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## Abstract

In this project, a novel framework for CHP optimization is proposed. The objective of the study was to develop an automatic optimization tool based on the integration of IPSEpro simulation software and MATLAB programming environment. The data exchange between these components was organized via COM interface. An experimentally validated model of the commercial AE-T100 CHP unit was utilized.

The CHP was considered as a part of a grid. Therefore electricity trading possibility was taken into account. The system was extended to polygeneration by implementing a solar panel as an additional power source. The objective was to minimize the cost function, which consists of operational and capital investments costs, under a set of constraints. For solving the problem, the Genetic Algorithm was applied. As an addition to the study, two other algorithms (Particle Swarm Optimization and Differential Evolution) were also tested.

The applying a tool to real data was not considered in the project. However, an optimization was done for test data to show the performance of a developed framework. The test optimization was done for the 24-hours period in July and December, with different electricity and gas price profiles and various ambient conditions.

The obtained results were analyzed in details. It was shown that the proposed optimization tool provides appropriate results. It is flexible and has a good potential to be further extended and developed.

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## List of Abbreviations

AB	Auxiliary Boiler
ALGA	Augmented Lagrangian Genetic Algorithm
CCHP	Combined Cooling, Heat and Power
CHP	Combined Heat and Power
COM	Component Object Model
DE	Differential Evolution
EA	Evolutionary Algorithm
GA	Genetic Algorithm
HHV	High Heating Value
HRSG	Heat Recovery Steam Generator
LHV	Low Heating Value
LP	Linear Programming
mCHP	micro-CHP
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
O&M	Operation and Maintenance
PSO	Particle Swarm Optimization
PV	Photovoltaic

# Chapter 1

## Introduction

### 1.1 Background of the Problem

Combined heat and power generation is the simultaneous producing electricity and useful heat from the combustion of fuel. By integrating heat and power production, it is possible to use the energy source in a more efficient way and by that to reduce the environmental impact including CO<sub>2</sub> emissions (Thorin et al., 2015). CHP systems are aimed at improving energy efficiency, which is the dominating tendency in European energy policy (Cardona & Piacentino, 2005).

However, to provide the maximum efficiency of CHP plants, various design, planning and optimization approaches should be used. Optimizing the behavior of CHP unit is a complicated task for many reasons, including complexity, uncertainties, high dimensionality and non-linearity

In the project, the experimentally validated model of the AE-T100 CHP unit is considered (Ansaldo Energia, n.d.). IPSEpro software by SimTech is used as a simulation environment. It is a powerful, flexible and useful tool for simulating processes of thermal power generation. However, it does not provide a sufficient optimization power.

On the other hand, to achieve high computational speed and optimization efficiency the MATLAB environment for optimization code can be used.

Finally, the aim of this research study is to integrate MATLAB and IPSEpro to develop a framework for automatic optimization tool of our CHP unit operation.

### 1.2 Statement of the Problem

Considering the background of the problem described above, following research questions can be addressed in the project:

- 1) The possibility of developing an optimization tool based on MATLAB and IPSEpro is not investigated enough and needs to be studied and described in details; the similar issue has been considered e.g. in (Kvarnström & Dahlquist, 2005), but very limited;
- 2) Different scenarios for optimal operation of a CHP unit depending on technology, application and condition should be investigated;
- 3) Finally, there are different approaches to CHP optimization. A suitable optimization approach for existing CHP model should be selected and tested.

The integration of MATLAB and IPSEpro can be done via COM interface. It allows transferring data between applications in Windows with high speed and reliability of data exchange.

### 1.3 Objectives and Scopes of the Study

Following are the objectives and scopes proposed for this study:

- 1) To study the CHP model in IPSEpro
  - Studying the theory about CHP
  - Working with IPSEpro model
- 2) To integrate MATLAB and IPSEpro
  - Studying publications which are relevant to this problem
  - Studying MATLAB documentation
- 3) To choose a proper optimization approach
  - Studying the mathematical concepts of optimization algorithms
  - Studying optimization approaches suggested in papers and publications
  - Studying MATLAB documentation
- 4) To test an optimization tool
  - Developing a mathematical formulation of the problem
  - Investigating different applications and strategies for optimum operation of a typical CHP system
  - Collecting the necessary data for the optimization
  - Analyzing optimization results

## **1.4 Methods and Approach**

Several methods are used in the Project to achieve objectives listed above.

First of all, a literature survey is a method which helps to understand the theory and collect up-to-date information about the project issue, consider different approaches to solving the problem. Literature survey gives sufficient knowledge for understanding CHP model and selecting optimization algorithm.

Then, modeling of the process in the simulation environment (IPSEpro). The CHP model allows studying power generation process regarding equipment characteristics, working fluids parameters, CHP unit performance, etc. IPSEpro model is used to investigate how an optimization algorithm can be applied to CHP unit.

Lastly, programming in MATLAB is the method to solve two objectives. Firstly, MATLAB allows using COM interface to exchange data with IPSEpro. Secondly, MATLAB has a variety of optimization options which can be used to optimize CHP model.

## **1.5 Significance of the Study**

While energy policy works towards a cheap, sustainable and clean energy production, an optimization of generation systems is an important and promising research area. Considering the latest tendencies in this field, additional researches are required in the optimization of CHP units as a part of micro-grids and polygeneration systems.

The project contributes to the studying of new efficient optimization approaches for future sustainable energy systems. It proposes a tool which can be used in a variety of applications, including practical problems and academic purposes. The suggested framework has a great potential for development and extension, providing a possibility for further researches in this field.

## Chapter 2

# Literature Review

### 2.1 CHP Concept and Application

CHP generation is the simultaneous producing electricity and useful heating from the combustion of fuel. By integrating heat and power production, it is possible to use the energy source in a more efficient way. A simplified scheme of a typical gas turbine-based CHP system is illustrated in Figure 1. The main components of a CHP are discussed further in this section.

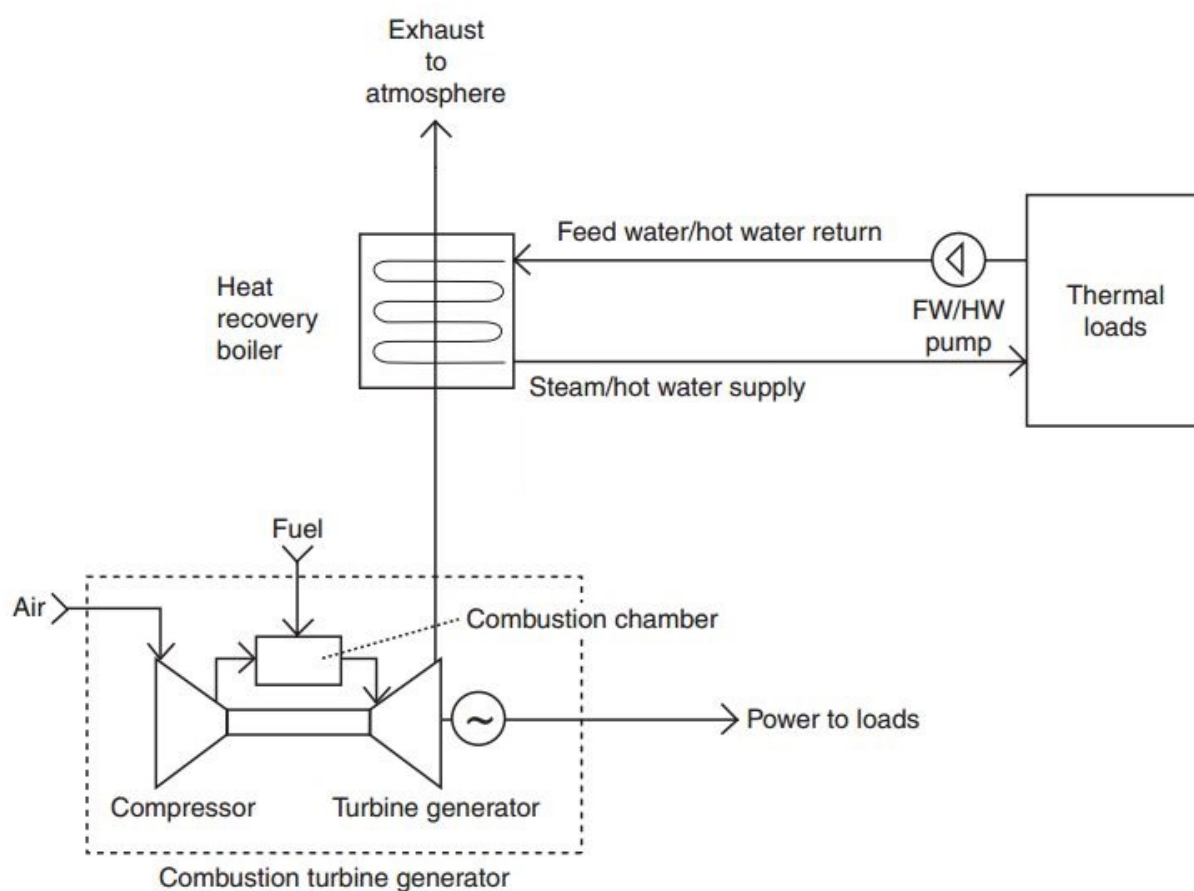


Figure 1. CHP system scheme (Meckler et al., 2010)

CHP production is on rising in many countries around the world. For example, the United Nations ESCAP Commission considers cogeneration as a solution of increase in energy efficiency and pollution control in Asia. The European Commission states that CHP is one of the very few technologies, which can make a significant short- or medium-term contribution to the energy efficiency issue in the European Union and can have a positive impact on the environment (Rong et al., 2006). Two dominant policy drivers will likely increase demand for CHP plants and assessments over the next decade: the increased availability of cheap natural gas supplies, and increased attention by energy users on the need to reduce operating costs. CHP demonstrates more

efficient consumption of primary fuel for producing heat and power than separate conventional methods, such as on-site boilers and power stations (ASHRAE, 2012). CHP plants generally convert 75-80% of the fuel source into useful energy, while the most modern CHP plants reach efficiencies of 90% or more. CHP plants also reduce network losses because they are sited near the end user (International Energy Agency, 2008). Energy efficiency of typical CHP compared to conventional plant is illustrated in Figure 2 (International Energy Agency, 2008):

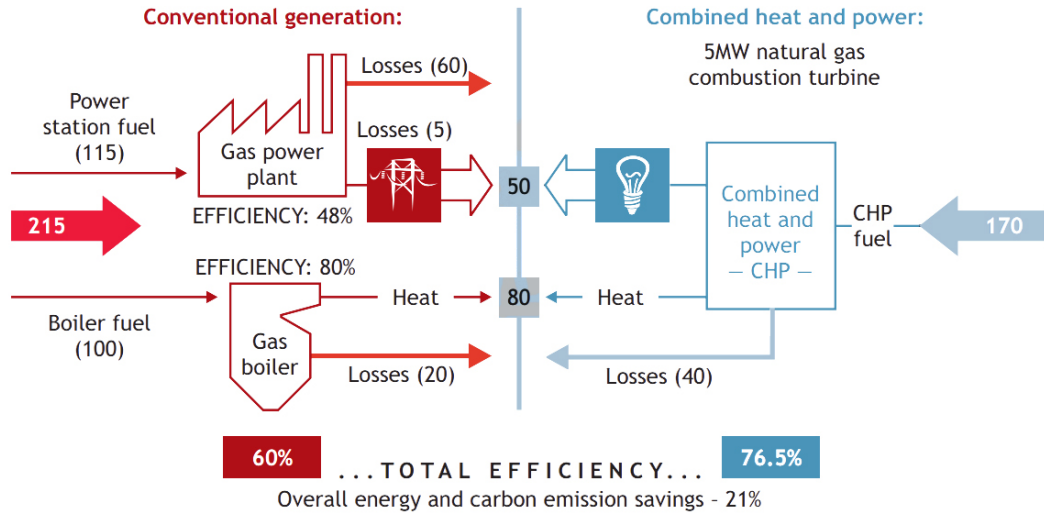


Figure 2. Energy efficiency of a CHP compared to conventional generation

The reduced use of fuel as a consequence of CHP will cause decreasing of atmospheric emissions (Breeze, 2005). For example, in the USA, CHP provides a 400 Mt annual reduction in CO<sup>2</sup> emissions, and in Europe, CHP has been estimated to have achieved 15% of greenhouse gas emissions reductions (57 megatons) between 1990 and 2005 (International Energy Agency, 2008).

The main components of most CHP systems are:

- 1) Prime mover.

There are different engine types which can be used as the prime mover to produce electric power. In this project, combustion gas turbine is considered as a prime mover. Combustion turbines are the most common type of prime movers and usually used in large facilities with electric loads from 1 MW to more than 100 MW. CHPs based on microturbines are called micro-CHP (mCHP). Microturbines are basically small-scale combustion turbine generators and are available in sizes up to approximately 250 kW (Meckler et al., 2010). Combustion turbines consist of an air compressor unit to increase combustion air pressure, a combination fuel/air mixing and combustion chamber (combustor), and an expansion power turbine section. Simple combustion gas turbines have thermal efficiency from 25 to 32% HHV (28 to 36% LHV). Recuperative combustion gas turbines have thermal efficiency levels of 35% HHV (39% LHV). Fuel is injected into the airstream and burned in the combustor, with exhaust gases reaching temperatures between 1600 and 2500°F. These high-pressure hot gases are expanded through a turbine providing the power for the air compressor and driving the load (ASHRAE, 2012).

Depending on the application, a CHP plant may consist of many components. The following are typical for many CHP:

- Fuel supply system(s);

- Gas compressors;
- Combustion air;
- Turbine inlet cooling;
- Exhaust systems;
- Exhaust heat recovery;
- Lube oil systems;
- Lube oil heat recovery or rejection;
- Engine jacket cooling water;
- Water treatment systems;
- Heat rejection systems such as cooling towers;
- Battery or compressed air starting system;
- Black start generator/backup power system;
- Plant and engine controls (Meckler et al., 2010).

### 2) Heat recovery boiler (e.g., Heat Recovery Steam Generator, or HRSG).

At the exit from the turbine, exhaust temperatures are between 850 and 1100°F. In general, the exit temperature of the heat recovery device should be no less than 250°F and more often should be above 300°F to avoid condensation and acid formation (Meckler et al., 2010). Depending on the initial exhaust temperature, approximately 50% to 60% of the exhaust heat can be recovered (ASHRAE, 2012).

Boilers are used to produce hot water or various steam pressures to provide the facility heating needs. Supplemental burner or duct burner can be used to allow more thermal energy to be added to the system (Meckler et al., 2010).

HRSGs are unfired boilers that produce steam using turbine exhaust gases. HRSGs can be equipped with economizers, superheaters, reheaters, and duct burners for improved steam production. The use of a duct burner combined with the HRSG has such advantages as extremely high duct burner efficiency (more than 90%), increasing the capacity of the HRSG and capability to fire the HRSG during those periods when the turbine is shut down (ASHRAE, 2015).

### 3) Power generation equipment and systems.

Criteria for selecting alternating current (AC) generators for CHP systems are: (1) system efficiency in converting mechanical energy into electrical output at various loads; (2) electrical load requirements, including frequency, power factor, voltage, and harmonic distortion; (3) phase balance capabilities; (4) equipment cost; and (5) motor-starting current requirements. For prime movers coupled to a generator, generator rotation speed is a direct function of the number of poles and the output frequency. For 60 Hz output, speed varies from 3600 rpm for a two-pole machine to 900 rpm for an eight-pole machine (ASHRAE, 2012).

Generators can be classified as either synchronous or induction.

Synchronous generators provide their own source of reactive power and can operate independent of or isolated from any external source of power. They are used in most of the modern CHP systems and are always found in larger applications (ASHRAE, 2015).

Induction generators are simple mechanisms; they are induction motors that are driven above their synchronous speed. Unlike synchronous generators, they do not have an own source of reactive power and, consequently, an induction generator can only operate when connected to some external reactive source. The reactive source is usually the utility grid (ASHRAE, 2015).

Besides main components described above, CHP system can include thermally activated components, facility thermal uses, emission control system, etc.

### 2.1.1 Combined Cooling Heat and Power

Except for electricity and heat, generated in CHP systems, Combined Cooling Heat and Power (CCHP) systems can also produce cooling from the same energy source. Therefore, CCHP systems are considered as an extension of CHP systems (Ersoz & Colak, 2016).

A typical CCHP plant includes five basic elements: the prime mover; electricity generator; heat recovery system; thermally activated equipment and the management and control system. A prime mover can be represented by steam turbines, reciprocating internal combustion engines, combustion turbines, micro-turbines, etc. Thermally activated equipment is a part of CCHP systems, needed to provide cooling or dehumidification. Thermally activated technologies include absorption chillers and desiccant dehumidifiers. Some existing systems also apply electric chillers, or engine-driven chillers integrated with prime movers (D. W. Wu & Wang, 2006).

### 2.1.2 CHP-based polygeneration systems

An important issue in sustainable and clean energy policy is increasing of renewable sources in energy generation. However, integration of non-dispatchable and fluctuating generators such as solar or wind systems to the grid is traditionally a complex engineering task. One of the approaches to providing stable and secure energy supply is to use distributed power generation systems which contain mCHP, solar (also called Photovoltaic, or PV) and wind power generators. According to that, a recent trend is an integration of CHP with renewables. CHP coupled with another energy source forms a polygeneration system. The optimization and economic dispatch of such polygeneration systems are an important and field of study (Azizipanah-Abarghooee et al., 2015; Ghaem Sigarchian et al., 2016; X. Ma et al., 2013; Widmann et al., 2017).

## 2.2 Optimization Approaches for CHP

A considerable amount of literature has been published on CHP optimization. These studies describe various approaches to the problem.

In mathematics or numerical analysis global optimization algorithms search the global optimum, which is a variable(s) of a function(s) to be minimized/maximized subject to some constraints. Such optimization problem can be formulated as follows (Safari, 2014):

$$\begin{aligned}
 & \min/ \max \quad f(x) \\
 & \text{subject to} \quad g_i(x) \leq 0 \\
 & \quad \quad \quad h_j(x) = 0 \\
 & \quad \quad \quad x \in S \subseteq \mathbb{R}^n
 \end{aligned} \tag{1}$$

where  $f(x)$  is the objective function;  $x$  is a decision variable(s);  $g$  and  $h$  are functions represents inequality and equality constraints, respectively;  $S$  is the search space domain.

### 2.2.1 Linear programming

There are a number of studies which suggest Linear programming (LP) methods for CHP optimization. LP is a powerful tool for solving optimization tasks with both objective function and constraints formulated as linear equations.

Lahdelma and Hakonen (2003) described a model of hourly CHP performance as an LP problem and developed an improved revised simplex algorithm called Power Simplex algorithm. A long-term CHP planning is decomposed into hourly models, which in turn can be formulated as an LP problem. The model considers one heat and one power balance equation as constraints. The objective is to minimize the energy production and purchase cost less possible sales income during the planning horizon. It is shown that a suggested Power Simplex algorithm provides an efficient solution of hourly CHP models and demonstrates high computation speed.

This algorithm was improved and extended by Rong et al. (2006) for multi-site CHP production. The Extended Power Simplex algorithm is formulated for multiple heat balances. Several test runs show that the problem can be solved efficiently.

Tibi and Arman (2007) described a mathematical LP model to optimize the operation of a CHP facility. The amount of the power required from each source and the parameters that represent the prices/costs are considered as decision variables. The objective of the model is to minimize the total annual amount of energy consumed. Heat and power demand is accounted in seasons, winter and summer. The possibility of selling electricity is also examined. The model was implemented in a real case. It is calculated that optimization of the energy cost and the installation cost allows saving significant capital resources.

A study by Cho et al. (2009) presented an energy dispatch algorithm for minimizing the cost of energy based on energy efficiency constraints for each component. The objective of this model is to minimize the overall cost of running the mCHP system over a time horizon that consists of  $T$  time periods to satisfy the total energy demand. The optimization problem is formulated as the minimization of the objective function which considers the cost of energy desired from the electric grid, power generation unit, supplementary heating device and the amount of energy sold back to the grid. The set of constraints controls that the flow of energy entering a node is equal to the demand plus the flow leaving the node. The algorithm has been applied to a real mCHP installation. It is shown that the algorithm provides the optimal cost throughout the simulation period.

Shaneb et al. (2011) presented a generic optimal online LP optimizer which has been developed for operating a CHP system. It is capable of minimizing the daily operation costs of such a system under a set of constraints. Three different simulation scenarios have been studied: the new feed-in tariff scheme, which has been introduced in the UK; the trade of electricity; the introduction of a carbon tax. The results have shown that the optimal online LP optimizer reduces operation costs in comparison with the conventional pre-determined operation strategies in all the scenarios.

The paper by Merkel et al. (2015) presented an optimization model for the capacity and dispatch planning of residential mCHP systems consisting of an mCHP unit, a peak load boiler and a hot



water storage tank. The objective function to be used is the sum of the total annual cost and revenues incurred for the mCHP system. The application of the model to the field data from the UK shows that economic savings up to 30% in total annual costs can be provided by optimal sizing and operation of the system.

### 2.2.2 Mixed Integer Linear Programming

A number of authors have considered mixed integer linear programming (MILP) models for CHP optimization. MILP is an LP problem in which some or all of the variables are required to be non-negative integers (Winston & Goldberg, 2004).

In a study conducted by Bojić and Stojanović (1998), the MILP method was used to control CHP energy system consisting of a boiler and a backpressure turbine. The LP objective function represents the minimization of the operating expenses.

Costa and Fichera (2014) also proposed the optimization tool based on MILP. The method is able to reach a double objective: minimizing the total operational cost of the micro-grid and finding the optimal size of the CHP. To validate the proposed model, the real data related to a hospital in the south of Italy have been taken into account. The obtained numerical results prove that the CHP optimal sizing and planning can provide a significant increase in energy performance and a notable cost saving.

Kopanos et al. (2013) considered modeling and optimization of the energy supply chain network based on residential-scale mCHP systems. The minimization of total expenses (including mCHP system's startup and operating costs as well as electricity production income) under full heat demand satisfaction was realized by using MILP framework.

Several studies proposed *Lagrangian relaxation* technique for solving MILP problems. Lagrangian relaxation is based on the observation that many difficult integer programming tasks can be considered as relatively easy problems complicated by a set of side constraints, which make them hard to solve. The method of Lagrangian relaxation is to replace the complicating constraints with a penalty term in the objective function (Fisher, 1985).

Thorin et al. (2005) developed a tool for long-term optimization of CHP systems using MILP and Lagrangian relaxation. It has been tested on a demonstration system based on an existing CHP installation. The tool can be applied to large CHP systems.

Sashirekha et al. (2013) presented a flexible algorithm to solve the CHP economic dispatch problem. The method uses Lagrangian relaxation on two optimization levels known as lower and upper levels. The upper level solves for the global constraints while the lower level deals with the optimization of individual units.

### 2.2.3 Mixed Integer Nonlinear Programming

In various studies of CHP optimization, an optimization problem was formulated as a nonlinear objective function with integer variables. The methodology for solving this type of problems is called mixed integer nonlinear programming (MINLP).

Ren et al. (2008) used MINLP model to minimize the annual cost of residential customer CHP plant, combining with a storage tank and a backup boiler. The model estimates the optimal CHP system capacities needed to meet electricity and thermal requirements.

The similar problem was considered by Beihong and Weiding (2006). The CHP sizing algorithm was formulated as MINLP problem with the constraints of energy demands, equipment performance characteristics and the energy relationships of the whole system. To prove the efficiency of the proposed method a numerical example of a gas turbine cogeneration plant in Shanghai is given.

In a study presented by Kim and Edgar (2014) MINLP approach for scheduling of a CHP plant was used. The framework includes practical constraints such as minimum/maximum power output and steam flow restrictions, start-up and shut-down procedures, and fuel limits. The results demonstrate that the optimized operating strategies can increase net incomes from electricity sales.

#### 2.2.4 Genetic Algorithms

Much of the research on optimization has been undertaken considering heuristic and metaheuristic techniques as an optimization strategy.

*Evolutionary Algorithms* (EA) are metaheuristic population-based optimization algorithms that are based on biology-inspired mechanisms like mutation, crossover, natural selection, and survival of the fittest to find an optimal set of solution candidates iteratively.

One of the most commonly used forms of EA is Genetic Algorithm (GA). At each step, the GA chooses individuals from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population goes toward an optimal solution. The GA can be applied to a variety of optimization problems that are not well suited for other optimization algorithms (MathWorks, n.d.-e).

The GA uses three main rules at every step to create the next generation from the current population:

- Selection rules select parents that contribute to the population at the next generation.
- Crossover rules combine two parents to form children for the next generation.
- Mutation rules apply random changes to individual parents to form children (MathWorks, n.d.-e).

Braun et al. (2016) investigated the multi-objective optimization of CHP plant. The authors proposed a GA strategy for modeling and optimizing a cogeneration process. The goal of the optimization was to minimize the fuel consumption and maximize both the generated electricity and the use of the heat. The results showed a significant increasing in the efficiency of the plant.

Manolas et al. (1996) applied GA for the optimization of the operation of a CHP plant, which produces electricity and steam at various pressure levels. A mathematical simulation model of the system has been developed taking into account the real properties of the main equipment. The GA was combined with the simulation model to solve the optimization problem under specified constraints.

Research by Ahmadi et al. (2012) deals with CHP system in a paper mill. GA is used for the optimization of the micro-turbine cycle in CHP unit. The design parameters of this cycle are compressor pressure ratio, isentropic compressor efficiency, gas turbine isentropic efficiency, combustion chamber inlet temperature, and turbine inlet temperature. Authors considered three

objective functions, including exergy efficiency, total cost rate of the system products, and CO<sub>2</sub> emission of the plant.

A paper by Yazdi et al. (2015) was based on the previously mentioned research. The GA was applied for multi-objective optimization. Three objective functions including exergy efficiency (to be maximized), the total cost of the product and environmental impact (to be minimized) and CO<sub>2</sub> emission (to be minimized) were considered.

Song and Xuan (1998) used GA to solve CHP economic dispatch problems. The research suggests an improved penalty function formulation to handle constraints effectively. The method has been tested and compared. The results showed its effectiveness.

Haghray et al. (2016) also used GA for economic dispatch problems, presenting real coded algorithm with the improved Mühlenbein mutation.

Huang and Lin (2013) applied evolutionary computing approach for CHP economic dispatch. GA here is used in combination with Harmonic Search method, which is a novel heuristic algorithm inspired from harmony improvisation in music. Authors prove that the suggested algorithm is capable of managing CHP optimization problem and provides high-quality solutions.

### 2.2.5 Particle Swarm Optimization

The particle swarm optimization (PSO) is a population-based stochastic algorithm for optimization which is based on social-psychological principles. It is similar to GA in that the system is initialized with a population of random variables. However, unlike EA, the PSO does not use selection. Particles interactions iteratively improves the quality of problem solutions with time (Eberhart & Kennedy, 1995; Kennedy, 2011).

Each particle keeps track of its coordinates in the search space which is related to the best solution (fitness) it has achieved so far. The “global” version of the particle swarm optimizer keeps track of the overall best value, and its location, obtained by any particle in the population. At each time step, the optimizer changes the velocity (accelerates) each particle toward its own best solution and global best solution (Eberhart & Kennedy, 1995).

To summarize, the PSO algorithm consists of three main steps:

- generating positions and velocities of particles;
- updating the velocities;
- updating the positions.

In the first step, position and velocity for each point are generated randomly within the upper and lower bounds of variables. In the second step, PSO calculates new velocities to move the particles to new positions. For calculation of the new velocities, PSO uses the best global position of particles in the current swarm and the best position of each particle over all previous and current steps, which are stored in the memory of each particle. PSO then employs these two values besides three coefficients  $\omega$ ,  $c_1$  and  $c_2$  to calculate new velocities for the next iteration, where:

- $\omega$  is the inertia factor, which is responsible for moving in the same direction as in the previous step;

- $c_1$  is the self-confidence factor, which is responsible for moving in the direction of the best position of a particle;
- $c_2$  is the swarm confidence factor, which is responsible for moving in the direction of the global best position (Safari et al., 2013).

Tichi et al. (2010) examined the optimal configuration of CHP systems, using PSO for minimizing the cost function for owning and operating various CHPs.

In the paper by Lingfeng and Chanan (2006) the stochastic model for CHP dispatch was formulated. An improved PSO is the utilized to optimize an economic CHP dispatch considering multiple conflicting objectives.

The problem of optimal economic operation of CHP system was considered by Z. Wu et al. (2011). CHP systems consist of a wind turbine, PV, fuel cell, waste heat boiler, gas boiler, battery, thermal and electric load. To solve this model, a PSO based on stochastic simulation is proposed.

Piperagkas et al. (2011) considered PSO algorithm for optimization of incorporated CHP and wind power units. Stochastic inequality constraints for the CO<sub>2</sub>, SO<sub>2</sub> and NO<sub>x</sub> emissions were taken into account.

Mohammadi-Ivatloo et al. (2013) implemented a novel time varying acceleration coefficients PSO algorithm to solve CHP economic dispatch problem. The method was tested in five different cases. The obtained results show the superiority of the proposed technique.

## 2.3 Optimization approaches for Polygeneration

Comodi et al. (2015) presented a paper methodology for sizing and managing hybrid systems with PV and micro-turbine is presented. Two management strategies were investigated to provide a defined day-ahead power output. The impact of the size of the PV plant on CO and NO<sub>x</sub> emission was considered. Natural gas savings and electricity specific cost reduction are assessed.

In the paper by Ghaem Sigarchian et al. (2016) an optimization of a hybrid micro-grid, consisting of PV modules and an LPG fueled engine-generator was considered. PSO algorithm was implemented. As a result, a high-quality design solution for an optimized micro-grid was determined with a relatively low computational cost.

Azizipanah-Abarghooee et al. (2015) proposed a stochastic multi-objective optimization framework for solving CHP economic load dispatch problem considering the stochastic characteristics of the wind and photovoltaic power outputs, customer's electrical and heat load demands. The system is based on chance constrained programming. Applying to 6 and 40 unit test systems, the ability of the suggested framework was confirmed.

L. Ma et al. (2016) deal with the energy management of micro-grids consisting of CHP and PV prosumers. Authors used a *Game Theoretic* approach. The efficiency of the model was verified via a practical example regarding determining micro-grid operation prices and optimizing net load characteristic, etc.

Piperagkas et al. (2011) proposed an extended stochastic multi-objective model for the economic dispatch of an energy generation system consisting on CHP and wind power unit. Inequality

constraints include the CO<sub>2</sub>, SO<sub>2</sub> and NO<sub>x</sub> emissions restrictions. The problem was solved via PSO technique. Results concerning minimum cost and emissions reduction were achieved.

## 2.4 Commercial Tools for Optimization

This section describes computer tools and systems which are designed to provide a possibility to simulate and optimize energy systems of various types and complexities. The review is focused on the commercial software which can be applied to CHP systems.

### 2.4.1 HOMER

HOMER is a user-friendly micro-power simulation and optimization tool developed in 1992 by the National Renewable Energy Laboratory in the USA. HOMER is capable of dealing with stand-alone and grid-connected power systems with any combination of wind turbines, PV arrays, run-of-river hydropower, biomass power, internal combustion engine generators, microturbines, fuel cells, batteries, and hydrogen storage, serving both electric and thermal loads (by individual or district-heating systems) (Connolly et al., 2010).

HOMER models a power system's physical behavior and its life-cycle expenses, which is the total cost of installing and operating the system over its life period (Lambert et al., 2006).

HOMER can solve three principal tasks: simulation, optimization, and sensitivity analysis. In the optimization process, HOMER simulates many different system configurations in search of the one that satisfies the technical constraints at the lowest cost (Lambert et al., 2006).

### 2.4.2 BALMOREL

BALMOREL is a partial equilibrium model for analyzing the electricity and combined heat and power industries. BALMOREL is implemented as a mainly linear programming optimization problem ("Balmorel," n.d.).

The tool can optimize investments in electricity and CHP technologies. The investments take into account specified restrictions, e.g., in relation to maximum investment addition per year, or maximum fuel available. Also, BALMOREL considers all costs within the energy system as well as SO<sub>2</sub> and NO<sub>x</sub> penalties (Connolly et al., 2010).

The developers of the BALMOREL project provides the report (Ravn et al., 2001) which investigate the power and CHP sectors in the Baltic Sea Region. It describes the motivations behind the development of the Balmorel model as well as the model itself. It is also mentioned that the solution of the model is done by solving an LP optimization problem.

### 2.4.3 Distributed Energy Resources Customer Adoption Model (DER-CAM)

The DER-CAM is an economic and environmental model. It has been in development at Berkeley Lab since 2000. The objective of the model is to minimize the operational expenses of on-site generation and CHP systems, either for individual customer sites or an mGrid (Berkeley Lab).

The DER-CAM system is able to:

- Find most economically effective configuration of generation and storage/dispatch that minimizes costs and CO<sub>2</sub> emissions;

- Consider load management options such as load shifting, load scheduling, load shedding;
- Consider force energy balance and technology behavior. (Berkeley Lab, 2012)

The tasks the DER-CAM is capable of solving can be divided into two branches:

#### 1) Investment and Planning DER-CAM

- Considers hourly loads of illustrative day-types based in historical or simulated data;
- Finds optimal investment strategy for a representative year, or investment plan up to 20 years;
- Investment decisions are based on a bottom-up approach.

#### 2) Operations DER-CAM

- Considers higher resolution time steps (1 min to 1 hour);
- Finds optimal dispatch of local energy resources on a week-ahead schedule;
- Utilize existing load information and weather forecasts to predict loads. (Berkeley Lab, 2012)

DER-CAM performs optimization procedure using MILP approach. The solution includes the capacity portfolio and economic dispatch. The system can handle a very large problem size (up to  $10^6$  variables and equations) (Berkeley Lab, 2012).

### 2.4.4 EnergyPLAN

EnergyPLAN simulates the operation of national energy systems on an hourly basis. EnergyPLAN is a model for analyzing the energy, environmental, and economic impact of various energy strategies. The main purpose is to model various options so that they can be compared with one another, instead of modeling one optimum solution based on defined pre-conditions. The EnergyPLAN is a deterministic model which can optimize the operation of an energy system defined by the user. The EnergyPLAN is able to provide an hourly-based simulation and to optimize the operation of a given system (Aalborg University, n.d.).

A number of researches have been done with EnergyPLAN.

The publication by Batas Bjelić and Rajaković (2015) models the achievement of the EU2030 energy policy goals. The authors use EnergyPLAN together with the generic optimization program to develop an optimal national energy master plan (as a case study, energy policy in Serbia was taken). CHP plants were a part of the scenarios considered in the study.

Lund and Münster (2003) analyze the national Danish electricity system using EnergyPLAN model. The purpose of the study is to propose optimization strategies, to manage the integration of CHP and wind power in the future Danish energy supply.

Østergaard (2015) provides a comprehensive review of the EnergyPLAN application, in particular to CHP systems.

Chen et al. (2010) consider thermoelectric generators application to CHP plants through the EnergyPLAN model.

### 2.4.5 MODEST

The MODEST Energy System Optimisation Model is a tool for calculating of how energy demand should be met at lowest possible cost. MODEST can be used for various kinds of energy systems, including different types of CHP plants. MODEST can consider:

- Energy supply and conservation;
- Short and long-term fluctuations of energy costs, demand, etc.;
- Energy supplies and plant capacities;
- Emission restrictions (Optensys Energianalys AB).

MODEST results include:

- Energy supply scheduling, times of day, week and year and in the long term;
- Optimal types, sizes and capacities for new equipment;
- Cash flow of energy costs and revenues for each year during the considered period;
- Annual and total expenses;
- Emissions (Optensys Energianalys AB).

MODEST was used as a simulation and optimization software in several research works. Danestig et al. (2007) investigated the potential for CHP generation in Stockholm, studying a model of the Stockholm district heating system in MODEST. The model has been developed to find the optimal way to meet the demand for heat and possibilities for electricity generation. In this case, the object of the optimization is to minimize system cost, which depends on fuel price, maintenance expenses, revenues from electricity, etc. The study has shown that CHP generation will play an important role in terms of satisfying increasing energy demand and reducing CO<sub>2</sub> emission.

The study by Henning (1998) describes the energy system optimization model MODEST, with a focus on heat storage and electricity load management of a CHP plant. MODEST may be used to find the optimal investments. The profitability of load management, considering seasonal, weekly and diurnal demand variations, is calculated.

In the research by Åberg et al. (2012) MODEST is used to construct a cost-optimization model in of a Swedish local district heating system considering power and heat generation on the CHP plant.

### 2.4.6 energyPRO

energyPRO is an advanced and flexible modeling software for complex techno-economic optimization and analysis of a variety of energy projects. energyPRO allows to model, optimize, simulate and analyze all types of energy plants. The program optimizes the operation of the modeled system taking into account all predefined conditions such as weather, technical properties of the different equipment, maintenance expenses, fuel prices, taxes, etc. The optimization methodology provides a fast and powerful tool for strategic energy planning, optimization of energy systems, the basis for investment decisions, system integration, etc. (EMD International A/S).

The energyPRO tool is specifically designed for a single thermal or CHP power plant investigation. It can model all types of thermal generation except nuclear, all renewable generation, and all energy storage units to complete the analysis. It also does not include transport

technologies. The analysis is performed with a one-minute time-step for a maximum duration of 40 years. Additionally, energyPRO considers for SO<sub>2</sub> and NO<sub>x</sub> penalties (Connolly et al., 2010).

Several papers about energyPRO implementation have been published. Lund et al. (2005) developed a Lithuanian energy strategy. The article analyses the replacement of boilers in the existing district heating supplies with CHP production. energyPRO was utilized to optimize the design and operation of CHP.

Streckiene and Andersen (2008) used energyPRO to find the optimal size of a CHP-unit for a German CHP-plant selling the electricity production at the spot market.

Fragaki and Andersen (2011) also considered CHP plant sizing problem in the IK energy market. CHP was modeled and optimized via energy PRO software.



## Chapter 3

# Methodology

### 3.1 CHP Model in IPSE-PRO

For testing an integration of MATLAB and IPSEpro and applying an optimization algorithm the model of mCHP in IPSEpro was used in this project. It is a steady state thermodynamic model which was developed and validated based on real-life data taken from the test rig. A comprehensive model library, which was used to build the model, is developed as a result of several simulation projects (Nikpey Somehsaraei et al., 2014). The screenshot from IPSEpro which demonstrates the model is shown in Figure 3.

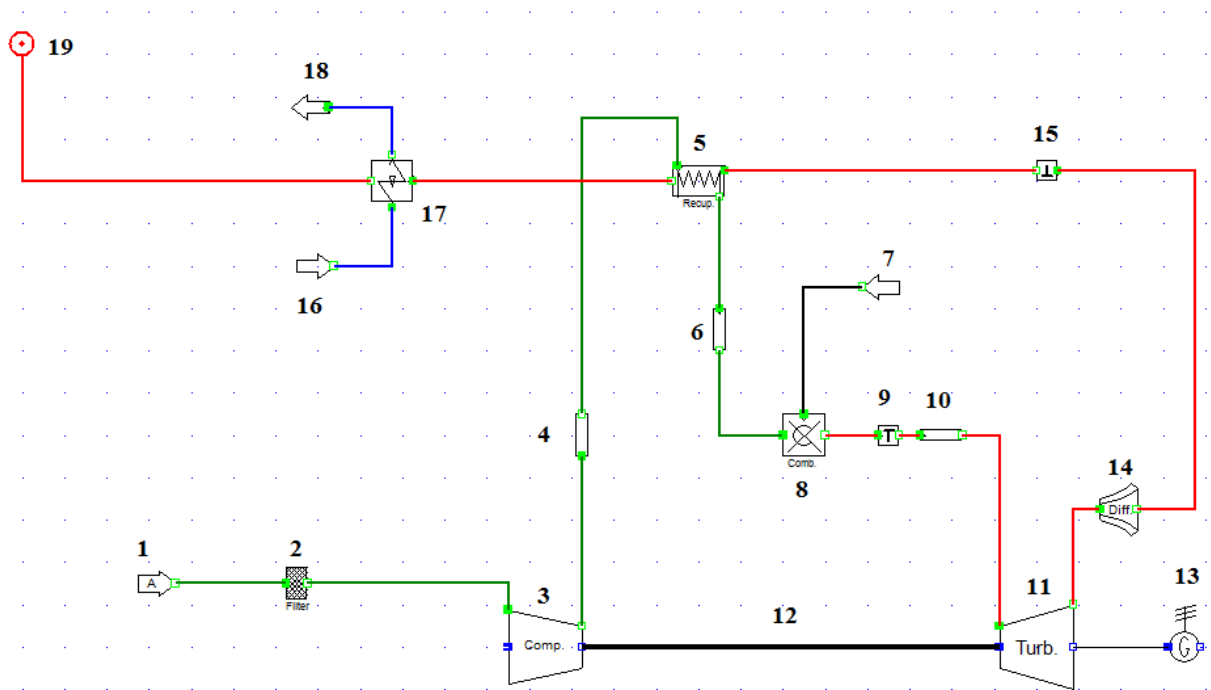


Figure 3. mCHP model in IPSEpro.

1 – The source of air under the ambient conditions; 2 – Filter; 3 – Compressor; 4, 6, 10 – Pipes; 5 – Recuperator; 7 – The source of fuel (Natural Gas); 8 – Combustion chamber; 9, 15 – Temperature control units; 11 – Turbine; 12 – Shaft; 13 – Generator; 14 – Diffuser; 16 – Water source; 17 – Heat exchanger; 18 – Water sink; 19 – Exhaust gas chimney.

A test rig is an mCHP unit based on the commercial AE-T100 power and heat generator. It consists of the Power module and an exhaust gas heat exchanger. This combination allows the AE-T100 to generate combined heat and power with very high overall efficiencies. A more detailed information given below is provided by the technical description of the installation.

The power module is based on a modular microturbine system AE-T100 (previously Turbec T100). It uses a radial centrifugal compressor to compress ambient air a high-speed generator to

generate electricity. The compressor and the turbine are placed on the same shaft as the generator. The electrical efficiency of the gas turbine is improved by a recuperator. The recuperator is a gas-to-air heat exchanger. The heat is transferred from the hot exhaust gases to the compressed air that enters the combustion chamber, where it is mixed with the fuel. The combustion chamber is of lean pre-mix emission type, providing low emissions of NO<sub>x</sub>, CO<sub>2</sub> and unburned hydrocarbons. The auxiliary systems in the Power module consist of the following parts:

- Lubrication system;
- Cooling system;
- Air intake and ventilation system;
- Fuel gas system including fuel booster;
- Buffer air system.

The exhaust gas-water countercurrent heat exchanger is used to produce hot water. The outflow water temperature depends on the inlet water conditions, temperature and mass rate.

The technical parameters of the T100 Power and Heat unit are summarized in Table 1.

*Table 1: Technical data for T100 P*

Parameter	Value
Maximum electrical output	100 kW
Electrical efficiency on maximum load	30%
Total efficiency on maximum load	80%
Ambient inlet temperature	-25°C to 40°C
Ambient inlet humidity	< 100 %
Compressor pressure ratio	4.5:1
Pressure in combustion chamber	4.5 bar
Turbine inlet temperature	950°C
Nominal turbine speed	70000 rpm
Turbine outlet pressure	nearly atmospheric
Turbine outlet temperature	approx. 650°C

The fuel used in the model is natural gas, the composition is shown in Table 2.

*Table 2: Fuel composition*

Component	Content [%]
CH <sub>4</sub>	78.73
C <sub>2</sub> H <sub>6</sub>	12.13
C <sub>3</sub> H <sub>8</sub>	1.95
CO <sub>2</sub>	6
N <sub>2</sub>	1.19

Based on the composition, the Low Heating Value (LHV) of the natural gas can be calculated using the following formula:

$$LHV = \sum LHV_i \cdot n_i, \text{ where} \quad (2)$$

$LHV_i$  - the Low Heating Value for a component;

$n_i$  - the mole fraction of a component.

For the given composition the LHV of the natural gas is found equal to 46063 kJ/kg

Ambient pressure, temperature and humidity are set to 1.013 bar, 15°C and 60%, respectively. Pressure and temperature of the fuel stream are set to 8 bar and 5°C. The pressure and temperature of the water on the inlet of the heat exchanger is 1.013 bar and 50°C. The temperature of the exhaust gas at the outlet of the chimney is 55 °C.

Simulation results for the model calculated for the maximum power load of 100 kW are listed in Table 3.

Table 3: Simulation results

Parameter	Value
Fuel mass rate	$6.95 \cdot 10^{-3}$ kg/s
Air mass rate	0.7635 kg/s
Thermal output	170.26 kW
Hot water temperature	68.7°C
Pressure and temperature at the outlet of the compressor	4.335 bar and 211.75°C
Pressure and temperature after the recuperator	4.219 bar and 611.2°C
Pressure and temperature after the combustion chamber	4.000 bar and 947.81°C
Pressure and temperature after the turbine	1.062 bar and 651.19°C
Pressure after and temperature the heat exchanger	1.014 bar and 55°C

Data illustrate that using recuperative cycle and heat exchanger allows utilizing a significant amount of exhaust gas thermal energy.

### 3.2 Integration of MATLAB and IPSEpro

The communication between the optimization and simulation programs can be organized using different methods. There are two techniques to achieve it:

1) One way is to use a file-based interface where the simulation software can provide the optimization software with simulation results using a file for data storage, and where the optimization software can provide the simulation software with input values. This method can be realized via the PSXLink option of IPSEpro (SimTech, n.d.). It allows transferring data from IPSEpro to Excel file and vice versa. The Excel file can, in turn, be manipulated from MATLAB to read and set data to the worksheet.

2) Another possibility is to use component-based software technology like Microsoft's Component Object Model (COM) where an interoperation between the simulation and optimization programs is accomplished.

The first approach is simpler, but quite ineffective and time-consuming, specifically when an expensive optimization task should be considered. The second is a more straightforward method for data exchange, where the information is sent directly to and from the different applications without using a file data storage. It provides faster and more reliable interaction. For this project, the second method based on COM technology is chosen (Kvarnström & Dahlquist, 2005).

According to (Microsoft, n.d.-a), “The Microsoft Component Object Model (COM) is a platform-independent, distributed, object-oriented system for creating binary software components that can interact.”

COM defines an object model and programming requirements that allow *COM objects* to interact with other objects. These objects can be parts of one process, other processes, and can even be on remote computers. COM is a binary standard that applies after a program has been translated into binary machine code. In a COM object, the access to an object's data is carried out exclusively through one or more sets of related functions. These function sets are called *interfaces*, and the functions of an interface are called *methods* (Microsoft, n.d.-a).

An important issue of COM is how *clients* and *servers* interact. A COM client is a program that makes use of COM objects, while COM objects that expose functionality for use are called COM servers (The MathWorks Inc, 2017). MATLAB can act as a client which interacts with contained controls or server processes or to be a computational server controlled by a client application program (Dahlquist, 2008). There are two main types of servers, *in-process* and *out-of-process*. In-process servers are implemented in a dynamic linked library (DLL), and out-of-process servers are implemented in an executable file (EXE) (Microsoft, n.d. ). In this project, MATLAB acts as a client and IPSEpro is an in-process server. Using MATLAB as a COM client provides a possibility to access IPSEpro applications that expose objects via *Automation*. Automation creates an environment where applications automation controllers (MATLAB) can access and manipulate (i.e. set properties of or call methods on) shared automation objects that are exported by Automation servers (IPSEpro) (The MathWorks Inc, 2017).

Before using COM object, its controls and servers must be registered. However, for IPSEpro they are registered by default (The MathWorks Inc, 2017). The registry contains data about all the COM objects installed in the system. When MATLAB creates an instance of a COM component, the registry provides the programmatic identifier (ProgID) of the component into the pathname of the server DLL or EXE. The ProgID is a unique string which identifies the COM object. It's needed to create a server (Microsoft, n.d.-b).

To create and manipulate objects in MATLAB the function *actxserver*, which runs a local Automation server, is used. The input to this function is *PSE.Application*, which is the ProgID of IPSEpro. The function returns a handle to the IPSEpro's main interface, which is used further to access the object's methods, properties or other interfaces (The MathWorks Inc, 2017).

To execute COM object's method, the function *invoke* is applied. The input of this function is an object's name, a method's name and other required parameters. Each method should be executed for a specific object. Table 4 contains the main methods which were used in the code and a short description of them.

Table 4: Methods used to operate IPSEpro from MATLAB

Method	Object	Description
<i>openProject</i>	handle of the method <i>actxserver</i>	Open an IPSEpro file with the model
<i>runSimulation</i>	handle of the method <i>openProject</i>	Runs a simulation in IPSEpro
<i>findObject</i>	handle of the method <i>openProject</i>	Refers to an element in the model. The name of the object should be specified. All objects are listed in “Object Manager” window in IPSEpro.
<i>findItem</i>	handle of the method <i>findObject</i>	Refers to a parameter of the object. The name of the parameter should be specified. All parameters of the objects are shown in the window after a double-click on the object’s name in “Object Manager”.
<i>inputValue</i>	handle of the method <i>findItem</i>	Assign a specified value to the parameter of the object.
<i>resultValue</i>	handle of the method <i>findItem</i>	Return a value of the parameter of the object. The handle of this function as a variable in MATLAB workspace, which contains this value.

This method allows organizing a real-time data exchange between MATLAB and IPSEpro, which is an important part of the project.

### 3.3 Optimization framework

#### 3.3.1 Extension to polygeneration system

To develop a sustainable energy system, it is essential to use renewable energy sources as a part of the power generation facility. In this project, it was decided to extend the system to polygeneration system and consider a PV panel as an additional power source. The strategy that was used is that the PV should produce as much power as it is possible depending on the available solar radiation. The rest part should be produced by CHP or bought from the grid.

The amount of energy which can be produced by the PV can be calculated according to the equation:

$$PV_{output} = A \cdot \eta_{PV} \cdot R \cdot PR, \quad (3)$$

where

$PV_{output}$  - energy output of the PV system [W];

$A$  - area of the panel [ $\text{m}^2$ ];

$\eta_{PV}$  - the efficiency of the PV panel;

$R$  - the amount of solar radiation on the panel [ $\text{W}/\text{m}^2$ ];

$PR$  - performance ratio coefficient for energy losses, which includes:

- inverter losses;
- temperature losses;
- AC/DC cables losses;
- losses due to dust, snow, etc.;
- other losses.

The parameters of PV were assumed to be the following:

$$A = 350 \text{ m}^2;$$

$$\eta_{PV} = 20\%;$$

$$PR = 0.75.$$

### 3.3.2 Problem formulation

In this project, a short-term operation planning was considered to test the integrated optimization tool. The aim of the optimization was to develop an optimal operational strategy for the 24-hours period. The CHP plant was considered to be installed within a grid; therefore, an electricity trading scenario was investigated. To demonstrate a flexibility of the proposed optimization tool, different profiles for power and thermal load, electricity price and gas price were considered. The detailed description of this data is given in the next section.

It was assumed for the test case that three CHP units are installed on the plant. The electricity can be bought from the grid and sold to the grid. A back-up conventional auxiliary boiler (AB) was considered to be used as an additional heat source. The AB is described by the following energy balance equation:

$$\dot{m}_f = \frac{\dot{m}_w \cdot \eta_b \cdot LHV}{\Delta h_w}, \text{ where} \quad (4)$$

$\dot{m}_w$  - water mass rate [ $\text{kg}/\text{s}$ ];

$\dot{m}_f$  - fuel mass rate [ $\text{kg}/\text{s}$ ];

$\eta_b$  - boiler efficiency;

$LHV$  - fuel low heating value [ $\text{kJ}/\text{kg}$ ];

$\Delta h_w$  - enthalpy difference for water [ $\text{kJ}/\text{kg}$ ].

It was assumed that the thermal efficiency of the boiler is 90%.

The cost of heat produced by the AB should be calculated and included in the objective function. From the equation (4) an amount of fuel burned can be expressed as a function of heat produced by the boiler:

$$m_f = \frac{Q_b \cdot 3600}{\eta_b \cdot LHV}, \quad (5)$$

where

$m_f$  - amount of fuel burned [kg];

$Q_b$  - heat produced by the boiler [kW].

The PV system, described in the section 3.3.1, was also considered in the optimization as a part of electricity generation system.

The objective of the optimization is to minimize operational costs at each point of the load while meeting the thermal and electricity load requirement. The results should give answers to the following questions:

- How many mCHP units should be operated at each time step?
- At what load mCHP units should be operated?
- When is it more efficient to buy electricity instead of producing it?
- When is it efficient to sell electricity to the grid?
- How much electricity is produced by mCHP units, PV panel, bought from the grid and sold to the grid at each time point?
- How much heat is produced by mCHP units and the AB at each time point?
- Is it efficient to use a conventional boiler and when it should be used?
- Is it efficient to use PV panel?
- What is the value of the cost function at each time point?
- What is the structure of the cost function?

The objective function can be expressed as follows:

$$\min F = \sum_{i=1}^n \dot{m}_{f_i} \cdot C_f \cdot 3600 + P_b \cdot C_{pb} - P_s \cdot C_{ps} + C_f \cdot \frac{Q_b \cdot 3600}{\eta_b \cdot LHV} + \sum_{i=1}^n (P_{CHP_i} \cdot C_{CHP}^{OM}) + Q_b \cdot C_b^{OM} + C_{cap} \quad (6)$$

$$s.t. \sum_{i=1}^n P_{CHP_i} + P_b + PV_{output} - P_s \geq P_d \quad (7)$$

$$\sum_{i=1}^3 Q_{CHP_i} + Q_b \geq Q_d \quad (8)$$

$$45 \leq P_{CHP} \leq 100 \quad (9)$$

$$0 \leq Q_b \leq 80 \quad (10)$$

where

- $F$  - cost function [€/hour];
- $n$  – number of CHP units;
- $\dot{m}_f$  - natural gas consumption [kg/s];
- $C_f$  - natural gas price [€/kg];
- $P_b$  - power bought from the grid [kW];
- $C_{pb}$  - price of electricity bought from the grid [€/kWh];
- $P_s$  - power sold to the grid [kW];
- $C_{ps}$  - price of electricity sold to the grid [€/kWh];
- $P_{CHP}$  - power produced by the mCHP unit [kW];
- $P_d$  - power demand [kW];
- $Q_{CHP}$  - heat produced by the mCHP unit [kW];
- $Q_d$  - heat demand [kW];
- $C_{cap}$  - capital investment costs [€/hour];
- $C_{OM}$  - operation and maintenance (O&M) cost [€/kW].

Equations (7) and (8) represent linear inequality constraints for the optimization which require that the heat and power demand should be satisfied.  $P_{CHP}$  is the input parameter for the IPSEpro model, while  $Q_{CHP}$  and  $\dot{m}_f$  are the output taken from the model. The detailed explanation of how data exchange is carried out is given in section 3.2. It can be noticed from (9) that  $P_{CHP}$  is required to be within 45 kW and 100 kW to avoid errors in IPSEpro. The boiler capacity in (10) is set to be in the range from 0 kW to 80 kW.

Capital costs are estimated for each device as an annualized investment. The process of annualizing is similar to pay off the capital cost of a system by a loan at a special interest of discount rate over the lifetime of the system (Teymourihamzehkolaei & Sattari, 2011). Then the annualized cost is recalculated for 1 hour. The formula is following:

$$(C_{cap})_{device} = \frac{C_{device} \cdot I \cdot (1+I)^{lifetime}}{(1+I)^{lifetime} - 1} \cdot \frac{1}{365 \cdot 24}, \quad (11)$$

where

- $C_{device}$  - the cost of the device;
- $I$  - the interest rate (was assumed equal to 3%);

The assumptions for the system's parameters are summarized in Table 5.



Table 5: Assumed equipment parameters

	<b>PV panel</b>	<b>AB</b>	<b>CHP</b>
Size	350 m <sup>2</sup>	1 unit	3 units
Efficiency	20%	90%	-
Capital cost	330 €/m <sup>2</sup>	6,000 €/unit	370,000 €/unit
Capacity range	0 – 45 kW	0 – 80 kW	45 – 100 kW (power)
O&M cost	-	0.002 €/kW	0.015 €/kW
lifetime	30 years	30 years	30 years

### 3.3.3 Data for optimization

#### *Load profiles*

Optimization in the project is done for two typical days in December and July. As far as the goal of current study is to develop and propose a novel integrated framework where applying the optimization tool for real data is not an issue, just sample profiles of electricity/heat loads and electricity prices were assumed. Nevertheless, all data are appropriate and based on comprehensive studying of relevant literature.

The power and heat load sample profiles are illustrated in Figure 4 and Figure 5. The pattern of load profiles is typical for an industrial, office or university campus building. The electrical demand is high during the working day approximately from 9 a.m. to 6 p.m. and low at night time. The magnitude is generally the same for summer and winter because less heating and lighting requirement in summer is compensated by the higher requirement for cooling. Heating load in winter is significantly higher than in summer. Winter heating load is higher at night time when an ambient temperature is lower and it's no people in the building, and lower at day time.

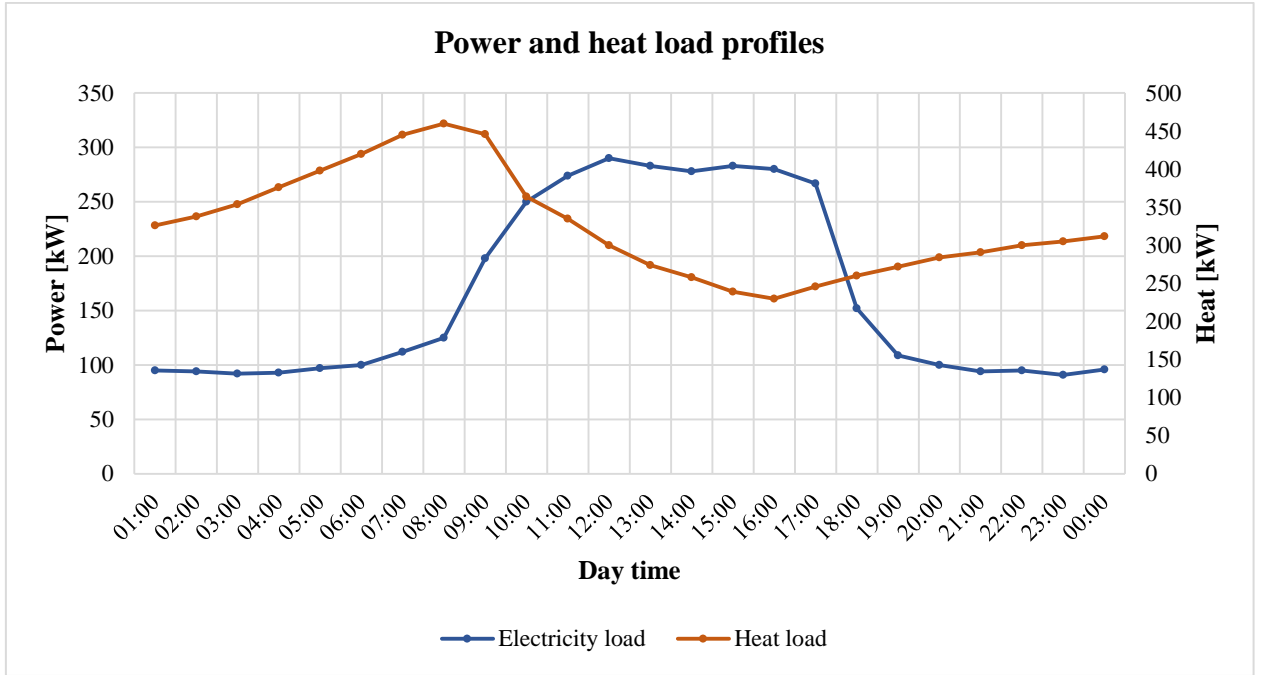


Figure 4. Load profiles for December

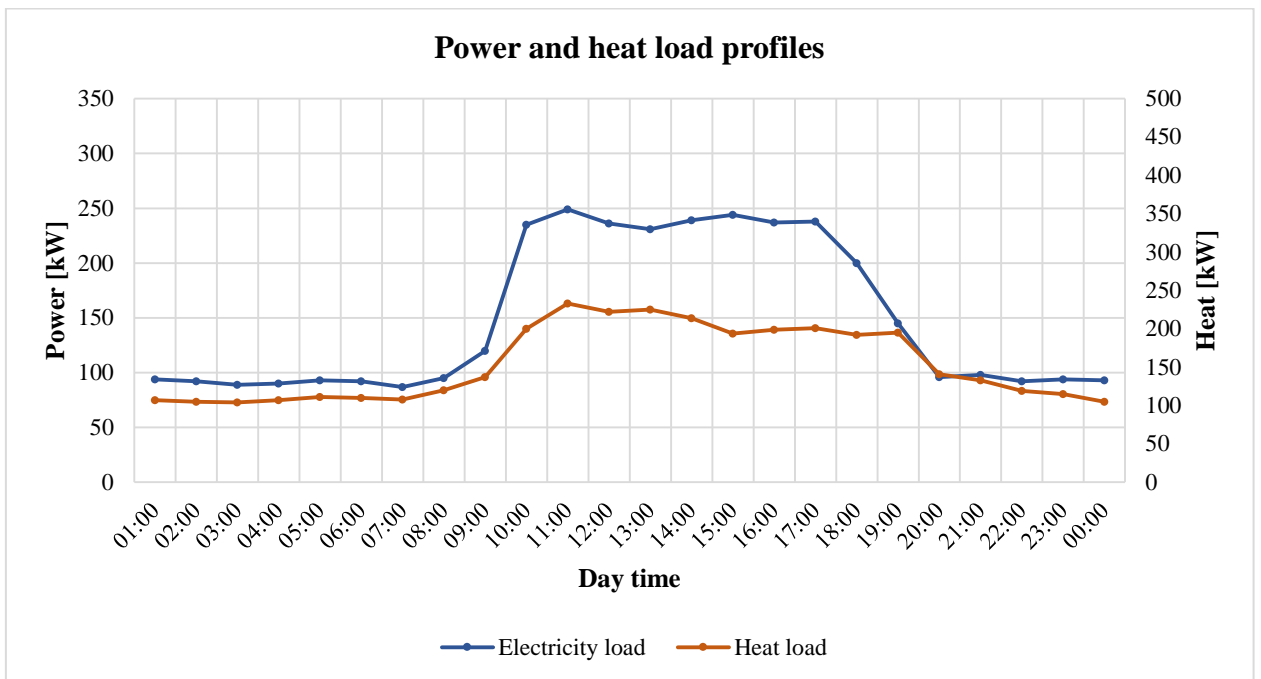


Figure 5. Load profiles for the 15<sup>th</sup> of July

**Natural gas prices**

The price of natural gas is considered to be constant during a 24-hour period because according to a contract a price can be either constant or linked to a price on the spot market and calculated on a daily basis. It even could be zero in case the government’s incentive for application of CHP is also in place). However, seasonal variations are taken into account. There are a lot of factors that influence the natural gas market, but the seasonal difference in gas demand is one of the most important.

Numbers of analytical researches (Fladmark & Grimstad, 2013; Zaccardi, 2017) report that July and December represent a relatively low and high gas price, respectively. The curve in Figure 6 represents the gas spot prices on the *NetConnect Germany Virtual Trading Point* in 2016 (in €/MWh). Based on the data from this figure, the gas price was assumed to be 12 €/MWh for July and 16 €/MWh for December.



Figure 6. Spot price of natural gas in Germany

### Electricity prices

Electricity prices estimation is based on the data from (Fraunhofer Institute for Solar Energy Systems ISE, n.d.). It is a web-resource which provides extensive information about electricity production, load and spot prices in Germany. The spot prices graphs in Figure 7 and Figure 8 demonstrate that the electricity price is varying during a day with peaks at approximately 10 a.m. and 8 p.m. The pattern is the same for both December and July, but the price is higher in December.

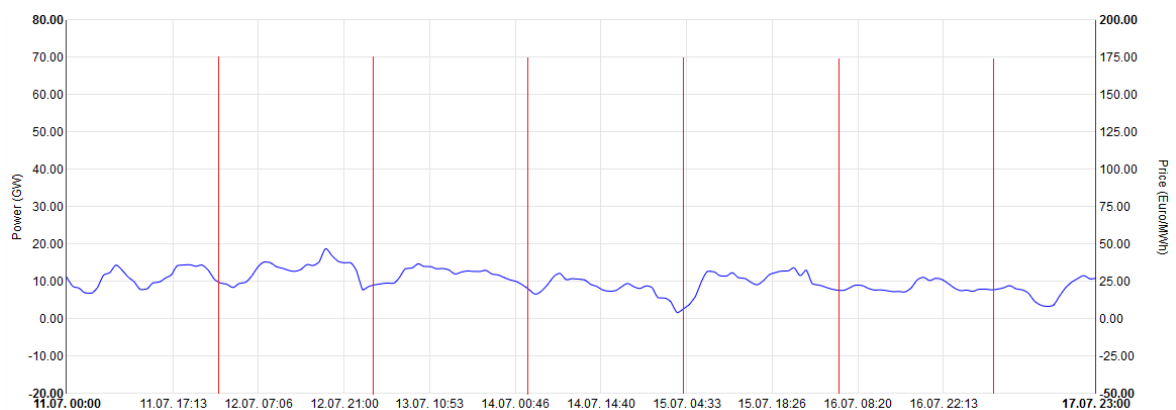


Figure 7. The spot price of electricity in July 2016 (Fraunhofer Institute for Solar Energy Systems ISE, n.d.)

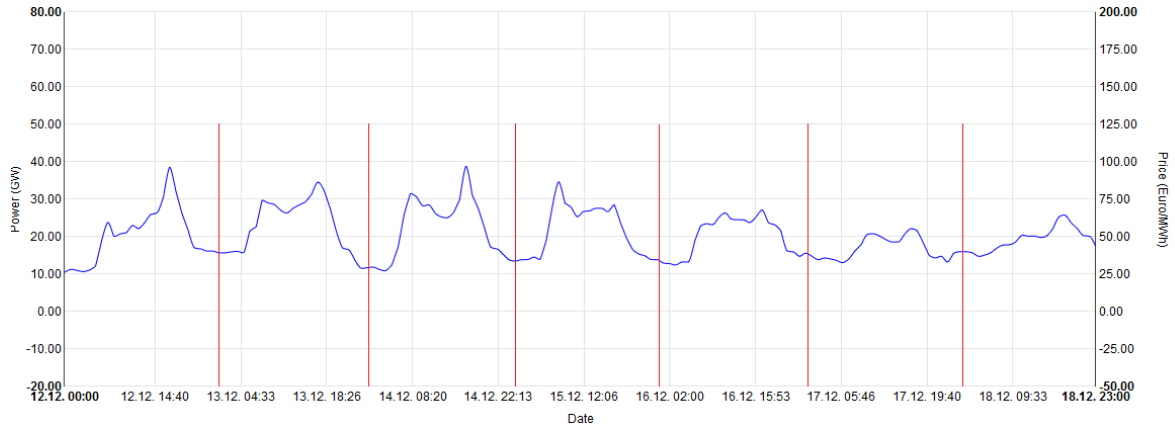


Figure 8. The spot price for electricity in December 2016 (Fraunhofer Institute for Solar Energy Systems ISE, n.d.)

Prices for selling electricity to the grid and buying it from the grid are considered to be different, depending on the time of operation and applied energy market policies/regulations.

The price of electricity produced by the CHP is mainly a function of the gas price. For one CHP unit working on the maximum load of 100 kW the fuel mass rate is  $6.9539 \cdot 10^{-3}$  kg/s, when the ambient temperature is constant and equal to  $15^{\circ}\text{C}$ . Taking into account the LHV for the natural gas, it can be roughly estimated that producing 1 MWh of electricity consumes 3,277 MWh of natural gas. Depending on the gas price, it is 39.24 €/MWh for July and 52.32 €/MWh for December. This estimation is valid only if the fuel consumption is a linear function of power production, thus ambient conditions influence is not considered in this calculation.

The electricity prices data discussed above is summarized in Figure 9 and Figure 10.

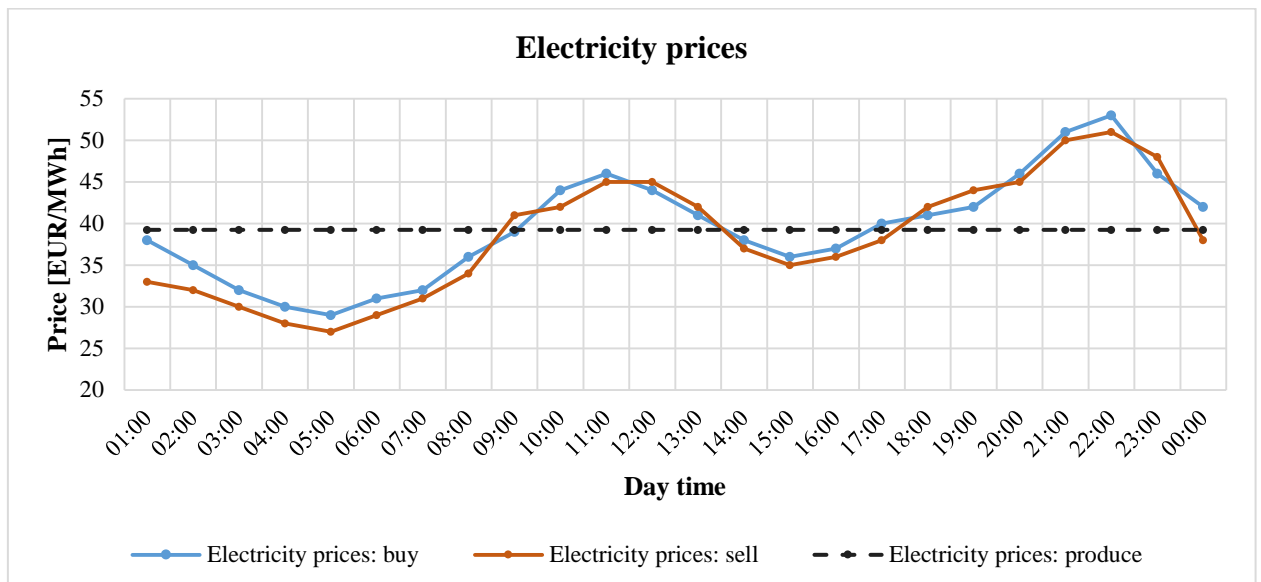


Figure 9. Electricity prices profile for July

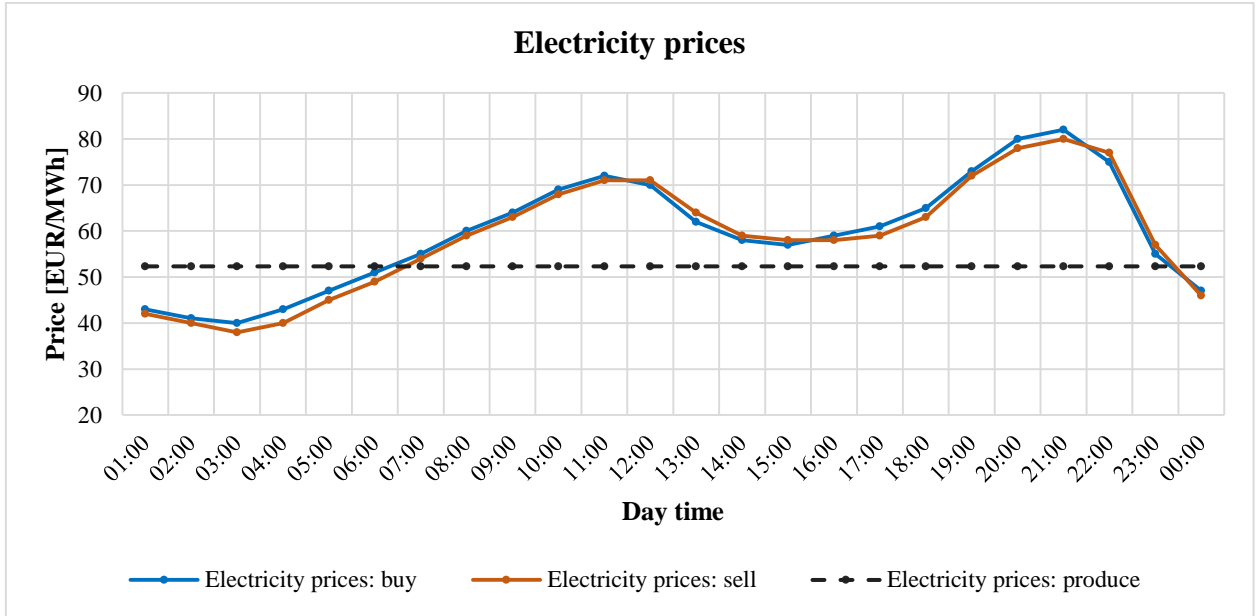


Figure 10. Electricity prices profile for December

### Solar radiation and ambient temperatures

To calculate the performance of the PV system, the amount of solar radiation available is needed. The necessary data were collected from the *Photovoltaic Geographical Information System*. It is an online map application, which provides a detailed estimation of the power output of solar panel, based on the available solar radiation. It allows to get an average hourly-based solar irradiation profile (in  $\text{W}/\text{m}^2$ ) for selected month, location and specified orientation and inclination of the PV panel. For this project, a central Germany location was chosen. The location is shown in Figure 11.



Figure 11. An assumed location of a proposed generation system

The PV panel was assumed to be oriented to the south and has an inclination of  $35^\circ$  to the horizon. Solar radiation profiles for July and December are shown in Figure 12.

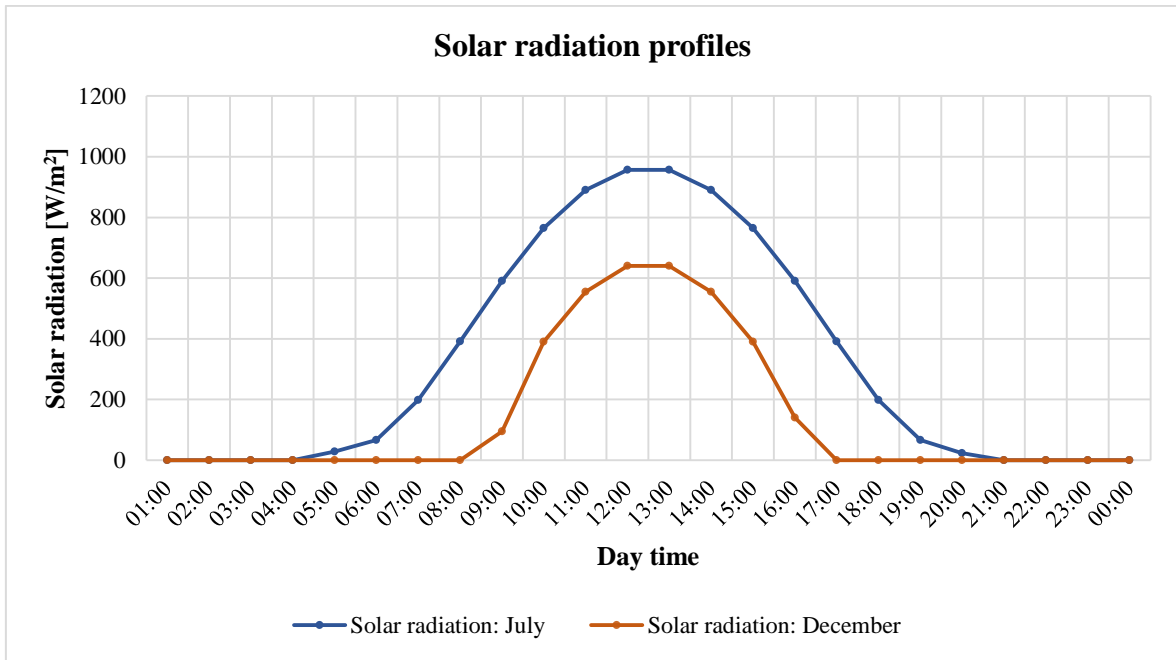


Figure 12. Solar radiation profiles

The information about air temperature was taken from the web resource [weatherbase.com](http://weatherbase.com), which provides a detailed archive data about weather conditions in specified regions. The temperature values were also collected for the central Germany location (see Figure 11) and summarized in Figure 13.

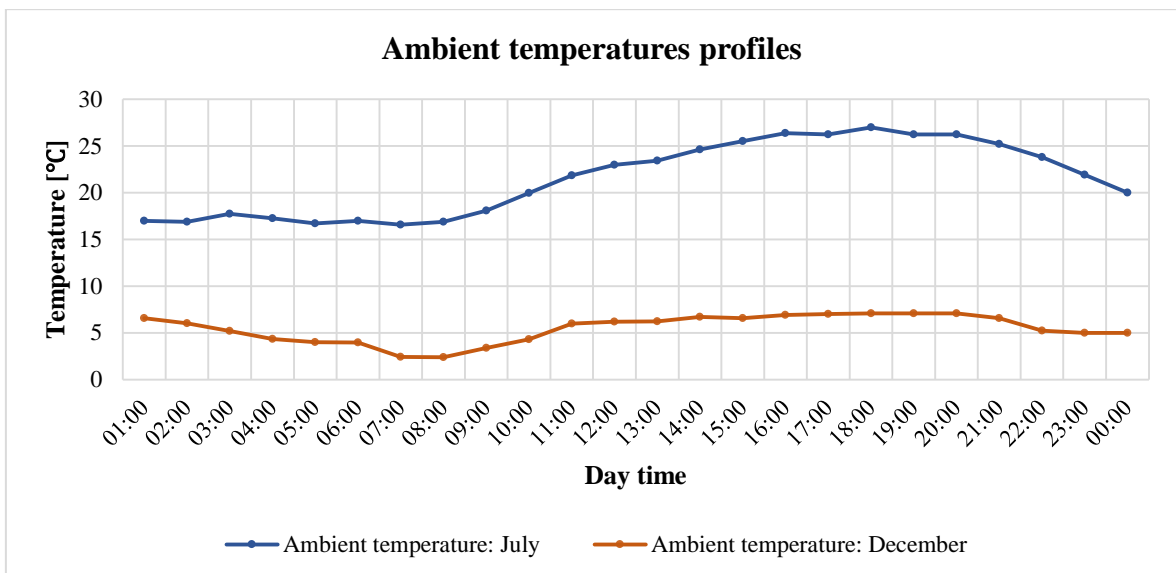


Figure 13. Ambient temperature profiles

### 3.4 Optimization algorithm

In this project, the GA was used. All results, presented in Chapter 4, were obtained via GA. As an additional study, the optimization was also run with PSO algorithm and Differential Evolution

(DE) algorithm. The results are compared in Section 4.6. The GA and the PSO have been briefly described in the subsections 2.2.4 and 2.2.5, respectively. In this section, the more extensive information about the GA and its implementation in MATLAB is given. The description of the DE, which was not discussed before, is also provided.

### 3.4.1 GA implementation in MATLAB

The GA works by updating the population in discrete iterations, called generations. It starts with an initial population, which acts as a set of parents from which a number of off-spring are produced, from which the next generation is created. These generations are produced by a set of genetic operators: mutation and crossover. As the generations increase, the fitness must increase. The fitness of any individual is its optimality in solving the problem. The algorithm keeps running until a predefined stopping criterion is met (Rowe, 2015; Shukla et al., 2010).

MATLAB Global Optimization Toolbox provides a function which implements the GA for a specified problem. The input parameter required by this function are:

- 1) The number of variables. The optimization vector is  $[P_1^{CHP}; P_2^{CHP}; P_3^{CHP}; P_b; P_b]$ , thus the number of variables is 5;
- 2) The fitness function, represented by the equation (6);
- 3) Linear constraints, represented by the equation (7);
- 4) Upper and lower bounds, represented by the equations (9) and (10);
- 5) Nonlinear constraints function, represented by the equation (8).

The main steps of the GA optimization are described below.

#### ***Initialization***

The GA starts with the generation of the initial population. It may be regarded as the random points in the highly dimensional search space (Shukla et al., 2010). The main questions related to the population: first its size and second the method by which its individuals are chosen. A too small population would not provide a sufficient exploring of the search area, while too large population would so decrease the computation time that no solution could be expected in a reasonable amount of time (Reeves, 2010). The default population size, used by the GA optimization solver in MATLAB, is 50 if the *Number of variables* is less than 5, and 200 otherwise. It can be set manually by the option *Population Size*. In this project, the default value was used, which equal to 50 because the number of variables does not exceed five (MathWorks, n.d.-a).

The initial population is nearly always assumed to be random. However, randomly chosen points do not necessarily cover the search space uniformly, and there may be advantages in terms of coverage if more sophisticated statistical methods are used (Reeves, 2010). MATLAB provides the ability to apply the option *Creation function* to choose one of the available initialization methods. For a problem contains linear/nonlinear constraints and upper/lower bounds MATLAB uses *Nonlinear Feasible population* function by the default. It creates a feasible initial population considering all bounds and constraints (MathWorks, n.d.-b).

MATLAB also allows a user to specify an initial population by the option *Initial population*. The initial population matrix must contain no more than *Population size* rows, and exactly *Number of variables* columns. If the matrix contains less than *Population size* rows, MATLAB generates the

remaining part of the population by the *Creation function*. In this project this option was used to increase the speed of the algorithm, defining the specified initial population which is expected to be close to the optimal solution.

### ***Scaling and selection***

The basic idea of the GA is the survival of the fittest. That is why the method to select the individuals with higher fitness to be parents for the next generation is needed. The fitness of the individual is defined by the value of the objective function in the search space point, which is the position of that individual. The possibility of surviving and being selected for the next generation is termed as the *expectation value*. Fitness scaling converts the fitness scores that are returned by the fitness function to values in a range that is suitable for the selection function (MathWorks, n.d.-b; Shukla et al., 2010).

MATLAB allows defining the scaling method by the option *Scaling function*. The simplest method of scaling is *Proportional*. In this method, the expectation value of the individual is in direct proportion to its fitness. Hence if an individual has an exceptionally large fitness value as compared to the others, it would have an exceptionally large expectation value be selected again and again in the selection process. This would make a few individuals occupy a prominent position in the genetic landscape at any generations. This can become a limitation in proportional scaling. The method which MATLAB uses by the default is *Rank* scaling. It removes the disadvantage of proportional scaling. Here the individuals get an expectation value based on their rank in the population. The rank of an individual is its position in the sorted scores. In this technique, the major factor is the relative score of the individuals and not the value of the score (MathWorks, n.d.-b; Shukla et al., 2010).

Selection options in MATLAB allow specifying how the GA chooses parents for the next generation. The original scheme is commonly known as the *Roulette-Wheel* method. It uses a probability distribution in which the selection probability of an individual is proportional to its fitness. The method called *Stochastic uniform* is similar to the Roulette-Wheel, but considered as more efficient and used by the default. It lays out a line in which each parent corresponds to a section of the line length proportional to its scaled value. The algorithm moves along the line in steps of equal size. At each step, the algorithm allocates a parent from the section it lands on (MathWorks, n.d.-b; Reeves, 2010).

### ***Creating the next generation***

At each step, the GA uses the current population to generate the children for the next generation. A group of individuals chosen by the selection function in the current population, called *parents*, who contribute their *genes* - the entries of their vectors - to their children. The GA creates three types of children for the next generation:

- Elite children are the individuals in the current generation with the best fitness values. They are automatically passed to the next generation. The option *Elite count* specifies the number of individuals that survive to the next generation. The default value is 5% of the population size;
- Crossover children are the individuals created by the function, defined by the option *Crossover function*. The crossover operator used in this project is *Intermediate*. It is used



when the problem has linear constraints and creates children by taking a weighted average of the parents;

- Mutation children are generated by adding random changes, or mutations, to a single parent. The method of introducing a mutation is defined by the option *Mutation function*. The function used in the project is *Adaptive Feasible*. This method of mutation chooses a direction and step length that satisfies bounds and linear constraints.

The options parameter *Crossover Fraction* lies in a range [0; 1] and defines which part of the next generation is produced by crossover. The default value is 0.8, which means that crossover produces 80% of the generation, except elite children (MathWorks, n.d.-b, n.d.-c).

### **Termination**

The GA runs until one of the stopping criteria is met. MATLAB allows manipulating termination parameters, specifying some of the options. In this project, the following termination criteria were used:

- *Generations* specify the maximum number of iterations, was set to 20;
- *Function tolerance* specifies the minimum average relative change in the best fitness function value, was set to 0.001.

The parameter *Constraint tolerance* was also defined and set to 0.1. It is not used as stopping criteria, but determine the feasibility with respect to nonlinear constraints (MathWorks, n.d.-b).

### **Augmented Lagrangian Genetic Algorithm**

The original GA should be extended to work with nonlinear constraints. An improved algorithm is called *Augmented Lagrangian Genetic Algorithm* (ALGA). To handle nonlinear constraints, a sequence of subproblems, which combine the objective function and nonlinear constraints, is formulated. A subproblem is defined as:

$$\Phi(x, \lambda, s, \rho) = f(x) - \sum_{i=1}^m \lambda_i s_i \log(s_i - c_i(x)) + \sum_{i=m+1}^{mt} ceq_i(x) + \frac{\rho}{2} \sum_{i=m+1}^{mt} ceq_i(x)^2, \quad (12)$$

where

$\lambda_i$  - nonnegative components of the vector  $\lambda$  known as Lagrange multiplier estimates;

$s_i$  - nonnegative elements of the vector  $s$  known as shifts;

$\rho$  - the positive penalty parameter.

$f(x)$  - objective function;

$c_i(x)$  - inequality constraint;

$ceq_i(x)$  - equality constraint;

$m$  - number of inequality constraints;

$mt$  - number of equality constraints;

The ALGA starts from the initial values of  $\lambda$ ,  $s$  and  $\rho$ . The algorithm minimizes a sequence of subproblems, which are approximations of the original problem. The subproblem is minimized to a required accuracy, then  $\lambda$ ,  $s$  and  $\rho$  are updated according to a special function. The updated values are used to formulate a new subproblem and minimization problem. These steps are repeated until the tolerance criteria are met (MathWorks, n.d.-d).

Figure 14 represents a simplified flowchart for the ALGA. The more detailed descriptions of the algorithm can be found in (Conn et al., 1997; Lewis et al., 2006).

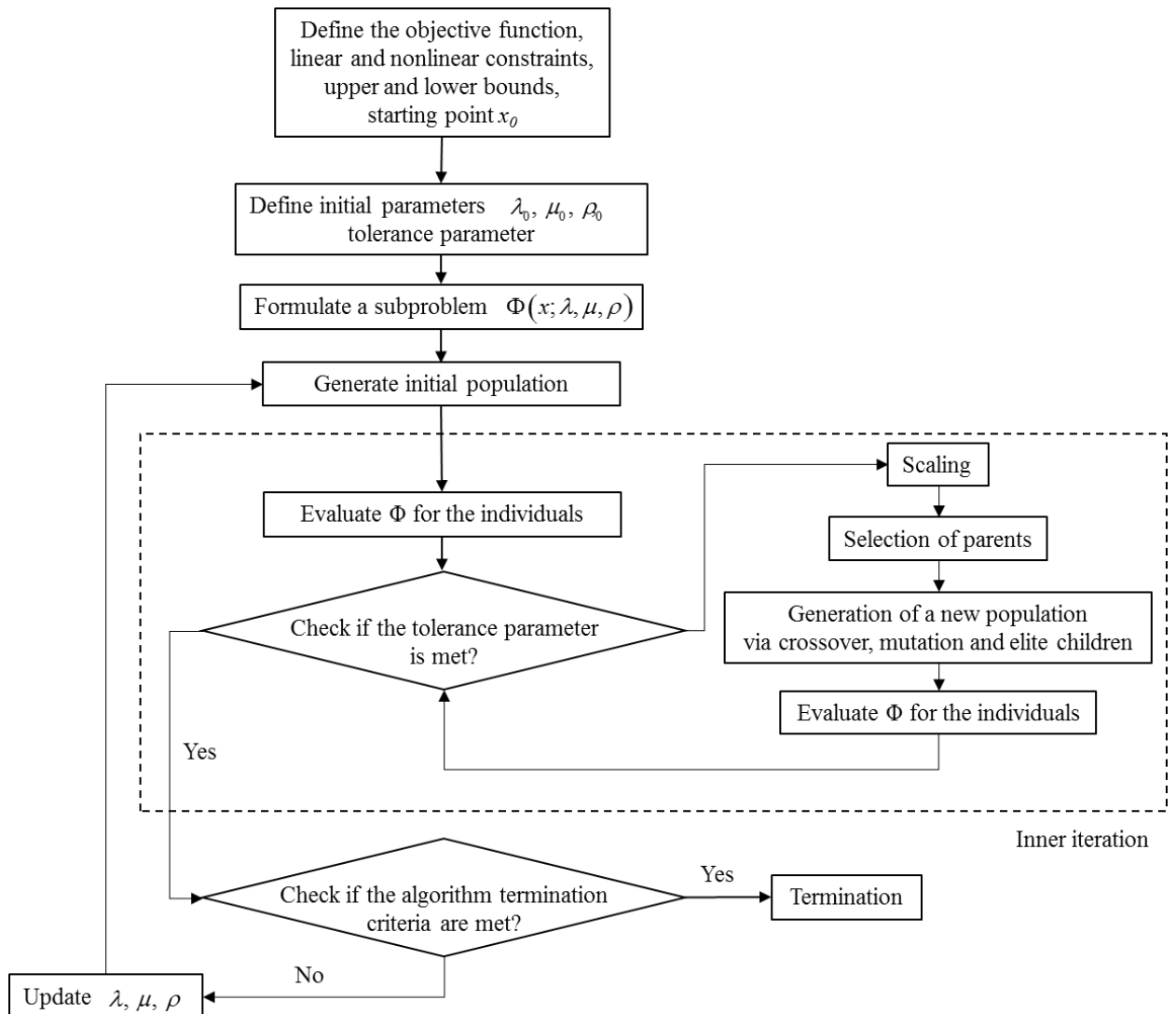


Figure 14. ALGA flowchart

### 3.4.2 DE algorithm

DE is a relatively new evolutionary algorithm, which is an effective adaptive approach to global optimization over continuous search spaces. Classical DE approaches use randomly generated initial population, differential mutation, probability crossover and greedy criterion of search. The basic idea behind DE is a method whereby it generates the trial parameter vectors. In each step, the DE mutates vectors by adding weighted, random vector differentials to them. If the fitness function of the trial vector is improved, the target vector is replaced by the trial vector in the next generation (Sauer et al., 2011).

DE procedure involves the following steps:

- individuals are generated randomly;
- each individual of the population goes through mutation operation with scale factor;
- crossover operation is applied to mutation vector and target vector;
- trial vector is evaluated and compared with the fitness value of the target vector. The vector with the greater fitness value enters the next generation.

Recombination incorporates the best solutions from the previous generation, and mutation expands the search area, similar to GA. Mutation, recombination, and selection continue until some termination criterion is reached (Safari et al., 2013).

## Chapter 4

# Results and Discussion

In this chapter, the results of optimizations are discussed. The optimization was performed for three different test cases, to analyze an effect of different factors more carefully. The Case 1 is a basic case where three CHP units and the AB are considered. The PV is not included, and an ambient temperature is constant and equal to 15°C. The Case 2 is done for a polygeneration system, which includes PV, but also does not account for ambient temperature changes. The Case 3 is the same to Case 2, but ambient temperature variations are considered. In cases 1, 2 and 3 capital investments and O&M costs are not considered. In the Case 4 these parameters are included in the objective function, and their influence on the optimization is investigated. Table 6 summarizes the test cases.

*Table 6: Test cases description*

Case	PV panel	Ambient temperature variations	Capital investment and O&M costs
1	-	-	-
2	+	-	-
3	+	+	-
4	+	+	+

### 4.1 Case 1

#### 4.1.1 July

The chart diagrams for power produced by CHP units and heat produced by CHPs and the boiler are represented in Figure 15 and Figure 16.

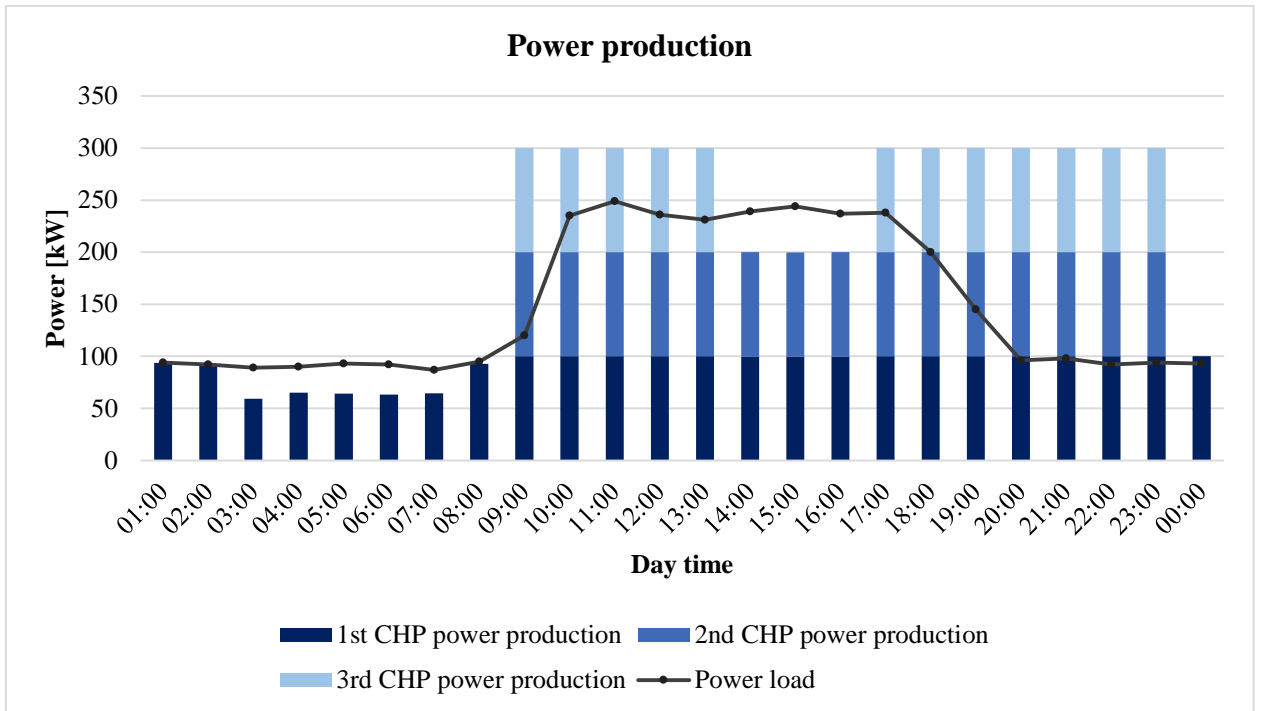


Figure 15. Power production in July (Case 1)

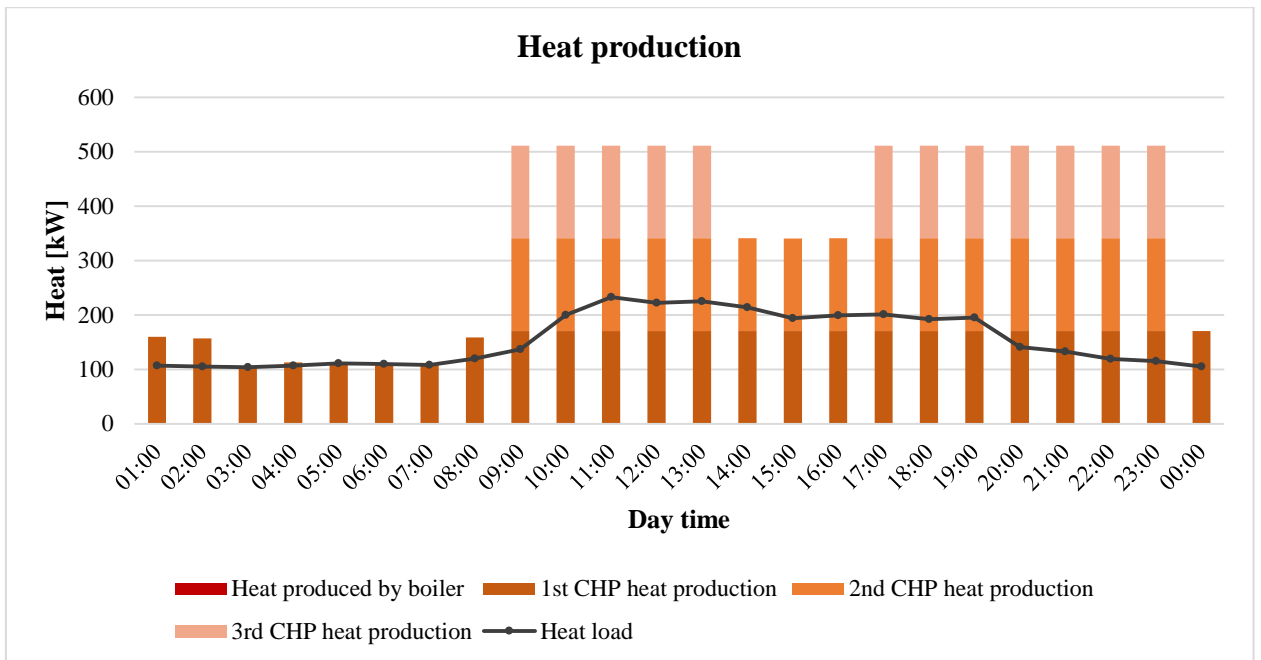


Figure 16. Heat production in July (Case 1)

The period from 1:00 to 8:00 is characterized by a relatively low heat and power loads. It can also be observed from Figure that the electricity price at this period is low and it's more expensive to produce electricity by CHPs then to buy in from the grid. However, the optimization results show that it is more efficient to use one CHP to cover the power and heat demand than to buy all required electricity from the grid and produce heat by the boiler. Therefore, one CHP unit is working from 1:00 to 8:00 at a load approximately equal to the power demand.

Electricity prices at the period from 9:00 to 13:00 are higher than the price of produced electricity (see Figure 9). Thus, it is more efficient to produce excessive power and sell it to the grid. This fact is confirmed by the optimization results, which report that the optimal solution for this period is all three CHP units working on the maximum load.

The next period from 14:00 to 16:00 the electricity prices in the grid are again below the electricity production price. However, the results show that the optimal solution is to run two CHP units on the maximum load and buy the rest power requirement from the grid. It can be explained by the tendency for the algorithm to avoid using AB. Despite the fact that thermal efficiency of the boiler is higher than thermal efficiency of CHP, it is more efficient in this case to use two CHP units which cover the heat demand and the most of the power demand, then to use one CHP unit and the boiler.

To prove this statement, consider a time step at 15:00 when the power load is 244 kW and the heat load is 194 kW. In the case of using one CHP at the maximum load, 144 kW electricity should be bought from the grid and 24 kW of heat should be produced by the boiler. Taken into account fuel and electricity prices at that time, it can be calculated that the value of the cost function would be 9.3506 €/hour, which is more than 9.2772 €/hour, reported by the algorithm. We can conclude that the optimization results are correct.

The rest period is similar to the period 9:00-13:00 because of high electricity price, except the point at 24:00, which is similar to the period 1:00-8:00.

Figure 2 illustrates the amount of power which is bought from the grid and sold to the grid.

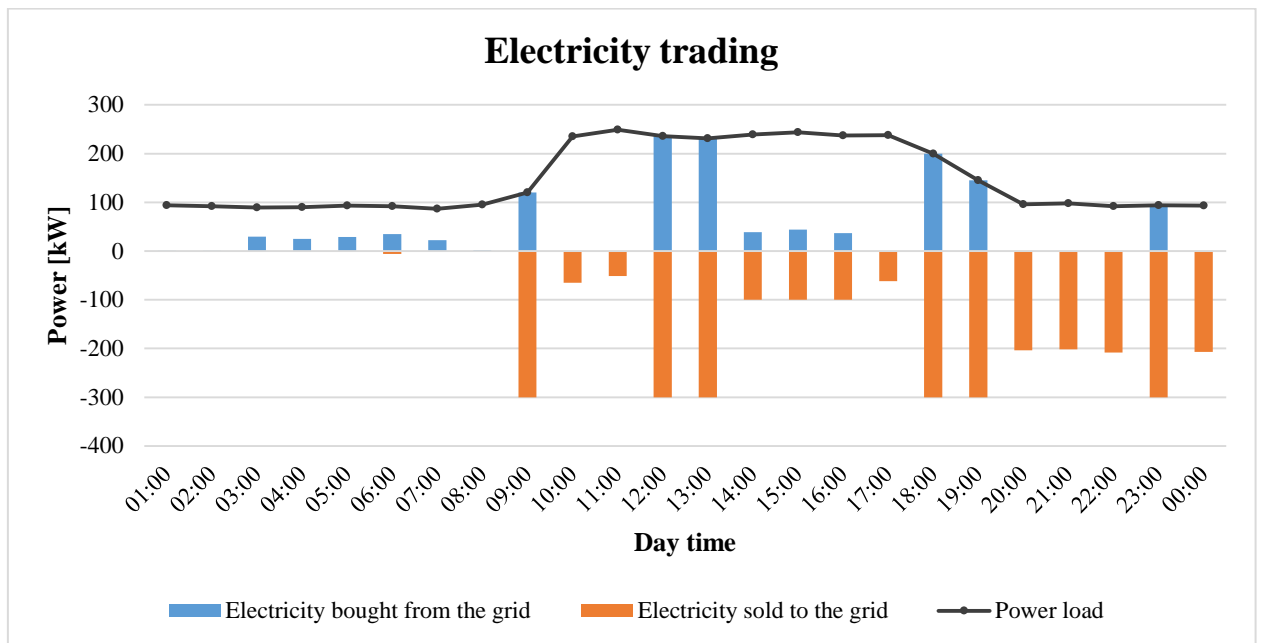


Figure 17. Electricity trading in July (Case 1)

It can be noticed that at time steps 9:00, 12:00, 13:00, 18:00, 19:00 and 23:00 the power demand is met by the electricity from the grid and the power produced by CHPs is sold to the grid at the same time. The Figure 9 shows that at these points the price for selling electricity is higher than the price for buying, and it is reasonable to buy and sell electricity simultaneously.

This fact is also confirmed by the Figure 18, which represents the cost function and its elements. At each point mentioned above the cost function value is reduced by the difference between the cost of sold and bought electricity.

In addition, the dashed line represents the cost function in the case when all CHPs are switched off. In other words, it shows the value of the cost function if all electricity would have been bought from the grid and all heat would have been produced by the AB. The figure shows that at each time step it is more efficient to use CHP units, even if the load is low. The option to sell electricity allows to reduce the cost significantly, especially when the electricity price is relatively high and the power load is low, e.g. from 19:00 to 22:00.

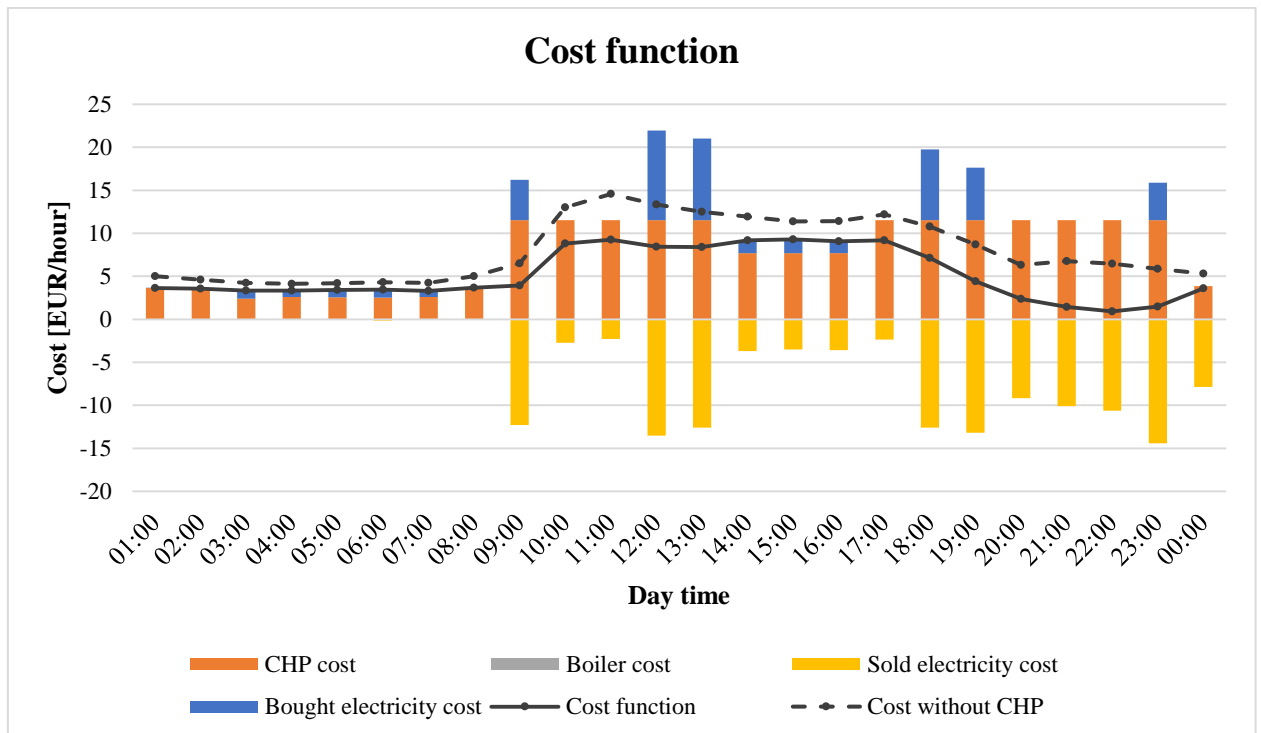


Figure 18. Cost function profile in July (Case 1)

#### 4.1.2 December

The optimization results for December could be generally explained by the same principles as for July.

The diagrams for power produced by CHP units and heat produced by CHPs and the boiler are shown in Figure 19 and Figure 20.

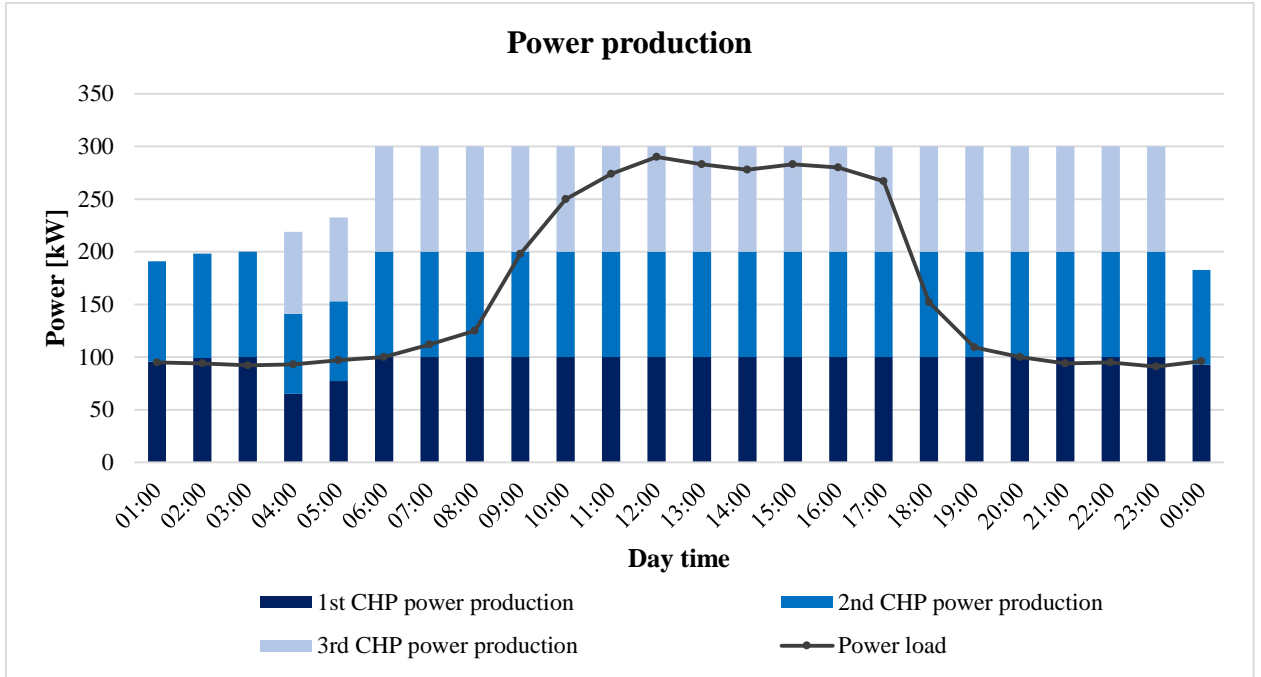


Figure 19. Power production in December (Case 1)

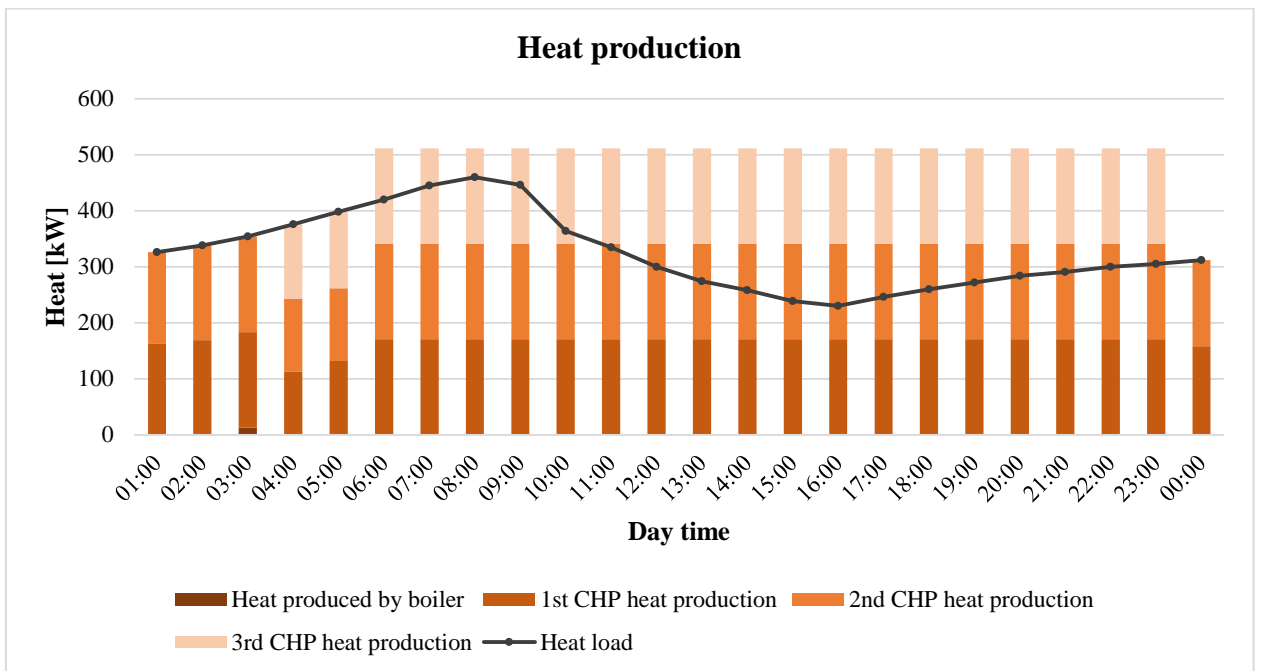


Figure 20. Heat production in December (Case 1)

The period from 1:00 to 5:00 is characterized by low gas price and power load, but relatively high heat load. At this period excessive electricity generation is not profitable. However, the heat demand needs to be satisfied, and the system is working according to heating-based strategy. Therefore, CHP units produce as much heat as required and the excessive power is sold to the grid.

The time step at 3:00 is the only point in both July and December when an AB is used. At this time, two CHPs produce 340 kW of heat, while the heat load is 354 kW. It is not efficient to run



an additional CHP to cover that small difference, and an AB is utilized. Starting from the next point, when the heat load is increasing, three CHP units are used.

At the remaining period from 6:00 to 23:00 the electricity prices in the grid are higher than the production price. Consequently, all CHP units work at the maximum load to maximize profit from selling electricity.

In Figure 21, the electricity trading data are illustrated. Similarly, to July, at periods 12:00-15:00 and 22:00-23:00 the electricity demand is bought from the grid and the produced power is sold, because of higher price. At the period from 1:00 to 8:00 a lot of electricity is sold, because the power load is low, while the heat load is high and CHPs work at near maximum loads.

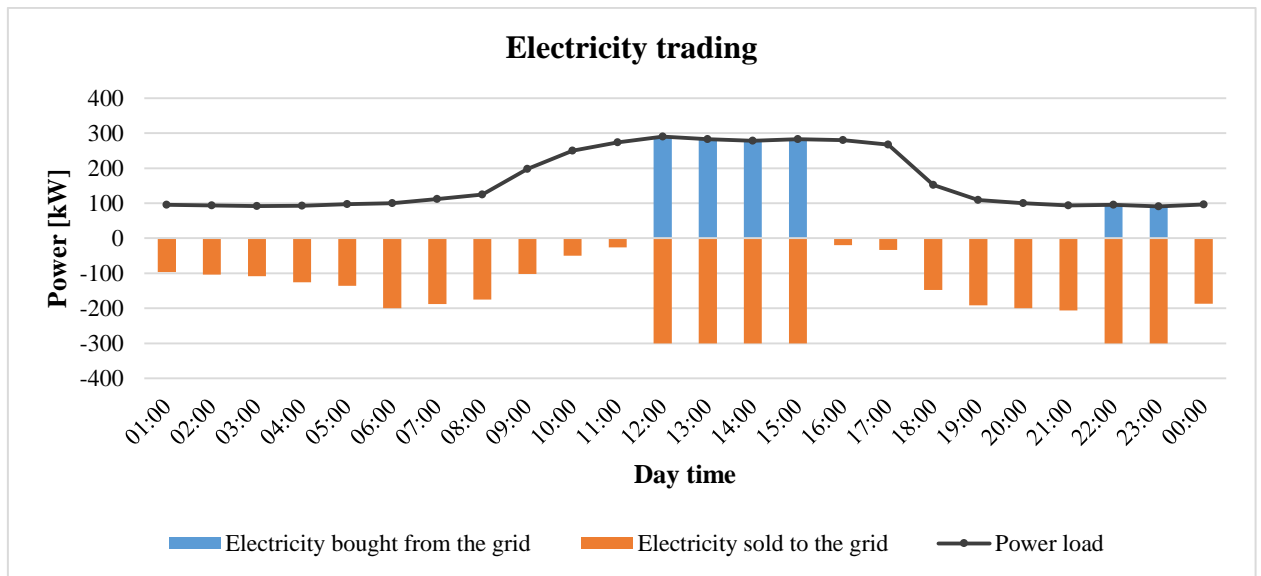


Figure 21. Electricity trading in December (Case 1)

Figure 22 illustrates the cost function profile in December. Similar to July, it shows that using CHP is efficient at each time point. The cost function value reaches its minimum at the period from 19:00 to 23:00 when the difference between electricity production prices and electricity selling prices is maximized. At points 20:00, 21:00 and 22:00 it has negative value, which meant that CHPs make a profit.

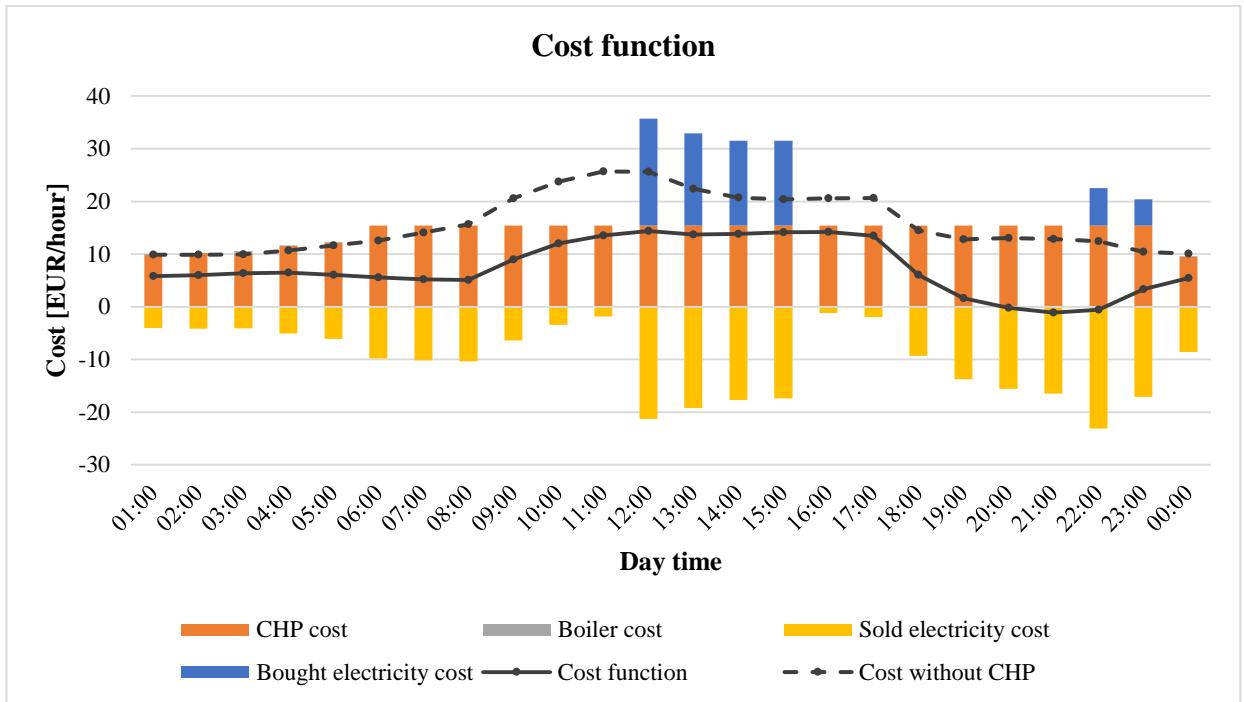


Figure 22. Cost function profile in December (Case 1)

## 4.2 Case 2

### 4.2.1 July

Figure 23 represents the power production by CHP units and PV, along with the CHP duty and power load. CHP duty is calculated as a difference between the load and the available solar energy, according to the strategy discussed in the section 3.3.1.

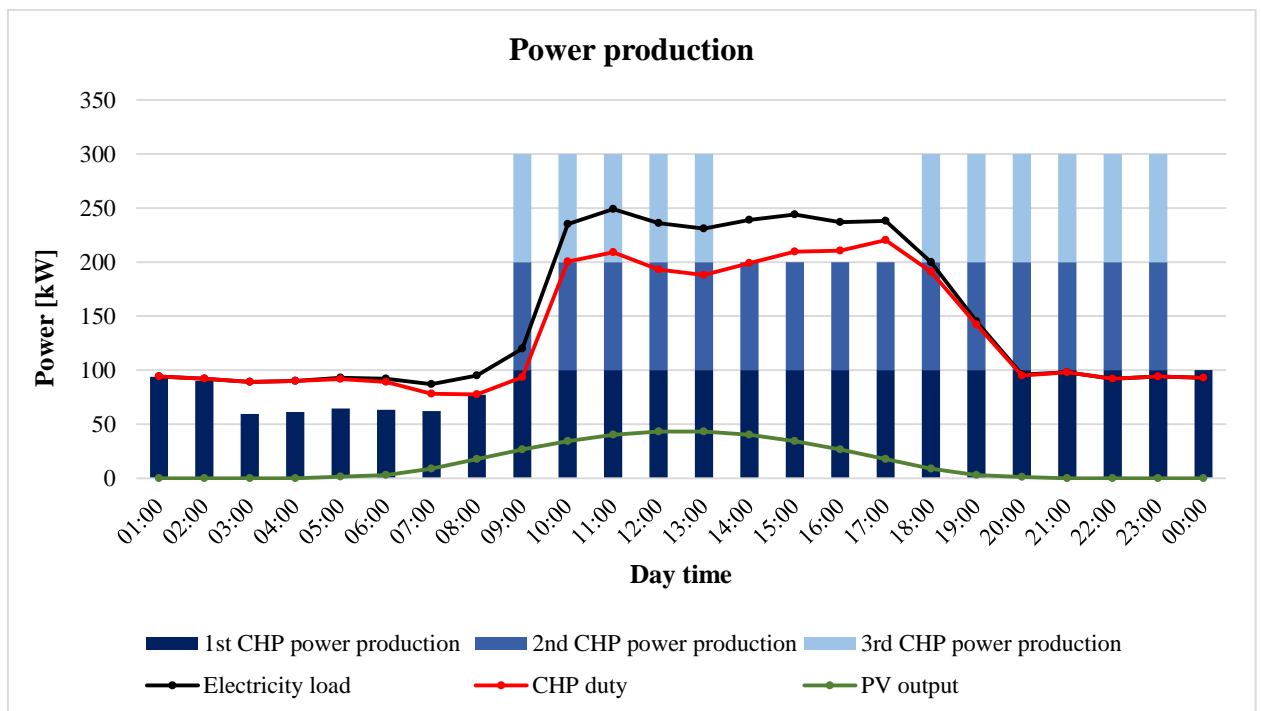


Figure 23. Power production in July (Case 2)

The PV allows reducing power load for CHP. However, the operation schedule for CHPs has the same pattern as in Case 1. It means that the fuel consumption is not reduced significantly, but more electricity can be sold to the grid.

#### 4.2.2 December

Figure 24 represents the power production by CHP units and PV, CHP duty and power load. The PV did not change the operational strategy for CHP units because in December the CHP performance is generally defined by the heating loads and electricity prices.

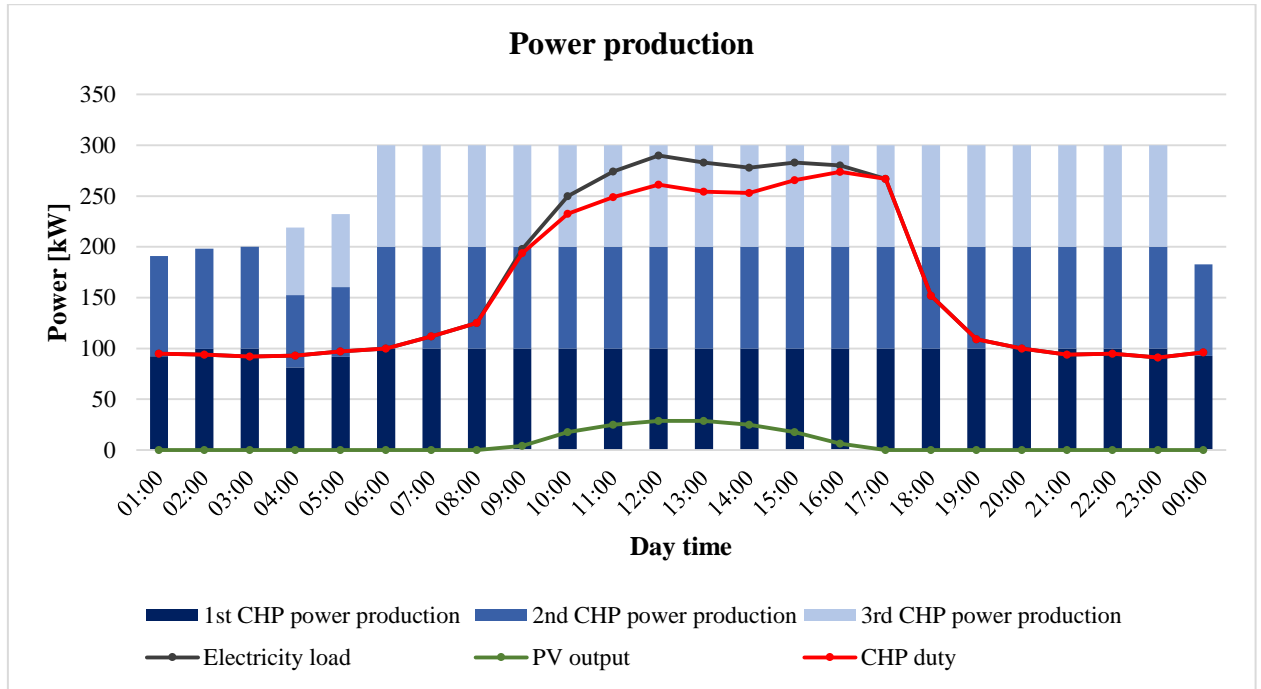


Figure 24. Power production in December (Case 2)

### 4.3 Case 3

Ambient temperature has a significant influence on a CHP performance. It can change the maximum output of the CHP and fuel consumption per unit of power. Therefore, the electricity production prices, which were estimated for ambient temperature 15°C and plotted in Figure 9 and Figure 10, should be recalculated. The Figure 25 and Figure 26 demonstrate the difference between electricity production price for ambient temperature 15°C and for real values of temperature in July and December.

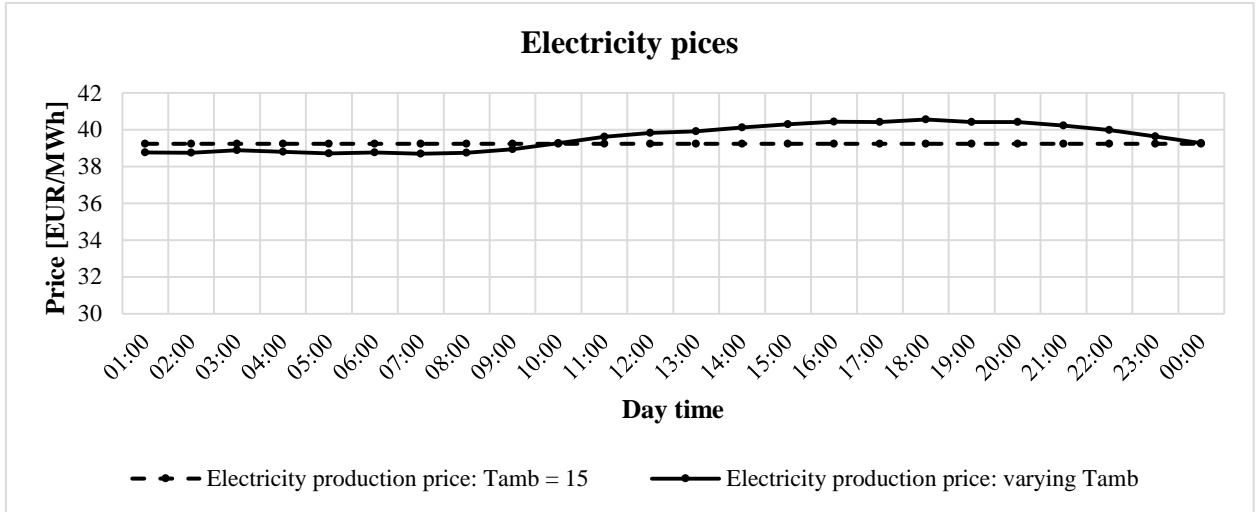


Figure 25. Electricity production price in July (Case 3)

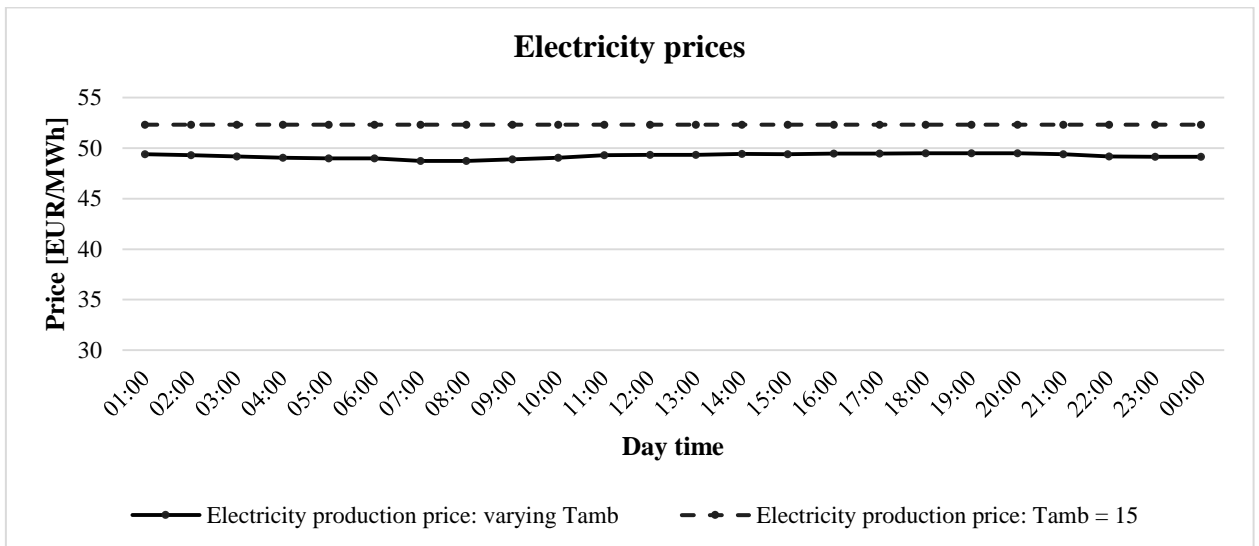


Figure 26. Electricity production price in December (Case 3)

A fuel consumption is decreasing with decreasing ambient temperature, thus reducing the cost of produced electricity. In July from 1:00 to 9:00 the temperature is lower than  $15^{\circ}\text{C}$  and electricity production cost is lower than in Cases 1 and 2, but it changes to the opposite from 10:00 to 0:00. In December daily temperatures are low, and electricity production cost is also lower during the whole day.

#### 4.3.1 July

The power and heat production diagrams are shown in Figure 27 and Figure 28. It can be noticed that at time steps 15:00 and 16:00 only one CHP unit is working, despite the high power load. At these points, the power production by CHPs is inefficient because of high ambient temperature. However, CHP generates 100 kW power and produce more than 190 kW of heat. It can be concluded that a high ambient temperature increases a heat output per unit of power.

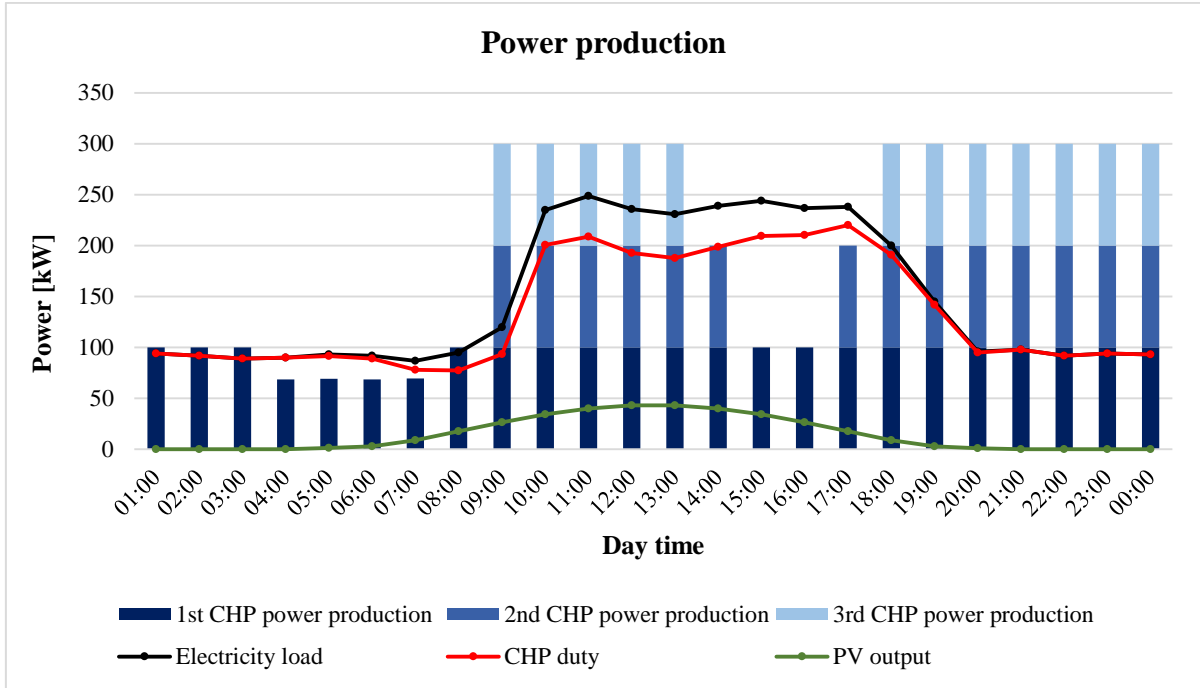


Figure 27. Power production in July (Case 3)

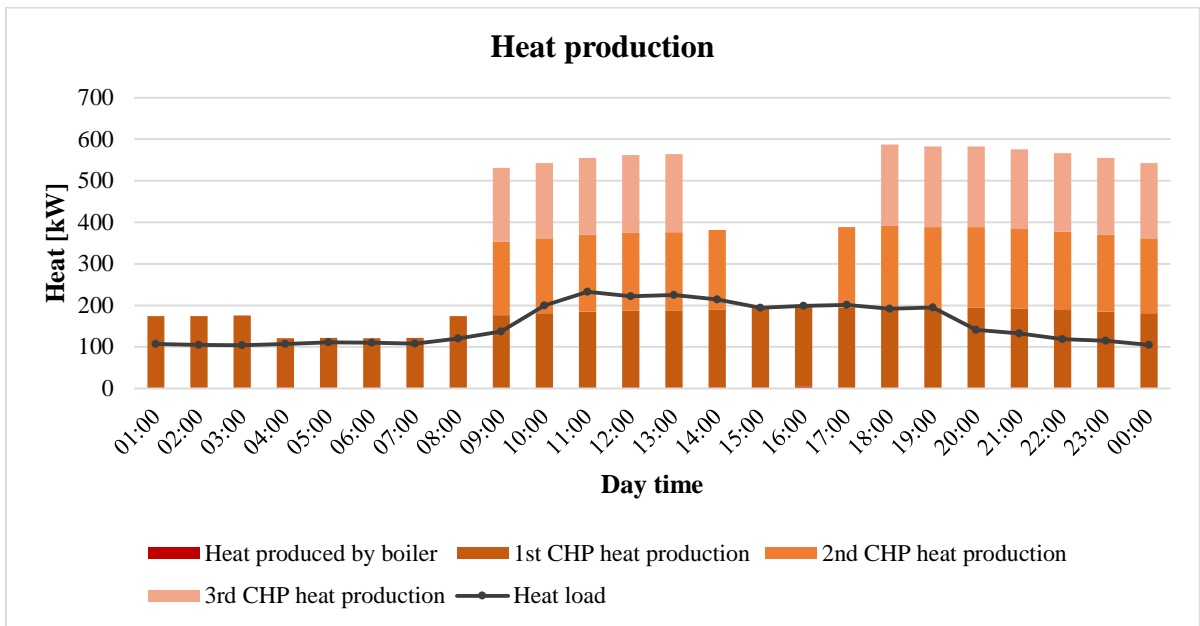


Figure 28. Heat production in July (Case 3)

### 4.3.2 December

The power and heat production diagrams are shown in the Figure 29Figure 27 and Figure 30Figure 28. The power production chart shows that the maximum CHP capacities are used from 4:00 to 0:00, because of lower electricity production expenses due to low ambient temperatures. However, the heat production per unit of power is reduced to approximately 150 kW of heat per 100 kW of power, as it can be noticed from the heat production chart. Because of this fact, an AB is used at points 1:00, 2:00, 3:00 and 8:00, which is more often than in cases 1 and 2.

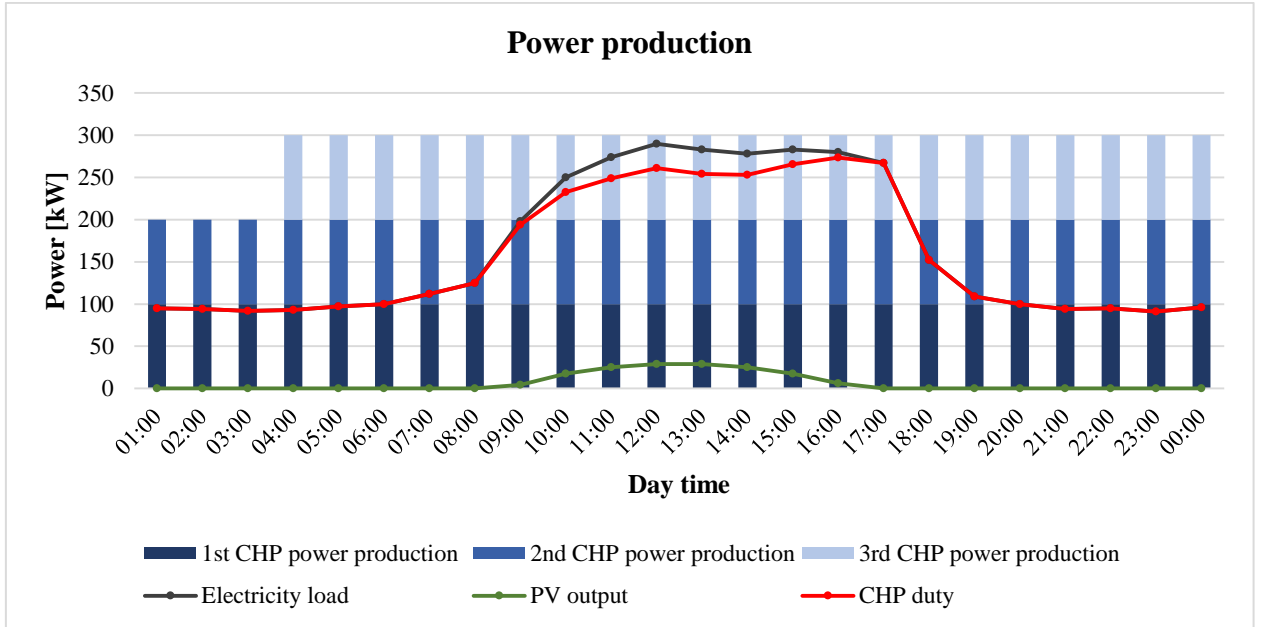


Figure 29. Power production in December (Case 3)

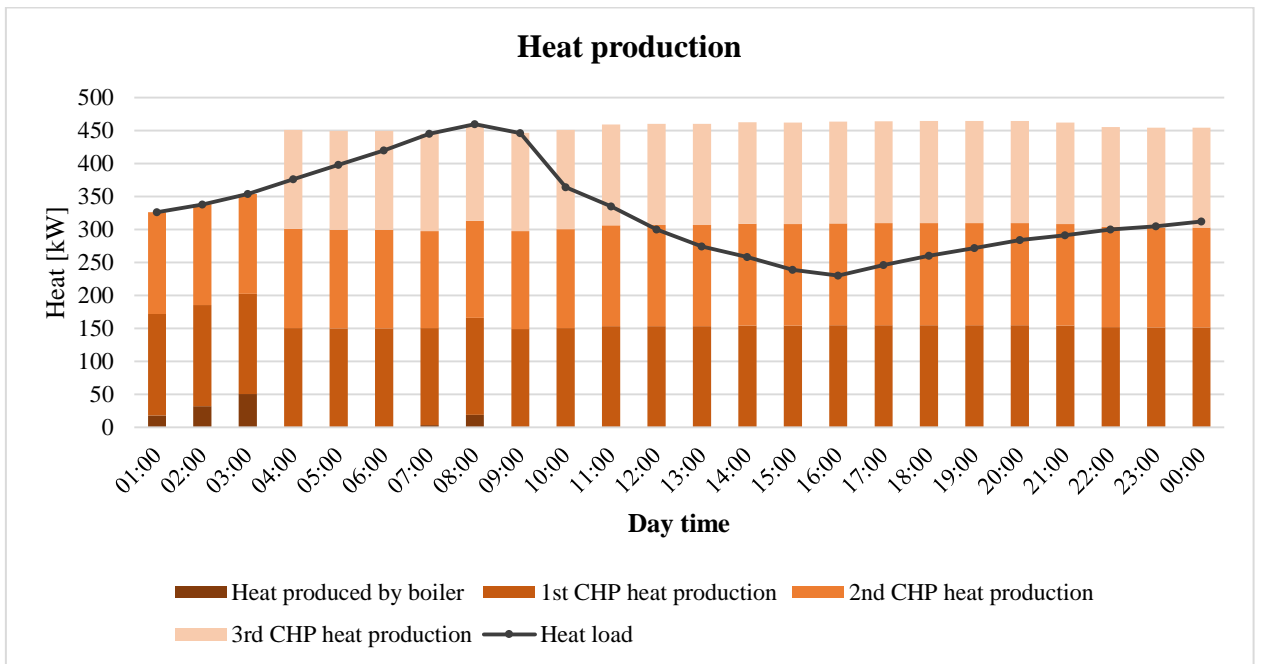


Figure 30. Heat production in December (Case 3)

### 4.4 Case 4

In this case, the electricity production price is different from the Case 3, because O&M costs are taken into account. Therefore, the Figure 25 and Figure 26 are not relevant to this case. It is not possible to predict the electricity production price before the optimization, because O&M costs depend on the power production. The capital investment cost doesn't influence the balance between production, buying and selling prices, because it is constant and doesn't depend on the power production and trading.

### 4.4.1 July

The power and heat production diagrams are shown in Figure 31 and Figure 32. The results show that O&M costs significantly influence the pattern. The CHPs, in this case, work according to the heat-led scenario, providing the heat requirement and producing electricity as a second product. The power production is much less than in previous cases. The boiler is used in some points, unlike previous cases.

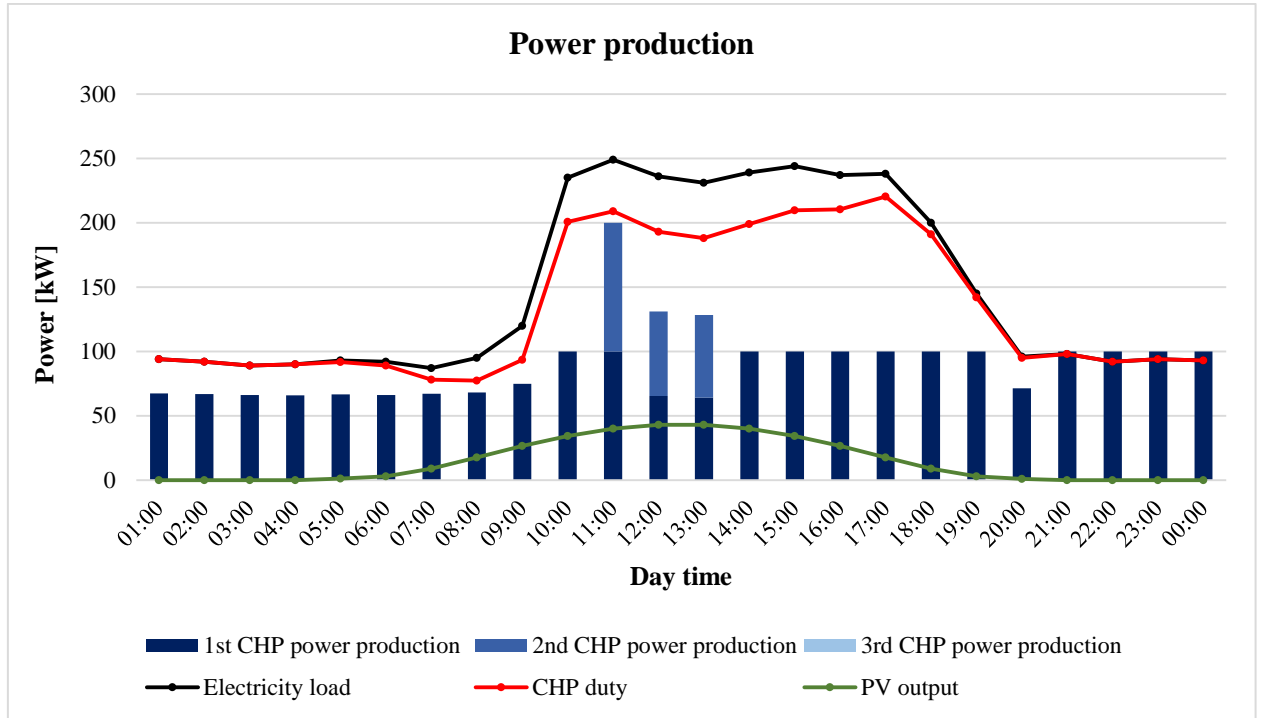


Figure 31. Power production in July (Case 4)

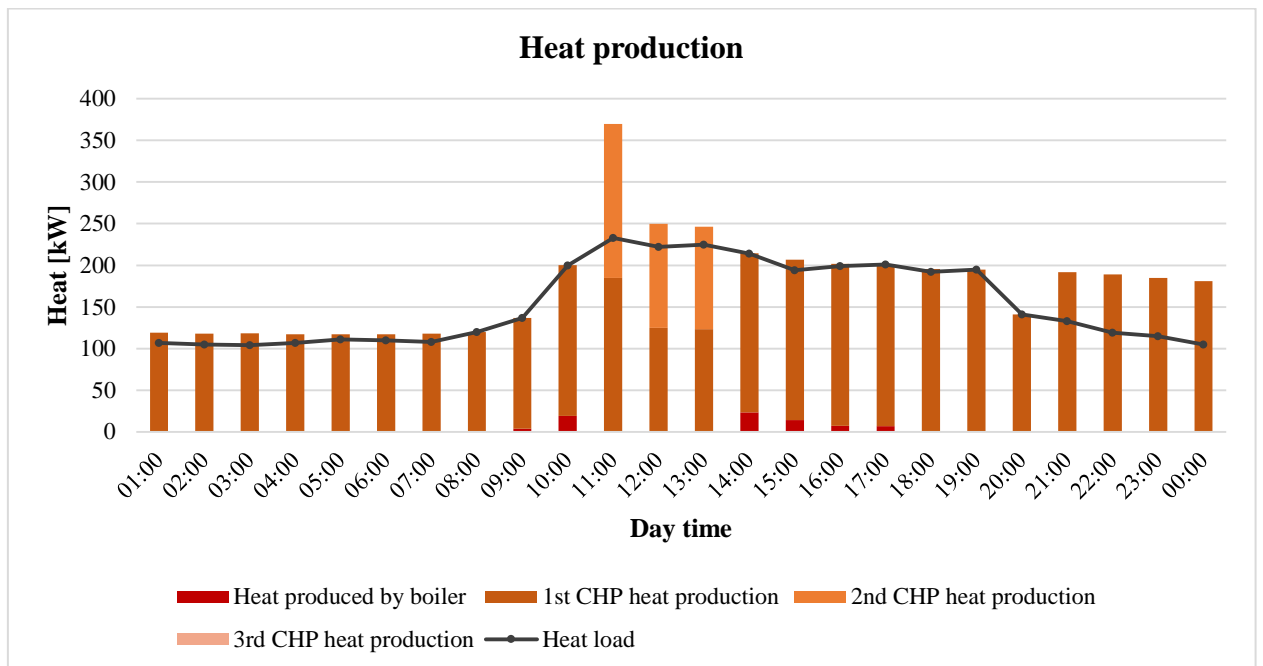


Figure 32. Heat production in July (Case 4)

Figure 33 represents the cost function and its components. The cost function is shown excluding capital investment costs. The diagram demonstrates that the weight of the O&M costs in the total cost function is significant. It is also shown that capital investment costs are averagely equal to the sum of operational costs.

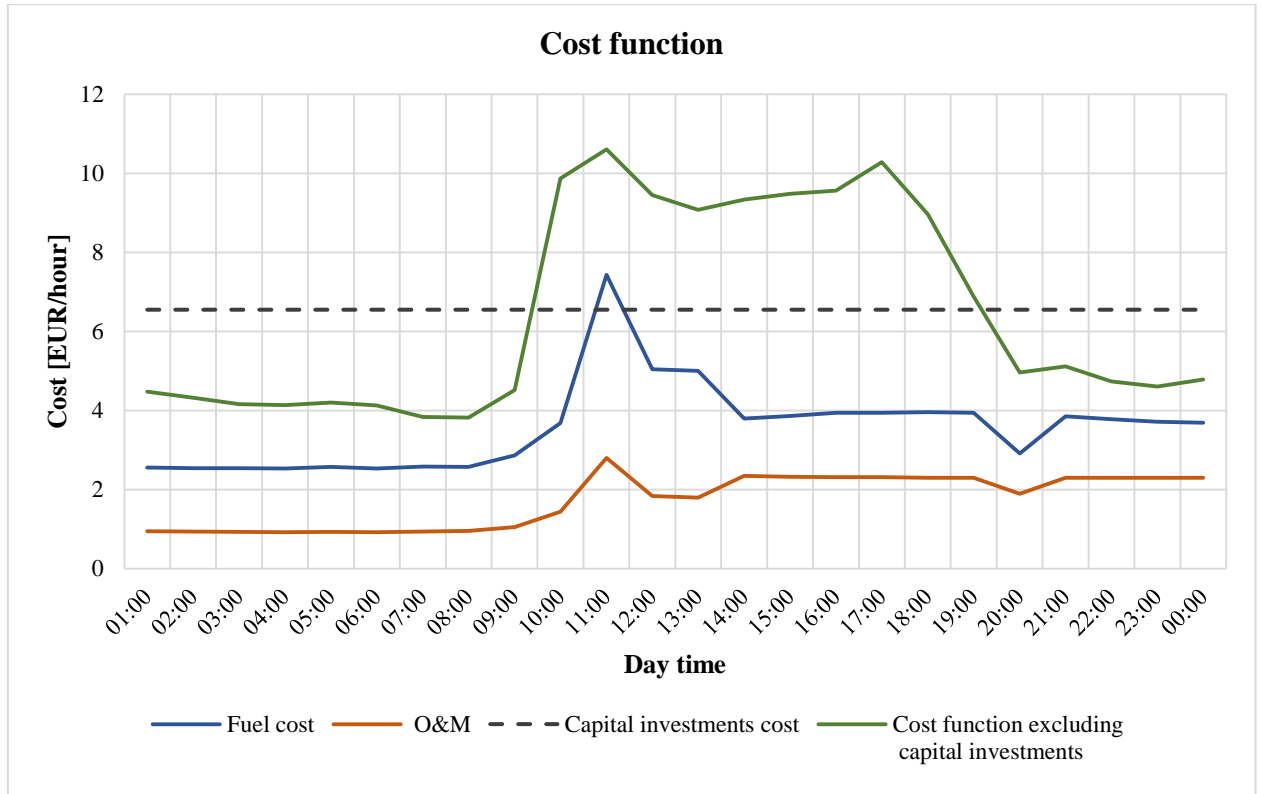


Figure 33. Cost function components in July (Case 4)

#### 4.4.2 December

The power and heat production diagrams are shown in Figure 34 and Figure 35. The results are similar to July. The algorithm tends to follow the heat-led strategy. The power production is less than in previous cases. The electricity production is still relatively high in periods 11:00-13:00 and 18:00-23:00 because of high electricity prices.



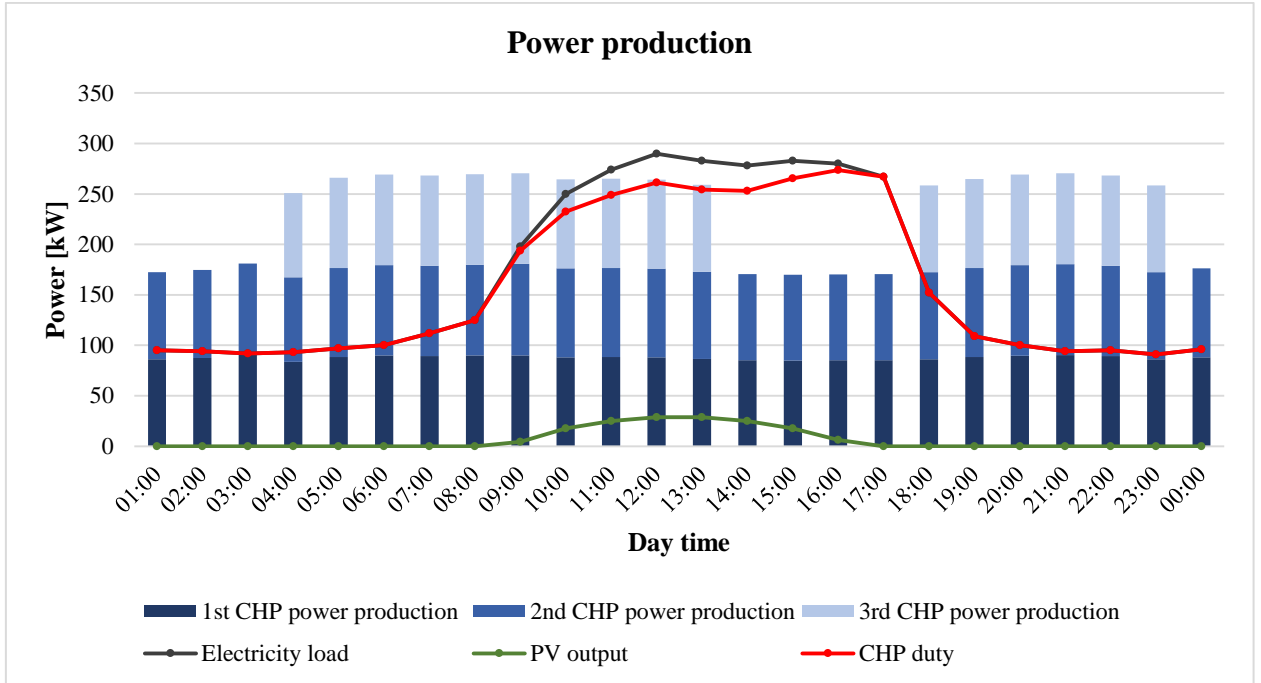


Figure 34. Power production in December (Case 4)

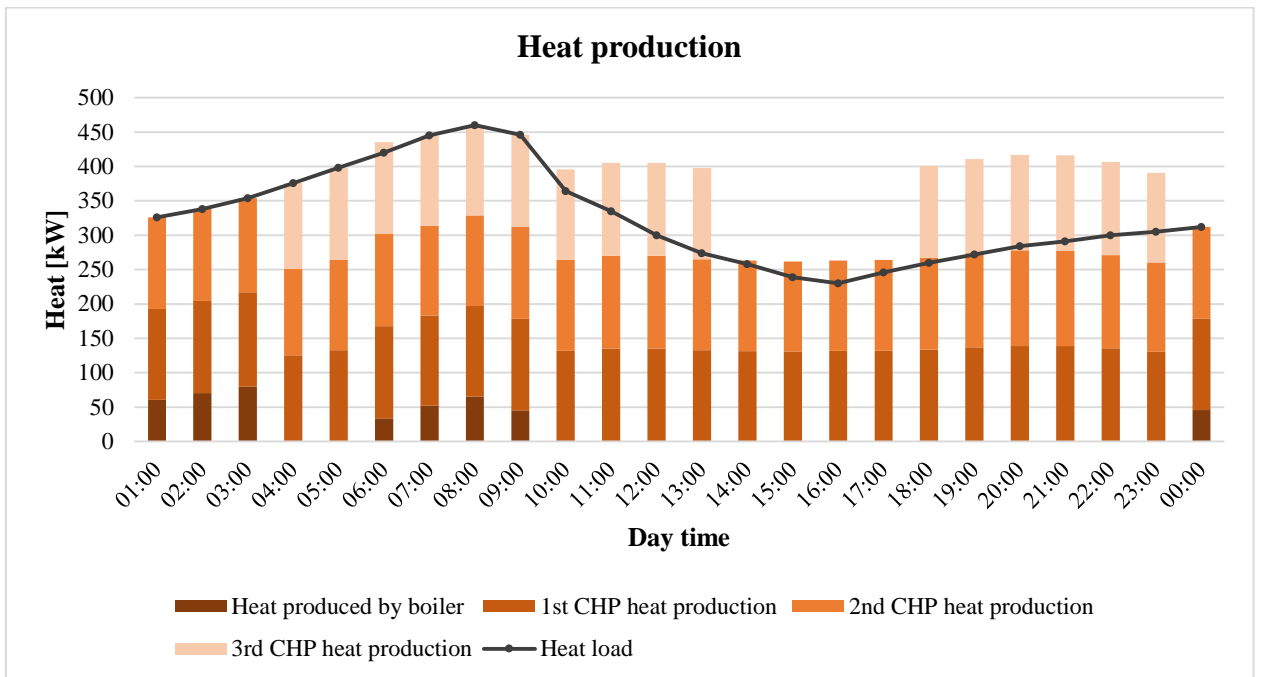


Figure 35. Heat production in December (Case 4)

Figure 36 represents the cost function and its components (similar to the Figure 33). It shows that the weight of both capital investment costs and O&M costs in the total cost function is less than in July. The fuel cost makes the biggest contribution to the cost function. That is the reason why adding capital investment and O&M costs did not change the results significantly.

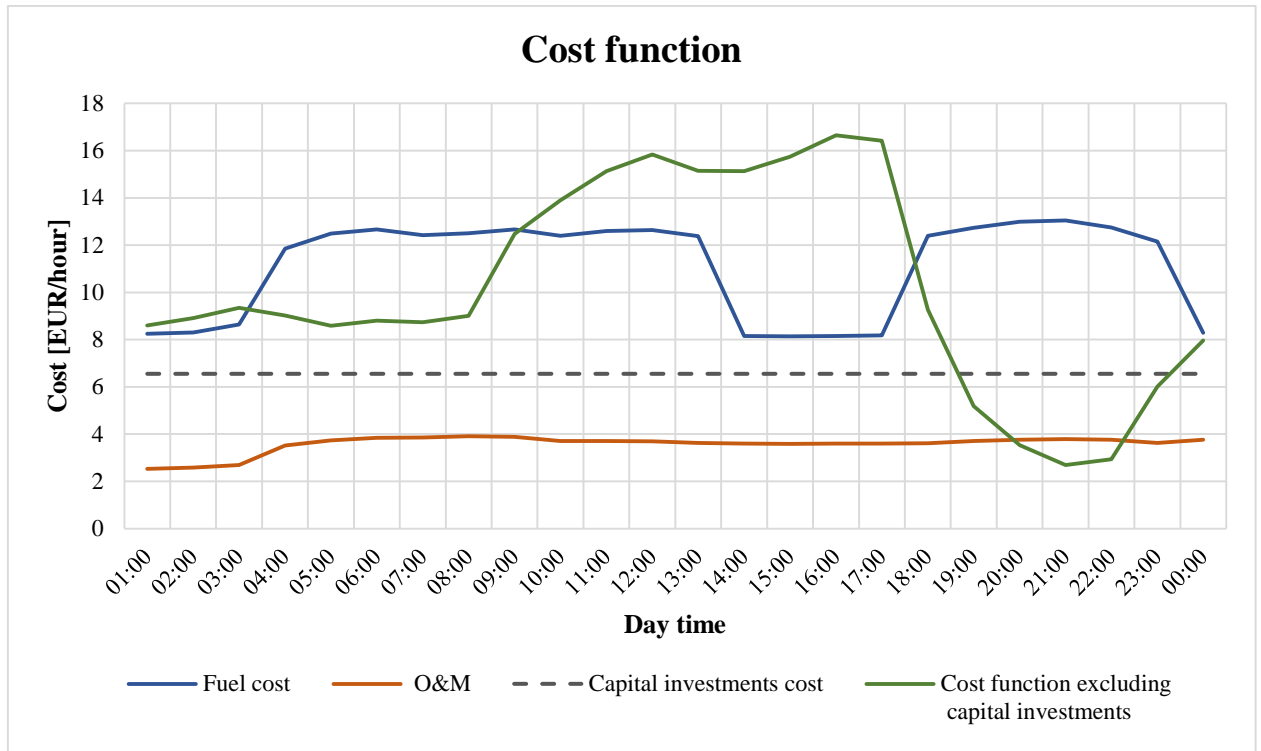


Figure 36. Cost function components in December (Case 4)

## 4.5 Summary

In this section, all three cases discussed above are compared and the acquired information is analyzed.

### 4.5.1 Power production

The Figure 37 and Figure 38 shows the power produced by CHPs in each case in July and December, respectively. In July the periods 9:00-13:00 and 18:00-0:00 are the same for cases 1, 2 and 3. In the period 14:00-17:00 the case 2 shows lower power production than the Case 1, because of the PV electricity generation. The Case 3 shows the lowest production, because of high ambient temperature during this period. The Case 4 demonstrates significantly lower production compared to other cases. In December the pattern is almost similar for cases 1,2 and 3 because the power production is defined by the heat demand and high electricity prices in this month. However, the Case 3 demonstrates higher production at points 4:00, 5:00 and 0:00, because of low ambient temperature and thus more efficient power generation by CHPs. The Case 4 has the lowest production, but the difference is not big compared to July. The production declines in periods 0:00-3:00 and 14:00-17:00 because of lower electricity prices. A jump in the power production at 11:00 in July is explained by the peak heat load at this time when two CHP units should be run, and thus more electricity is produced.

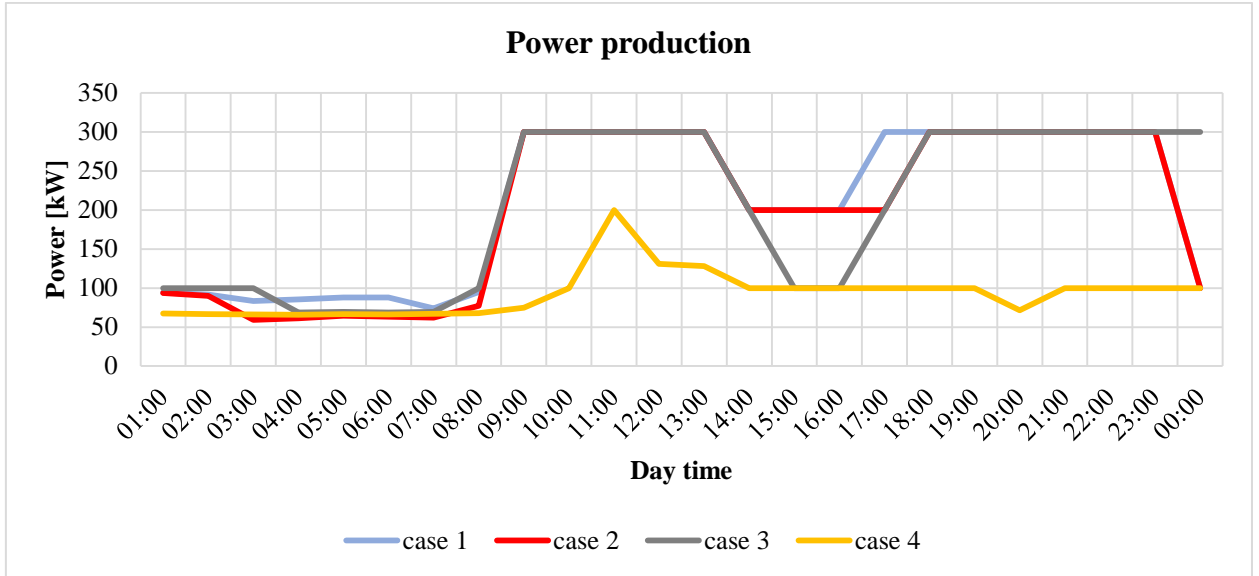


Figure 37. Power production in July (summary)

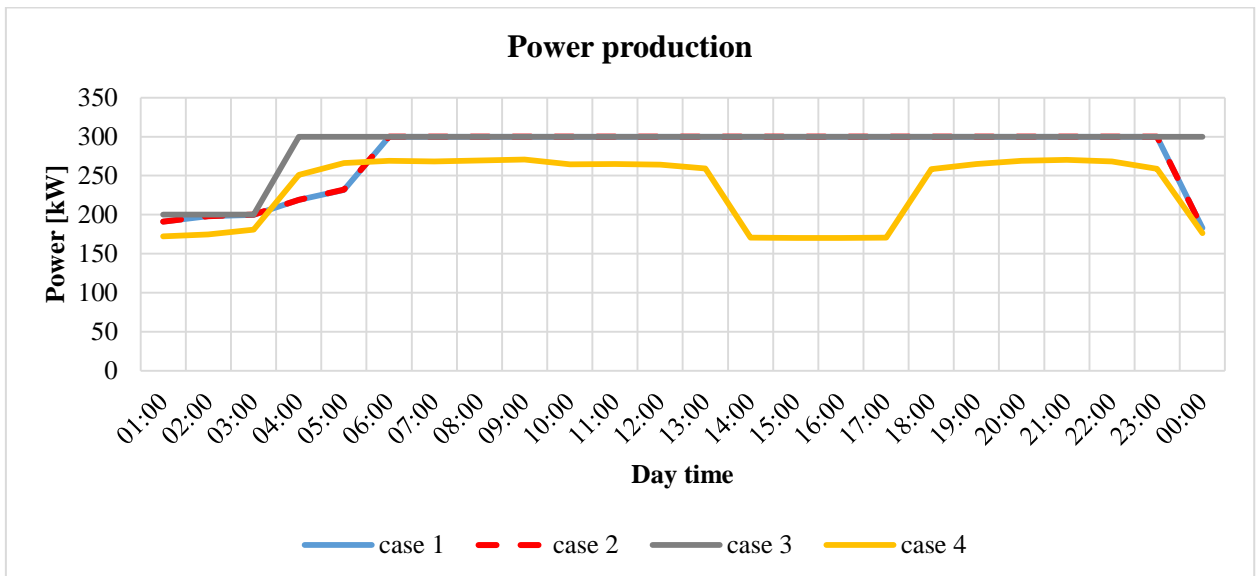


Figure 38. Power production in December (summary)

#### 4.5.2 Cost function

The cost function profiles for July and December are shown in Figure 39 and Figure 40. Adding the PV to the generation system in the Case 2 allows reducing the cost, especially in July when more solar radiation is available. The Case 3 shows that the cost function is higher in July and lower in December, compared to the Case 2, because high ambient temperature in July increase fuel consumption, while in December it is opposite. The Case 4 demonstrates the highest values of the cost function, because of adding capital investment and O&M costs

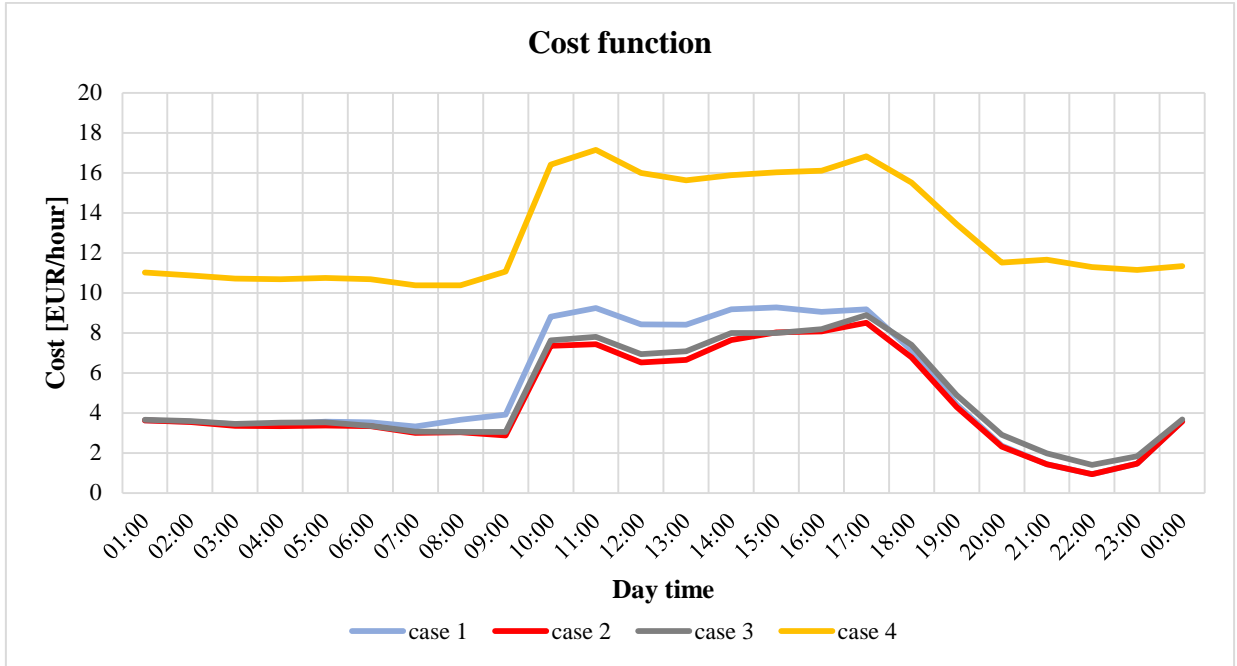


Figure 39. Cost functions in July (summary)

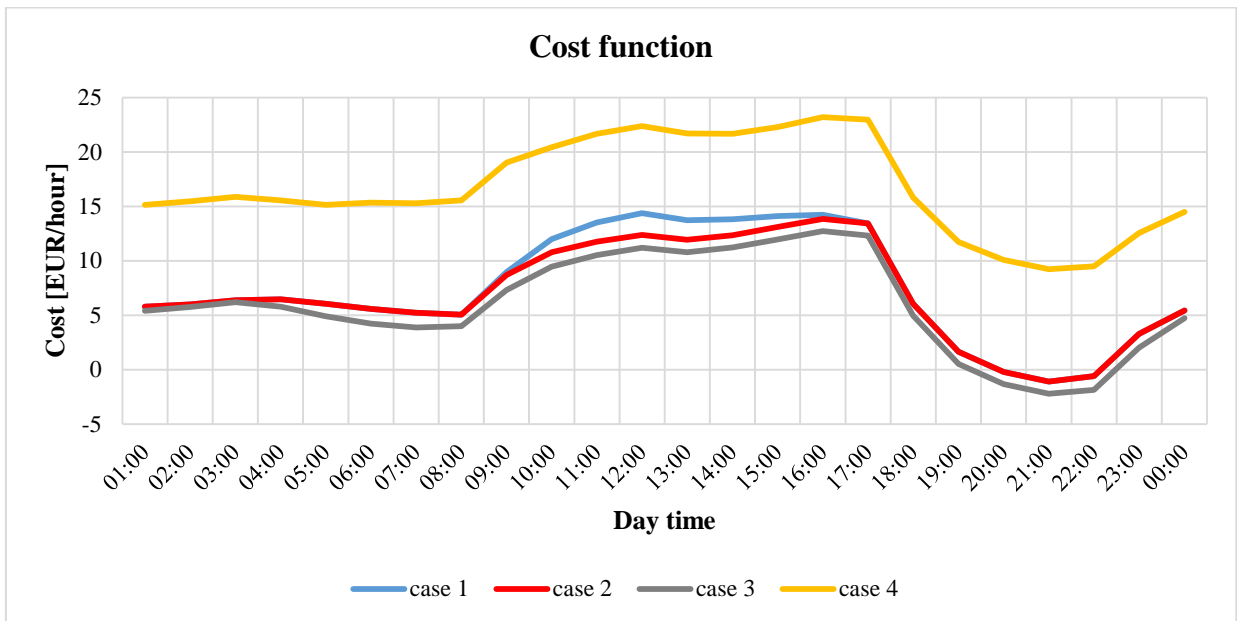


Figure 40. Cost functions in December (summary)

### 4.5.3 Fuel consumption

The total fuel consumption, including CHP units and the AB, is demonstrated in Figure 41 and Figure 42.

The curves pattern generally follows the power production graph behavior. In the Case 1 and Case 2, the fuel consumption is directly proportional to the power production. It can be seen that adding the PV panel allows saving fuel at points 8:00, 16:00 and 17:00. The Case 3 shows, that higher ambient temperature increases the fuel consumption per unit of power. In December the fuel consumption in the Case 1 and Case 2 are the same because adding the PV panel does not affect

the operation strategy for CHPs. The Case 3 shows that the fuel consumption is significantly reduced because of the low ambient temperature.

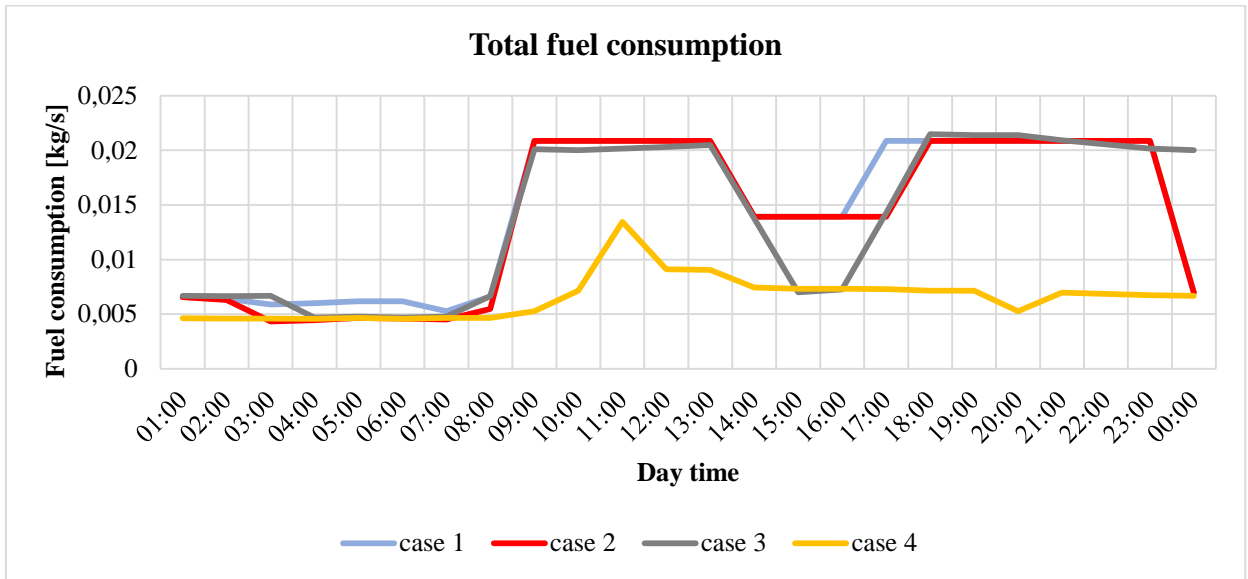


Figure 41. Total fuel consumption in July (summary)

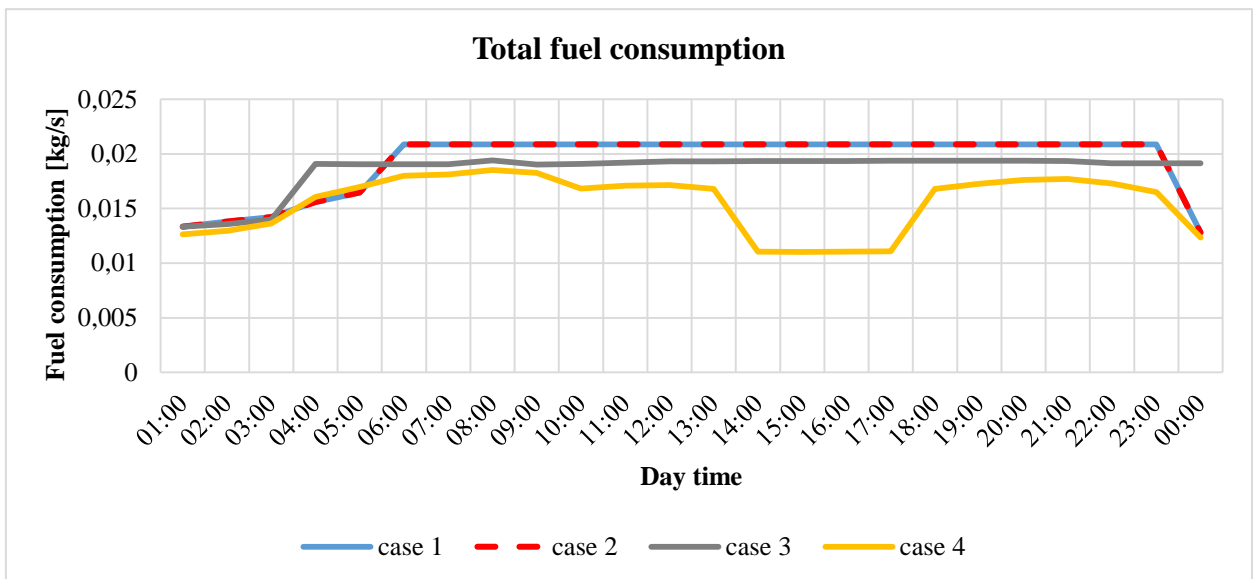


Figure 42. Total fuel consumption in December (summary)

#### 4.5.4 Electricity trading

The power trading data for July are represented in Figure 43 and Figure 44. Comparing the Case 1 and Case 2, it can be concluded that installing the PV panel allows to sell more electricity to the grid and buy less electricity from the grid, which makes it profitable and efficient to use the PV panel. If ambient temperatures are considered (Case 3), the behavior in the period 14:00-17:00 changes. Despite the additional power source from the PV, it is more efficient in this period to buy electricity from the grid and not sell it, because of low electricity price and high production expenses. The Case 4 demonstrates a different pattern compared to other cases, because less electricity is produced and thus more power can be traded.

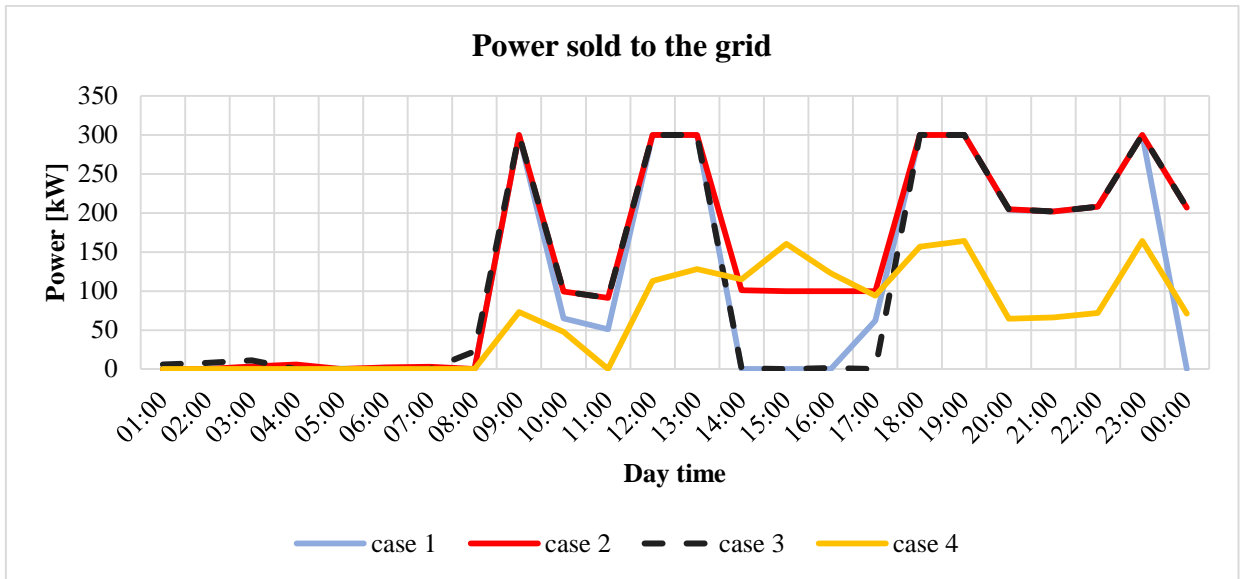


Figure 43. Power sold to the grid in July (summary)

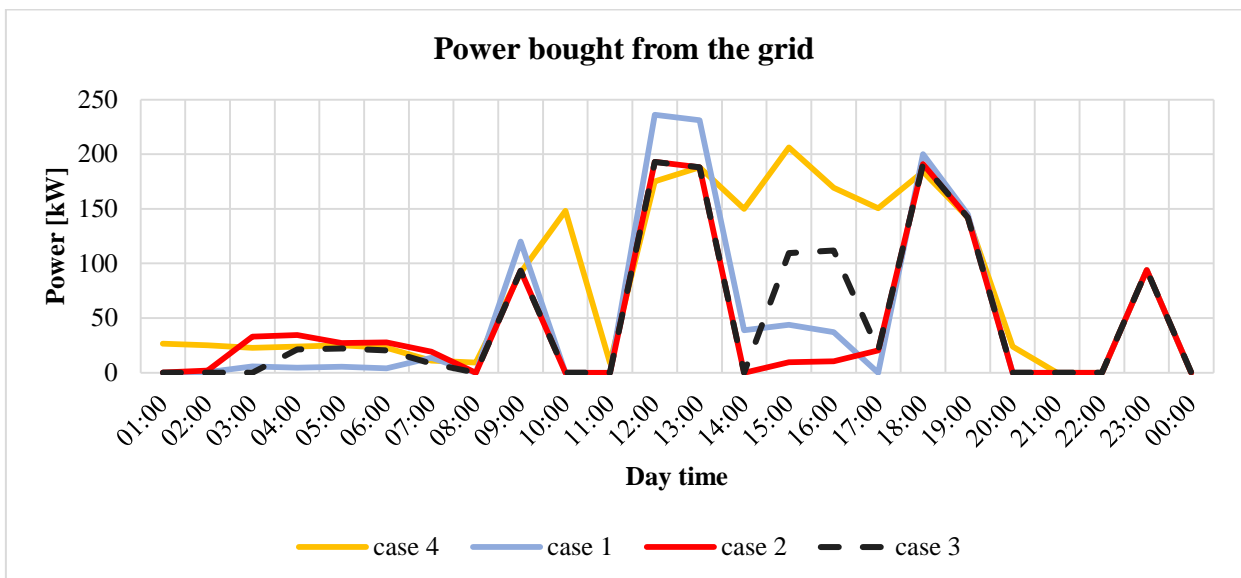


Figure 44. Power bought from the grid in July (summary)

The same plots made for December are presented in Figure 45 and Figure 46. The comparison of the Case 1 and Case 2 shows that the PV panel allows to sell more electricity (points 10:00 and 11:00) and buy less electricity (period 12:00-15:00). Taking ambient temperature into consideration does not affect this pattern significantly, except the period 4:00-5:00, when the low temperature allows to produce power more efficient and sell excess electricity.

The Case 4 reports more power bought and less power sold in both months. As it was mentioned earlier, the power production is much less in the Case 4; then the algorithm satisfies the demand by buying electricity.

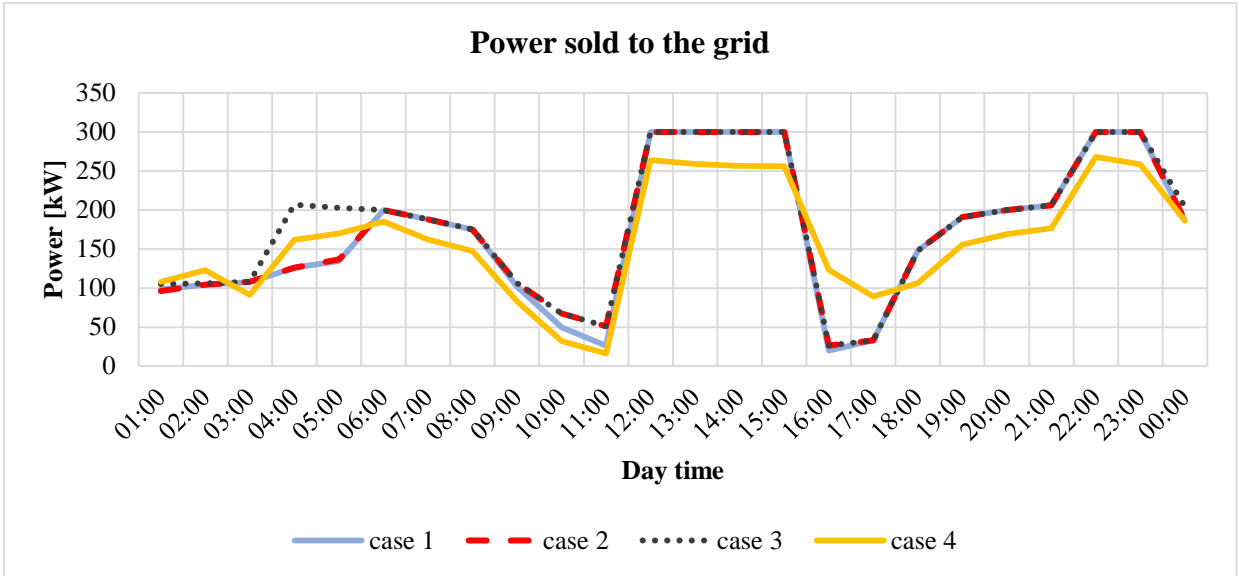


Figure 45. Power sold to the grid in December (summary)

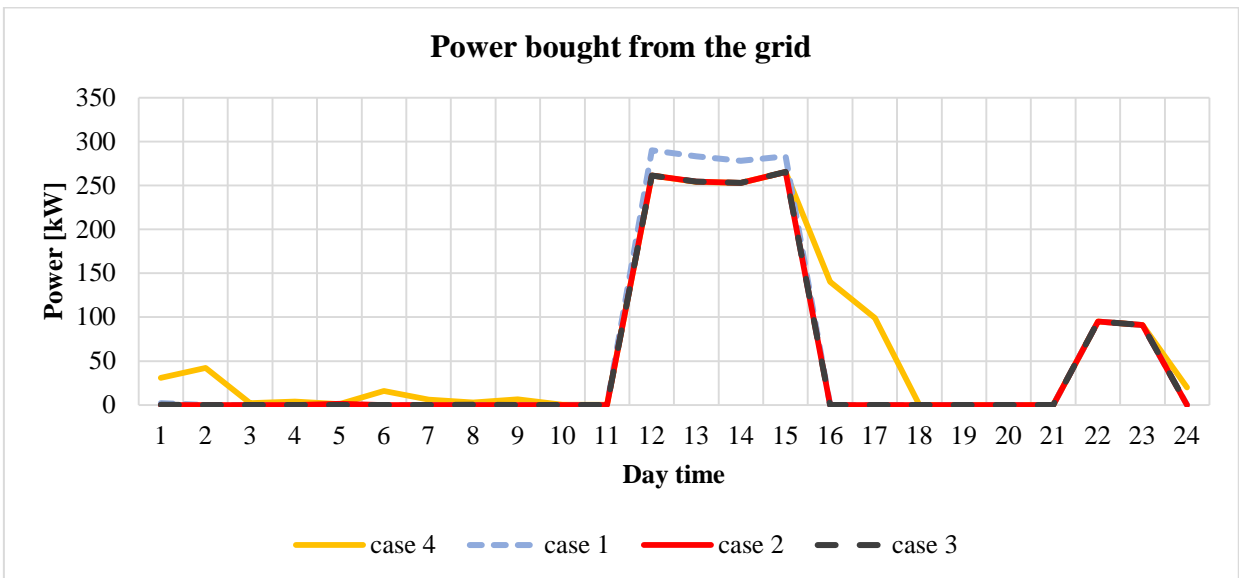


Figure 46. Power bought from the grid in December (summary)

Table 7 represents the total summary of all cases. All parameters were summarized for 24 hours.

Table 7: Total Summary

Case	July				December			
	1	2	3	4	1	2	3	4
Cost function [€/day]	124.51	110.56	107.84	312.63	179.31	169.48	144.61	402.25
Fuel cost (CHP) [€/day]	188.83	184.16	185.04	85.87	340.30	340.28	325.62	266.74
Fuel cost (AB) [€/day]	0.00	0.00	0.08	1.02	0.23	0.23	2.18	8.06
Sold electricity cost [€/day]	134.70	139.73	126.35	67.66	248.09	252.06	259.23	229.13
Bought electricity cost [€/day]	51.99	43.94	49.03	75.72	82.27	76.42	76.00	96.35
CHP fuel consumption [kg/day]	1229.79	1199.41	1205.16	559.25	1662.21	1662.15	1590.54	1302.93
AB fuel consumption [kg/day]	0.00	0.00	0.52	6.63	1.13	1.12	10.63	39.39
Heat produced by AB [kWh/day]	0.01	0.03	6.04	76.40	12.97	12.91	122.41	453.65
Electricity bought from the grid [kWh/day]	1288.83	1085.61	1215.22	1898.59	1320.77	1230.14	1220.26	1590.91
Electricity sold to the grid [kWh/day]	3104.87	3227.94	2863.40	1614.45	4096.40	4158.49	4326.31	3850.44
CHP power production [kWh/day]	4894.35	4771.43	4876.24	2239.72	6623.63	6623.13	6900.00	5622.47
CHP heat production [kWh/day]	8355.26	8147.06	9089.31	4174.52	11297.85	11297.83	10502.51	8533.02
PV power output [kWh/day]	-	349.50	349.50	349.50	-	153.22	153.22	153.22
CHP capital costs [€/day]	-	-	-	142.57	-	-	-	142.57
PV capital costs [€/day]	-	-	-	13.84	-	-	-	13.84
Boiler capital costs [€/day]	-	-	-	0.84	-	-	-	0.84
O&M costs [€/day]	-	-	-	41.39	-	-	-	85.67

## 4.6 Comparison of different algorithms

In this section, the results of three different algorithms are compared. As it was said in section 3.4, the optimization in Cases 1-4 was done via GA. As an additional study, the optimization of the Case 4 (a final one) was also performed with PSO and DE algorithms. The cost function value is used as a parameter for comparison because it represents the quality of the optimization. Table 8



shows the results. The cost function is in €/hour. The best solution at each time step is written in bold font. The same data is also illustrated in Figure 47 and Figure 48.

Table 8: Cost function value calculated by different algorithms

July							
Day time	GA	PSO	DE	Day time	GA	PSO	DE
1:00	<b>11.02851</b>	11.02854	11.03159	13:00	15.63312	<b>15.63301</b>	15.63730
2:00	<b>10.87665</b>	10.87669	10.87772	14:00	15.88641	<b>15.82942</b>	15.83423
3:00	<b>10.71383</b>	10.71386	10.71453	15:00	16.03984	<b>15.74363</b>	15.74711
4:00	<b>10.69280</b>	10.69285	10.69619	16:00	16.11901	<b>16.01840</b>	16.01868
5:00	<b>10.75456</b>	10.75460	10.75577	17:00	16.84202	<b>16.78190</b>	16.79315
6:00	<b>10.68364</b>	10.68368	10.68392	18:00	15.51761	<b>15.51044</b>	<b>15.51044</b>
7:00	<b>10.39093</b>	10.39093	10.39229	19:00	<b>13.43985</b>	13.43986	13.43986
8:00	<b>10.37829</b>	10.37832	10.38192	20:00	11.51548	<b>11.51511</b>	11.51735
9:00	11.07053	<b>11.06669</b>	11.06852	21:00	11.67145	11.67145	11.67145
10:00	16.42389	<b>16.32519</b>	16.32872	22:00	<b>11.29282</b>	11.29282	11.37646
11:00	17.15978	<b>16.94252</b>	16.94538	23:00	11.15800	<b>11.11609</b>	11.11610
12:00	16.00570	<b>15.98772</b>	15.98858	0:00	11.33996	<b>11.08199</b>	11.08275
December							
Day time	GA	PSO	DE	Day time	GA	PSO	DE
1:00	15.15075	<b>15.10293</b>	15.11995	13:00	21.69575	<b>20.81191</b>	20.82126
2:00	15.46570	<b>15.42278</b>	15.42596	14:00	21.67998	<b>20.80423</b>	20.80427
3:00	15.89112	<b>15.88102</b>	15.89978	15:00	22.30059	<b>21.33993</b>	21.34023
4:00	15.57198	<b>15.55989</b>	15.62135	16:00	23.19655	<b>21.96263</b>	21.97982
5:00	15.13295	<b>15.08028</b>	15.16054	17:00	22.96668	<b>21.88607</b>	21.90123
6:00	15.36058	<b>14.88435</b>	14.96261	18:00	15.81643	<b>15.25574</b>	15.27100
7:00	15.29247	<b>14.79484</b>	14.90989	19:00	11.73580	<b>11.52186</b>	11.52359
8:00	15.55603	<b>14.49209</b>	14.62157	20:00	10.08459	<b>10.00473</b>	10.02655
9:00	19.02905	<b>17.58975</b>	17.61943	21:00	9.23737	<b>9.23737</b>	9.25701
10:00	20.44722	<b>19.30101</b>	19.31558	22:00	9.49232	<b>9.49230</b>	9.50307
11:00	21.69057	<b>20.61839</b>	20.64104	23:00	12.56045	<b>12.55925</b>	12.58859
12:00	22.38633	<b>21.38837</b>	21.39421	0:00	14.50893	<b>14.48297</b>	14.48918

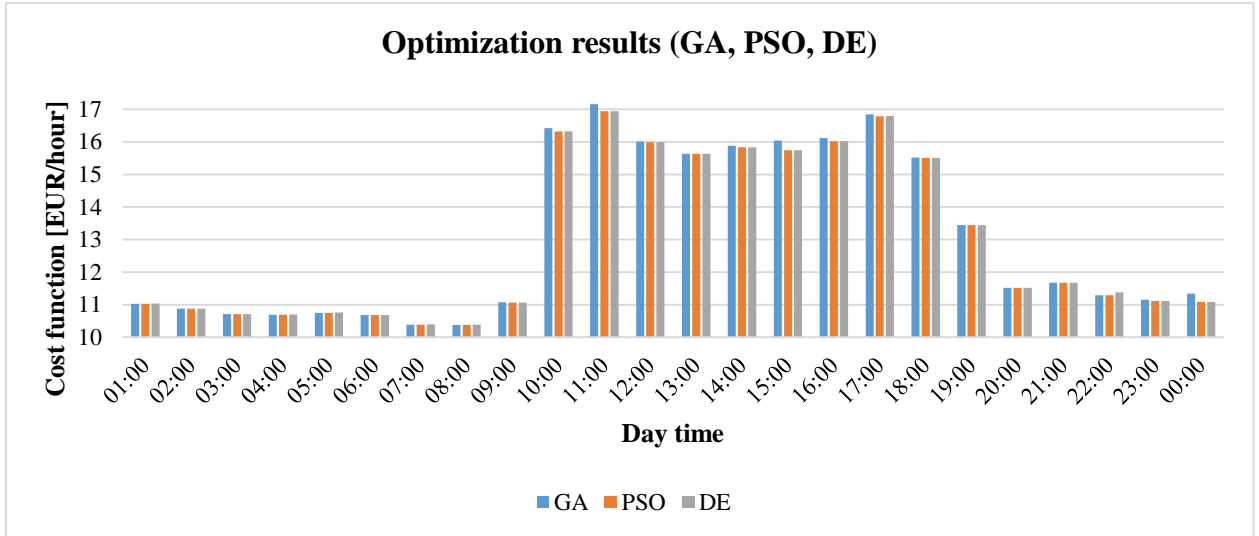


Figure 47. Cost function optimized by GA, PSO and DE (July)

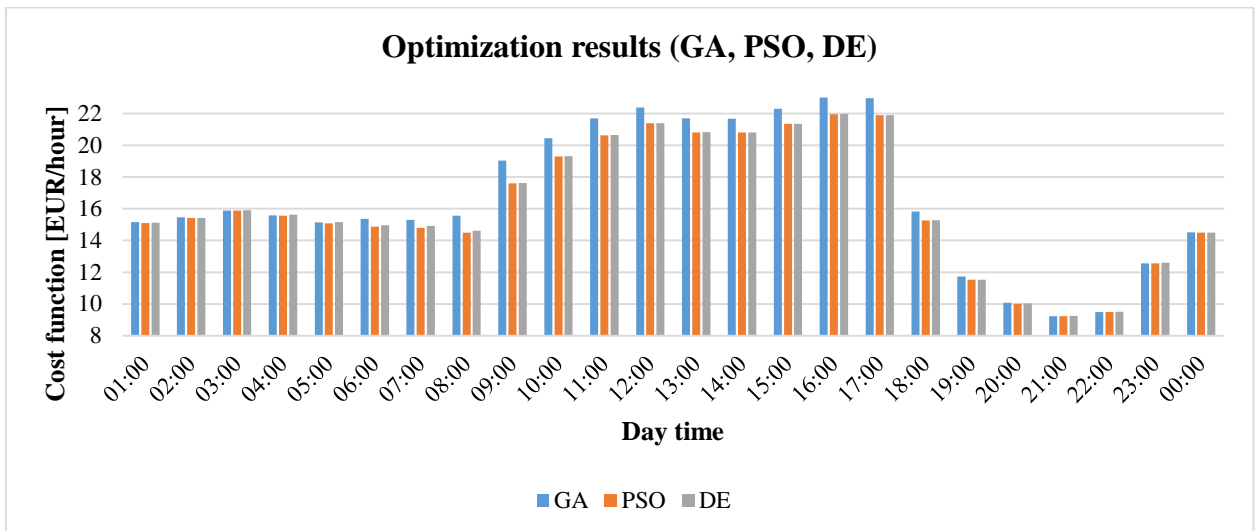


Figure 48. Cost function optimized by GA, PSO and DE (December)

It can be observed that generally, all algorithms converge at almost the same values. In July the best results were shown by GA and PSO. However, in some points (11:00, 15:00, 0:00) GA reports results, which are worse than PSO and DE. DE demonstrates stable results, always close to the best solution.

In December the GA shows significantly worse results than PSO and DE in the period 6:00-19:00. The PSO algorithm shows the best solutions at each point. However, DE also achieves good results very close to the optimum.

It can be concluded that, despite slightly different results, the data show that the specific problem studied in this project is not much sensitive to the optimization algorithm.

The second important parameter is a computation time, which was measured for each optimization run. Table 9 illustrates the obtained results. The data show that GA and PSO have almost the same speed, while DE is much slower.

*Table 9: Computation time for different algorithms*

<b>Algorithm</b>	<b>Computation time (seconds)</b>	
	<b>July</b>	<b>December</b>
GA	399.009	359.531
PSO	394.407	354.702
DE	2446.348	1616.260

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## Chapter 5

### Conclusion

This project was undertaken to design a novel framework for CHP optimization and examine its performance. The main goal was to propose an optimization tool, based on the integration of MATLAB programming environment with IPSEpro simulator and an automatic data exchange between these programs.

This research contributes to existing methods of the optimization of cogeneration and polygeneration systems, which is of importance regarding developing future sustainable energy systems.

In this investigation, the scopes were:

- to combine IPSEpro and MATLAB, in order to use the experimentally validated model of the AE-T100 CHP unit;
- to integrate it with the selected optimization algorithm;
- to develop an optimization framework, which provides a possibility to optimize the CHP unit along with other components (e.g. the AB and PV panel) under different pricing policy and various ambient conditions;
- to test the proposed optimization tool with different input data and analyze the results.

The applying of the proposed optimization tool to real data was not a part of the study. Therefore the optimization results were needed only to investigate the algorithm performance.

The present study suggested using COM interface to organize data interchanging between IPSEpro and MATLAB. This technology provides data sharing between two applications with a sufficient speed and remote control of a client application by the server application. The MATLAB code, developed within the scope of this project, allows to set values from MATLAB to any parameters of the IPSEpro model, run the simulation and receive the simulation results back to the MATLAB workspace.

A comprehensive literature survey was made to investigate different approaches to CHP optimization. Various algorithms, problem formulations and optimization strategies were reviewed and studied. In addition, the review of commercial optimization software was done.

The formulated optimization framework included three CHP units, the AB and the PV panel. Therefore, the cogeneration system was extended to polygeneration. An electricity trading option was included in the problem formulation. The objective function to be minimized contained the sum of operational costs and capital investments costs, calculated for 1 hour. Operational costs

The optimization goal was to optimize the operational strategy for the developed system during the period of 24 hours. The input data such as power and heat load, electricity prices and weather conditions were varying during a day according to assumed hourly-based profiles. The optimization was made for two representative days in July and December, to obtain the results for two different seasons. Thus, the optimization showed:

- the optimal number of CHP units, which should be working at each time step (including the possibility to turn off all CHP units, produce heat by the AB and buy electricity from the grid);
- the optimal load for each CHP unit and an AB;
- the amount of electricity which should be bought from the grid and/or sold to the grid, including the possibility to buy all electricity demand and sell all produced power;
- if the strategy is heat-led or power-led;
- what is the value of the cost function at each time step, *etc.*

The GA was used as an optimization algorithm. The detailed description of the algorithm, its implementation in MATLAB and applying to the considered problem was provided. The PSO and DE algorithms were also tested within an additional study. The investigation showed that all algorithms report close results. However, in most of the cases, PSO was better than GA.

Four test cases were studied; each represents a certain step in the model developing. Therefore, comparing these cases, the reaction of the algorithm on adding new components or changing the conditions was investigated, and the contribution of added parameters was observed.

The testing confirmed that the proposed optimization tool demonstrates a high flexibility and adaptation to different input parameters. It was observed that the algorithm tracks the changing in optimization conditions and reflects these changes by modifying the operational strategy. The optimization tool allows to extract a variety of optimization data and therefore provides an opportunity for careful investigation of the process. The results obtained by optimizations were studied in details and found to be relevant and adequate.

To sum it up, the result of the study is a developed automatic optimization tool, which allows optimizing operation of a polygeneration system under various conditions. Thus, it can be concluded that the objective of the research was attained.

An issue that was not addressed in this study is an environmental factor, including taxes for CO<sub>2</sub> and NO<sub>x</sub> emissions. Another source of weakness in this project is a rough model of the PV panel, which considers the efficiency of the solar cells to be constant, while it depends on the ambient temperature. Thirdly, the study did not consider optimization of CHP units number and PV panel area, assuming them to be constant. Further studies need to be carried out to take into account these limitations.

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## References

- Aalborg University. (n.d.). Introduction to EnergyPLAN. Retrieved from <http://www.energyplan.eu/training/introduction/>
- Åberg, M., Widén, J., & Henning, D. (2012). Sensitivity of district heating system operation to heat demand reductions and electricity price variations: A Swedish example. *Energy*, *41*(1), 525-540. doi:<http://dx.doi.org/10.1016/j.energy.2012.02.034>
- Ahmadi, P., Almasi, A., Shahriyari, M., & Dincer, I. (2012). Multi-objective optimization of a combined heat and power (CHP) system for heating purpose in a paper mill using evolutionary algorithm. *International Journal of Energy Research*, *36*(1), 46-63. doi:10.1002/er.1781
- Ansaldo Energia. (n.d.). Micro turbines. Retrieved from <http://www.ansaldoenergia.it/easynews/newsleggi.asp?newsid=11>
- ASHRAE. (2012). 2012 ASHRAE Handbook - Heating, Ventilating, and Air-Conditioning Systems and Equipment (SI Edition): American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
- ASHRAE. (2015). *Combined Heat and Power Design Guide* (Vol. 368): ASHRAE Technical Committee.
- Azizipanah-Abarghooee, R., Niknam, T., Bina, M. A., & Zare, M. (2015). Coordination of combined heat and power-thermal-wind-photovoltaic units in economic load dispatch using chance-constrained and jointly distributed random variables methods. *Energy*, *79*, 50-67. doi:<https://doi.org/10.1016/j.energy.2014.10.024>
- Balmorel. (n.d.). Retrieved from <http://www.balmorel.com/>
- Batas Bjelić, I., & Rajaković, N. (2015). Simulation-based optimization of sustainable national energy systems. *Energy*, *91*, 1087-1098. doi:<http://dx.doi.org/10.1016/j.energy.2015.09.006>
- Beihong, Z., & Weiding, L. (2006). An optimal sizing method for cogeneration plants. *Energy and Buildings*, *38*(3), 189-195. doi:<http://dx.doi.org/10.1016/j.enbuild.2005.05.009>
- Berkeley Lab. Distributed Energy Resources Customer Adoption Model (DER-CAM). Retrieved from <https://building-microgrid.lbl.gov/projects/der-cam>
- Berkeley Lab. (2012). DER-CAM. Decision support tool for decentralized energy systems.
- Bojić, M., & Stojanović, B. (1998). MILP optimization of a CHP energy system. *Energy Conversion and Management*, *39*(7), 637-642. doi:10.1016/S0196-8904(97)00042-3

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- Braun, M. A., Seijo, S., Echanobe, J., Shukla, P. K., del Campo, I., Garcia-Sedano, J., & Schmeck, H. (2016). A neuro-genetic approach for modeling and optimizing a complex cogeneration process. *Applied Soft Computing*, 48, 347-358.  
doi:<http://dx.doi.org/10.1016/j.asoc.2016.07.026>
- Breeze, P. (2005). *Power Generation Technologies* Burlington: Elsevier Science.
- Cardona, E., & Piacentino, A. (2005). Cogeneration: a regulatory framework toward growth. *Energy Policy*, 33(16), 2100-2111. doi:<https://doi.org/10.1016/j.enpol.2004.04.007>
- Chen, M., Lund, H., Rosendahl, L. A., & Condra, T. J. (2010). Energy efficiency analysis and impact evaluation of the application of thermoelectric power cycle to today's CHP systems. *Applied Energy*, 87(4), 1231-1238.  
doi:<http://dx.doi.org/10.1016/j.apenergy.2009.06.009>
- Cho, H., Luck, R., Eksiöglu, S. D., & Chamra, L. M. (2009). Cost-optimized real-time operation of CHP systems. *Energy & Buildings*, 41(4), 445-451. doi:10.1016/j.enbuild.2008.11.011
- Comodi, G., Renzi, M., Cioccolanti, L., Caresana, F., & Pelagalli, L. (2015). Hybrid system with micro gas turbine and PV (photovoltaic) plant: Guidelines for sizing and management strategies. *Energy*, 89, 226-235. doi:<https://doi.org/10.1016/j.energy.2015.07.072>
- Conn, A. R., Nick, G., & Ph, L. T. (1997). A globally convergent Lagrangian barrier algorithm for optimization with general inequality constraints and simple bounds. *Mathematics of Computation of the American Mathematical Society*, 66(217), 261-288.  
doi:10.1090/S0025-5718-97-00777-1
- Connolly, D., Lund, H., Mathiesen, B. V., & Leahy, M. (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, 87(4), 1059-1082. doi:<http://dx.doi.org/10.1016/j.apenergy.2009.09.026>
- Costa, A., & Fichera, A. (2014). A mixed-integer linear programming (MILP) model for the evaluation of CHP system in the context of hospital structures. *Applied Thermal Engineering*, 71(2), 921-929. doi:<http://dx.doi.org/10.1016/j.applthermaleng.2014.02.051>
- Dahlquist, E. (2008). *Use of Modeling and Simulation in Pulp and Paper Industry*: COST.
- Danestig, M., Gebremehdin, A., & Karlsson, B. (2007). Stockholm CHP potential—An opportunity for CO2 reductions? *Energy Policy*, 35(9), 4650-4660.  
doi:<http://dx.doi.org/10.1016/j.enpol.2007.03.024>
- Eberhart, R., & Kennedy, J. (1995). *A new optimizer using particle swarm theory*. Paper presented at the Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on.
- EMD International A/S. energyPRO. Retrieved from <http://www.emd.dk/energypro/#>

- 
- Ersoz, I., & Colak, U. (2016). Combined cooling, heat and power planning under uncertainty. *Energy*, *109*, 1016-1025. doi:<https://doi.org/10.1016/j.energy.2016.04.071>
- Fisher, M. L. (1985). An Applications Oriented Guide to Lagrangian Relaxation. *Interfaces*, *15*(2), 10-21.
- Fladmark, B., & Grimstad, G. B. (2013). *Seasonality in natural gas prices : an empirical study of Henry Hub natural gas futures prices*
- Fragaki, A., & Andersen, A. N. (2011). Conditions for aggregation of CHP plants in the UK electricity market and exploration of plant size. *Applied Energy*, *88*(11), 3930-3940. doi:<http://dx.doi.org/10.1016/j.apenergy.2011.04.004>
- Fraunhofer Institute for Solar Energy Systems ISE. (n.d.). Energy Charts. Retrieved from <https://www.energy-charts.de/price.htm>
- Ghaem Sigarchian, S., Orosz, M. S., Hemond, H. F., & Malmquist, A. (2016). Optimum design of a hybrid PV–CSP–LPG microgrid with Particle Swarm Optimization technique. *Applied Thermal Engineering*, *109, Part B*, 1031-1036. doi:<https://doi.org/10.1016/j.applthermaleng.2016.05.119>
- Haghray, A., Nazari-Heris, M., & Mohammadi-ivatloo, B. (2016). Solving combined heat and power economic dispatch problem using real coded genetic algorithm with improved Mühlenbein mutation. *Applied Thermal Engineering*, *99*, 465-475. doi:<http://dx.doi.org/10.1016/j.applthermaleng.2015.12.136>
- Henning, D. (1998). Cost minimization for a local utility through CHP, heat storage and load management. *International Journal of Energy Research*, *22*(8), 691-713. doi:[10.1002/\(SICI\)1099-114X\(19980625\)22:8<691::AID-ER395>3.0.CO;2-E](https://doi.org/10.1002/(SICI)1099-114X(19980625)22:8<691::AID-ER395>3.0.CO;2-E)
- Huang, S.-H., & Lin, P.-C. (2013). A harmony-genetic based heuristic approach toward economic dispatching combined heat and power. *International Journal of Electrical Power & Energy Systems*, *53*, 482-487. doi:<http://dx.doi.org/10.1016/j.ijepes.2013.05.027>
- International Energy Agency. (2008). *Combined Heat and Power: Evaluating the benefits of greater global investment*. Retrieved from Paris, France:
- Kennedy, J. (2011). Particle swarm optimization *Encyclopedia of machine learning* (pp. 760-766): Springer.
- Kim, J. S., & Edgar, T. F. (2014). Optimal scheduling of combined heat and power plants using mixed-integer nonlinear programming. *Energy*, *77*, 675-690. doi:<http://dx.doi.org/10.1016/j.energy.2014.09.062>



- 
- Kopanos, G. M., Georgiadis, M. C., & Pistikopoulos, E. N. (2013). Energy production planning of a network of micro combined heat and power generators. *Applied Energy*, *102*, 1522-1534. doi:<http://dx.doi.org/10.1016/j.apenergy.2012.09.015>
- Kvarnström, A., & Dahlquist, E. (2005). *Process optimization utilizing an external simulation model*. Paper presented at the Proceedings of the 46th Scandinavian Conference on Simulation and Modeling (SIMS2005), Trondheim, Norway.
- Lahdelma, R., & Hakonen, H. (2003). An efficient linear programming algorithm for combined heat and power production. *European Journal of Operational Research*, *148*(1), 141-151. doi:10.1016/S0377-2217(02)00460-5
- Lambert, T., Gilman, P., & Lilienthal, P. (2006). Micropower System Modeling with HOMER. *Integration of Alternative Sources of Energy*.
- Lewis, R. M., Torczon, V. J., Kolda, T. G., & United States. Department Of, E. (2006). A generating set direct search augmented Lagrangian algorithm for optimization with a combination of general and linear constraints: Sandia National Laboratories.
- Lingfeng, W., & Chanan, S. (2006, 0-0 0). *Stochastic combined heat and power dispatch based on multi-objective particle swarm optimization*. Paper presented at the 2006 IEEE Power Engineering Society General Meeting.
- Lund, H., & Münster, E. (2003). Modelling of energy systems with a high percentage of CHP and wind power. *Renewable Energy*, *28*(14), 2179-2193. doi:[http://dx.doi.org/10.1016/S0960-1481\(03\)00125-3](http://dx.doi.org/10.1016/S0960-1481(03)00125-3)
- Lund, H., Šiupšinskas, G., & Martinaitis, V. (2005). Implementation strategy for small CHP-plants in a competitive market: the case of Lithuania. *Applied Energy*, *82*(3), 214-227. doi:<http://dx.doi.org/10.1016/j.apenergy.2004.10.013>
- Ma, L., Liu, N., Zhang, J., Tushar, W., & Yuen, C. (2016). Energy Management for Joint Operation of CHP and PV Prosumers Inside a Grid-Connected Microgrid: A Game Theoretic Approach. *IEEE Transactions on Industrial Informatics*, *12*(5), 1930-1942. doi:10.1109/TII.2016.2578184
- Ma, X., Wang, Y., & Qin, J. (2013). Generic model of a community-based microgrid integrating wind turbines, photovoltaics and CHP generations. *Applied Energy*, *112*, 1475-1482. doi:<https://doi.org/10.1016/j.apenergy.2012.12.035>
- Manolas, D., Gialamas, T. P., Frangopoulos, C., & Tsahalis, D. (1996). A genetic algorithm for operation optimization of an industrial cogeneration system. *Comput. Chem. Eng.*, *20*, S1107-S1112.

- 
- MathWorks. (n.d.-a). Find minimum of function using genetic algorithm. Retrieved from <https://se.mathworks.com/help/gads/ga.html#btzwmpg>
- MathWorks. (n.d.-b). Genetic Algorithm Options. Retrieved from <https://se.mathworks.com/help/gads/genetic-algorithm-options.html#f6633>
- MathWorks. (n.d.-c). How the Genetic Algorithm Works. Retrieved from <https://se.mathworks.com/help/gads/how-the-genetic-algorithm-works.html>
- MathWorks. (n.d.-d). Nonlinear Constraint Solver Algorithm. Retrieved from [https://se.mathworks.com/help/gads/description-of-the-nonlinear-constraint-solver\\_bqf9jvg-1.html](https://se.mathworks.com/help/gads/description-of-the-nonlinear-constraint-solver_bqf9jvg-1.html)
- MathWorks. (n.d.-e). What Is the Genetic Algorithm? Retrieved from <https://se.mathworks.com/help/gads/what-is-the-genetic-algorithm.html>
- Meckler, M., Hyman, L. B., Maor, I., Reddy, T. A., Stadnik, A., Foley, G., . . . Brambley, M. R. (2010). *Sustainable on-site CHP systems: design, construction, and operations*. New York: New York: McGraw-Hill.
- Merkel, E., McKenna, R., & Fichtner, W. (2015). Optimisation of the capacity and the dispatch of decentralised micro-CHP systems: A case study for the UK. *Applied Energy*, 140, 120.
- Microsoft. (n.d.-a). The Component Object Model. Retrieved from [https://msdn.microsoft.com/en-us/library/windows/desktop/ms694363\(v=vs.85\).aspx](https://msdn.microsoft.com/en-us/library/windows/desktop/ms694363(v=vs.85).aspx)
- Microsoft. (n.d.-b). Registering COM Applications. Retrieved from [https://msdn.microsoft.com/en-us/library/windows/desktop/ms683954\(v=vs.85\).aspx](https://msdn.microsoft.com/en-us/library/windows/desktop/ms683954(v=vs.85).aspx)
- Microsoft. (n.d. ). COM Clients and Servers. Retrieved from [https://msdn.microsoft.com/en-us/library/windows/desktop/ms683835\(v=vs.85\).aspx](https://msdn.microsoft.com/en-us/library/windows/desktop/ms683835(v=vs.85).aspx)
- Mohammadi-Ivatloo, B., Moradi-Dalvand, M., & Rabiee, A. (2013). Combined heat and power economic dispatch problem solution using particle swarm optimization with time varying acceleration coefficients. *Electric Power Systems Research*, 95, 9-18.  
doi:<https://doi.org/10.1016/j.epsr.2012.08.005>
- Nikpey Somehsaraei, H., Mansouri Majoumerd, M., Breuhaus, P., & Assadi, M. (2014). Performance analysis of a biogas-fueled micro gas turbine using a validated thermodynamic model. *Applied Thermal Engineering*, 66(1–2), 181-190.  
doi:<http://dx.doi.org/10.1016/j.applthermaleng.2014.02.010>
- Optensys Energianalys AB. The MODEST Energy System Optimisation Model. Retrieved from <http://www.optensys.se/index-filer/Page677.htm>

- 
- Østergaard, P. A. (2015). Reviewing EnergyPLAN simulations and performance indicator applications in EnergyPLAN simulations. *Applied Energy*, *154*, 921-933.  
doi:<http://dx.doi.org/10.1016/j.apenergy.2015.05.086>
- Piperagkas, G. S., Anastasiadis, A. G., & Hatziargyriou, N. D. (2011). Stochastic PSO-based heat and power dispatch under environmental constraints incorporating CHP and wind power units. *Electric Power Systems Research*, *81*(1), 209-218.  
doi:<https://doi.org/10.1016/j.epr.2010.08.009>
- Ravn, H. F., Munksgaard, J., Risø National Lab., R. S. A. D., Amternes og Kommunernes Forskningsinstitut, C. I. o. L. G. S., Ramskov, J., Grohnheit, P. E., . . . Energetics, I. o. P. (2001). *Balmorel: A Model for Analyses of the Electricity and CHP Markets in the Baltic Sea Region. Appendices* (9788798696933). Retrieved from
- Reeves, C. R. (2010). Genetic Algorithms. In M. Gendreau & J.-Y. Potvin (Eds.), *Handbook of Metaheuristics* (pp. 109-139). Boston, MA: Springer US.
- Ren, H., Gao, W., & Ruan, Y. (2008). Optimal sizing for residential CHP system. *Applied Thermal Engineering*, *28*(5-6), 514-523.  
doi:<http://dx.doi.org/10.1016/j.applthermaleng.2007.05.001>
- Rong, A., Hakonen, H., & Lahdelma, R. (2006). An efficient linear model and optimisation algorithm for multi-site combined heat and power production. *European Journal of Operational Research*, *168*(2), 612-632. doi:10.1016/j.ejor.2004.06.004
- Rowe, J. E. (2015). Genetic Algorithms. In J. Kacprzyk & W. Pedrycz (Eds.), *Springer Handbook of Computational Intelligence* (pp. 825-844). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Safari, A. (2014). *Numerical Simulation Driven Product Design Optimization for Improved Performance : A focus on high-dimensional expensive blackbox optimization problems*. (PhD), University of Stavanger, Stavanger.
- Safari, A., Lemu, H. G., Jafari, S., & Assadi, M. (2013). A Comparative Analysis of Nature-Inspired Optimization Approaches to 2D Geometric Modelling for Turbomachinery Applications. *Mathematical Problems in Engineering*, *2013*, 15.  
doi:10.1155/2013/716237
- Sashirekha, A., Pasupuleti, J., Moin, N. H., & Tan, C. S. (2013). Combined heat and power (CHP) economic dispatch solved using Lagrangian relaxation with surrogate subgradient multiplier updates. *International Journal of Electrical Power & Energy Systems*, *44*(1), 421-430. doi:<http://dx.doi.org/10.1016/j.ijepes.2012.07.038>

- 
- Sauer, J. G., dos Santos Coelho, L., Mariani, V. C., de Macedo Mourelle, L., & Nedjah, N. (2011). A Discrete Differential Evolution Approach with Local Search for Traveling Salesman Problems. In N. Nedjah, L. dos Santos Coelho, V. C. Mariani, & L. de Macedo Mourelle (Eds.), *Innovative Computing Methods and Their Applications to Engineering Problems* (pp. 1-12). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Shaneb, O. A., Taylor, P. C., & Coates, G. (2011). Optimal online operation of residential  $\mu$ CHP systems using linear programming. *Energy & Buildings*.  
doi:10.1016/j.enbuild.2011.10.003
- Shukla, A., Tiwari, R., & Kala, R. (2010). Genetic Algorithm *Towards Hybrid and Adaptive Computing: A Perspective* (pp. 59-82). Berlin, Heidelberg: Springer Berlin Heidelberg.
- SimTech. (n.d.). PSXLink: Integration with Microsoft Excel Retrieved from  
<http://www.simtechnology.com/CMS/index.php/ipsepro/program-modules/psxlink>
- Song, Y. H., & Xuan, Q. Y. (1998). COMBINED HEAT AND POWER ECONOMIC DISPATCH USING GENETIC ALGORITHM BASED PENALTY FUNCTION METHOD. *Electric Machines & Power Systems*, 26(4), 363-372.  
doi:10.1080/07313569808955828
- Streckiene, G., & Andersen, A. N. (2008). Analyzing the optimal size of a CHP-unit and thermal store when a German CHP-plant is selling at the Spot market *Intelligent Energy Europe*.
- Teymourihamzehkolaei, F., & Sattari, S. (2011). Technical and economic feasibility study of using Micro CHP in the different climate zones of Iran. *Energy*, 36(8), 4790-4798.  
doi:10.1016/j.energy.2011.05.013
- The MathWorks Inc. (2017). *MATLAB External Interfaces*.
- Thorin, E., Brand, H., & Weber, C. (2005). Long-term optimization of cogeneration systems in a competitive market environment. *Applied Energy*, 81(2), 152-169.  
doi:10.1016/j.apenergy.2004.04.012
- Thorin, E., Sandberg, J., & Yan, J. (2015). *Combined Heat and Power*.
- Tibi, N., & Arman, H. (2007). A linear programming model to optimize the decision-making to managing cogeneration system. *Clean Technologies and Environmental Policy*, 9(3), 235-240. doi:10.1007/s10098-006-0075-2
- Tichi, S. G., Ardehali, M. M., & Nazari, M. E. (2010). Examination of energy price policies in Iran for optimal configuration of CHP and CCHP systems based on particle swarm optimization algorithm. *Energy Policy*, 38(10), 6240-6250.  
doi:https://doi.org/10.1016/j.enpol.2010.06.012

- 
- Widmann, C., Lödige, D., Toradmal, A., & Thomas, B. (2017). Enabling CHP units for electricity production on demand by smart management of the thermal energy storage. *Applied Thermal Engineering*, *114*, 1487-1497.  
doi:<https://doi.org/10.1016/j.applthermaleng.2016.08.065>
- Winston, W. L., & Goldberg, J. B. (2004). *Operations Research: Applications and Algorithms*: Thomson Brooks/Cole.
- Wu, D. W., & Wang, R. Z. (2006). Combined cooling, heating and power: A review. *Progress in Energy and Combustion Science*, *32*(5–6), 459-495.  
doi:<https://doi.org/10.1016/j.pecs.2006.02.001>
- Wu, Z., Gu, W., Wang, R., Yuan, X., & Liu, W. (2011, 24-29 July 2011). *Economic optimal schedule of CHP microgrid system using chance constrained programming and particle swarm optimization*. Paper presented at the 2011 IEEE Power and Energy Society General Meeting.
- Yazdi, B. A., Ehyaei, M. A., & Ahmadi, A. (2015). OPTIMIZATION OF MICRO COMBINED HEAT AND POWER GAS TURBINE BY GENETIC ALGORITHM. *Thermal Science*, *19*(1), 207-218. doi:10.2298/TSCI121218141Y
- Zaccardi, M. (2017). Natural Gas Outlook: Seasonality Trends Bullish For Spring. Retrieved from <https://www.seeitmarket.com/natural-gas-price-outlook-seasonality-trends-bullish-spring-trading-16666/>