lower pressure and a different speed of rotation for the generator. However, practical considerations dictated that the expander must rotate at 3000 rpm, which was the basis for the genetic algorithm.

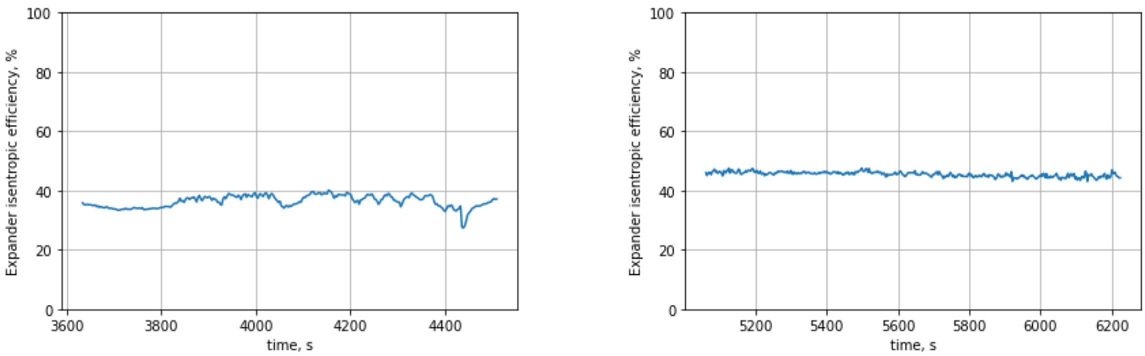

Figure 8. Expander isentropic efficiency before (left side) and after (right side) implementation of genetic algorithm

Implementing the results of the genetic algorithm was not entirely successful, as the parameters provided by the heat exchanger manufacturers differed from actual values. Consequently, only 11 bar was obtained in the evaporator instead of the expected 14 bar. Despite this, the ORC system's efficiency was still improved.

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