Representing Long-term Impact of Residential Building Energy Management using Stochastic Dynamic Programming

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Abstract—Scheduling a residential building short-term to optimize the electricity bill can be difficult with the inclusion of capacity-based grid tariffs. Scheduling the building based on a proposed measured-peak (MP) grid tariff, which is a cost based on the highest peak power over a period, requires the user to consider the impact the current decision-making has in the future. Therefore, the authors propose a mathematical model using stochastic dynamic programming (SDP) that tries to represent the long-term impact of current decision-making. The SDP algorithm calculates non-linear expected future cost curves (EFCC) for the building based on the peak power backwards for each day over a month. The uncertainty in load demand and weather are considered using a discrete Markov chain setup. The model is applied to a case study for a Norwegian building with smart control of flexible loads, and compared against methods where the MP grid tariff is not accurately represented, and where the user has perfect information of the whole month. The results showed that the SDP algorithm performs 0.3 % better than a scenario with no accurate way of presenting future impacts, and performs 3.6 % worse compared to a scenario where the user had perfect information.

Index Terms—Demand-side management, Grid tariff, Operational planning, Stochastic dynamic programming

NOMENCLATURE

Index sets

S_g set of state variables
$\mathcal{T}$ Set of time steps within the day
G set of days within the month

Parameters

$\dot{E}^{B,dch}, \dot{E}^{B,ch}$ Discharge/charge capacity for battery [$\frac{kWh}{h}$]
$\dot{E}^{Max}$ Maximum EV charging capacity [$\frac{kWh}{h}$]
$\dot{Q}^{sh}$ Capacity for space heating radiator [$\frac{kWh}{h}$]
$\eta^B_{dch}, \eta^B_{ch}$ Discharge/charge efficiency for battery [%]
η^{EV}_{ch} EV charging efficiency [%]
C^{grid} DSO energy tariff for imported energy [$\frac{EUR}{kWh}$]
C_i, C_e Heat capacity for interior and building envelope [$\frac{kWh}{°C}$]
D^{EV} Hourly EV discharge when not connected [kWh]
$E^{B,Cap}$ Battery storage capacity [kWh]

$E^{EV,Cap}$ EV storage capacity [kWh]
N_P Number of discrete peak power values
N_S Number of nodes for stochastic variables
$P^{imp,max}$ Maximum power import to building [$\frac{kWh}{h}$]
P^p_0 Initial peak power [$\frac{kWh}{h}$]
P^p_n Peak power at point n [$\frac{kWh}{h}$]
R_{ie}, R_{eo} The thermal resistance between the interior-building envelope and building envelope-outdoor air [$\frac{°C}{kWh}$]
$SoC^{B,min}, SoC^{B,max}$ Battery soc limits [kWh]
$SoC^{EV,min}, SoC^{EV,max}$ Min/Max EV soc capacity [kWh]
$T^{in,min}_t, T^{in,max}_t$ Lower/upper interior boundary [$°C$]
VAT Value added tax for purchase of electricity [$p.u$]

Decision variables

γ SOS-2 variables for the Expected future cost curve
$C^p_{y^p, s^e_{t+1}}$ Expected future cost from peak power [$\frac{EUR}{\frac{kWh}{h}}$]
p^p Peak of imported energy [$\frac{kWh}{h}$]
q^{sh}_t Power usage for space heating [$\frac{kWh}{h}$]
SoC^B_t State of charge for Battery for time step t [kWh]
SoC^{EV}_t State of charge for EV for time step t [kWh]
T^{in}_t, T^e_t Interior and building envelope temperature [$°C$]
$y^{B,ch}_t, y^{B,dch}_t$ Power to/from the battery for time step t [$\frac{kWh}{h}$]
$y^{EV,ch}_t$ Input power to EV for time step t [$\frac{kWh}{h}$]
y^{imp}_t, y^{exp}_t Energy imported/exported to household [$\frac{kWh}{h}$]

Stochastic variables

δ^{EV}_t EV connected to building $\{0,1\}$
δ^{Occ}_t Occupancy presence $\{0,1\}$
D^{el}_t Consumer-specific load in time step t [kWh]
P^{spot}_t Electricity spot price in time step t [$\frac{EUR}{kWh}$]
T^{out}_t Daily average outdoor temperature [$°C$]
y^{PV}_t Photovoltaic production from installed system [kWh]

I. INTRODUCTION

In Norway, the Norwegian regulator (NVE) has proposed that the grid tariff must be updated to better reflect the actual costs associated with the operating of the distribution grid [1]. The nationwide rollout of smart meters gives an opportunity to implement more sophisticated pricing structures. Residential consumption is trending towards a more peak intensive profile, requiring investments to cover the relatively few peak-load and

scarcity hours in the distributional grid. Therefore, NVE has proposed a new grid tariff with cost elements related to both capacity and energy.

In a hearing from NVE, they discuss two types of capacity-based tariffs; measured-peak (MP) and subscribed capacity tariffs [2]. Measured-peak prices the highest measured peak as the base for the cost the customer has to pay over a specified period, whereas subscribed capacity requires the customer to subscribe to a certain amount of capacity, and then pays a low or high energy cost if the consumption is under or over the subscribed capacity, respectively. The MP grid tariff is affected by the active import of electricity, and can be costly if the end-user is not aware of their electricity consumption. The proposed period for the MP grid tariff for residential buildings is 1 day, but this tariff already exists for many commercial/industrial customers today with periods over 1 month. Thus, it is not unlikely that this tariff could be implemented for longer periods for residential buildings, making it important to consider previous and future actions to prevent a costly electrical bill.

With the smart meters rollout in over Norway, it is only a matter of time before smart controllers for the flexible appliances in the building are common. Smart building controllers try to reduce the electricity bill using the optimal scheduling of available flexibility in the buildings on a short time-scale. Reference [3] optimizes the building flexibility using a model predictive control (MPC)-based optimal scheduling strategy with a non-linear programming model for the next 24 hours. Moreover, it minimizes cost and CO2 emissions simultaneously. In [4], authors present a methodology for an energy management system, aiming to find optimal scheduling of a hybrid renewable energy system. The methodology is based on multi-objective receding horizon optimization, and investigated optimal scheduling using a time view from 6-24 hours with predicted inputs. The findings showcase that a longer time horizon in input predictions, contribute to increase the renewable energy share for covering the demand. Dynamic programming was used in [5] to operate a battery optimally. The objective is to minimize the electricity cost subject to grid tariffs based on peak consumption. The battery is optimized over 24 hours with hourly steps, and tested for both a deterministic and stochastic setup to reduce the demand charge costs.

The above literature consider the short-term optimization, with uncertainty reflected in the hourly future impact. However, the analysis period and the number of hours/days into the future limits the amount of information they have. Mostly, there is no need to go further as short-term optimization utilizes flexibility that is shifted a couple of hours, and has no indicated impact in the future. However, if longer periods must be considered, like what grid tariffs promotes, then it is required to connect the future unknown scheduling of flexibility realization together with daily operational decision-making to make more accurate decisions.

This problem has been addressed previously regarding hydropower scheduling, where the water stored in the reser-

voirs should be used optimally. As presented in [6], the planning problem for a hydropower producer is complex due to the interactions with power systems with thermal power production. To find optimal operation, the problem is decomposed into several smaller optimization problems, for instance long-, medium-, and short-term scheduling. The long-term scheduling includes uncertainty and the objective is to find the marginal value of using water now to produce power versus the value of storing it for later. The calculation is done using stochastic dynamic programming (SDP) to find these marginal values called water values, as also shown in [7], [8]. The ending water values are used in a short-term model to optimize production. This setup is able to represent the future impact of current decision-making, and could therefore be implemented into a building model as well to complement the problems discussed. Using the proposed MP grid tariff is a good way of analyzing the performance of such a setup. Dynamic Programming was used in [5] to optimally operate a battery to minimize cost under MP grid tariffs, but only considers a 24 hour horizon, which would be insufficient with a monthly tariff where uncertainty for 1 month must be taken into consideration.

In this paper, we propose a backwards SDP algorithm that generates non-linear future cost curves for a residential building for every day over the course of a month, inspired by the long-term model used frequently in hydropower scheduling. Our contributions are the following:

- We present a SDP optimization framework to minimize costs by predicting and planning for the highest peak with uncertain demand
- We compare the results of the SDP algorithm to cases where the MP grid tariff is either considered short-term or not considered, and with cases where the residential building has perfect information for the entire month

The rest of the paper is organized as follows: Section II describes the mathematical formulation and the SDP layout. Section III describes the performed case study, whereas Section IV presents and discusses the results. The conclusion is found in Section V.

II. METHODOLOGY

The methodology takes into consideration a single all-electric residential building that is connected to the power grid with bi-directional power flow options. The building considers smart control of different application such as space heating, electric vehicle (EV) charging, battery control and a photovoltaic (PV) system connected on the roof.

A. Model overview

The overall objective is to find the operation strategy for the end-user over a month that minimizes the total electricity bill for the building when a one-time MP grid tariff cost based on the highest peak power imported is included. The whole month is modelled as a multi-stage stochastic optimization problem, where the stochastic variables within the building are realized for each scheduling day with scenarios. The probability

distributions for each stochastic scenario are assumed to be discrete, and it is assumed that we can decompose the problem into daily decision stages. For each day, the only information carried over are the state variables, which in this work is the achieved peak power p^p.

The motivation behind decomposing the problem is due to the complexity of the original model, which can be affected by dimensionality issues if all possible combinations of outcomes were included. The SDP keeps sufficient levels of information present, while still being capable of showcasing how system costs are impacted by state variables under uncertainty.

Some of the shortcomings of SDP, however, is that some information is lost when decomposing the problem. Only the state variables can be carried over between days, which means other variables with information must be simplified to a fixed start/end parameter value at the start/end of each day. Fixing variables during the transition will lead to loss of accuracy as the interaction between could provide better performance. The other drawback is scalability, in that if the case is complex and the number of decision stages that must be run are high, the computation time might take too long. One solution to this is to decrease the number of state variables for the SDP to calculate, giving an accuracy versus computation time issue.

When decomposing the SDP problem, we include a set of state variables $\mathcal{S}_g$ that contains all information carried over between the decision stages $g-1$ to g. This set is divided into two subsets. Subset $\mathcal{S}_{P,g} \in \mathcal{S}_g$ consist of the state variables that are tied together with the optimization problem, which will be explained further in Section II-C. Subset $\mathcal{S}_{S,g} \in \mathcal{S}_g$ contains all the stochastic variables that are being realized as parameters at the beginning of each day g, described in more detail in Section II-B. Then, the decomposed decision problem for a given state $s_g^s, s_g^p \in \mathcal{S}_g$ at the start of decision stage g will be based on the current scheduling and the weighted impact of the future cost for all scenarios, which is the objective function of the optimization problem found in (1).

B. Stochastic variables

The stochastic variables, which are unknown values for the system until a scenario has realized their values, are assumed to be Markovian. The future cost in the optimization problem in (1) can then be represented as a Markov decision process. The Markovian setup defines the future probable states that can occur to only be dependent on the current state. Hence, we can connect the impact of the stochastic variables between the stages, and represent them for stage g as an expected future cost (EFC) for all future states in stage $g+1$. The EFC will be the weighted possible outcome of all discrete scenarios N_S in $\mathcal{S}_{S,g+1}$. In this work, there are 6 different stochastic variables per scenario: Electric-specific non-shiftable demand, electricity spot price, EV availability, PV production, occupancy presence in the building and outdoor temperature.

C. Decision problem and SDP algorithm

The decomposed decision problem for one day g is formulated as a MILP problem given in (1)–(6d). The stochastic variables in s_g^s is known and has been realized, and the state variable $s_g^p = (P_0^p)$ as well.

1) Objective function: The objective function in (1) tries to minimize the total cost of the end-user. This is denoted by the cost of purchasing electricity from the grid (C^{Import}), the benefit of selling excess electricity to the grid (C^{Export}), and the EFC based on the achieved peak power p^p (C^{Future}).

$$min\ [C^{Import} - C^{Export} + C^{Future}] \tag{1}$$
$$C^{Import} = \sum_{t\in\mathcal{T}} y_t^{imp} \cdot (C^{grid} + P_t^{spot}) \cdot (1 + VAT)$$
$$C^{Export} = \sum_{t\in\mathcal{T}} y_t^{exp} \cdot P_t^{Spot}$$
$$C^{Future} = C_{p^p, s_{t+1}^s}^p$$

2) Expected future cost: The EFC is depicted within (2a) to (2e). The highest amount of power that is imported to the building is found in p^p, which depends on the highest peak within the decision stage and the initial value given from the state variable. The peak power achieved at the end is used to set the EFC, which consist of discretized peak power of $n = 1...N_P$ points, from $[P_1^p = 0, P_{N_P}^p = P^{imp,max}]$. The EFC curve (EFCC) is then given as a piecewise-linear function using a SOS-2 set. SOS-2 is an ordered set of non-negative variables, where at most two variables can be non-zero, under the requirement that they are adjacent to each other in the set. The variables must sum up to 1. The SOS-2 set depicts where in the piecewise-linear function the peak power is at (2d), and finds the resulting cost in (2c) [9]. The obtained future cost from p^p is included into the objective function. Calculation of the EFCC is explained further in Section II-D.

$$p^p \geq P_0^p \tag{2a}$$
$$p^p \geq y_t^{imp} \quad \forall t \tag{2b}$$
$$C_{p^p, s_{t+1}^s}^p = \sum_{n\in\mathcal{N}_P} \gamma_n \cdot C_n^p \tag{2c}$$
$$p^p = \sum_{n\in\mathcal{N}_P} \gamma_n \cdot P_n^p \tag{2d}$$
$$\sum_{n\in\mathcal{N}_P} \gamma_n = 1 \tag{2e}$$

3) Energy balance and electric vehicle: The electric energy balance of the house is given in (3). The EV section is formulated in (4a) to (4c). The EV is modelled as a battery that has an availability pattern based on the stochastic variable δ_t^{EV}. The EV discharges electricity as a load only when it has departed and can only be charged when present. The EV has a constraint in (4c) that states the EV must be within a certain range in its state-of-charge, and this boundary is dependent on if the EV is present, travelling, or about to travel. If it is about to depart, the SoC has a stricter boundary, to meet the safety margins of the user.

$$y_t^{imp} - y_t^{exp} + y_t^{PV} + y_t^{B,dch} =$$
$$D_t^{El} + y_t^{EV,ch} + q_t^{sh} + y_t^{B,ch} \quad \forall t \tag{3}$$

$$SoC_t^{EV} - SoC_{t-1}^{EV} = y_t^{EV,ch}\eta_{ch}^{EV}\delta_t^{EV}$$
$$- D^{EV}(1 - \delta_t^{EV}) \qquad \forall t \backslash t \neq 1 \qquad (4a)$$

$$0 \leq y_t^{EV,ch} \leq \dot{E}^{Max} \quad \forall t \qquad (4b)$$

$$SoC_t^{EV,min} \leq SoC_t^{EV} \leq SoC_t^{EV,max} \quad \forall t \qquad (4c)$$

In this paper, the EV energy discharge (D^{EV}) is considered as an input parameter per hour of unavailability. Thus, the total energy discharge varies based on the travelling duration. Introducing uncertainty to this component would lead to more uncertain input which increases the dimension of the problem.

4) Battery: The building has a stationary battery installed that can be charged or discharged whenever needed in (5a) to (5d). The battery has a specific capacity and must keep the SoC within a range to ensure the battery is not in risk of damage.

$$SoC_t^B - SoC_{t-1}^B = y_t^{B,ch}\eta_{ch}^B - \frac{y_t^{B,dch}}{\eta_{dch}^b} \qquad \forall t\backslash t \neq 1 \quad (5a)$$

$$0 \leq y_t^{bat,ch} \leq \dot{E}^{Bat,ch} \quad \forall t \in \mathcal{T} \qquad (5b)$$

$$0 \leq y_t^{bat,dch} \leq \dot{E}^{bat,dch} \quad \forall t \in \mathcal{T} \qquad (5c)$$

$$SoC^{B,min} \leq Soc_t^B \leq SoC^{B,max} \quad \forall t \qquad (5d)$$

5) Space heating: All considerations regarding heating of the building is formulated in (6a) to (6d). The building has an electric radiator for space heating that can be turned on/off continuously. The heat dynamics in the building is seen as a grey-box model, in which the physical behavior is formulated using linear state-space models [10], [11]. Using a state-space model, the dynamics between the interior temperature and the outdoor temperature can be captured alongside disturbances as heat input, which will include the impact of time-dependent temperature deviations. The heat system is represented as a 2R2C, where the building envelope is included as a middle-area between the interior and outdoor [11]. The only disturbances in the system considered is the heater. The interior temperature has a time-dependent boundary that must be held.

$$0 \leq q_t^{sh} \leq Q^{sh} \quad \forall t \qquad (6a)$$

$$T_t^{in,min} \leq T_t^{in} \leq T_t^{in,max} \quad \forall t \qquad (6b)$$

$$T_t^{in} - T_{t-1}^{in} = \frac{1}{R_{ie}C_i}[T_{t-1}^e - T_{t-1}^{in}] + \frac{1}{C_i}q_t^{sh} \quad \forall t\backslash t \neq 1 \qquad (6c)$$

$$T_t^e - T_{t-1}^e = \frac{1}{R_{ie}C_e}[T_{t-1}^{in} - T_{t-1}^e]$$
$$+ \frac{1}{R_{ea}C_i}(T_{t-1}^{out} - T_{t-1}^e) \quad \forall t\backslash t \neq 1 \qquad (6d)$$

6) Initial conditions: All variables that have some energy storage property are given an initial value at the beginning/end of the scheduling day. These variables are T_t^{in}, T_t^e, SoC_t^{EV} and SoC_t^B. All energy equilibrium equations have an initial equation for the time step $t = 1$, being (4a), (5a), (6c) and (6d), where the previous time step is replaced with an initial

value condition. This same is true for the last time step $t = 24$, setting the values to the initial condition. This is necessary to make it possible to represent the problem using SDP when decoupling each day, to make the end value of one day the same as the start value of the next day. This is a simplification as none of these variables are included as state variables, which is done to simplify the model.

D. Solution Strategy

```
1  for g = G, G - 1, .., 1 do
2      for n ∈ N_P do
3          P_0^p ← P_n^p
4          for s_g^s ∈ N_S do
5              {P_t^{spot}, D_t^{El}, δ_t^{EV}, y_t^{PV}, T_t^{out}, δ_t^{Occ}} ←
                  StochVar(g, s_g^s)
6              C_i^p ← Φ(i, s_{g+1}^s, g + 1) for i = 1..N_P
7              C_{s_g^s,n} ← Optimize(1) − (6)
8          end
9          for s_g^s ∈ N_S do
10             Φ(n, s_g^s, g) = ∑_{s_{g+1}^s=1}^{N_S} C_{s_g^s,n} · ρ(g, s_{g+1}^s|s_g^s)
11         end
12     end
13 end
```

Algorithm 1: The SDP algorithm

The solution strategy for the SDP is shown in Algorithm 1. The SDP algorithm sets up the optimization problem for the building and goes backwards in the procedure to find the expected future cost curves (EFCCs) for the start of the period. We compute this for the number of discrete points $n \in N_P$ specified in line 2-3 and the number of scenarios $s_g^s \in N_S$ given in line 4. For each scenario, we realize the stochastic variables with values from StochVar in line 5, and in line 6 the EFC for the future scheduling day $g + 1$ is realized in C_i^p. StochVar consists of the realized stochastic variables based on the scheduling day g and scenario s_g^s. The optimization problem is then solved in line 7 to find the daily decision problem result, which is denoted as $C_{s_g^s,n}$. Furthermore, the EFC $\Phi(n, s_g^e, g)$ for each node s_g^s is calculated based on the results in $C_{s_g^s,n}$ and the probability $\rho(g, s_{g+1}^s|s_g^s)$ in line 10, whereas the latter is denoted as the Markov-specific probability for the future scenario s_{g+1}^s based on the current scenario s_g^s and day g.

The combined EFCs for all $n \in \mathcal{N}_P$ makes up for the resulting EFCC for the given node s_g^s. Thus, there exists an EFCC for every scenario, which can be used in the next stage $g - 1$ to represent the future uncertainty up to this point. For the initial case of $g = G$, $\Phi(n, s_g^e, G+1)$ represents the ending cost for the MP tariff for all $n \in N_P$.

III. Case Study

The presented model has been applied to case study of a Norwegian building, exposed to the presented MP grid tariff. The building used is considered a single-family house (SFH) placed in the south-eastern part of Norway, and smart

controls are used for the different applications. The analysis is for January 2017 with hourly time resolution per day, and the stochastic variables consist of historical data or assumed behavior. A total of four stochastic nodes per day have been generated to illustrate the uncertainty in future scheduling.

A. Building structure

The building represented in this work is modelled as a single room. For the heat dynamics of the building, the resistances and heat capacity values are based on observed values from the Living Lab building built by Zero Emission Building and NTNU [12]. The interior temperature must stay between $20.5 - 24$ °C or $19 - 26$ °C, if residents are home or not, respectively. The building is heated through a 3 kW radiator. A 24 kWh EV is considered with a 3.7 kW smart charger, and must be between 20-90 % capacity at all time, and between 60-90 % when departing. When the EV is not present, a constant load of 1 kWh is assumed per hour to simulate discharge due to driving. The stationary battery is based of a 5 kWh, 2.5 kW battery from SonnenBatterie [13], and must be between 10-100 % SoC. The PV system consist of 4.65 kW installed capacity of PV with a 95 % efficient inverter.

The energy storage variables, as mentioned in Section II-C, have the following start and end condition values: $T_0^{in} = 22$ °C, $T_0^e = 20$ °C, $SoC_0^{EV} = 60$ %, $SoC_0^B = 50$ %. The MP grid tariff is based on the proposal from NVE in 2017 [2], adjusted for a 1 month period, with a volumetric cost of $0.00625 \frac{EUR}{kWh}$ and a power tariff at $7.2075 \frac{EUR}{\frac{kWh}{h}}$ for the month, including 25 % VAT.

B. Stochastic variables

The stochastic variables have different scenarios between each stochastic node and day, with a total of $N_S = 4$ scenarios per day each. Each scenario probability is only dependent on the current scenario and the future scenario, upholding the Markovian setup. The scenarios do not have the same probability; for a scenario transition on the same node, the probability is higher than the others. The electricity prices are obtained from NordPool, and only January 2017 for NO1 has been used. The PV irradiation and outdoor temperature series are from historical data for January 2014-2017 obtained from Nibio [14], while the electric-specific non-shiftable load are from different buildings in January 2017, but with similar consumption obtained from Ringerikskraft [15], a power company in southern Norway. The occupancy for EV, which also affects temperature boundary, is based on assumed behaviour regarding leaving for work and weekend travelling, with four different patterns.

C. Model cases

To keep the level of accuracy for the EFCC piecewise-linear function, the peak power value was discretized to be $\mathcal{N}_P = 41$, ranging from 0-10 $\frac{kWh}{h}$. This gives a total of 5084 nodes to analyze for the SDP algorithm. The main case $Peak_{SDP}$ will analyze how the proposed SDP algorithm contributes with finding the cost-optimal initial peak power for

the building with the MP grid tariff, and what the expected total cost for the residents will be over the month. To achieve this, the EFCC will be used in a simulation phase where the days are run sequentially day by day, with the peak power achieved included in the transition and the EFCC representing the future, to find the total cost for that simulated month. The transition of each day is decided by the Markovian probability. 1000 simulations will be performed to get an accurate description of the uncertainty in the model.

In addition to the main case, there will be 4 other cases analyzed and compared against. Case $Peak_{no}$ is a case where the resident does not consider the peak power in the scheduling decision and case $Peak_{min}$ is where the resident minimizes the peak from day one without any knowledge of the future. The last two cases considers the entire month scheduled as one holistic problem, with perfect information on the whole period. Case Hol_{init} is with the initial condition for the energy variables being kept true for every 24 hours, while case Hol is without the initial condition except for the last scheduling day.

IV. RESULTS & DISCUSSION

A. Expected future cost curves

From the SDP algorithm in Algorithm 1, EFCCs are created for every day of the month, and for every scenario within the days, based on the highest peak power. For each additional future day the EFCC represents, the total future cost will increase. To give a comparable overview of the EFFCs over the period, the values plotted in Fig. 1 are the marginal EFCC of increasing the peak power by 1 $\frac{kWh}{h}$.
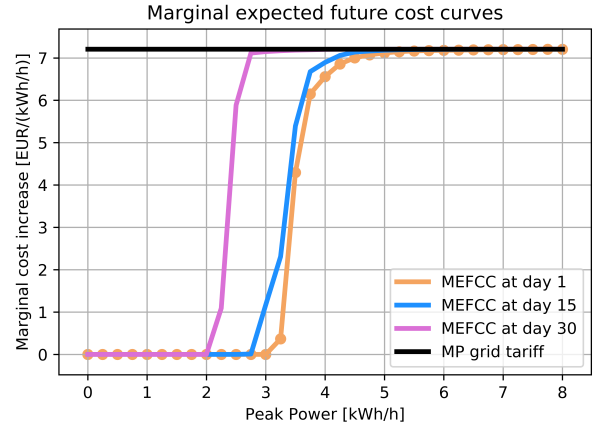

Fig. 1. Plot of the non-linear marginal expected future cost curve for three different days and a given scenario node.

In general, each EFCC has three main parts that can be distinguished. The start of the curves are flat, where initializing on these values will result in a re-adjustment later on. The middle section of the curves are where the non-linearity is present, as increasing the initial peak power will result in a marginal cost increase. The varying marginal value is a trade-off between paying for more flexibility from import versus

scheduling with less flexibility. The end of the curve is flat as the increase in import peak gives no extra incentives in scheduling and only a cost increase equal to the MP grid tariff.

The plot shows that the point in which the non-linear curve starts appearing changes as more days are included. If a day has scenarios with high demand, the optimal peak power might have to be larger than calculated in later days, which changes the starting flat curve level further on. Thus, the critical days will be reflected in the EFCC for day 1. However, as uncertainty is included in the model, these EFCC only gives the cost-optimal future cost based on probability. Thus, the cost-optimal peak power from the EFCC can give simulations where the peak power is exceeded due to critical scenarios being realized, and simulations where the actual lowest peak power level would be below the initial value. This is the consequence of adding uncertainty into the mix.

Based on the marginal EFCC in Fig. 1, the optimal initial level of the peak power in day 1 is $3 \frac{kWh}{h}$, as that is the highest peak power with the lowest cost. For each day, the EFCC curves are included to reflect the future impact on the current decision-making, and indicates what cost-optimal level of peak power the building should try to achieve. It considers the cost of load shifting to reduce the peak power to the cost of increasing peak power and the future impact, and optimizes based on the expected cost-effective solution.

B. Simulation results

The results from the simulations regarding all cases are shown in Table I, with both the average total cost, and the average peak power achieved. The SDP algorithm manages to keep the average total cost below what would be the case if the resident was unaware and had no prediction of the future scenarios, when comparing case P_{SDP} to cases P_{no} and P_{min}.

Case P_{no} uses the smart control and the internal flexibility to minimize cost from the variation in spot prices, ignoring the penalty paid at the end of the month in the daily decision-making. Thus, the cost increase of 36.1 %, compared to the P_{SDP} result, is to be expected as the achieved peak is $10 \frac{kWh}{h}$. For case P_{min}, the user has no information on the future predictions, and react by keeping the peak as low as possible by considering achieved values. The loss of value due to the effort of load shifting to keep the import level at an unnecessary low level early, is the reason this setup is 0.3 % higher in average total cost, despite having a 0.3 % lower average import peak, compared to P_{SDP}.

TABLE I
AVERAGE TOTAL COST AND PEAK POWER FOR THE 5 CASES.

Cases	P_{SPD}	P_{no}	P_{min}	P_{Hol}	$P_{Hol,init}$
Total cost [EUR]	131.2	178.6	131.6	126.5	130.4
Peak [$\frac{kWh}{h}$]	3.24	10.0	3.23	2.69	3.22

A drawback of the SDP algorithm is that for each day, the start and end condition for variables considering energy storage must be equal, as mentioned in II-C6. This is not the optimal case if the whole period is already known, due to load shifting between days. For the holistic case with the initial condition limitations $P_{Hol,init}$ kept, the difference of the average total cost is lowered by 0.6 % and 0.6 % lower average peak power compared to P_{SDP}. However, when neglecting the limitation in case P_{Hol}, the average total cost is 3.6 % lower compared to P_{SDP}, and the average peak power is 17.0 % lower. The results from both cases with perfect information illustrates the weakness of simplifying energy storage values when transitioning from one day to the next, as this increases the total cost. The current SDP algorithm cannot load shift between the days, limiting the complete benefit of flexibility which is shown in the holistic cases. This shows the value of deviating from the initial conditions.

We demonstrated the benefit of including not only the peak power from the grid, but other information of the building that is carried over between scheduling days. This is a concept that the SDP algorithm can include, however, this can create scalability issues if the number of state variables increases too much. Including the critical energy variables and simplifying the rest can improve the performance. Another point of interest is to find logical and season-optimal initial conditions for the energy variables. The ones for this case study might be ill-suited for the transition. The findings from the holistic solutions support that the SDP algorithm can improve in performance if the initial conditions are analyzed further, both regarding initial values and including them as state variables in the algorithm.

V. CONCLUSION

With new capacity based grid tariffs being proposed in Norway by NVE, the value of load shifting for the end-users will come in focus. If the total cost depends on a longer horizon, the long-term impact should be represented today, especially with uncertainty included. We present a model that aims at representing the future cost for the system based on current decision-making for a building when considering the MP grid tariff. The model manages to represent the EFC for the building as a cost curve depicting the optimal peak power to aim for based on expected future behaviour. The Markovian setup defines the probable future states of the problem, which depend only upon the present state, and are not conditioned on the sequence of states and actions that preceded them. If these dependencies are considered, it will cause an explosion in the size of the state representation, and correspondingly, the algorithm becomes computationally infeasible.

This model was applied to a realistic Norwegian household for January 2017 to find the optimal peak power and the expected total electricity cost. This was compared to two situations where the future cost from the grid tariff is unknown or not considered for the building, and two cases with perfect information regarding stochastic inputs. For the cases where the peak power is either minimized daily or not considered into the daily scheduling, they have a 0.3 % and 36.1 % cost increase compared to the proposed method, respectively. For holistic setups where the initial condition was kept at each day or ignored, the results showed a cost save of 0.6 % and 3.6

% compared to the proposed methodology, respectively. This showcases the importance of these initial conditions.

VI. Future Work

The findings showcase the potential the representation of the long-term uncertainty has on the overall result. However, the results also indicated that further investigation into the initial conditions that consider energy storage in the building must be done to find the impact they have on the system. Whether they need to be given an accurate initial condition or included into the future cost curve will be a key question to answer.

VII. Acknowledgment

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