Flexible behind-the-meter Battery Storage Model for enhanced mid- to long-term Load Forecasting

1st Simon Schramm
System Development
Austrian Power Grid
Vienna, Austria
simon.schramm@apg.at

2nd András Kádár
Long-Term System Planning Department
MAVIR Ltd.
Budapest, Hungary
kadara@mavir.hu

3rd Alexander Haas
System Development
Austrian Power Grid
Vienna, Austria
alexander.haas@apg.at

***Abstract*—This paper presents a general behind-the-meter (btm) Battery Energy Storage Systems (BESS) model to properly account for the impact of btm-BESS in combination with rooftop Photovoltaic (PV) systems. The appearance of these systems will significantly impact the shape of electrical load curves which requires a thorough assessment under a transparent, well-established framework. As motivating examples, the model is applied to publicly available synthetic household data and national-level data for Austria. The potential influence of the resulting changes of the net load is examined, along with a discussion of the limitations imposed by model assumptions. Different btm-BESS operation modes are presented and realised within the same model by means of flexible model parametrisation. Finally, possible extensions are proposed to evolve the model into a more comprehensive prosumer model, such as integrating a specific heat pump model or analysing the effects of flexible end-user tariffs.**

***Index Terms*—behind-the-meter, battery storage systems, demand side management, forecasting, prosumer**

I. Introduction

In European countries there is a massive roll-out of renewable energy resources (RES) ongoing in recent years. While windfarms – whether onshore or offshore – are mainly directly connected to the high-voltage transmission grid, photovoltaic (PV) systems are predominantly installed on residential rooftops behind-the-meter (btm). Taking Austria as an example, the capacity of installed behind-the-meter Battery Energy Storage Systems (btm-BESS) more than doubled from 2022 to 2023 [1]. In the absence of a widespread coverage of advanced smart-meter systems, generation from these installations often cannot be directly measured by transmission or distribution system operators. Furthermore, combining RES with BESS leads to a partial temporal decoupling of volatile generation and residential load, thus having a significant impact on residential electricity load profiles.

However, decentralized generation and consumption patterns can enhance system flexibility and resiliency, crucial for the energy transition. Despite suboptimal market conditions, the deployment of flexible technologies like battery storage systems is increasing, supported by price signals and potential market development and public support schemes [2], [3]. They can provide firm capacity in peak load periods when certain systemic problems usually arise. Alternatively, these technologies can also contribute to less grid feed-in of rooftop-PV generation due to smarter energy usage. Both examples have positive system-level effects and should be assessed appropriately.

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The lack of high-quality measurements, the challenge of finding suitable approaches as well as significant disparities in metering and billing systems across Europe [4] make it difficult to consider behind-the-meter Battery Energy Storage Systems (btm-BESS) in Load Forecasting. This necessitates the development of flexible modelling approaches to account for these uncertainties and to better understand the underlying dynamics of btm-BESS.

This paper proposes a model to mimic the behavior of residential btm-BESS systems with adjustable incentives and operation modes. Being a flexible framework, it aims to approximate many possible modes of btm-BESS operations based on case-specific parametrisation. In the following, Chapter II presents the model formulation before discussing possible parametrisations of this model and two use cases in Chapters III and IV. The paper ends with some notes on model limitations and conclusion.

II. Model formulation

We present the btm-BESS model as an Energy Reservoir Model following the categorisation of [5]. In that work the authors stress the importance of the design of a BESS controller and review the possible BESS models that can be used in a real-world BESS or Energy Management System (EMS). The model as such is based on an optimisation problem. The model slices the entire simulation horizon into several independent problems in the size of the parameter *interval* and a resolution Δt. For example, when setting the optimisation *interval* to 24 hours, the model will solve 365 independent problems consecutively when simulating an entire year in an hourly resolution. The basis of the presented btm-BESS dispatch model has the objective function in the form of (1).

$$\textbf{maximize} \sum_{i=1}^{interval} (c_i \cdot x_i) \tag{1}$$

Here, subset *i* refers to the resolution of every *interval* (e.g. hours). The variable x_i refers to the btm-BESS dispatch and is the main decision variable that is under investigation. The principle idea of the model is to have a proxy term for real-world data that incentives the battery in its dispatch behavior. This is realized by the c_i term. In general, this incentivising term can be of different forms like market price signals or a residual load. The latter will be used and explained in section III-B with respect to the modelling guidelines of the European Resource Adequacy Assessment (ERAA) [6]. The btm-BESS dispatch variable x_i is further split up to a charging and discharging variable regarding (2) following the sign convention of (3).

$$x_i = discharge_i + charge_i \tag{2}$$

$$x_i = \begin{cases} discharge_i, & \text{for } x_i > 0 \\ charge_i, & \text{for } x_i < 0 \end{cases} \tag{3}$$

In order to obtain further control of the btm-BESS behavior and to manipulate the model regarding certain use cases we introduce two penalty terms. Eq. (4) represents a penalty term in the spirit of an L2-norm regularisation. This term enables to dampen the amplitude of the btm-BESS dispatch value x_i [5]. The coefficient α controls the regularisation term and is normalised on the maximum discharging limit of the btm-BESS as shown in (5).

$$p_1(x_i) = \alpha \cdot \sum_{i=1}^{interval} x_i^2 \tag{4}$$

$$\alpha = \frac{\tilde{\alpha}}{Discharge_{max}} \tag{5}$$

We also introduce a second penalty term and use it to restrict the cycle numbers of the btm-BESS. The term $Losses$ refers to round-trip efficiency losses over the entire interval and is defined in (14) while β is the control coefficient for this penalty term. This term can also be viewed as a regularisation term analogous to the L1-norm in machine learning applications.

$$p_2(x_i) = \beta * Losses(x_i) \tag{6}$$

These two penalty terms consider possible battery degradation effects that are usually taken into account in real-world applications aiming at prolonging battery lifetime [5]. Eventually, we obtain the objective function shown in (7).

$$\textbf{maximize} \sum_{i=1}^{interval} (c_i \cdot x_i - p_1(x_i) - p_2(x_i)) \tag{7}$$

In order to get to a complete model formulation of a btm-BESS model, the objective function of (7) is subject to a set of constraints.

1) Power Boundaries: In (8) the btm-BESS dispatch is limited by its nominal power boundaries defined by the electrical characteristics of the battery system. $Charge_{max}$ and $Discharge_{max}$ are model parameters that can be set when parametrising the model. Additionally, (9) limits the model to either charge or discharge in accordance with [5].

$$Charge_{max} \leq x_i \leq Discharge_{max} \tag{8}$$

$$discharge_i \cdot charge_i = 0 \tag{9}$$

2) State-of-Charge modelling: The model is further defined by its evolution of State-of-Charge (SOC). In (10) the change of the SOC at timestamp *i* due to charging and discharging is displayed where Δt refers to the simulation timestamp length being 1 hour in our application. Since the SOC is counted in relative values between 0 and 1, the charging and discharging rates are divided by the nominal storage capacity *BattCapacity*. To account for efficiency losses, the round-trip-efficiency η_{rt} is introduced and multiplied by the charging rate.

$$SOC_i = SOC_{i-1} - \frac{discharge_i + charge_i \cdot \eta_{rt}}{BattCapacity} \cdot \Delta t \tag{10}$$

The model is further constrained by a set of SOC boundaries. Limiting the minimum and maximum SOC as well as defining starting and end conditions (11), (12), (13) allows for model calibration through the parameters SOC_{max}, SOC_{init} and SOC_{end}.

$$SOC_{min} \leq SOC_i \leq SOC_{max} \tag{11}$$

$$SOC_{i=0} = SOC_{init} \tag{12}$$

$$SOC_{interval} \geq SOC_{end} \tag{13}$$

The losses due to round-trip efficiency are accounted for in (14).

$$Losses = (1 - \eta_{rt}) \cdot \sum_{i=1}^{interval} -charge_i \tag{14}$$

3) behavioral constraints: In addition to power and SOC constraints, (15) constrains btm-BESS charging only to the currently available PV generation. This constraint can be turned off and on regarding the required operation mode of the btm-BESS.

$$x_i \geq -PV_i \tag{15}$$

The proposed model is sensitive to input data. Under certain edge cases it may exhibit counter-intuitive behavior. To prevent btm-BESS discharging when rooftop PV generation exceeds the electrical Gross Load, constraints (16) and (17) are applied using a bigM-formulation. These constraints are specific to the use case and input data presented in this work

$$rooftopPV_i - Load_i \leq M \cdot y \tag{16}$$

$$x_i \leq M \cdot (1 - y) \tag{17}$$

III. Model Parametrisation

As stated in chapter I, modelling btm-BESS is required to account for unmeasured contribution to the grid load. While the control scheme behind every btm-BESS operation mode often remains unknown from a grid perspective, every single btm-BESS might also allow for various operation schemes making it even harder to define its behavior by only looking at the grid load. Therefore, the proposed model in chapter II is intended to be flexible both with its formulation and implementation. This way the model is able to mimic various possible operation modes a btm-BESS can have.

A. Operation modes

To parametrise the btm-BESS model for different operation modes, various behavior types must be identified and explained, despite the lack of regulatory or mathematical definitions. Commonly known objectives like cost minimisation, grid support, and autarky can help to describe different behavior types graphically or by certain KPIs. Literature provides general roadmaps and analyses of BESS modeling approaches, highlighting cost-effective control schemes that leverage feed-in tariffs for PV in combination with BESS [7]–[9]. Fig. 1 based on [10] also shows different illustrative control schemes for Demand Side Management (DSM).

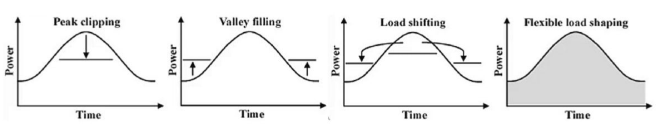

Fig. 1. Advanced operation strategies for btm-BESS [10].

In this paper the btm-BESS model is parametrised to resemble three different control schemes common in real-world settings. The first, straightforward use case is the *greedy behavior*, where a btm-BESS charges whenever PV generation is available and discharges when local load exceeds PV production until storage limits are reached. With forecasted weather and load data, this use case is extended to charge during low residual load periods and discharge during peak load periods. This behavior is common in most installed btm-BESS today. Following the common objectives of btm-BESS as well as the shown strategies in Fig. 1 we introduce two more control schemes for BESS. On one hand, the *autarky* mode with the aim of maximising auto-consumption and therefore increasing the autarky level. Finally, the *load-shifting* mode trying to cut off peak load periods while increasing low load outliers as shown in Fig. 1. In terms of the btm-BESS model these use cases can be achieved by changing the model parameters and assumptions. The concrete configuration possibilities of the proposed model are explained in III-B.

B. Model Parameters

The idea of the proposed work is to mimic the btm-BESS operation modes introduced in section III-A by varying parametrisations of the model from section II. In the following part the set of adjusted parameters of the btm-BESS model are explained in order to achieve this flexibility.

1) c_i: A recent field study investigated different EMS of the most common btm-BESS systems on the market. All of them used for their prediction-based control different forms of PV generation and local load estimations [11]. Therefore, in this use case the incentivising term c_i is formulated with respect to a residual load. We introduce two possible formulations of this c_i term in the objective function in (1). The first one refers to a normalized residual load only taking into account the Gross load and the available rooftop-PV generation as shown in (18) without any btm-BESS contributions. It will be further on referred to as *static residual ($residual_i^{static}$)*. In (19) the term of (18) is extended by the btm-BESS dispatch variable x_i. It will be further referred to as *dynamic residual ($residual_i^{dynamic}$)*.

$$c_i = residual_i^{static} = \frac{Load_i - rooftopPV_i}{max(Load_{interval})} \tag{18}$$

$$c_i = residual_i^{dynamic} = \frac{Load_i - rooftopPV_i - x_i}{max(Load_{interval})} \tag{19}$$

2) Grid charging: As mentioned in section II-3 the btm-BESS can be constrained to only be charged with the locally available PV generation. This constraint can be turned off or on regarding whether equation (15) is binding.

3) $\tilde{\alpha}$: The penalty term from (4) added to the objective function is controlled by the factor $\tilde{\alpha}$ meaning that the higher $\tilde{\alpha}$ is, the more the btm-BESS dispatch values get constrained in their amplitude.

4) β: The penalty term from (6) and added to the objective function is controlled by the factor β meaning that the higher β is, the less charging and discharging cycles of the btm-BESS are initiated by the model.

5) $interval$: The optimisation interval of every subproblem of the entire simulation period is defined by the parameter $interval$. The optimisation period acts as the perfect foresight horizon of the model in terms of Gross Load and PV generation prediction. The resolution is in hours.

Table I shows the configured operation modes for this publication and their corresponding parameter settings. These configurations were empirically determined through systematic experimentation with the model. It is important to note that these configurations are not unique and that there exist numerous alternative settings to achieve comparable behavior.

TABLE I
BTM-BESS OPERATION MODES AND THEIR CONFIGURATION

mode	**residual**	**grid-charging**	$\tilde{\alpha}$	β	**interval**
greedy	*static* (18)	no	0	0	24
autarky	*dynamic* (19)	no	0	0	24
load-shifting	*static* (18)	yes	0.1/0.5	0	24

IV. Use Cases

The btm-BESS model presented in section II and its operation mode configurations explained in section III are further tested and investigated in different use cases in this chapter. In section IV-A the btm-BESS model with its defined operation modes is investigated on a single household data set. The same model is then applied to the single node input data for Austria in the context of the ERAA [6] study in section IV-B. In all use cases PV generation is calculated by multiplying the installed PV capacity with the rooftop PV generation factors from the Pan-European Climate Data (PECD) for a particular Climate Year (CY) [6]. For comparison reasons on how the different btm-BESS operation modes impact the load curve, we introduce a fourth operation mode called *default* to which the remaining operation modes from section III-A are compared to. The *default* operation mode is characterised by the same available PV generation while lacking btm-BESS installations. This way the load curve forming impact of btm-BESS can be evaluated for every operation mode. Table II shows the fixed model parameters for all following simulation runs.

TABLE II
Global Simulation parameters for btm-BESS model.

Parameter	Unit	Value
SOC_{min}	a.u.	0
SOC_{max}	a.u.	1
SOC_{start}	a.u.	0.5
SOC_{end}	a.u.	0.3
η_{rt}	%	95
M	/	100,000

A. Synthetic Household data

To demonstrate a real-world use case of the btm-BESS model, we simulate the btm-BESS dispatch of an exemplary synthetical household equipped with rooftop-PV installation. The household load data is a benchmark dataset of [12] with the ID CHH14. The approach behind [12] is a behavioral agent-based model and the CHH14 dataset refers to a Multigeneration home consisting of a working couple, two children and two seniors. The installed capacities and charging/discharging limits displayed in Tab. III are those of an average Austrian household with similar conditions to the Multigeneration home described in [12].

TABLE III
rooftop PV and Battery data for a Multi-Generation household.

Parameter	Unit	Value
installed PV_{peak}	kW	8
installed Battery capacity	kWh	10
max. charging/discharging power	kW	5

The Gross Load curve of the household for a winter day in February can be seen in App. A Fig. 2 in the bottom plot as the grey filled area. We observe a global daily load peak at 1 pm with approximately 3.3 kW beside having local load peaks in the morning at 6 am and in the evening at 7 and 9 pm. The available photovoltaic generation is shown in Fig. 2 in the top plot that resembles a typical PV generation curve between 7 am and 5 pm with a peak generation of 3.7 kW at 12 pm.

To evaluate the effect of PV generation and btm-BESS operation modes on Net Load curves, we calculate the overall demand and peak load based on the resulting Net Load. Additionally, to evaluate the load shaping capabilities of the presented operation modes (i.e. the wiggliness of the Net Load), we calculate the Total Variation (TV) for every timeseries. The applied TV metric is normalised on the sum of the Gross Load for every combination of study year and climate year. Higher or lower TV_{norm} means a more wigglier or less wigglier Net Load, respectively. A definition of the TV metric is given in [13], while a similar application of TV on RES generation timeseries is presented in [14].

In Fig. 2 the brown area curve corresponding to the *greedy* mode shows a sharp discharging pattern around local load peaks at 9 am and 9 pm leading to a negative Net Load. This over-discharging results from having a *static residual* and $\tilde{\alpha} = 0$ which means no penalty on the discharge of btm-BESS. The purple curve for *autarky* behavior and the grey one for the *load-shifting* btm-BESS mode show a smoother charging/discharging pattern due to either a *dynamic residual* incentivising term or having a non-zero alpha parameter with respect to (4) limiting the dispatch.

Table IV shows quantitively what can be observed graphically in Fig. 2: While the *default* operation mode without btm-BESS contribution has a load peak of 7.4 kW, the *greedy* model can already reduce the peak by 1.5 kW. Operating the btm-BESS in *autarky* or in *load-shifting* mode leads to further reduction of the load peak with the *load-shifting* mode achieving a peak reduction of more than 50%. In case of the total Net Demand metric, the negative value for the default case is a consequence of excess solar energy during mid-day hours. When comparing the three btm-BESS operation modes to each other, the *autarky* mode reaches the highest level of self-sufficiency, while its grid feed-in peak during noon is half of what the *default* case shows in Fig. 2. Looking at the TV_{norm} metric we see an increase from the *default* case to the *greedy* one. This comes from the sharp charging and discharging periods during local load peak moments and peak PV generation, respectively as can be seen in Fig. 2. Having the btm-BESS model running in either *autarky* or *load-shifting* mode reduces the TV_{norm} and correspondingly the wiggliness of the resulting Net Load. Especially the *load-shifting* operation mode achieves a comparably flat Net Load curve by making use of low load periods during night times to charge the BESS in order to meet the SOC constraints.

B. Single Node Country data

Mid- and long-term load forecasting for European studies had been one application of the btm-BESS model proposed in this paper. Therefore, the model is applied in a second use case on aggregated single-node data for Austria in regard to

TABLE IV
OVERVIEW OF NET LOAD RESULTS AFTER BTM-BESS MODEL RUN FOR CHH14 HOUSEHOLD DATA.

	default (no-battery)	**greedy**	**autarky**	**load-shifting**
Net Load$_{\text{peak}}$ [kW]	7.4	5.9	4.4	3.4
$\Delta_{default}$		-20.3%	-40.5%	-54.0%
Net Load$_{\text{sum}}$ [MWh]	-0.016	0.17	0.097	0.192
$\Delta_{default}$		-	-	-
TV$_{\text{norm}}$ [a.u.]	0.748	1.24	0.418	0.370
$\Delta_{default}$		+56.8%	-44.1%	-50.5%

the data delivery and forecasting process of the ERAA [6]. Table V shows the aggregated input data for rooftop PV and btm-BESS for Austria in the year 2030.

TABLE V
AGGREGATED BEHIND-THE-METER PV AND BATTERY DATA FOR AUSTRIA IN 2030.

Parameter	**Unit**	**Value**
installed PV$_{\text{peak}}$	MW	9,184
installed Battery capacity	MWh	2,281
max. charging/discharging power	MW	1,825

For Austria (AT00) the Gross Load is shown in the bottom plot of Fig. 3 in App. C for an exemplary day in March. We observe the daily load peak in the morning at 7 am with approx. 14.9 GW. The load curve shows a typical form by having a second local peak around the early evening and a load valley during night hours. In the top plot of Fig. 3 we see the available PV generation on this day with a maximum of 5 GW at 11 am. Furthermore, the btm-BESS dispatch for this particular day is shown in the top plot from Fig. 3.

TABLE VI
OVERVIEW OF NET LOAD RESULTS AFTER BTM-BESS MODEL RUN FOR AT00 DATA ON PEAK LOAD DAYS[a]. TARGET YEAR 2030 AND CLIMATE YEAR 2030.

	default (no-battery)	**greedy**	**autarky**	**load-shifting**
Net Load$_{\text{peak}}$ [GW]	17.55	17.38	16.93	16.53
$\Delta_{default}$		-1.0%	-3.4%	-5.8%
Net Load$_{\text{sum}}$ [GWh]	10.678	10.683	10.681	10.686
$\Delta_{default}$		+0.04%	+0.02%	+0.07%
TV$_{\text{norm}}$ [a.u.]	0.061	0.064	0.051	0.044
$\Delta_{default}$		+4.9%	-16.4%	-27.9%

[a] The highest 10% of days with respect to their daily load peak

Table VI shows the same metrics as Tab. IV earlier. Additionally, the model is evaluated for every operation mode on three Climate Years (see Appen. C Tab. VII-IX). System Adequacy studies, such as the ERAA, have a special focus on peak load periods [6]. Therefore, to stress the model's impact on these situations, the presented metrics are evaluated only on the highest 10% of days with respect to their daily load peak.

All btm-BESS configurations show peak load reduction compared to no btm-BESS installations in the *default* case. The highest reduction of 5.8% is achieved by the *load-shifting* mode. Since this operation mode is not limited to PV generation for charging, it can charge during low load periods and hence has more energy available to discharge during peak load periods compared to the *autarky* use case being limited to PV charging only. This behavior can be seen in the bottom plot of Fig. 3. Despite the household use case in section IV-A, for aggregated national data Gross Load always exceeds rooftop PV generation (e.f. Fig. 3 top plot). Therefore, only in the *load-shifting* case an increased demand due to more btm-BESS charging can occur. The slightly higher values for total demand in the remaining operation modes in Tab. VI compared to the *default* case result from round-trip-efficiency losses. Table VII-IX in Appen. C give an overview for all operation modes over the three Climate Years. Regarding the wiggliness of the resulting Net Load curves, we observe for all three CYs an increase of the TV$_{\text{norm}}$ in the *greedy* operation mode compared to the *default* one. Similarly to the household use case, this is due to sharp charging and discharging patterns on specific periods throughout the day, as can be seen by the brown btm-BESS dispatch in the top plot in Fig. 3. For the *autarky* and *load-shifting* modes the TV$_{\text{norm}}$ can be reduced by up to 16.4% and 27.9% respectively compared to no btm-BESS contribution in the *default* case. The effect is most present in the bottom plot of Fig. 3 when focusing on peak load and peak PV generation hours.

V. MODEL LIMITATIONS

The model presented in this work underlies a set of assumptions that are important to emphasize. First, the model works with the assumption of perfect foresight for every optimisation *interval*. This applies for both cases of the c_i term, for price signals just as for local residual load.
Second, the model parametrisation is crucial as depicted in section III. There are no standards about btm-BESS operations, so both the definition of operation modes as well as their configuration is arbitrary and relies on expert knowledge about the domain and the model itself.
Lastly, in section IV-B the input data for whole Austria is aggregated to a single-node dataset. This is due to the ERAA [6] process that has provided the main application platform for this model to date. Especially btm-BESS and rooftop PV systems are by their nature highly distributed and therefore rather rely on local load and local solar radiation patters than national ones. Since the presented model is input data sensitive, this aggregation of a highly distributed phenomena leads certainly to a bias in the results.

VI. CONCLUSION

In order to consider btm-BESS contribution to electrical load forecasting this work presents a general btm-BESS model. A flexible parametrisation allows for a broad bandwidth of applications as shown in section IV. Various model parametrisations have demonstrated different behaviors for diverse objectives and use cases, while maintaining the same model formulation. Despite the arbitrary definition of operation modes, the model results align with intuitive behaviors, enabling applications from greedy home-storage behavior to active load curve shaping. Although the model is sensitive to its input data, it is robust enough to be applied both on the single-household level and on aggregated national data for European processes. An important aspect of the presented model is its parametrisation which requires expert knowledge about both model functioning and present control schemes in the domain of btm-BESS.

Future work on this model may include a systematically derived proposal for standard configurations. Additionally, extending the model towards a more prosumer-like model including flexible load components like heat-pumps and electric vehicles could further improve load forecasting in a rapidly changing energy system. An improvement in accuracy could be also obtained by running the model in a distributed manner to account for the highly distributed nature of its input data.

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Appendix A
Household Model Output

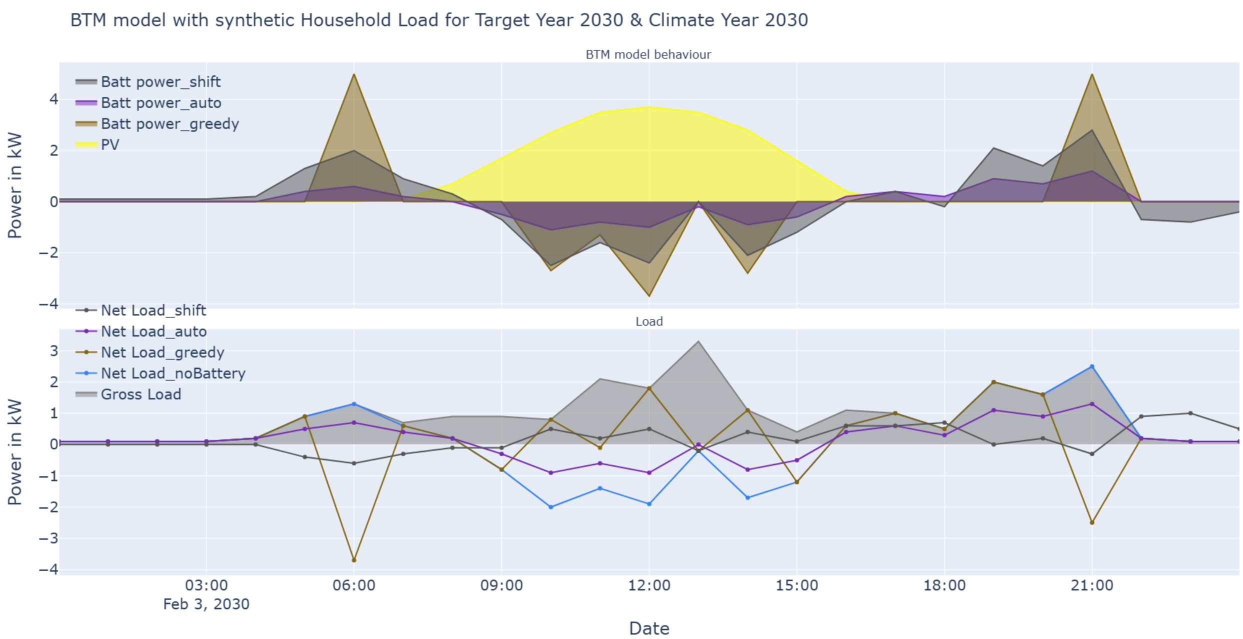

Fig. 2. btm-BESS model results for a synthetic household load for 2030 and Climate Year 2030.

Appendix B
AT00 Model Output

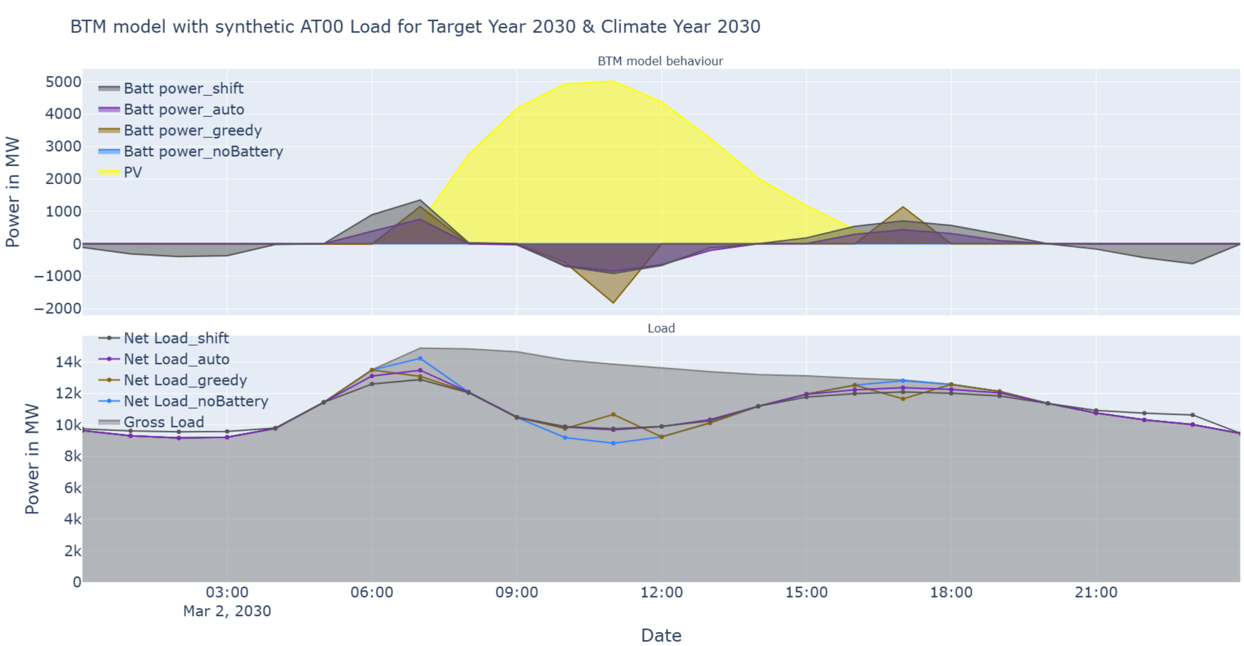

Fig. 3. btm-BESS model results for a synthetic national load of Austria for 2030 and Climate Year 2030.

Appendix C
Detailed results Single Node AT00

Following the Monte-Carlo approach of a stochastic modelling as the one in ERAA, climate conditions play a major role and provide a degree of uncertainty to both input data as well as results. To consider this stochastic climate-dependency in a reduced manner we evaluate the btm-BESS model behavior of every operation mode for three different climate conditions labelled as 2030, 2042 and 2054. More information can be found about the PECD database and methodology in [15]. Every climatic set, or Climate Year, consists of its particular Gross Load time-series and PV generation factor time-series.

TABLE VII
Overview of Peak Loads in MW for Net Loads after btm-BESS model run for AT00 data for 2030 for the critical period.

	no-battery	**greedy**		**autarky**		**load-shifting**	
CY	abs	abs	Δ	abs	Δ	abs	Δ
2030	17,547	17,377	-1.0%	16,934	-3.4%	16,530	-5.8%
2042	17,882	17,450	-2.4%	17,456	-2.4%	17,201	-3.8%
2054	16,071	15,856	-1.3%	15,712	-2.2%	15,285	-4.9%

TABLE VIII
Overview of Total Demand in TWh for Net Loads after btm-BESS model run for AT00 data for 2030 for the critical period.

	no-battery	**greedy**		**autarky**		**load-shifting**	
CY	abs	abs	Δ	abs	Δ	abs	Δ
2030	10,678	10,683	+0.04%	10,681	+0.03%	10,686	+0.07%
2042	11,277	11,281	+0.04%	11,279	+0.02%	11,283	+0.05%
2054	10,566	10,570	+0.04%	10,569	+0.03%	10,573	+0.07%

TABLE IX
Overview of normalised Total Variation (TV) in a.u. for Net Loads after btm-BESS model run.

	no-battery	**greedy**		**autarky**		**load-shifting**	
CY	abs	abs	Δ	abs	Δ	abs	Δ
2030	0.061	0.064	+4.9%	0.051	-16.4%	0.044	-27.9%
2042	0.052	0.059	+13.5%	0.044	-15.4%	0.038	-26.9%
2054	0.056	0.062	+10.7%	0.047	-16.1%	0.041	-26.8%