# Installation of a dynamic controller for the optimal operation of a CHP engine in a supermarket under uncertainty

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**Abstract:**

This work is concerned with the integration and coordination of decentralized combined heat and power (CHP) systems in commercial buildings. Although extensive research has been performed on theoretically optimizing the design, sizing and operation of CHP systems, less effort has been devoted to an understanding of the practical challenges and the effects of uncertainty in implementing advanced algorithms to real-world applications. This paper provides details of an undergoing field trial involving the installation of a dynamic controller for the optimal operation of an existing CHP engine, which provides electricity and heat to a supermarket. The challenges in developing and applying an optimization framework and the software architecture required to implement it are discussed. Deterministic approaches that involve no measure of uncertainty provide limited useful insight to decision makers. For this reason, the methodology here develops a stochastic programming technique, which performs Monte Carlo simulations that can consider the uncertainty related to the exporting electricity price. The method involves the formation of a bi-objective function that represents a compromise between maximizing the expected savings and minimizing the associated risk. The results reveal a risk-return trade-off, demonstrating that conservative operation choices emerging from the stochastic approach can reduce risk by about 15% at the expense of a noticeably smaller reduction of about 10% in expected savings.

**Keywords:**

Combined heat and power, CHP, Control system, Distributed energy, Energy management, Internal combustion engine (ICE), Optimization.

# 1. Introduction

The integration and coordination of distributed energy resources (DERs) – decentralized generation – can lead to reduced fossil fuel consumption and offer significant financial savings to end-users. The global drive for increased efficiency has led to a continually growing development of combined heat and power (CHP) systems, which incorporate the simultaneous local generation of both electricity and heat. Such technologies can recover heat that would be otherwise wasted in traditional systems [1]. The selection and operation of CHP engines has been widely studied and shows great potential for microgrid networks [2–5]. However, although extensive research has been done in how to select, size and operate CHP units, controllers for their optimal utilization have not yet been widely used in buildings, causing huge amounts of energy and financial losses. The ability to modulate the CHP engine's operation level based on real-time electricity prices can have a remarkable impact on the sustainability and costs of the system. Furthermore, in a time where renewable technologies and grid unpredictability are increasing faster than ever, including real-world uncertainty in the optimal control strategy becomes particularly important, since it allows decision makers to acquire information regarding the risk involved in their choices.

## 1.1. Field trials on CHP operation

Several experimental studies on small-scale CHP units have been performed. One study [6], for example, assesses the performance of a biomass-fuelled micro-CHP-ORC prototype under different operating conditions. Although the prototype confirms the potential benefits of the system, no optimization technique is tested. Similarly, another study [7] tests a novel CHP unit based on woodchip combustion under steady-state nominal operation and dynamic start-up, however no control under real-life conditions is examined. A series of operational tests is also performed on a CHP installation involving a biomass downdraft gasifier [8], while other experimental tests on CHP units involve solid oxide fuel cells [9] and large temperature lift heat pumps [10].

Although experimental work is taking place, very little literature describes real trials on optimizing the operation of CHP systems operating in the real market. Most studies explore various real-life scenarios and utilize data from manufacturer's data sheets and weather/price documentations, however evidence for the application of optimization techniques on the actual machines is very limited. The non-profit company Carbon Trust conducted a trial [11], by installing 87 micro-CHP systems made of Stirling and internal combustion engine units around the UK. The study demonstrated that a typical micro-CHP system can result to about 16% overall carbon savings, but the control approach just involved the CHP unit following the heat requirements of each building, underestimating the potential savings. Another trial that has been conducted is the European-wide field trial for residential fuel cell micro-CHP "ene.field project" [12], where 1046 small fuel cell CHP units were installed around 10 countries and were operated to be either electricity-led or heat-led, not utilizing any complex optimization techniques.

## 1.2. Operation under uncertainty

Most DER system optimization studies are deterministic, meaning that they involve no randomness when predicting future system inputs. This means a significant drawback: they do not provide insights to the user of the possible risks associated with the suggested operation. In real-world applications, risk management is vital; decision makers want to know the risk-return trade-off before they trust an optimization algorithm to make choices for them.

Detailed approaches which can describe uncertainty in probabilistic scenarios are required, making the best possible operation choice according to the degree of risk decision makers are willing to take. Such approaches often involve stochastic programming, which incorporates uncertainty in some variables of the optimization problem, characterized by a probability distribution [13], thus providing a distribution of possible results for each choice of inputs. Stochastic methods specifically for DER applications are not uncommon. Since such methods are usually computationally expensive, they are often preferred in design [14–17] studies, where the problem has to be solved only once. When optimizing operation, on the other hand, the problem needs to be continuously solved at every specified time step, so that the controller adjusts operation according to new measurements [18–20]. It must be noted that in design studies, as well as scheduling studies with large time steps, the number of uncertain parameters is considerably large –

the uncertainty in future electricity demand, heating demand, weather and electricity prices needs to be integrated within the design problem, usually requiring scenario reduction approaches [14,15,18–20] and/or evolutionary algorithms [16,17]. Since stochastic approaches by nature do not result to one optimal decision, the techniques discussed above present results in the following ways: In Refs. [15–18], the optimal decision is taken as the one which maximizes the expected cost savings, while Refs. [14,20] face the trade-off between economic and environmental performance by setting limit values to costs and/or emissions. In Ref. [19], the authors provide Pareto-optimal solutions and leave the decision approach to be chosen by the decision maker. These methods are risk-neutral and provide limited information about the risk associated with each choice.

The need for techniques that provide risk-associated insights has led to increasing notice being given to Conditional Value at Risk (CVaR), a risk measure which has recently appeared in optimal energy control problems. The inclusion of this measure in the optimization problem captures the desire of decision makers to keep risk under control. For instance, CVaR is considered in the optimal operation of a photovoltaic-battery system [21]. Similarly, CVaR also appears in the scheduling optimization problem of residential appliances [22] and in the day-ahead optimization of DERs [23].

This paper aims to build on previous studies to provide two main contributions. First, unlike previous literature, it aims to demonstrate the challenges in applying an optimization framework to an actual CHP engine, including a discussion of the software architecture required. Then, it applies the CVaR measure in order to develop a stochastic framework for the real-time control of the CHP engine. This is done by the formation of a bi-objective function that allows decision makers to assign a user-controlled weight, which represents how much risk they are willing to take. To achieve this, the paper first discusses the two-level control system required for the implementation of the optimization technique. It then provides a description of the model and the stochastic framework, followed by the formulation of the optimization function. Finally, results reveal the arising risk-return trade-off and demonstrate the different strategies that can be adopted using the proposed method in real-world applications.

## 2. System description

The CHP engine considered in this study is a 250 kWe gas-fired combustion engine used to supply both heat and electricity to a supermarket. A schematic representation of the environment in which the unit operates is provided in Fig. 1.

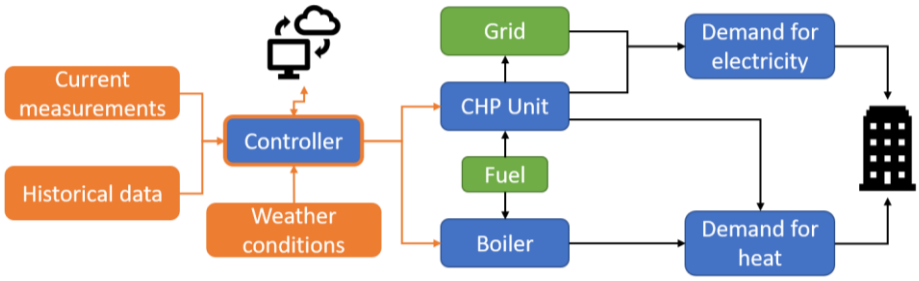


*Figure 1. Schematic representation of the CHP system.*

The electricity and heat demand of the supermarket can be met in different ways. In traditional approaches, the CHP unit is run to either follow the electric or thermal load. If at a specific partload, which is the level at which the unit operates, the heat provided is not enough to meet the heating requirements of the building, a backup boiler is used. If, on the other hand, more heat is provided than what required, it is wasted; removed with the use of a radiator. Furthermore, if excess or insufficient electricity is provided in relation to what is required, electricity can be exchanged with the grid. Traditional strategies are simple to implement but do not guarantee optimal operation.

The proposed management system aims at making the best possible operation choice by continuous monitoring and automation and is implemented through a two-level control system made of a cloud-based controller and an on-premises controller. The function of the cloud-based controller is to utilize continuous measurements of electricity demand, heat demand and importing electricity price to solve the optimization problem and therefore plan the energy strategy of the system. The on-premises

controller then actuates the instructions received from the cloud-based controller, acting as a safety system and secondary control logic in case of any wrong instructions or unexpected problems.

## 2.1 Cloud-based controller

The evolution of intelligent communication has expanded the capabilities of the information technology infrastructure. Internet of things (IoT) software platforms, by exchanging data over the Internet, can be used to integrate equipment and electronic devices and therefore allow for the real-time control of machine operation [24]. In the proposed approach, telemetry data coming from the site is continuously published to an Amazon Web Service (AWS) IoT broker [25]. A specifically designed microservice architecture reads and processes data in real-time, performing tasks such as forecasting, optimization and conditional monitoring. The overriding idea of this work is to test optimization and forecasting algorithms, therefore the architecture is designed to be reliable and flexible to configure. In particular, data is processed and sent to Amazon DynamoDB [26], a Non-Structured Query Language (NoSQL) database for low-latency access from the various microservices. The database includes real-time weather data and electricity prices provided by third-party application program interfaces (APIs). This data is used in a neural network framework to make predictions, which then act as inputs into the optimization model. For the importing electricity price, a cost function is used to add all the different network charges (Distribution Network Use of System charges, Transmission Network Use of System charges, etc.) on top of the electricity commodity price [27], as provided by the electrical energy market "Nord pool".

## 2.2 On-premises controller

The on-premises control system is integrated with the CHP system as well as the Heating, Ventilation and Air Conditioning (HVAC) unit and can capture data from all the necessary sensors at high frequency (< 1s). The controller has been designed to capture around 300 telemetry points including temperatures, valve positioning, and metering. Integration work is required to read from the different systems installed in the supermarkets (HVAC, external electricity meters, CHP system data points). The data points are then sent to the cloud via Message Queuing Telemetry Transport (MQTT), utilizing both a value change rule for the important points (around 20) and a poll instruction for the less important ones. The system is configured so that data is published at an average frequency of 5 min. The important data points are the ones without which the cloud-controller would be limited in the optimization capabilities; those include: CHP gas consumption, electricity production, hot water temperature, electricity import and export meter. At the same time, the on-premises controller receives instructions from the cloud-based controller on how to operate the CHP engine, mainly: when to switch the engine on/off, which partload to use or when to run the engine with a basic operation (load follow, heat follow, fixed setpoint). The logic is such that a basic operation can always be implemented whenever something goes wrong (e.g. the connection to the server is lost). Also, the controller serves as a second security layer to process and discard any unexpected values received from the cloud.

# 3. Problem design

This section presents the model used by the microservice architecture of the cloud-based controller to solve the optimization problem and explains the stochastic framework developed.

## 3.1 Model

Converting a single fuel into both electricity and heat means that CHP systems involve high overall efficiencies and can therefore reduce energy costs of buildings like supermarkets significantly [28, 29]. The CHP system considered involves a spark-ignition, gas-fired reciprocating engine acting as the prime mover. Heat is recovered by the engine block and an exhaust gas heat exchanger in the form of low temperature hot water. Depending on the partload, the thermal and electrical efficiencies vary. For modelling the system, linear regression was used to obtain relationships between the system's partload, fuel input requirement, generated heat and electricity. This was done by using values from manufacturers' technical datasheets [30]. The three linear functions developed in matrix form are:

$$\begin{bmatrix} F \\ G_{\mathrm{th}} \\ G_{\mathrm{el}} \end{bmatrix} = \begin{bmatrix} a_{\mathrm{f}} \\ a_{\mathrm{th}} \\ a_{\mathrm{el}} \end{bmatrix} PL + \begin{bmatrix} \beta_{\mathrm{f}} \\ \beta_{\mathrm{th}} \\ \beta_{\mathrm{el}} \end{bmatrix} \quad (1)$$

where $F$, $G_{\mathrm{th}}$ and $G_{\mathrm{el}}$ are the fuel input required, generated heat and generated electricity at partload $PL$ respectively, while $a_{\mathrm{f}}$, $a_{\mathrm{th}}$, $a_{\mathrm{el}}$, $\beta_{\mathrm{f}}$, $\beta_{\mathrm{th}}$ and $\beta_{\mathrm{el}}$ are the fixed linear regression parameters. It must be noted that the linear relationship is a large assumption of this model; for more accurate analysis and specifically for CHP system design, detailed approaches which capture the non-linear efficiency characteristics and include promising heat recovery technologies [31–33] would be required.

## 3.2 Uncertainty and Monte Carlo method

The uncertainty considered in optimal operation problems such as the one in this paper, is not the same as that in optimal design problems. In the first, only the short-term uncertainty of the immediate future is of interest, while in the second, the long-term uncertainty of the variables needs to be considered. In the field trial described, the controller continuously updates the problem with new measurements and schedules operation only for the current time step. The only uncertain variable at the point of the decision is the price of exporting electricity, which has to be forecasted. This prediction will happen with the use of neural networks, a method utilizing artificial neurons that, using historical data and weather conditions, get trained to predict the current price within certain prediction intervals for a specified confidence level. The technique has been set-up within the cloud-based controller but has not yet been implemented, therefore the simulations of this study will assume already obtained forecasts.

The CHP engine's operation problem could be solved using a deterministic approach; this would involve using the value of the exporting electricity price forecasted by the neural networks directly in the objective function and solving for the optimum partload. However, to capture the risk associated with each decision, quantifying the uncertainty of the price in the decision problem is crucial. For this reason, a Monte Carlo simulation technique is adopted. Monte Carlo is a famous method used to allow project managers to quantify risk and uncertainty [34], and plays a key role in dealing with uncertainty in power systems [35]. The technique involves parameters with uncertainty being modelled by Probability Density Functions (PDFs). Based on these PDFs, a large number $N$ of random samples is generated; large enough to capture all the possible scenarios; therefore $N$ vectors of inputs are formed. The simulation is performed for every single input vector, therefore providing $N$ outputs.

In the CHP operation problem considered in this paper, there is only one uncertain variable. This makes this process easy, in the sense that no reduction methods are required and all possible scenarios can be tested. Historical data and previous studies [15,18] demonstrate that forecasts of electricity prices can be assumed to follow the normal distribution. This means that at each time step, the value of forecasted exporting electricity price and its prediction intervals provided by the forecasting technique can be used to fit a normal distribution. Then, $N$ values from this normal distribution are randomly selected and the problem is solved $N$ times, resulting to $N$ optimum partload values; each corresponding to a random exporting electricity price. The set of partload values defines the PDF of the result, which can be used to provide more useful insights than the deterministic approach. Solving the formed optimization problem is very fast, which makes a large number of simulations feasible.

# 4. Optimization problem

The objective function in this study comprises two components. The first involves maximizing the total expected savings resulting from the utilization of the CHP engine compared to a scenario where the CHP engine is not used. The second component considers the CVaR risk measure, which aims to minimize the risk associated with the uncertainty in the exporting electricity price. This section presents how the integration of the two components results in a useful tool for decision makers.

In the proposed objective function, the price of fuel and boiler efficiency are assumed fixed. Furthermore, since the controller operates in real time, the cost savings to be maximized are those of the current time step only. In the absence of a CHP engine, the heat and electricity demand of the supermarket would be met by utilizing a boiler to generate heat and by buying electricity from the grid. The associated cost per unit of time, at time $t$, would therefore be:

$$C_{\mathrm{noCHP},t} = \left({}^{D_{\mathrm{th},t} \cdot P_{\mathrm{fuel}}}/_{\eta_{\mathrm{b}}}\right) + \left(D_{\mathrm{el},t} \cdot P_{\mathrm{im},t}\right) \quad (2)$$

where $C_{\mathrm{noCHP},t}$ is the cost without the CHP unit, $D_{\mathrm{th},t}$ the demand for heat, $D_{\mathrm{el},t}$ the demand for electricity, $\eta_{\mathrm{b}}$ the boiler efficiency, $P_{\mathrm{fuel}}$ the price of fuel and $P_{\mathrm{im},t}$ the price of importing electricity.

## 4.1 Cost including CHP engine

When the CHP engine is in operation, depending on the prices and demand, the controller decides whether to sell electricity back to the grid and whether to utilize the gas boiler for generating heat. These options mean the existence of two binary values in the objective function. For each scenario $s$, at time $t$, the total cost per unit of time is the sum of the cost of utilizing the gas boiler, the cost of the fuel required for the CHP engine and the net cost arising from importing and exporting electricity:

$$C_{\mathrm{CHP},s,t} = C_{\mathrm{boiler},s,t} + C_{\mathrm{fuel},s,t} + \left(C_{\mathrm{el},s,t} - S_{\mathrm{el},s,t}\right) \quad (3)$$

where $C_{\mathrm{CHP},s,t}$ is the total operation cost of that scenario, $C_{\mathrm{boiler},s,t}$ the cost of utilizing the boiler, $C_{\mathrm{fuel},s,t}$ the cost of operating the CHP, $C_{\mathrm{el},s,t}$ the cost of importing electricity and $S_{\mathrm{el},s,t}$ the savings arising from exported electricity for that scenario. Using Eq. (1), the four costs can be shown to be:

$$C_{\mathrm{boiler},s,t} = \left(D_{\mathrm{th},t} - \left(a_{\mathrm{th}} \cdot PL_{s,t} + \beta_{\mathrm{th}}\right)\right) \cdot P_{\mathrm{fuel}} \cdot \left({}^{1}/_{\eta_{\mathrm{b}}}\right) \cdot y_{\mathrm{th}} \quad (4)$$

$$C_{\mathrm{fuel},s,t} = \left(a_{\mathrm{f}} \cdot PL_{s,t} + \beta_{f}\right) \cdot P_{\mathrm{fuel}} \quad (5)$$

$$C_{\mathrm{el},s,t} = \left(D_{\mathrm{el},t} - \left(a_{\mathrm{el}} \cdot PL_{s,t} + \beta_{el}\right)\right) \cdot P_{\mathrm{im},t} \cdot y_{el} \quad (6)$$

$$S_{\mathrm{el},s,t} = \left(\left(a_{\mathrm{el}} \cdot PL_{s,t} + \beta_{el}\right) - D_{\mathrm{el},t}\right) \cdot P_{\mathrm{ex},s,t} \cdot (1 - y_{el}) \quad (7)$$

where $P_{\mathrm{ex},s,t}$ is the price of exporting electricity of that scenario and $y_{\mathrm{th}}, y_{\mathrm{el}}$ the two binary variables. The fact that each scenario uses a random value for the PDF of the exporting electricity price means that the total expected cost $\overline{C_{\mathrm{CHP},t}}$ utilizing all $N$ scenarios together is equal to:

$$\overline{C_{\mathrm{CHP},t}} = \sum_{s=1}^{N} C_{\mathrm{CHP},s,t} \cdot \pi_s \quad (8)$$

where $\pi_s$ is the probability of each scenario and in Monte Carlo simulations is equal to $1/N$. The expected cost can be compared to the cost of the scenario where there is no CHP so that an expected value of cost savings $\overline{S_{\mathrm{CHP},t}}$ is calculated using:

$$\overline{S_{\mathrm{CHP},t}} = \frac{C_{\mathrm{noCHP},t} - \overline{C_{\mathrm{CHP},t}}}{C_{\mathrm{noCHP},t}} \cdot 100\% \quad (9)$$

Lastly, correctly representing the system requires certain constraints to be satisfied at every sampling time $t$. The specifications of the CHP engine set a minimum partload at which the engine can be operated, therefore the partload at any point in time can be either set to 0 or between the minimum partload $PL_{\mathrm{min}}$ and 1. The binary value $y_{\mathrm{th}}$ is equal to 1 when the demand for heat is higher than the generated heat, otherwise it is equal to 0. Similarly, $y_{\mathrm{el}}$ is equal to 1 when the demand for electricity is higher than generated electricity, otherwise it is also equal to 0.

## 4.2 Conditional value at risk

The second component of the objective function aims to aid decision makers to keep control of the risk associated with their operation choice. Depending on the predicted price, there are situations when the partload at which the expected savings are maximized involves the highest risk. In order to quantify this risk, a popular measure in financial analysis is the Value at Risk (VaR), which represents a breakpoint; it is the worst-case result of a decision associated with a probability [36]. It is usually used to represent the worst-case losses that can be expected for a given level of confidence $Q$.

In the case of the CHP engine operation, risk represents the odds of having low or even negative savings compared to the no-CHP case. Therefore, VaR represents the minimum savings that decision makers, with $Q$ confidence, can expect. However, VaR does not provide information about what the savings would be, if it happens that they are below that breakpoint. For this reason, this study attempts to instead use the more pessimistic Conditional Value at Risk (CVaR), a coherent risk measure representing the average of the savings that is below the VaR [37] and therefore providing decision makers with information about what happens beyond the VaR breakpoint.

Determining the CVaR of a probability distribution requires computing VaR first. The definition of VaR, for $Q$ being the confidence level and $S_{\mathrm{CHP},t}$ representing a return value of cost savings is:

$$VaR_Q\left(S_{\mathrm{CHP},t}\right) = inf\left\{x \in \mathbb{R} :\ F_{S_{\mathrm{CHP},t}}\left(S_{\mathrm{CHP},t}\right) > (1-Q)\right\} \tag{10}$$

where $VaR_Q\left(S_{\mathrm{CHP},t}\right)$ is the Value at Risk and $F_x\left(S_{\mathrm{CHP},t}\right)$ is the cumulative distribution function of the savings. Once VaR is computed, CVaR is simply the average of all the values below it:

$$CVaR_Q\left(S_{\mathrm{CHP},t}\right) = \mathbb{E}\left[S_{\mathrm{CHP},t} \mid S_{\mathrm{CHP},t} \le VaR_Q\left(S_{\mathrm{CHP},t}\right)\right] \tag{11}$$

where $CVaR_Q\left(S_{\mathrm{CHP},t}\right)$ is the Conditional Value at Risk. A high value of CVaR indicates high minimum cost savings, which is desirable. For each possible partload of the CHP engine, the expected savings, but also the value of CVaR vary. At times, they may both indicate towards a specific partload, but at other times they may conflict, highlighting the need for a bi-objective function.

## 4.3 Bi-objective function

The objective function comprises a combination of the two main objectives: to maximize the expected savings and maximize the value of CVaR. For their integration, a new variable $w_{\mathrm{r}}$ is introduced, where $w_{\mathrm{r}} \in [0,1]$. The purpose of this is to be utilized as a user-controlled weight which can set the relative importance of each of the two objectives, based on the risk the decision makers are willing to take. Therefore, at every time step $t$ and depending on the assigned weight $w_{\mathrm{r}}$, the controller needs to identify the optimum partload for which the following bi-objective function is maximized:

$$\max_{PL,y^{\mathrm{th}},y^{\mathrm{el}}} \qquad w_{\mathrm{r}} \cdot \overline{S_{\mathrm{CHP},t}} + (1-w_{\mathrm{r}}) \cdot CVaR_Q\left(S_{\mathrm{CHP},t}\right) \tag{12}$$

A value of $w_{\mathrm{r}}$ equal to 1 represents a risky decision maker, who aims to maximize the expected savings without consideration of the associated risk. On the other hand, a value of 0 represents a decision maker that only aims to minimize the risk and is not interested in maximizing the expected savings. Since $w_{\mathrm{r}}$ can take any value between 0 and 1, decision makers can make any choice depending on the importance they want to give to each objective. The feasible region of solutions to the proposed problem is a polyhedron. By exploiting the fact that the optimum solution lies on a vertex of the feasible region [38], the problem is solved based the simplex method, which involves moving along the polyhedron edges to find the one that maximizes the function.

# 5. Performance analysis

This section presents the results of the simulations of this study, which are divided into two parts. First, the performance of the controller is analysed for a peak-demand scenario at a specific time step, demonstrating the trade-offs between different partload choices. Then, a whole-day simulation is performed, showing how the weight choice affects the operation decision. The control technique is tested using real-world 30-min demand and price data collected from the supermarket store in which the controller has been installed in the winter of 2017. The decision problem, due to its linear nature, is very fast to solve, allowing the use of the Monte Carlo method to perform 500000 simulations at each time step, high enough to capture all possible scenarios [39]. In all simulations, the boiler is assumed to have a constant efficiency of 70%. The manufacturer of the CHP engine, whose specifications can be found in Ref. [30], suggests a minimum operation level of 60% to avoid damage and corrosion in the long-term. This is set as the minimum limit in the decision problem.

## 5.1 Peak demand case

Simulation results are presented for a scenario in which the electrical and heat demands at the chosen supermarket are high – this represents a cold winter day at rush hour. At the chosen time step, the controller is assumed to measure the electrical demand at 80 kW, the heat demand at 174 kW and the import electricity price at £0.15/kW. The price of natural gas required to run the boiler or CHP unit is £0.023/kW. Also, at this time step, it is assumed that neural networks predict that the export electricity price is between £0.05/kW and £0.12/kW with a 95% confidence level. For demonstration purposes, the results of 9 different partload values between 60% and 100% are presented.

Using this information, the controller forms a PDF of the exporting electricity price and randomly selects values to perform the simulations and measure the cost savings relative to the no-CHP case. Each different partload choice means a different PDF of cost savings, which in turn has its own expected savings and its own worst-case CVaR values. For example, the expected savings at a maximum partload of 1 are about 81% compared to the no-CHP case, which is higher than the expected savings of 66% achieved at minimum partload of 0.6. However, the CVaR value at maximum partload is 34%, whereas the minimum partload is a significantly less risky choice, providing a CVaR value of 48%. The trade-off between expected profit and risk in Fig. 2 shows that the higher the partload, the higher the expected profit but also the higher the risk. This is attributed to the fact that a lower partload means less exported electricity and therefore less dependence on price uncertainties.

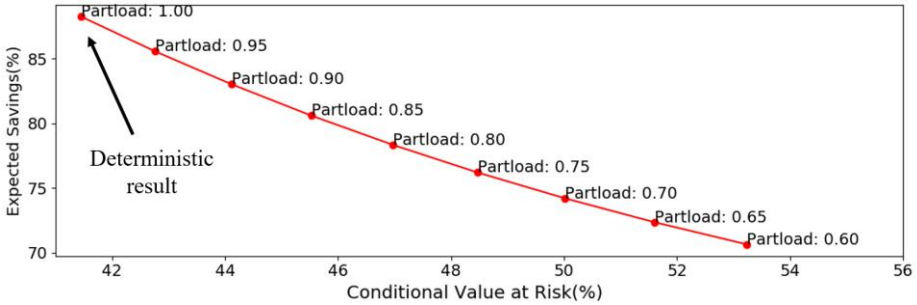


*Figure 2. Trade-off between expected savings and CVaR for different partload values.*

If a deterministic approach is chosen instead, the forecasted value of the exporting electricity price is used in the simulation without considering its bounds. As indicated in Fig. 2, the result in that case would be maximum partload. However, the optimum partload suggested by the proposed approach may differ from the that of the deterministic approach, depending on how much risk decision makers are willing to take. Fig. 3 displays the objective function result for different partload values, assuming a risk-averse decision maker ($w_r$=0.3) and a risk-seeking decision maker ($w_r$=0.7).

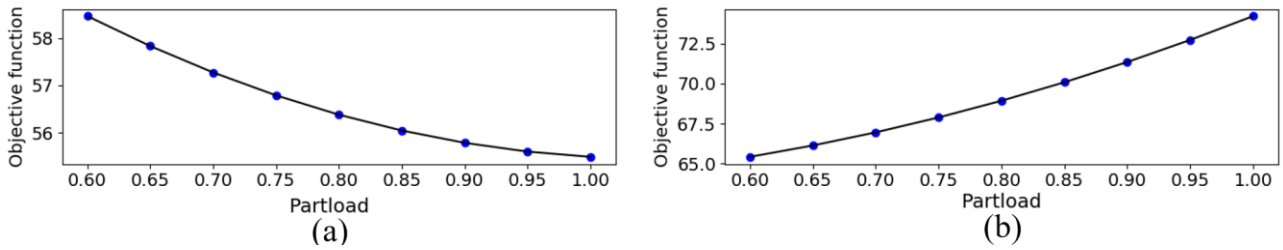


*Figure 3. Objective function at different partload values for: a) $w_r$=0.3, and b) $w_r$=0.7.*

As shown, since the optimum choice is the one that maximizes the objective function value, the risk-averse decision maker would choose a partload of 60% while the risk-seeking one would instead choose a partload of 100%. This demonstrates that traditional deterministic approaches may result in decision makers choosing high operation levels, which in the end can prove to have been too risky.

## 5.2 Whole-day simulations

To highlight how the choice of weight affects the decision, whole day simulations were conducted for different weight values ($w_r$=1, 0.5, 0). Fig. 4 shows the price of importing and exporting electricity for

the selected day, which represents a typical weekday in March 2017. The export electricity price is unknown at the time of the decision; therefore, it enters the simulation as a forecasted value with high and low bounds. For the purpose of the simulation, the upper and lower bound are assumed to be 66.67% above and below the forecasted value with a confidence level of 95% respectively.

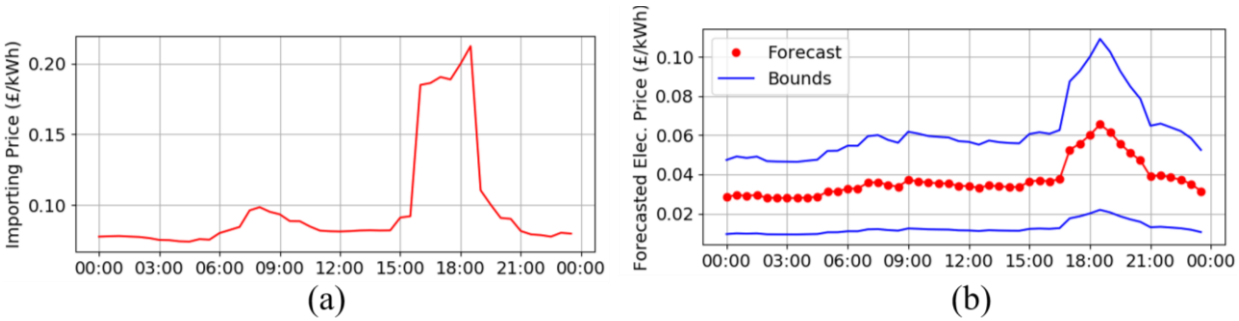


*Figure 4. Price during simulation for: a) importing, and b) forecasted exporting electricity.*

The CHP engine installed in the supermarket is considerably oversized; it has a maximum electrical and thermal output of 229 kW and 357 kW respectively, while at peak periods of the year, the electrical and thermal demand of the supermarket only reaches about 80 kW and 170 kW respectively. For this reason, simulations show that the minimum partload of 60% is always sufficient to meet both electrical and thermal demand; therefore, the partload rises above this value only when there is a high potential of exporting electricity at a beneficial price. Fig. 5 presents the simulation output for electrical and thermal power at a maximum weight factor $w_r$=1.

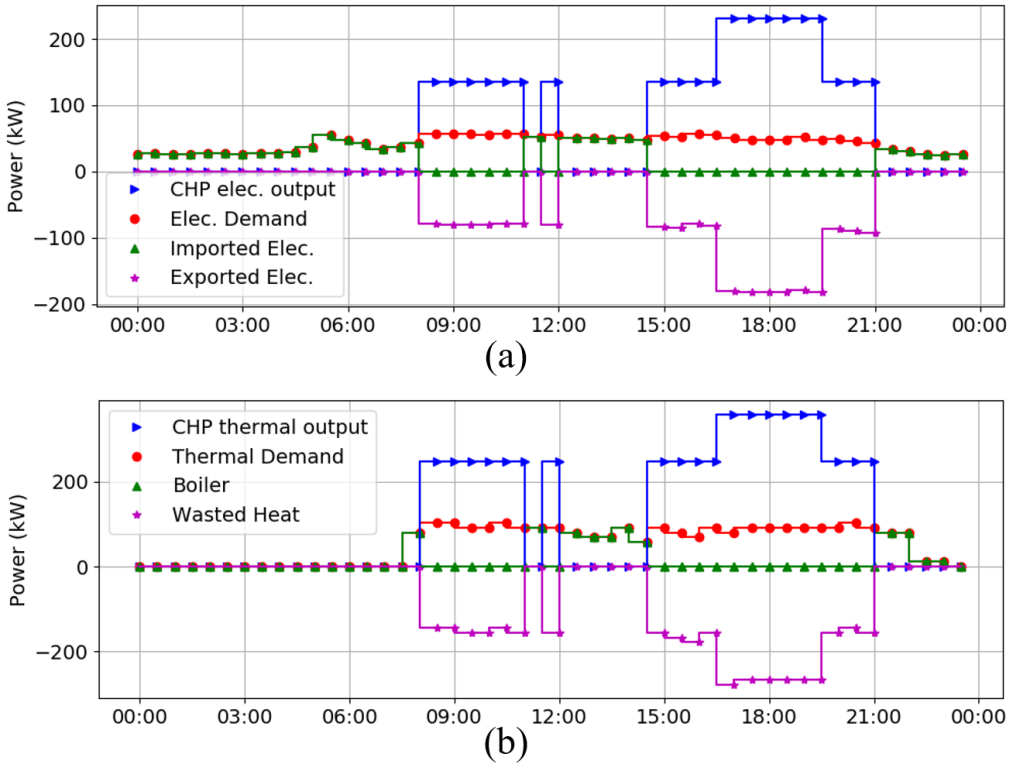


*Figure 5. Simulation output for $w_r$=1 for: a) electrical, and b) thermal power.*

The simulation results lead to some interesting observations: 1) When there is only demand for electricity, the controller prefers to buy the electricity from the grid, since the cost of operating the CHP engine would be higher; 2) When there is also demand for heat, the CHP engine is noticeably preferred to the boiler, which is worth of use only for small time intervals; and 3) The fact that the CHP engine is oversized for this application results to a significant amount of heat waste.

Different weight values mean different optimal decisions. Fig. 6 shows the comparison between the optimum partload for the weight $w_r$=1 and for a more conservative weight $w_r$=0.5, where the decision maker would choose a compromise between maximizing expected savings and minimizing risk.

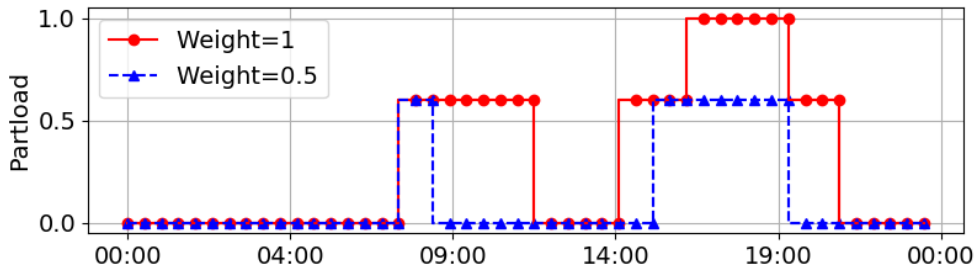


*Figure 6. Optimum partload for $w_r$=1 and $w_r$=0.5.*

As shown, when $w_r$=1, the CHP engine is switched on for a significantly larger period compared to the $w_r$=0.5 case. Also, there is a time in the afternoon when the controller chooses to operate the engine at full load, even if it could meet demand with a lower partload. This is attributed to the fact that at that time, the exporting electricity price is predicted to be high, therefore the controller chooses to sell as much as possible. On the other hand, when using $w_r$=0.5, the risk associated with the price prediction is also considered in the objective function and the controller decides that it is not worth the risk to run the engine at full power. The day costs associated with the control of the CHP engine at different weights compared to the case where no CHP engine is utilized are shown in Table 1.

*Table 1. Total expected cost and worst-case cost with different strategies for 24 hours.*

| Strategy | Boiler Cost (£) | Imported Elec. Cost (£) | Expected Exported Elec. Savings (£) | CHP Cost (£) | Total expected cost (£) | Worst-case cost using CVaR (£) |
|---|---|---|---|---|---|---|
| Without CHP | 42.11 | 103.23 | - | - | 145.34 | - |
| With CHP, $w_r$=1 | 10.39 | 38.38 | 55.39 | 120.50 | 113.86 | 160.17 |
| With CHP, $w_r$=0.5 | 27.19 | 63.27 | 21.10 | 50.49 | 119.85 | 137.60 |
| With CHP, $w_r$=0 | 33.61 | 73.82 | 13.23 | 30.30 | 124.50 | 135.65 |

As Table 1 presents, the utilization of the CHP engine results to significant cost savings relative to the no-CHP case. More specifically, for a risk-taking approach ($w_r$=1), the total operation cost savings can be expected to be as high as 21.7% (£31.48). Also, results demonstrate the importance of the weight factor; using a value of $w_r$=0, for example, results to 9.3% (£10.64) less expected savings compared to $w_r$=1, but at the same time, this means 15.3% (£24.52) less risk.

# 6. Conclusions and outlook

The decentralized real-time control of locally based CHP systems can provide improved efficiency and economic benefits to end-users. This paper first discusses the practical challenges in the development of a cloud-based platform that can be used to apply optimization strategies to an existing CHP engine in a case-study supermarket. It then proceeds to develop a stochastic, cost-effective strategy for the optimal operation of the CHP engine under the uncertainty of exporting electricity price. The technique involves the formulation of a bi-objective function that considers maximizing the expected savings while also controlling the associated risk. A user-assigned weight can be set to represent the degree of risk decision makers are willing to take, attributing relative importance between the two objectives.

Whole-day simulations using real-world data from the supermarket show that the utilization of the CHP engine can provide expected savings of about 22% compared to the no-CHP case. Also, results demonstrate that deterministic approaches tend to choose high levels of operation, while considering risk may lead decision makers to make more conservative operation choices, which can reduce risk by more than 15% in the expense of a much smaller reduction in the expected savings (less than 10%).

The end-goal of this research is to apply the developed operational strategy to the CHP engine under consideration. The cloud-based platform has already been implemented and the necessary hardware has been installed at the supermarket. Future work will therefore involve utilizing this platform to apply the discussed strategy on the supermarket store, test different weight factors and evaluate the performance and significance of the forecasting method. Furthermore, work may focus on replacing

the black-box CHP model with a detailed thermodynamic model, which will allow the optimization not only of the operation, but also the design of the CHP engine under uncertainty.

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