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Optimal battery energy storage investment in buildings

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ABSTRACT

In most countries, electricity is charged depending on the time of use, which usually includes two tariffs: the low tariff, during night time, and the high tariff, during daytime. On top of their energy payment, large electricity consumers pay a monthly fee per kW of peak demand. Therefore, installation of stationary battery storage can reduce electricity payments for large consumers in two ways: by reducing the peak demand and by shifting consumption from the high tariff to the low tariff. The aim of this paper is to formulate a model to determine optimal energy and power capacity of a stationary battery storage in order to minimize electricity payments. Since the future electricity consumption is uncertain, after formulating the deterministic model, two additional models that consider uncertainty are introduced. The first one is the stochastic model, which considers uncertain scenarios, and the second one is the robust model, where uncertainty is represented by only an uncertainty set, without an assumption on the distribution of uncertainty within this set.

The proposed models are tested and compared on a real-world load data of a hotel in Croatia. The case study indicates that deterministic and stochastic formulations result in slightly better investment decisions than the robust formulation.

1. Introduction

Acronyms

For easier referencing, the acronyms used throughout the text are listed below:

AC Alternating Current.
CBA Cost-Benefit Analysis.
CDF Cumulative Distribution Functions.
CHP Combined Heat and Power.
DC Direct Current.
EU European Union.
Li-ion Lithium-ion.
NaS Sodium sulfur.
PbA Lead-acid.
PUN *Prezzo Unico Nazionale*, Italian for “single national price”.
USA Unites States of America.

Electricity consumers can be divided into three categories: domestic, commercial and industry consumers. All of them purchase electricity in retail market from a chosen supplier. The supplier formulates a tariff system for different consumers, depending on the peak load, quantity and quality of electricity, voltage level of the consumer, and other characteristics. Elements of the commercial/industry tariff system are: consumed active energy (kWh), active peak load (kW), over-consumption of reactive energy (kVAr), measurement service fee, transmission and distribution system utilization fees, and lately a fee for supporting renewable energy sources. Consumed active energy, active peak load and over-consumption of reactive energy can be directly affected by the consumer's behavior and/or investments, while the remaining elements of the tariff system are either regulated or related to the consumption, e.g. transmission and distribution fees are usually set per kWh of consumed electricity

The quantity of active energy consumed over a time period, e.g. a month, is determined based on readings from a power meter. Tariff systems usually differentiate between the active energy consumed under the high tariff, i.e. during the day, and under the low tariff, i.e. during the night. Although the two-tariff metering systems have been used for many years, they are still in effect in many countries. The highly encouraged deployment of smart meters, essential for adoption of dynamic tariffs, is slow due to high investment costs and questionable benefits [1]. For example, the EU Member States are required to ensure the implementation of smart metering, but this implementation is subject to a long-term cost-benefit analysis (CBA) conducted for each country individually. If the results of CBA are positive, the roll-out target for year 2020 is 80% penetration of smart meters [2].

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Another element of the tariff systems for large consumers in many countries is the peak active power, which is priced based on the maximum of all average 15 min or 30 min loads. Depending on the electricity prices and peak load policy in effect, peak load payments can constitute as low as few percent of the overall consumer's electricity bill, all the way to half of the overall electricity bill, e.g. in San Diego Gas & Electric utility [3]. This indicates that an energy storage device could reduce customer's electricity bill in two ways, first by moving the demand from the high to the low tariff, and second by reducing the peak load payments.

This paper focuses on commercial/industry facilities that are charged both consumed active energy and active peak load. The goal is to find optimal battery energy storage investment, in terms of kW and kWh, that minimizes the sum of overall operating and investment costs. The main contribution is the formulation of a rigorous mathematical model that considers the uncertainty of the annual load curve using stochastic and robust optimization. Monte Carlo method is used to obtain cumulative distribution functions (CDF) used to compare the performance of the optimization methods.

2. Literature review and contributions

Energy storage has spurred a lot of interest in the research community recently. At large scale, i.e. transmission level, there have been many studies dealing with integration of energy storage. For example, impact of large-scale battery storage on operating costs in systems with wind uncertainty is examined in [4]. Another method for system-wide siting and sizing of energy storage is presented in [5], which, instead of characteristic days in [4], considers each day of the year individually. Both [4,5] indicate that distribution of wind power plants significantly affect the location and sizes of energy storage. When deciding on energy storage investment, it is essential to consider and appropriate storage technology. A comparative overview of large-scale energy storage technologies is available in [6,7], while a detailed review of battery technologies used for large-scale energy storage is found in [8].

The work presented in this paper is focused on small-scale energy storage connected behind the meter at the networks user's premises. In order to implement optimal control of energy flows between a consumer with energy storage and the power grid, a control device, such as the one developed in [9], is needed.

An implementation of Berkeley Labs Distributed Energy Resources Customer Adoption Model for optimal selection of flexible technology, e.g. heat and chemical storage, efficiency investments, and combined heat and power (CHP), in commercial buildings is described in [10]. The performed case study on an imaginary hotel in San Francisco results in a reciprocating engine and an absorption chiller investments. These investments are estimated to provide 11% cost savings and 8% carbon emission reductions. A multi-energy model for minimizing total operating cost of a building is proposed in [11]. The presented case study shows that thermal storage units and water tanks are most effective in reducing overall energy costs and that battery storage might become attractive in case of reduced investment cost and longer lifetime.

Arbitrage potential of a small-scale battery energy storage in Korean electricity market is studied in [12]. Charging and discharging schedules are derived using the Hotelling rule. The results indicate that the cost of Li-ion and sodium sulfur (NaS) batteries is too high and such investment would result in monetary losses. This conclusion is based on energy prices in the observed spot market. Energy storage performs arbitrage between the highest and the lowest price throughout the day. If the difference is insufficient, the storage will not retrieve the investment. However, there are some fundamental differences between energy storage acting in electricity market, as an independent market player, and energy storage being installed at the end user's facility:

- Performing optimal arbitrage in electricity market is difficult due to unknown market prices at the bidding stage. In other words, it is difficult to identify the optimal hours for selling/buying electricity in the market. On the other hand, end users are under time-of-use tariff and electricity prices are known in advance for each hour of the day. However, end users face their uncertain local demand, the issue which large-scale energy storage performing only arbitrage does not have.
- Reducing peak load reduces peak demand charges to the end users, while this source of income (savings) does not exist in the electricity market.
- Both market player with energy storage and end user with energy storage could take part in ancillary services market providing up and down reserve. The difference is that the end user cannot provide such services directly (due to insufficient capacity), but only through a mediator, e.g. aggregator.

Battery energy storage investment is reported to be economically feasible in households when combined with photovoltaic system in case of a steady growth of the retail electricity prices [13]. Sensitivity analysis is performed using different investment timing (reduction of investment cost in the future is assumed), different increase of electricity price and various sets of remuneration tariffs. A technique for sizing of battery storage in Belgian households with photovoltaic panels is proposed in [14]. Optimal battery capacity is determined based on correlations with the measured data. The authors indicate the importance of battery storage in reducing the peak demand. A more recent economic assessment of energy storage in households with photovoltaic panels is presented in [15]. The results include sensitivity analysis of the major input parameters, i.e. cost of energy storage, cost of electricity when purchasing and selling, and electricity generated by the rooftop solar system. The authors conclude that diminishing feed-in tariffs and expected reduction of energy storage investment cost will result in higher integration of energy storage in households. In [16], energy storage is used in a household to reduce electricity charges using the actual Con Edison's electricity tariffs. The authors use an agent-based model of appliances to randomly generate demand profiles. The case study indicates that the proposed operational strategy can result in up to 48% savings.

Time-of-use pricing has been used for many years to offset some of the consumption during peak hours to the low-consumption periods, i.e. night hours. In time-of-use pricing, each day is divided in blocks, which consists of one or more hours, with the same price of electricity. The price of electricity varies between consecutive blocks, but not within any of the blocks [17]. The simplest time-of-use tariff system comprises of two blocks, the low-cost block during the night hours and the high-cost block during the daytime. The cost of electricity in each block is known ahead of time and is the same every day. Even this simple static time-of-use tariff, which is still commonly used by the suppliers and utilities, results in implicit demand response, e.g. when a consumer decides to turn on a home appliance during the low-cost period. A proposal of a four-day tariff system for industrial loads is carried out in [18]. In this four-day tariff system, the week is divided in four day types: Monday, Tuesday-Friday, Saturday and Sunday. The authors report that the proposed tariff benefits both the utility company and the industrial customer with energy storage. Paper [19] develops a pricing scheme for energy storage operated by customers. The designed energy storage operation strategy minimizes electricity costs to the customers using responsive time-of-use tariffs. Techno-economic analysis of battery energy storage in a student dormitory in South Africa under the time-of-use tariff is presented in [20]. The results show that none of the three battery

technologies considered in the case study (PbA, NaS, and Li-ion) is economically viable for the current electricity prices and tariff system. The authors point out that the main reason for this is the high cost of installation of battery storage system, while the impact of peak electricity price is lower. This is confirmed by the economic assessment of behind-the-meter energy storage in Italy presented in [21]. This study considers li-ion, advanced PbA, zinc-oxide, NaS and flow battery technologies. Although zinc-oxide, li-ion and flow batteries result in best rate of return, it is still insufficient to make them economically attractive.

A method for benefit assessment of an energy storage in a community with renewable sources is proposed in [22]. The results indicate that the optimal capacity of a battery energy storage is the one ensuring a full discharge during the peak load period. Another study on optimal energy storage investment in local communities with high adoption of photovoltaics is presented in [23]. The case study, performed on actual locations in Cambridge, USA, shows that the optimal energy storage capacity at the community level is 35% lower than the combined energy storage at the individual households level. Additionally, electricity exchange between the community and the distribution network is reduced. An interested reader can find a comprehensive review of challenges and perspectives of community energy storage in [24].

An electricity cost minimization strategy for a medium-scale public facility with energy storage is presented in [25]. The authors assume hourly real-time pricing at the retail level and use NaS batteries to move consumption to low-cost time periods. The results of the Italian case study indicate that the return of investment is 10 years in case of correlation of the retail prices with the Sicilian zonal prices and 30 years in case of correlation with the PUN (*Prezzo Unico Nazionale*) values.

A probabilistic approach for optimal sizing of battery energy storage under time-of-use tariff is proposed in [26]. The proposed Monte Carlo model considers uncertainties of energy prices, load profile, and interest rate. A number of samples generated from random uncertain input data is applied to discrete battery energy storage capacities. After obtaining the average total cost over all Monte Carlo samples for each battery storage capacity, the optimal battery capacity is identified as the one that yields the minimum overall cost of electricity, including the battery investment cost.

Optimal sizing problem of a battery storage in industrial facility is addressed in [27]. In the presented approach, different investment alternatives, i.e. battery energy storage capacities, are applied to different future realizations of demand profiles. Among the obtained results, the best investment is identified as the minimum of the total operating cost, min-max regret, or a combination of the two. The authors conclude that the probabilities of the assumed demand profiles significantly affect the investment decisions.

With respect to the literature review above, the contributions of this paper are:

1. Formulation of a linear mathematical program that finds optimal battery storage investment in a commercial building. The capacity of battery energy storage is used to decrease the electricity bill in two ways: (i) it offsets a part of the demand from the high-cost tariff to the low-cost tariff; (ii) it decreases the peak load payments. The model above is extended to accommodate the uncertainty of the local annual load curve. Two models under uncertainty are formulated: the stochastic model and the robust model.
2. Application of the proposed models on an actual hotel load curve. The investments obtained using all three models, i.e. deterministic, stochastic and robust, are applied to a number of Monte Carlo scenarios (realizations of the uncertain annual load curve) in order to quantify the performance of the proposed models.

The presented models should be useful to owners of commercial and industry facilities interested in reducing their operating cost by investing in new technologies, i.e. batteries.

3. Mathematical formulation

3.1. Nomenclature

3.1.1. Indices

- t Index of hours in the year, belonging to set Ω^{T}.
- m Index of months in the year, belonging to set Ω^{M}.
- w Index of stochastic scenarios, belonging to set Ω^{W}.

3.1.2. Parameters

- $C^{\mathrm{e}}_{t,m}$ Cost of energy at hour t in month m, Eur/kWh.
- C^{p} Cost of peak monthly load, Eur/kW.
- $D_{t,m}$ Average load during hour t in month m, kW.
- K^{e} Cost of energy storage installed energy capacity, Eur/kWh.
- K^{p} Cost of energy storage installed power capacity, Eur/kW.
- L Energy storage lifetime.
- P^{distr} Maximum power drawn from the distribution network, kW.
- P^{max} Maximum allowed battery power capacity, kW.
- R Interest rate.
- S^{max} Maximum storage state of charge.
- S^{min} Minimum storage state of charge.
- η^{ch} Battery charging efficiency.
- η^{dis} Battery discharging efficiency.
- Δ^{T} Time step, i.e. 1 h.

3.1.3. Variables

- $d_{t,m}$ Average load during hour t in month m, kW (used only in robust formulation).
- e^{bat} Battery energy capacity, kWh.
- p^{bat} Battery power capacity, kW.
- $p^{\mathrm{ch}}_{t,m}$ Average battery charging power during hour t of month m, kW.
- $p^{\mathrm{dis}}_{t,m}$ Average battery discharging power during hour t of month m, kW.
- p^{peak}_{m} Peak power withdrawn from the network during month m, kW.
- $r_{t,m}$ Auxiliary variable used only in the robust model.
- $s_{t,m}$ Battery state of charge at hour t of month m, kWh.
- $u_{t,m}$ Auxiliary variable used only in the robust model.
- $v_{t,\,m}$ Auxiliary variable used only in the robust model.

3.2. Deterministic model

Objective function of the deterministic model minimizes the annualized battery storage investment cost (P_1), energy payments throughout the year (P_2), and monthly peak load payments throughout the year (P_3):

$$\text{Minimize } \; P_1 + P_2 + P_3, \tag{1}$$

where

$$P_1 = \left(p^{\mathrm{bat}} \cdot K^{\mathrm{p}} + e^{\mathrm{bat}} \cdot K^{\mathrm{e}}\right) \cdot \frac{(1+R)^L}{L}, \tag{2}$$

$$P_2 = \sum_t \sum_m C^{\mathrm{e}}_{t,m} \cdot \Delta^{\mathrm{T}} \cdot \left(D_{t,m} + p^{\mathrm{ch}}_{t,m}/\eta^{\mathrm{ch}} - p^{\mathrm{dis}}_{t,m} \cdot \eta^{\mathrm{dis}}\right), \tag{3}$$

$$P_3 = \sum_m C^{\mathrm{p}} \cdot p^{\mathrm{peak}}_m, \tag{4}$$

The cost of battery energy storage installation P_1 consists of two parts: installation of power capacity, $p^{\mathrm{bat}} \cdot K^{\mathrm{p}}$, which reflects the cost of power converter that interfaces the AC power grid and DC battery system (in kW), and installation of energy capacity, $e^{\mathrm{bat}} \cdot K^{\mathrm{e}}$,

which represents the cost of battery stack (in kWh). Since the energy storage investment is made at the beginning of the observed period, net present value is used to levelize the investment cost to annual basis. Energy payments, P_2, are the result of energy drawn from the grid at each hour. This energy is used to supply the load and to charge the battery. Variable p^{ch} denotes only power used to increase the battery state of charge. However, the power withdrawn from the network needs to include inefficiency of the power converter and the battery charging process. These inefficiencies are included in parameter η^{ch}, which is lower than 1. Accordingly, battery discharge inefficiencies are captured in η^{dis}. Peak load payments for the entire year, P_3, are calculated based on the peak monthly load.

The deterministic model is subject to the following constraints:

$$p_m^{\text{peak}} \geq D_{t,m} + p_{t,m}^{\text{ch}}/\eta^{\text{ch}} - p_{t,m}^{\text{dis}} \cdot \eta^{\text{dis}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{5}$$

$$s_{t,m} = s_{t-1,m} + p_{t,m}^{\text{ch}} \cdot \Delta^{\text{T}} - p_{t,m}^{\text{dis}} \cdot \Delta^{\text{T}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{6}$$

$$SOC^{\min} \cdot e^{\text{bat}} \leq s_{t,m} \leq SOC^{\max} \cdot e^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{7}$$

$$p_{t,m}^{\text{ch}} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{8}$$

$$p_{t,m}^{\text{dis}} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{9}$$

$$D_{t,m} - p_{t,m}^{\text{dis}} \cdot \eta^{\text{dis}} \geq 0, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{10}$$

$$D_{t,m} + p_{t,m}^{\text{ch}}/\eta^{\text{ch}} \leq P^{\text{distr}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{11}$$

$$e^{\text{bat}}, p^{\text{bat}}, p_{t,m}^{\text{ch}}, p_{t,m}^{\text{dis}}, p_m^{\text{peak}}, s_{t,m} \geq 0, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{12}$$

Peak monthly load, p_m^{peak}, used to calculate monthly peak load payments is calculated in constraint (5). Eq. (6) calculates battery storage state of charge, which is limited from the lower and the upper side in (7). Battery charging and discharging powers are limited in (8) and (9) by the installed battery power capacity. Battery model (6)–(9) does not include degradation costs as they are already included in Eq. (2). Parameter L denotes the assumed battery lifetime considering the expected number of cycles per day and overall number of cycles the battery can perform. For example, if the battery can perform 3650 cycles before its capacity is reduced to an unacceptable level and one charging/discharging cycle per day is expected, parameter L will be set to 10 years. After this period, the battery will be considered worn out and should be replaced.

Constraint (10) disables reverse power flow, i.e. flow of energy into the distribution network. This is needed as otherwise the consumer would need to register as a producer as well. Constraint (11) limits the power drawn from the distribution network. Finally, non-negativity of variables is defined in (12).

The model above yields optimal solution in case all the parameters are known ahead of time. However, annual load curve cannot be perfectly forecasted. Therefore, its uncertainty should be incorporated into the model. The most common technique for accommodating uncertainty in optimization models is stochastic optimization, where the uncertain parameter is represented with a set of stochastic scenarios, each with an assigned probability of occurrence. Another technique is the robust optimization, which does not consider stochastic scenarios, but only the range of uncertainty. This means there is no characterization of uncertainty within the uncertainty set. The following subsections formulate the stochastic and the robust models.

3.3. Stochastic model

Stochastic formulation minimizes objective function (1) over a set of stochastic scenarios w. Constraint (2) does not change, since the investment is the same across all stochastic scenarios. However, all the other constraints need to be updated to accommodate the stochastic scenarios. Therefore, the stochastic formulation of constraints (3)–(12) is:

$$P_2 = \sum_w \pi_w \sum_t \sum_m C_{t,m}^{\text{e}} \cdot \Delta^{\text{T}} \cdot \left(D_{t,m,w} + p_{t,m,w}^{\text{ch}}/\eta^{\text{ch}} - p_{t,m,w}^{\text{dis}} \cdot \eta^{\text{dis}}\right), \tag{13}$$

$$P_3 = \sum_w \pi_w \sum_m C^{\text{p}} \cdot p_{m,2}^{\text{peak}}, \tag{14}$$

$$p_{m,2}^{\text{peak}} \geq D_{t,m,2} + p_{t,m,2}^{\text{ch}}/\eta^{\text{ch}} - p_{t,m,2}^{\text{dis}} \cdot \eta^{\text{dis}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{15}$$

$$s_{t,m,w} = s_{t-1,m,w} + p_{t,m,w}^{\text{ch}} \cdot \Delta^{\text{T}} - p_{t,m,w}^{\text{dis}} \cdot \Delta^{\text{T}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{16}$$

$$SOC^{\min} \cdot e^{\text{bat}} \leq s_{t,m,w} \leq SOC^{\max} \cdot e^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{17}$$

$$p_{t,m,w}^{\text{ch}} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{18}$$

$$p_{t,m,w}^{\text{dis}} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{19}$$

$$D_{t,m,w} - p_{t,m,w}^{\text{dis}} \cdot \eta^{\text{dis}} \geq 0, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{20}$$

$$D_{t,m,w} + p_{t,m,w}^{\text{ch}}/\eta^{\text{ch}} \leq P^{\text{distr}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}}, w \in \Omega^{\text{W}} \tag{21}$$

$$e^{\text{bat}}, p^{\text{bat}}, p_{t,m,w}^{\text{ch}}, p_{t,m,w}^{\text{dis}}, p_{m,w}^{\text{peak}}, s_{t,m,w} \geq 0 \tag{22}$$

3.4. Robust model

Robust optimization takes a different approach towards uncertainty as compared to the stochastic optimization. Instead of stochastic scenarios, robust models are based on uncertainty sets [28]. This means there is no assumption on the uncertainty distribution within the uncertain range. The goal of the robust optimization is to optimize against the worst realization of uncertainty within this uncertain range. To achieve this, the initial deterministic model (1)–(12) can be expressed in the following general term:

$$\text{Minimize} \sum_{j=1}^{J} c_j \cdot x_j \tag{23}$$

subject to

$$\sum_{j=1}^{J} a_{i,j} \cdot x_j \leq b_i, \quad \forall i \in I \tag{24}$$

$$x_j \geq 0, \quad \forall j \in J \tag{25}$$

In problem (23)–(25) some of the coefficients $a_{i,j}$ are uncertain and take values within range $\left[a_{i,j}, a_{i,j} + \hat{a}_{i,j}\right]$, where $\hat{a}_{i,j}$ indicates a deviation of uncertain parameter $a_{i,j}$ from its desirable value. Budget of uncertainty, commonly denoted as Γ_i, is used to control which values of uncertain parameters can be taken from the range $\left[a_{i,j}, a_{i,j} + \hat{a}_{i,j}\right]$, thus controlling the conservatism of solution. Γ_i takes values from interval $[0, |J|]$, where $J = \left\{j \mid \hat{a}_{i,j} \geq 0\right\}$. The most optimistic solution is achieved for $\Gamma = 0$, since no deviations from the most desirable value of uncertain parameter are considered. On the other hand, the most pessimistic solution is achieved for $\Gamma = |J|$, when the worst deviation is considered.

The robust version of the initial deterministic model (1)–(12) is formulated as follows:

$$\text{Minimize } P_1 + P_2 + P_3 \tag{26}$$

subject to

$$P_1 = \left(p^{\text{bat}} \cdot K^{\text{p}} + e^{\text{bat}} \cdot K^{\text{e}}\right) \cdot \frac{(1+R)^L}{L}, \tag{27}$$

$$P_2 = \sum_t \sum_m C^{\text{e}}_{t,m} \cdot \Delta^{\text{T}} \cdot \left(d_{t,m} + p^{\text{ch}}_{t,m}/\eta^{\text{ch}} - p^{\text{dis}}_{t,m} \cdot \eta^{\text{dis}}\right), \tag{28}$$

$$P_3 = \sum_m C^{\text{p}} \cdot p^{\text{peak}}_m, \tag{29}$$

$$p^{\text{peak}}_m \geq d_{t,m} + p^{\text{ch}}_{t,m}/\eta^{\text{ch}} - p^{\text{dis}}_{t,m} \cdot \eta^{\text{dis}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{30}$$

$$s_{t,m} = s_{t-1,m} + p^{\text{ch}}_{t,m} \cdot \Delta^{\text{T}} - p^{\text{dis}}_{t,m} \cdot \Delta^{\text{T}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{31}$$

$$SOC^{\min} \cdot e^{\text{bat}} \leq s_{t,m} \leq SOC^{\max} \cdot e^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{32}$$

$$p^{\text{ch}}_{t,m} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{33}$$

$$p^{\text{dis}}_{t,m} \leq p^{\text{bat}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{34}$$

$$d_{t,m} - p^{\text{dis}}_{t,m} \cdot \eta^{\text{dis}} \geq 0, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{35}$$

$$d_{t,m} + p^{\text{ch}}_{t,m}/\eta^{\text{ch}} \leq P^{\text{distr}}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{36}$$

$$e^{\text{bat}}, p^{\text{bat}}, p^{\text{ch}}_{t,m}, p^{\text{dis}}_{t,m}, p^{\text{peak}}_m, s_{t,m} \geq 0, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{37}$$

$$d_{t,m} = D^{\min}_{t,m} + u_{t,m} \cdot \Gamma_{t,m} + v_{t,m}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{38}$$

$$u_{t,m} + v_{t,m} \geq \left(D^{\max}_{t,m} - D^{\min}_{t,m}\right) \cdot r_{t,m}, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{39}$$

$$u_{t,m}, v_{t,m} \geq 0, r_{t,m} \geq 1, \quad \forall t \in \Omega^{\text{T}}, m \in \Omega^{\text{M}} \tag{40}$$

In the above model, formulation (26)–(37) correspond to the deterministic model (1)–(12), with an exception that new variable $d_{t,m}$ now represents the demand instead of parameter $D_{t,m}$. Value of $d_{t,m}$ is determined in (38) using auxiliary variables $u_{t,m}$ and $v_{t,\,m}$, as well as the robustness parameter $\Gamma_{t,m}$, which takes values between 0 and 1. Robustness parameter $\Gamma_{t,m}$ is used to control the level of conservatism of the solution by controlling the expected load level ranging between $D^{\max}_{t,m}$ and $D^{\min}_{t,m}$, where $D^{\max}_{t,m}$ is the maximum load and $D^{\min}_{t,m}$ the minimum load observed over all scenarios at time period t of month m. In the most optimistic case $\Gamma_{t,m}$ is equal to 0, i.e. the load is equal to $D^{\min}_{t,m}$ at all time periods of each month. On the other hand, in the most pessimistic case $\Gamma_{t,m}$ is equal to 1, i.e. the load is equal to $D^{\max}_{t,m}$ at all time periods of each month. Any value in between 0 and 1 can be chosen for $\Gamma_{t,m}$ to fine tune the level of conservatism of the robust optimization model. Note that $\Gamma_{t,m}$ can take different values at different time periods. Auxiliary variables $u_{t,m}$ and $v_{t,\,m}$ are non-negative, while $r_{t,m}$ is greater or equal to 1. Detailed information on how constraints (38)–(40) are derived, along with mathematical proofs, can be found in [29].

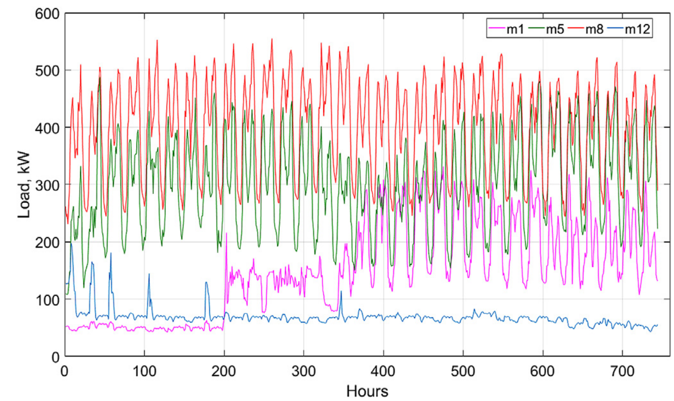

Fig. 1. Hourly load levels for the deterministic case during January (m1), May (m5), August (m8) and December (m12).

4. Case study

The presented deterministic, stochastic and robust formulations for finding optimal battery energy storage capacity are applied to an actual hotel in the coastal part of Croatia. Ten stochastic scenarios of the recorded one-year hourly loads are used for stochastic formulation[1] Deterministic formulation is performed on a single scenario obtained by the forward selection scenario reduction technique [31]. Deterministic hourly load levels for some distinct months are visualized in Fig. 1. The hotel is closed for the most of December (m12) and the load levels are thus very low. The load starts picking up in the second week of January (m1), when the preparations for a new season begin. The demand in May (m5) is already quite high and reaches its maximum in August (m8), after which it gradually decreases until it reaches its minimum in December.

All the data on electricity cost, network charges and peak load charges used in this case study are collected from the website of the Croatian Power Utility - HEP [32]. Cost of electricity is 0.0875 Eur/kWh in the low tariff and 0.15625 Eur/kWh in the high tariff. During the daylight saving time, the low tariff starts at 22:00 and ends at 8:00, while during the winter time it starts at 21:00 and ends at 7:00. Peak load is priced at 7.5 Eur/kW.

Battery energy storage installation cost is 300 Eur/kW and 100 Eur/kWh, which is the price expected by the year 2025 [33]. Interest rate is 6% and expected battery lifetime 10 years [34]. Both charging and discharging efficiencies are 0.95, resulting in 0.9 roundtrip efficiency [35].

Two different peak load payment policies are examined in this case study. In the first one, all hours of the day are subject to peak load payments, while the second one considers only the high tariff hours when calculating the peak load payments. This means that, theoretically, in the second case all the load could be moved to the low tariff hours and peak load payments would be zero. This is visualized in Fig. 2, where the optimal load profiles are derived solely on the peak load payments (other demand profiles may be optimal in case energy payments are considered as well). There are many real-life examples of both of these policies. For example, the *peak load payments applicable to all hours* policy is used in Energex's[2] NTC3000 tariff [36], while the *peak load payments applicable only to high-tariff hours* policy is employed in Energex's

[1] As shown in [30], the choice of ten stochastic scenarios represents a suitable trade-off between computational complexity and cost performance of a stochastic model.

[2] Energex is a power distribution company serving over 1.4 million consumers, a subsidiary of Energy Queensland Limited, which is owned by the Australian government.

Table 1
Objective function value, costs, installed battery capacity and expected cost based on 500 out-of-sample simulations for all three problem formulations.

	Deterministic	Stochastic	Robust				
			$\Gamma = 0.0$	$\Gamma = 0.25$	$\Gamma = 0.5$	$\Gamma = 0.75$	$\Gamma = 1.0$
Objective Function, Eur	321,243	321,414	291,530	306,018	320,604	335,308	350,224
Energy Cost, Eur	275,157	275,743	249,447	262,956	276,370	289,894	303,460
Peak Load Cost, Eur	27,785	27,825	25,215	26,255	27,421	28,524	29,730
Storage Cost, Eur	18,301	17,847	16,869	16,807	16,812	16,890	17,033
Storage Power, kW	100.23	100.62	95.47	92.97	90.61	91.31	93.74
Storage Energy, kWh	721.20	694.68	655.54	659.60	666.96	669.19	669.91
Expected Cost, Eur	322,312	322,303	322,425	322,468	322,505	322,486	322,434

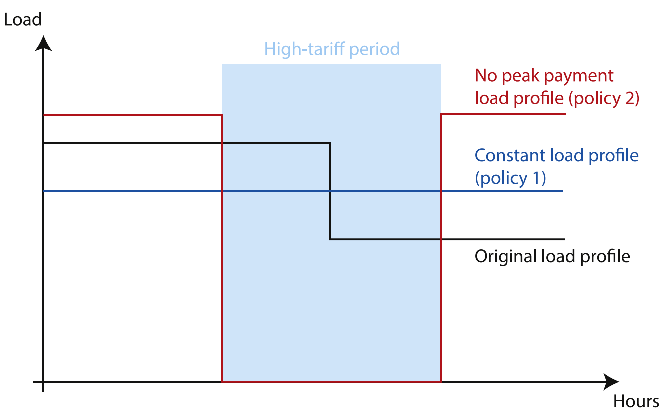

Fig. 2. Optimal load profile under different peak load policies when considering only peak load payments. The original load profile is denoted with black line. If peak load payments apply to all the hours of the day (policy 1), the optimal load profile is flat, since it incurs minimum peak load payments. However, if peak load payments are applicable only to the high-tariff hours (policy 2), the optimal load profile is zero during the high-tariff period, since it avoids any peak load payments.

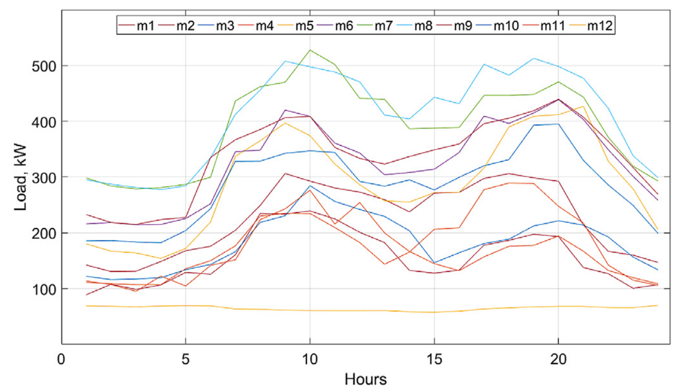

Fig. 3. Hourly load levels on the 21st day of each month.

NTC7400 tariff [36]. The latter policy is also effective in Croatia [37], where the case study is conducted. The following subsections examine each of the two policies individually.

4.1. Peak load payments applicable to all hours

This subsection examines results when the peak load in constraint (5) considers all hours, both the ones in the low tariff and the ones in the high tariff. The case study results for deterministic, stochastic and robust formulations are shown in Table 1. The objective function value is divided into energy cost, peak load cost and battery energy storage installation cost. Deterministic and stochastic formulations result in very similar objective function values. However, the deterministic model invests more in energy capacity of storage (721.20 kWh compared to 694.68 kWh), which incurs higher storage cost, but is compensated through lower energy cost. In order to assess the quality of the objective function values from the first row of Table 1, they are evaluated on a set of 500 out-of-sample scenarios. These scenarios are obtained from the original 10 scenarios using the random forest algorithm described in [38]. The deterministic model (1)–(12) is then run for each of the 500 scenarios, which represent possible realizations of uncertainty, for storage power and energy capacities from Table 1 taken as fixed. In other words, p^{bat} and e^{bat} are now parameters instead of variables. The resulting expected cost over the 500 out-of-sample scenarios are shown in the last row of Table 1. Again, the deterministic and the stochastic models yield almost identical expected cost. This comparison indicates there is no gain in using stochastic formulation over the deterministic one in terms of the quality of the solution. Furthermore, the stochastic solution is achieved in 5 min 47 s, while the deterministic one is calculated in only 9 s. The main reason for stochastic formulation failing to outperform the deterministic one in terms of the quality of the solution is the similarity of the load curve for each day. Fig. 3 shows hourly load levels on the 21st day of each month. Regardless on the month (excluding December, when the load level is flat and very low), the load curves look very similar, with two characteristic peaks. The only distinct feature is the position of the curve, i.e. higher overall demand in summer months and lower overall demand in winter months. Since all the curves have the same shape and the area under each curve depends solely on the seasonality, there is no gain in solution quality by considering uncertainty of the load curve shape.

In case no battery storage is installed, the objective function value in the deterministic case is 325,565 Eur, which is 1.35% higher as compared to the deterministic case when the storage is installed.

Objective function values of the robust formulation in Table 1 increase as the budget of uncertainty Γ increases. When $\Gamma = 0$, the lowest load at each time period over the ten stochastic scenarios is assumed. Therefore, the expected overall cost is lower than for the deterministic (or stochastic) formulation. This can be seen in Fig. 4, which shows ten stochastic scenarios, as well as the load curves for three values of Γ on May 2nd. The yellow load curve for $\Gamma = 0$ has lower or equal values than any of the ten stochastic scenarios, including the scenario used in the deterministic model. Since overall energy consumed is significantly lower than in any stochastic scenario, the objective function value is much lower as well. Therefore, objective function values of the robust model should not be directly compared to the values of the deterministic and stochastic models. Instead, the results of their out-of-sample analysis should be compared, which is discussed in the following paragraphs.

Objective function value of the robust model increases with the level of conservatism and for $\Gamma = 1$ it is 9% higher than for the deterministic (or stochastic) formulation and 20% higher than for

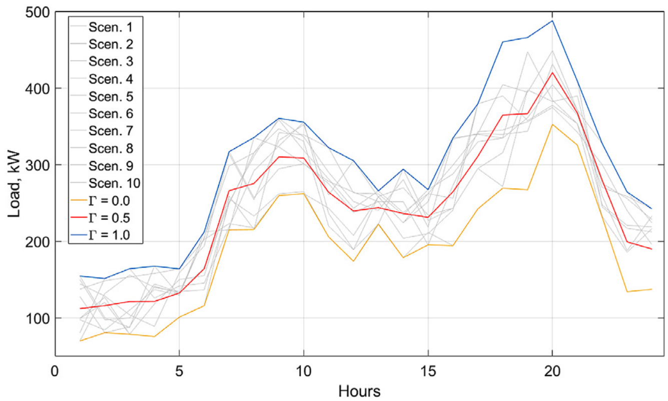

Fig. 4. Ten stochastic scenarios and load curves for $\Gamma = 0.0$, $\Gamma = 0.5$ and $\Gamma = 1.0$ on May 2nd.

$\Gamma = 0$. For $\Gamma = 0.5$, robust formulation results in similar objective function value as the deterministic one. Similar observation is applied to both the energy and power payments, which increase with the overall demand and peak load. However, the storage investment cost is similar regardless of the uncertainty budget Γ and lower than both in the deterministic and stochastic formulations. This indicates that robust formulation tends to install less storage capacity than deterministic and stochastic formulations. This is a direct result of the lack of the characterization of uncertainty in the robust optimization. Since the robust formulation only relies on boundary values of the uncertain parameter, i.e. the load, it tends to make the load curve smoother, which provides less opportunity for storage to reduce peak loads. This phenomenon is visualized in Fig. 4. Clearly, all three load curves used in the robust formulation are less volatile than any of the scenario curves, thus reducing the benefit of battery storage. The flatter profile of the robust load *scenarios* makes peak shaving more difficult since more energy needs to be discharged from the battery during consecutive hours to achieve significant peak load reduction.

As previously said, the only relevant comparison of robust, deterministic and stochastic solutions is in terms of the expected cost. Although the lowest expected cost of the robust model is achieved for $\Gamma = 0.0$, all the expected costs are close to each other. However, none of the solutions achieved using the robust optimization is as cost-effective as the ones achieved by using deterministic or stochastic optimization.

The resulting cumulative distribution functions are given in Fig. 5. Deterministic and stochastic formulations result in almost identical curves, which is expected due to very similar battery storage investments. On the other hand, robust formulation generally results in higher expected overall costs. The best performance of the robust model is achieved for $\Gamma = 0.0$, while the second best performance is achieved for $\Gamma = 1.0$, which yields the highest battery storage investment among all robust solutions (see Table 1). For Γ equal to 0.25, 0.5 and 0.75, battery storage investments are very similar and the resulting cumulative distribution functions for these three values of the budget of uncertainty are very close to each other.

Fig. 6 shows actual load, battery storage charging and discharging actions and net load (actual load plus battery charging power minus battery discharging power) during the first three days of April for the deterministic case. The optimization set the April peak load at around 249 kW, which means that storage always discharges when the load is above this value, even during the low tariff, e.g. in hour 9. The battery storage installed power capacity is around 100 kW and the figure shows this capacity is being exploited extensively. Generally, battery storage operates in a way to reduce the peak load and to shift demand from the high to the low tariff. With couple of exceptions, such as hours 11 and 32, battery storage discharges during the high tariff.

Fig. 7 shows a breakdown of electricity payments between the energy cost and the peak load cost by months. The highest payments appear in summer months, when the hotel load is the highest (compare to Fig. 3). Energy payments are much higher than the peak load payments and they range from 82% of the overall bill in m12 to 98% in m8.

4.2. Peak load payments applicable only to high-tariff hours

This subsection analyzes the results of simulations when only the high-tariff hours affect peak load payments. The optimization results are shown in Table 2. The overall costs are 1–2% lower as compared to the case when low-tariff hours affect the peak load payments as well. Again, deterministic and stochastic formulations yield very similar results. Energy and peak load costs are drastically reduced by 12% and 43%, respectively. This is a direct result of a heavy investment in battery energy storage, which is more than tripled (compare to Table 1). Much higher capacity of energy storage enables moving larger volumes of electricity from the high-cost periods to the low-cost periods. Energy-to-power ratio of the installed batteries in all formulations is 10, because this corresponds to the number of low-tariff hours. Further increase of energy-to-power ratio would not provide additional charging opportunities. The lowest expected cost is achieved for the stochastic optimization. Robust formulation for $\Gamma = 0.75$ is the second best, while the deterministic formulation results in third best expected cost. The worst expected cost is achieved for $\Gamma = 0.0$. Again, all the expected costs are very close together, without significant outliers.

The battery operation and net load curves in Fig. 8 are much different than ones in Fig. 6. Since only net load during the high-tariff periods (denoted with green background) is considered for peak load payments, majority of the load is shifted to the low-cost time periods. The net load during the high-tariff periods is reduced from 249 kW to only 100 kW. As a consequence, the peak load during the low-tariff periods spikes above 500 kW. This is a direct result of the peak load pricing policy. Battery storage charging curve in Fig. 8 indicates that the storage is charged at the highest possible rate during all low-tariff hours, dramatically increasing their net load. The stored energy is used during the day to discharge and keep the peak load at lowest possible level. Utilization of the battery energy storage is very high, as in each hour in Fig. 8 the battery is either charging or discharging.

Fig. 9 shows a breakdown of electricity payments between the energy cost and the peak load cost by months when peak load payments are applicable to only high-tariff hours. When compared to Fig. 7, the energy payments are lower as there is more energy storage installed, which can move more consumption from the high-tariff to the low-tariff periods. The peak load payments are also reduced and they constitute at most 7% of the overall bill in m8. Interestingly, in m12 there are no peak load payments as the entire consumption, which is quite low and flat, is moved to the low-tariff periods.

5. Conclusions, limitations and future work

Decreasing prices of battery energy storage should make it an attractive investment for reducing electricity cost in buildings in the near future. Battery energy storage creates a positive effect by reducing consumption in the high-tariff periods, which consequently increases consumption in the low-tariff periods, and by reducing he peak load. Based on the results of the case study, the following conclusions are derived:

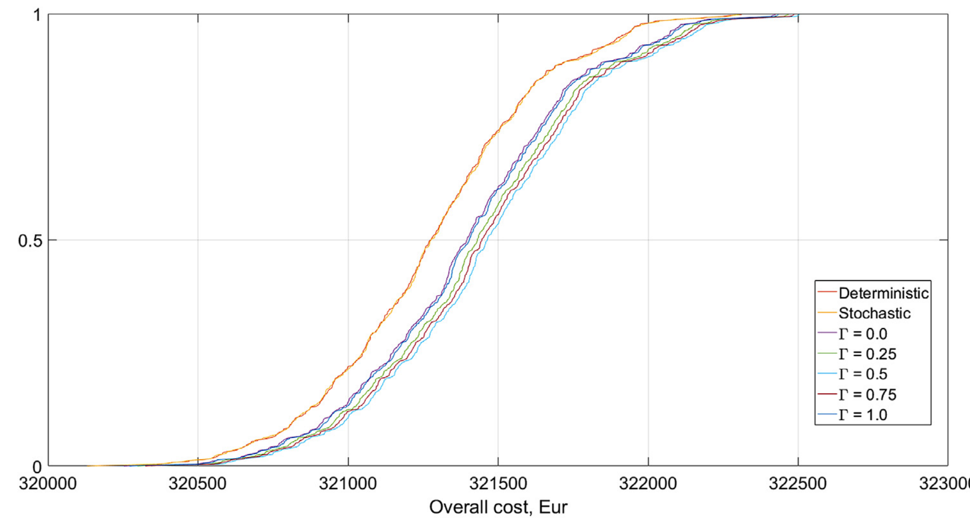

Fig. 5. Cumulative distribution functions based on 500 out-of-sample scenarios for deterministic, stochastic and robust formulations.

Table 2
Objective function value, costs, installed battery capacity and expected cost based on 500 out-of-sample simulations for all three problem formulations when peak load payments consider only high-tariff hours.

	Deterministic	Stochastic	Robust				
			$\Gamma = 0.0$	$\Gamma = 0.25$	$\Gamma = 0.5$	$\Gamma = 0.75$	$\Gamma = 1.0$
Objective Function, Eur	316,558	316,563	287,520	301,792	316,164	330,606	345,131
Energy Cost, Eur	240,820	239,158	217,886	229,127	240,909	253,140	263,333
Peak Load Cost, Eur	15,767	15,236	14,365	14,701	15,297	16,080	16,320
Storage Cost, Eur	59,972	62,170	55,269	57,964	59,959	61,386	65,478
Storage Power, kW	257.60	267.04	237.40	248.97	257.54	263.67	281.25
Storage Energy, kWh	2576.00	2670.41	2374.01	2489.73	2575.43	2636.74	2812.53
Expected Cost, Eur	316,920	316,889	317,052	316,966	316,921	316,898	316,934

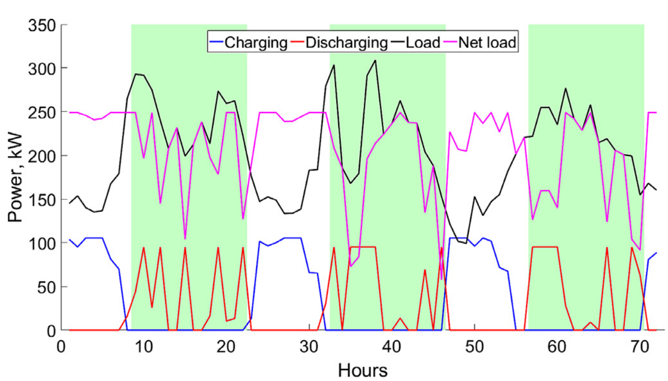

Fig. 6. Load, battery storage charging and discharging quantities and net load (actual load plus battery charging power minus battery discharging power) during the first three days of April for the deterministic case when peak load payments are applicable to all hours. Colored background denotes the high-tariff periods.

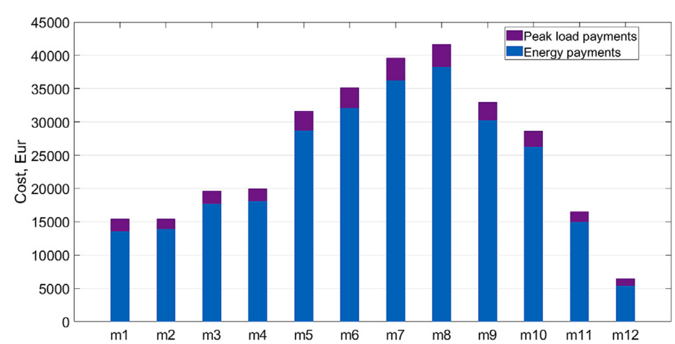

Fig. 7. Energy and peak load costs per month when peak load payments are applicable to all hours.

1. Deterministic and stochastic formulation result in very similar objective function values, but somewhat different energy storage investments. This can be attributed to the flatness of the objective function. In other words, at the optimal point, slightly higher (lower) investment in energy storage results in a similar reduction (increase) in operating costs. This indicates that the objective function value is not very sensitive to a slight change in the storage investment.
2. Deterministic and stochastic formulations result in very similar objective function values because the building used in the case study is a hotel with a consistent ratio of consumption in the low-tariff and the high-tariff periods. Slight changes in consumption generally just shift the load curve up (in case of higher consumption) or down (in case of lower consumption), but the shape remains almost the same. Hence, for this type of buildings, there is no additional value in using stochastic formulation as opposed to the deterministic one.
3. Although robust formulation generally performs worse than the deterministic or stochastic formulation, all the expected costs are within 0.1%, which is a negligible difference. This small difference is because the robust formulation does not capture the load curve shape, but only the range of stochastic load curves. As a result, the worst-case load curve used in objective function of the robust formulation is flatter than any of the scenarios. This drives down the installed battery storage capacity and yields slightly sub-optimal investment decisions. In order to achieve the best performance using the robust formulation,

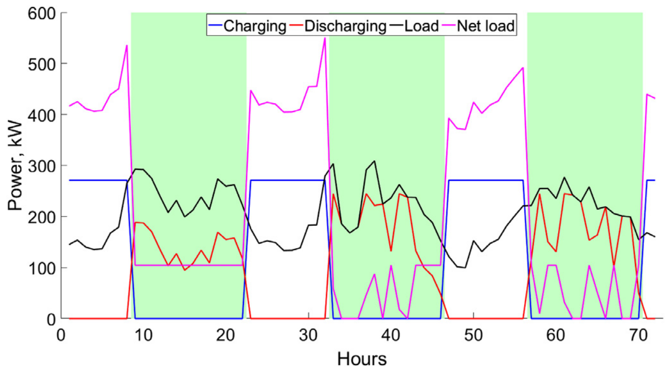

Fig. 8. Load, battery storage charging and discharging quantities and net load (actual load plus battery charging power minus battery discharging power) during the first three days of April for the deterministic case when peak load payments are applicable to only high-tariff hours. Colored background denotes the high-tariff periods.

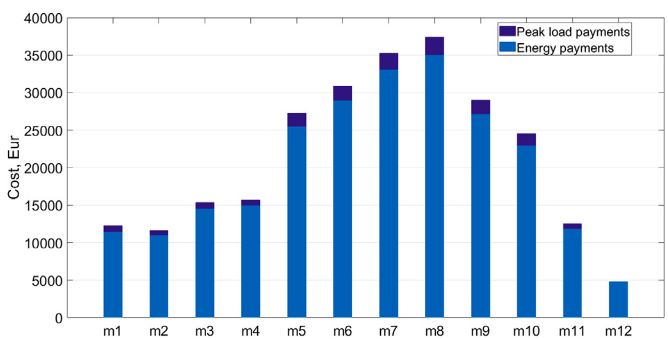

Fig. 9. Energy and peak load costs per month when peak load payments are applicable to only high-tariff hours.

the budget of uncertainty needs to be carefully selected and verified.

4. When comparing the two peak pricing policies, the one that bases the peak load payments only on the high-tariff hours is more attractive to the building. This policy results in larger energy storage with higher energy-to-power ratio. The high-capacity battery storage significantly reduces peak load payments and shifts more consumption to the low-tariff periods.
5. Battery investment cost used in this case study is lower than the current cost, which indicates that, at least for the case study in question, this investment will become attractive in the near future, assuming the battery costs will reduce. With current battery cost over 200 Eur [33], the investment is not economically sound.

The presented model includes only the uncertainty on the consumer's side and does not address the uncertainty of energy prices (set by the supplier) and network tariff uncertainties (set by the utility and approved by the energy regulator). Risk of change in energy prices can be somewhat alleviated by signing long-term supply contracts. Regardless, an additional sensitivity analysis on the electricity prices should be performed in order to determine the value of energy storage at higher or lower electricity prices and differences between the high-tariff cost and low-tariff cost. On the other hand, policy changes that affect network tariffs (payments for utilization of the network and peak load payments) are difficult to anticipate. The future of peak load payments ranges from their repeal to a dramatic change in their structure, see e.g. [36], which includes peak, off-peak and shoulder tariff.

A further monetary benefit a battery energy storage can bring to its investor is reserve provision to the power system operator. Since this service would result in additional cycling of the battery, which is not included in the battery investment cost in Eq. (2), the reserve provision model should include battery degradation costs. A linear and a depth-of-discharge dependent battery degradation models available in [39] are well-suited for this purpose.

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