Hybrid Lithium-Ion Battery Storage Solution with Optimizing Energy Management and Online Condition Monitoring for Multi-use Applications

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Abstract. The paper presents current research results of the HYBAT project, in which a hybrid lithium-ion battery storage solution is being developed for three types of application: self-consumption optimization in industry and commerce, capacity-firming in a renewable energy park and buffer storage for electric vehicle charging stations. First, an overview of the principle structure and the functionalities of the HYBAT system is given. It features a hybrid storage approach consisting of a high energy and a high power lithium-ion battery and a multi-objective optimizing energy management. The paper describes the developed energy management concepts based model predictive control and mixed integer linear programming, dynamic programming and reinforcement learning. For the application field of self-consumption optimization in industry and commerce, a model predictive, dynamic programming based energy management is presented in detail. Selected results of simulation-based investigations evaluate the developed energy management concept based on technical and economic performance criteria. The advantages of using the developed hybrid battery storage solution for multi-use applications with optimization-based energy management concepts are elaborated. In particular, an improved technical utilization of the storage system, increased efficiency as well as reduced operating costs will be addressed.

Keywords: hybrid energy storage system (HESS) · energy management system (EMS) · model predictive control (MPC) · dynamic programming (DP) · lithium-ion battery · multi-use application

1 Introduction

The transformation of the energy supply system to accommodate a very high share of renewable energy generation requires the expansion and intelligent operation of energy storage systems at all grid levels [1]. Energy storage systems make a significant contribution to the temporal decoupling and adaptation between the fluctuating regenerative energy supply and electricity demand. Further advantages result from the utilization of

P. Schossig et al. (Eds.): IRES 2022, AHE 16, pp. 76–92, 2023.
https://doi.org/10.2991/978-94-6463-156-2_7

energy storage systems in the context of decentralized energy supply. Typical storage applications include optimizing self-consumption of solar or wind power in the residential and commercial sectors as well as the provision of grid services (e.g. frequency regulation, black start capability, uninterruptible power supply). Different energy storage technologies are also utilized for peak-shaving applications. Multi-use concepts are able to improve economic efficiency and better exploit the technical potentials of energy storage systems [2–5]. According to [5], batteries in single-use applications remain unused in 50% to 95% of their lifetime. In [3] and [5] the technical and economic combination of different applications are evaluated. This shows that in many cases a multi-use of two or more applications is possible. In [6] and [7] it is shown that the combination of multiple applications increases the economic benefit in all investigated cases.

Hybrid energy storage systems (HESS) are experiencing increasing importance in stationary [8–12] and mobile applications [12–14, 14, 15] due to their ability to improve efficiency, performance, and component lifetime while reducing system costs compared to single-storage solutions. There have been several research projects involving HESS and multi-use applications. In "Smart Region Pellworm", a lithium-ion and a redox-flow battery have been combined into a HESS, which in turn plays a central role in the intelligent management of the island of Pellworm's energy resources [16, 17]. In the "M5BAT" project, a demonstration plant combining various lithium-ion and lead-acid batteries was built and various energy management strategies have been tested [18]. One of the first large-scale commercial HESS in Germany was the "hybrid storage Braderup", where a lithium-ion battery and a redox-flow battery have been combined to store energy from a wind farm when the grid is overloaded [19]. The "NETfficient" project, demonstrated gains in energy efficiency and economics for smart communities through hybridization of a lithium-ion battery providing energy-related services and a supercap providing power-related services to the grid and the community [20].

However, so far, the potential of HESS is rarely fully exploited. Most importantly, there is a lack of suitable, optimizing energy management concepts for power flow control and linkage with highly accurate models of voltage-current characteristic, charging losses, and aging behavior of the storage systems.

Figure 1 shows the overall system structure of the hybrid lithium-ion battery storage solution HYBAT featuring 1500 V power converter technology, innovative thermal management, online condition monitoring and a multi-objective optimizing energy management. A HYBAT system consists of a high energy and a high power lithium-ion battery.

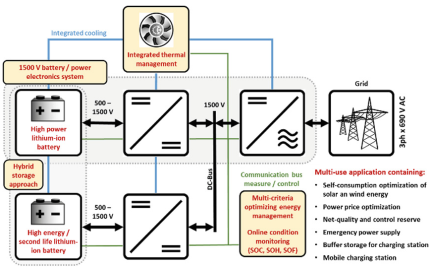

Fig. 1. Principle structure of the developed hybrid lithium-ion battery storage solution HYBAT.

These are connected to the DC-bus via a DC-DC converter. The maximum power of each DC-DC converter and each inverter is 150 kW. The energy management is responsible for the central control of the overall system. Intelligent operating approaches can, for example, increase the SOC range and performance while maintaining the same lifetime. Moreover, the HYBAT system includes an integrated cooling system, and an online condition monitoring, that determines essential information about the charging, aging, functional conditions and temperature of the batteries, which are not presented in this article.

The paper is structured as follows. In Sect. 2 an overview of the considered fields of application and the developed energy management concepts is given. Section 3 presents the simulation model of the HYBAT system. In Sect. 4 the energy management concept for the application example extended self-consumption optimization in industry and commerce including the problem formulation, the performance criteria and the simulation settings is presented. Furthermore, results of simulation-based analyses are shown. The paper closes with a short summary and gives an outlook on future research and project activities.

2 Hybrid Lithium-Ion Battery Storage Solution

2.1 Fields of Application

Extended self-consumption optimization

An important objective of residential battery storage systems is to maximize self-sufficiency by optimally utilizing solar energy from local sources [21–23]. High purchase prices for electrical energy and significantly lower feed-in tariffs, especially for private households, make an increase of solar energy in self-use attractive from an economic perspective as well. An additional objective is to minimize curtailment losses. When using time-variable energy tariffs, the minimization of electricity costs through time-shifting of the purchase or the feed-in of surpluses plays an important role [24–26]. The minimization of the grid consumption power is particularly relevant in Germany for industry and commerce with a total annual consumption of more than 100000 kWh. Further suitable applications are spot market trading, balancing group management, providing local network services and emergency power supply [7, 27–29].

Capacity firming

Capacity firming is intended to smooth and stabilize power generation from renewable energies [29–31]. The objectives are to reduce grid repercussions due to voltage and power fluctuations, to comply with generation schedules or avoid penalties, and to increase the reliability and availability of power generation. Further suitable applications are providing local grid services [31].

Buffer storage for electric vehicle charging station

The task of a battery buffer storage at an electric vehicle charging station is to reduce the load peaks that occur and the associated grid power peaks [32, 35]. This reduces the electricity costs and the investment costs, since less powerful power converters are needed and a possible grid expansion is not required. In addition, the power grid is relieved by the avoidance of load peaks. Further applications are participation in the balancing group management and providing local grid services [33, 34, 40].

2.2 Energy *M*anagement *Concepts*

For each of the three identified application areas, a new, customized energy management concept was developed, functional tests were carried out and the performance was compared with conventional energy management approaches. In the following, an overview of the basic functionalities and the special features of the respective energy management concepts are presented.

2.2.1 Model Predictive Dynamic Programming-Based Optimizing Energy Management

The model predictive control (MPC) is often used for the optimization of the power flows in battery storage systems with a PV plant [21, 34, 35, 40]. The optimization is carried out using PV and load forecasts. Due to the fact that the forecasts are subject to errors, the determined power flow will also only provide optimal results with respect to the selected input data. One possibility to compensate the occurring forecast errors is the model predictive control, which re-evaluates the optimization problem in regular intervals. Only a part of the optimal control trajectory is given to the real system. In the next optimization time step, the optimization is repeated with updated system states and forecast information.

Dynamic programming is a method for solving optimization problems by dividing the problem into sub-problems, which was introduced by Bellman in 1954 [36]. Depending on the discretization, the results represents the global optimum. No special solver is required to determine the optimal trajectory. Since it is still a deterministic procedure, it is already clear at the beginning of the optimization how many calculation steps are necessary. This method doesn't involve any restrictions for the objective function, the constraints and the system model. The disadvantage is that the result is only available at the end of the optimization. Furthermore, the number of calculation steps increases progressively with the number of system states considered.

The model predictive, dynamic programming based energy management (MPC-DP) is presented in detail for the application field self-consumption optimization in industry and commerce in Sect. 4.

2.2.2 Model Predictive Mixed Integer Linear Programming-Based Optimizing Energy Management

A MPC in combination with the mixed integer linear programming is very often used as a solution approach for the energy management of renewable energies with energy storage systems [10, 24–26, 37, 44]. The disadvantage that objective function and constraints have to be linear can be limited by piecewise linearization. For convex functions, this can also be implemented in a very computationally efficient way. In the project, the method was used for the application field capacity firming. Taking into account the PV forecast, spot market prices and information from the high energy batteries (state of charge limits and aging behaviour), the grid capacity is optimized until the end of the current day. To find out the marginal cost of the storage for the arbitrage, the expected degradation is translated into costs and explicitly considered in the objective function (piecewise linearization). To reduce model and forecast uncertainties, the optimization is performed in a model predictive approach. The PV forecast and the state information of the high energy battery are updated in a regular time interval.

2.2.3 Reinforcement Learning-Based Energy Management

Reinforcement Learning (RL) is another method, that can be used to derive locally optimal energy management policies from a data-driven, simulation-based training procedure prior to the actual usage of the energy management [38–40]. RL is a promising approach to overcome many of the limitations of the widely used energy management concepts. Firstly, no restrictions need to be imposed on the modelling of the objective function as opposed to linear programming, which assumes a linear objective function. Secondly, RL can optimize the energy management over an infinite horizon by estimating the state values with a separate fitted estimation function. This is different from MPC approaches, where optimization is carried out over a finite horizon, and especially useful for long-term optimization targets such as reducing battery aging. Furthermore, no models of the system dynamics or forecasts need to be formulated for the energy management as they are implicitly learned during the training procedure. This also saves computational power during the application of the energy management, because no model of the system needs to be simulated.

The energy management policy maps system states to actions and is represented by an artificial neural network (ANN). During the iterative training procedure, the parameters of the policy ANN are optimized in such a way, that actions leading to higher rewards become more likely and actions leading to lower rewards become less likely and thus maximizing the expected value of received rewards. In case of the HYBAT system under consideration the state vector contains the state of charge of the high energy and the high power battery, the power of the PV plant and the load in the previous time steps. The action vector contains the set points of the power for the high energy and the high power battery. The reward function, acting as target for the policy optimization, is a weighted sum of all operational cost, that are to be considered, such as energy cost, feed-in compensation, cost of battery degradation or power demand fees for example. Using RL for the energy management of a hybrid energy storage system poses some challenges, however. The energy management policy is not guaranteed to converge to an optimal policy during the training and the stochastic nature of the processes of the load and PV generation make convergence even more difficult. Therefore, it is investigated if the theoretical advantages of RL-based approaches translate to the practical application of the energy management of hybrid energy storages.

3 Simulation Model

In order to investigate the developed energy management concepts for the different fields of application a generic simulation model was implemented. The approach allows the number of high energy and high power batteries, DC-DC converters, and inverters to be freely selected depending on the application example. The structure of the generic topology-coupling architecture is shown in Fig. 2.

The lithium-ion batteries are modelled using an electrical circuit based approach [48]. All parameters in the proposed model are functions of the state of charge *SOC* and the

Table 1. Specification of the utilized lithium-ion batteries

Name	**A**	**B**	**C**	**D**
$C_{batt,nom}$ in Ah	150	37	37	60
$U_{batt,nom}$ in V	665	666	661	486
$P_{max,ch/disch}$ in kW	80/100	77/77	36/50	175/175
$E_{batt,nom}$ in kWh	98	33	24	29
Cycle life	>4000	>3000	>3000	>16000

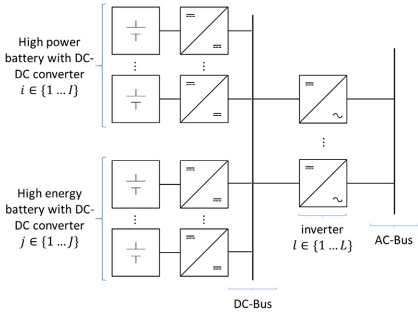

Fig. 2. Principle structure of the generic simulation model.

current I_{batt}. The chosen model consists of a voltage source U_{OCV}, a serial resistance R_0, and two RC-elements. The nonlinear relationship between the open circuit voltage U_{OCV} and the battery state of charge *SOC* is represented by the OCV-SOC-characteristic. The serial resistance R_0 characterizes the ohmic losses. The two RC-elements represent the dynamic behavior of the battery. The state of charge *SOC* is calculated from Coulomb-counting with the battery current I_{batt} as input. Charge and discharge losses are neglected in this model. The aging model of the lithium-ion battery is based on the semi-empirical approach presented in [41]. Based on extensive measurements the remaining capacity and the internal resistance are fitted with mathematical functions depending on the voltage, the temperature, current throughput and the depth of discharge. Table 1 shows the datasheet details of selected batteries used for the investigations.

The losses of the DC-DC converters and the inverter are modelled on the basis of voltage dependent efficiency power curves. These curves have been computed on the basis of dynamic simulations of the power electronic converter topologies at Fraunhofer ISE. Exemplary the Efficiency curves of two voltage levels on DC side are shown in Fig. 3.

The simulation model is implemented on the basis of object-oriented programming in MATLAB. All components and energy management sub-modules are written in the form of classes. This approach ensures a clear structure and also enables a generic structure of the HYBAT topologies. Furthermore, the contents of the classes can be exchanged

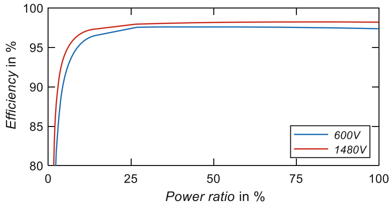

Fig. 3. Efficiency curves for the whole conversion path (AC to DC) for a DC voltage of 600 V (blue line) and 1480 V (red line).

without any problems. In order to realize an increase of the computation speed, the parallelization of the data processing takes place on several computing cores.

4 Case Study – Extended Self-consumption Optimization

In this section the energy management concept MPC-DP for the application field self-consumption optimization in industry and commerce will be described in detail. The objectives are minimizing the electricity costs taking into account time-variable tariffs (energy price and capacity charge), minimizing the PV system losses and enhance lifetime of the HYBAT system. The input variables are quarter-hourly resolved forecasts of PV and load power profiles over a prediction horizon of 24 h as well as the current state of charge of the high energy battery.

However, a major challenge is the coupling of the partly competing energy management objectives, which are additionally characterized by different impact horizons. Conceptual considerations on the overall structure of the energy management concept have shown that a division into an upper level energy management and a lower level energy management is advantageous. The upper level energy management is oriented towards the application side (e.g. peak shaving, maximization of PV utilization, reduction of power exchanged with the grid, reaction to external incentive signals). The lower level energy management is responsible for the power flow partitioning within the hybrid energy storage system, which focuses on increasing conversion efficiency and component lifetime. The subdivision into lower and upper level makes it possible to combine several energy management variants with different individual strategies in a modular way.

4.1 Problem *Formulation*

4.1.1 Upper Level Energy Management

For the discrete time case, the system behavior can be formally described by the system state *x[k]* and the control variable *u[k]* in a transition function:

$$x[k+1] = f(x[k], u[k]) \quad (1)$$

The strategy $\pi = \{u[0], u[1], \ldots, u[N\text{-}1]\}$ denotes a control sequence that generates the cost *g(x[k],u([k]),k)* when the decision *u* is chosen in the state *x*. The total cost *J* is calculated after applying the strategy π. The cost function g describes the transition costs from state $x[k]$ to state $x[k + 1]$.

$$J = g(x[N]) + \sum_{k=0}^{N-1} g(x[k], u[k], k) \tag{2}$$

The objective is to minimize the quality functional J over the decision horizon N by an optimal sequence.

For the storage system under consideration, the state variable x represents the state of charge of the high energy battery SOC_{HE}. The control decision u corresponds to the power of the high energy battery $P_{batt,HE}$. The transition costs g (Eq. 3) are composed of the electricity costs C_{ec} (work price), the maximum grid feed-in power $C_{P,fi}$, the maximum grid import power $C_{P,imp}$, and the distance to 50% of the charge level C_{SOC}.

$$g = C_{ec} + \alpha \cdot C_{P,fi} + \beta \cdot C_{P,imp} + \gamma \cdot C_{SOC} \tag{3}$$

All individual costs are expressed via monetary quantities. The conversion losses are implicitly taken into account via the cost share of the energy fed-in and purchased. The weighting of the objectives is carried out empirically on the basis of expert knowledge.

$$C_{ec} = E_{grid,imp} \cdot k_{EGP} - E_{grid,fi} \cdot k_{FIT} \tag{4}$$

$$C_{P,fi} = \left(P_{fi} - P_{fi,max}\right)^2 \forall P_{fi} > P_{fi,max} \tag{5}$$

$$C_{P,imp} = \left(P_{grid,imp}\right)^2 \tag{6}$$

$$C_{SOC} = |SOC - 0,5| \tag{7}$$

The state of charge limits of the lithium-ion battery must not be exceeded.

$$SOC_{min} < SOC_{batt} < SOC_{max} \tag{8}$$

The limits of the maximum charging and discharging power of the lithium-ion battery must not be exceeded.

$$P_{batt,min} < P_{batt} < P_{batt,max} \tag{9}$$

In the simulation, it is assumed that the grid connection point is controlled within a few milliseconds. The set point adjustment is carried without delay. Therefore, the power balance on the AC-side applies for the calculation of the battery power (Eq. 10).

$$P_{batt,HE}[k] = P_{grid,set}[k] + P_{PV}[k] + P_{load}[k] \tag{10}$$

Optimization is performed using a simple system model and forecasts for PV power, load, energy cost, and feed-in tariff. The optimization is performed over the decision horizon t_{pred} with a resolution t_{step}. The re-execution in the interval t_{ex} using the current estimated system state corresponds to a feedback of the variable to be controlled and thus to a control loop structure. The result of the optimization is the trajectory of the control variable over the decision horizon. The model predictive control consists of re-execution of dynamic programming to minimize the objective function. It increases the robustness of the control method against forecast errors and model inaccuracies. Further information on the implementation of the MPC-DP energy management, especially the limitation of state transitions, shortening of the decision horizon and the analysis of the influence of the weighting factors, can be found in [42].

4.1.2 Lower Level Energy Management

The control of the power of the high energy and high power lithium-ion battery takes place along the tasks of each battery: The high energy battery takes over the power demand planned at the upper level energy management. The high power battery takes over the deviations from the real power demand, which result from forecast and model errors.

$$P_{batt,HP}[k] = P_{grid,set}[k] + P_{PV}[k] + P_{load}[k] - P_{batt,HE}[k] \tag{11}$$

If the state of charge of the high power battery approaches the limit, it is splitted according to the division between high energy and high power batteries presented in [51]. The power ratio of the batteries is calculated from the ratio of the currently available capacity of the high energy battery to the available capacity of the whole hybrid energy storage.

The upper level energy management returns the hybrid storage to the non-critical SOC range in the next optimization interval, if this is possible under the system constraints.

4.2 Reference Application

For the modelling of the PV plant, the global radiation measurement of the HTW-Berlin is available for the period 01.11.2020–30.10.2021. The calculation of the PV power is based on the single-diode model. The annual generation of the PV plant was scaled to the company's annual consumption of 1189 MWh.

Figure 4 shows an example week of the data set of HTW Berlin. The feed-in limit is set to 500 kW. For the forecast of the PV time series, in addition to the ideal forecast (averaging of the measured data in 15 min intervals), commercial forecasts from the German weather service on the one hand and a practical approach [37] based on the

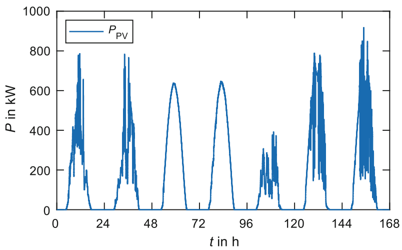

Fig. 4. Weekly power profile of the PV plant.

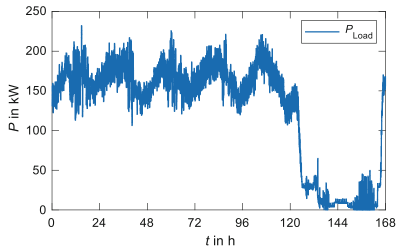

Fig. 5. Weekly power profile of the reference company.

clear sky index in combination with the maximum power of the last days (csi-envelope) on the other hand are used.

Chemnitzer Präzisionstechnik GmbH (CPT) was chosen as a typical industrial reference application. CPT produces complex turned and milled parts on 30 CNC lathes and milling machines with a high capacity utilization. The annual energy consumption of CPT is about 1189 MWh with a 15-min peak load of 240 kW. An example week is shown in Fig. 5. The measurement data originate from a measurement campaign which is documented in [43]. For the forecast of the consumption it is assumed that the occupancy of the machines and the parts to be produced is known for the next 24 h. Thus, the load time-series is only averaged to 15 min values.

The basic structure of the HYBAT system configuration selected for the application example consists of seven high energy batteries (type A, Table 1) and eleven high power batteries (type B, Table 1). Two inverters are used. The energy price k_{EP} varies between 4 and 10 Eurocent/kWh depending on the time of the day. The feed-in tariff k_{FIT} amounts to 5 Eurocent/kWh. The energy content of the whole HYBAT configuration is 960 kWh. Further simulation settings are summarized in Table 2.

Table 2. Simulation settings

Name	**Value**
Simulation time t_{sim} in years	1
Simulation time step $t_{timestep}$ in min	1
Decision horizon T_{pred} in h	24
Optimization time step T_{opt} in min	15
SOC discretization D_{SOC}	0,002
Execution interval T_{ex} in min	15

4.3 Performance Criteria

For the evaluation of the simulations, several performance criteria were employed. Because of the system being used for self-consumption, first the degree of self-sufficiency

$$k_{ss} = 100\% \cdot \frac{\sum\left(P_{load} - P_{grid,imp}\right)}{\sum(P_{load})} \tag{12}$$

and the degree of self-consumption

$$k_{sc} = 100\% \cdot \frac{\sum\left(P_{PV} - P_{grid,fi}\right)}{\sum(P_{PV})} \tag{13}$$

as well as the operating costs k_{ec} considering the feed-in Tariff k_{FIT}, the capacity charge k_{cc} and the energy price k_{EP} should be evaluated.

$$\begin{aligned} k_{ec} = &\sum\left(P_{grid,fi} \cdot k_{FIT} - P_{grid,imp} \cdot k_{EP}\right) \cdot t_{timestep} \\ &+ P_{max,15min} \cdot k_{CC} \end{aligned} \tag{14}$$

Curtailment losses occur when the power fed into the grid is greater than the maximum feed-in power limitation.

$$k_{ct} = 100\% \cdot \frac{\sum\left(P_{PV,ct}\right)}{\sum(P_{PV})} \tag{15}$$

The battery full cycles k_{cycl} are an indicator of the utilization of the lithium-ion batteries. They are calculated from the battery power in relation to the nominal energy amount.

$$k_{cycl} = \frac{\sum|P_{Batt}| \cdot t_{timestep}}{2 \cdot E_{Batt}} \tag{16}$$

Finally, the maximum power imported by the grid, averaged over 15 min in relation to the maximum power of the original time series is taken into account.

$$k_{P,red} = 100\% \cdot \frac{\max(P_{grid,imp,15})}{\max(P_{load,15})} \tag{17}$$

4.4 Simulation *Results*

4.4.1 Qualitative Analysis of an Example week

For the PV and load profiles shown in Fig. 4 and Fig. 5, the power curves and the resulting state of charge curve are shown in Fig. 6. The maximum grid power in this week is 160 kW. This corresponds to a reduction of 24% compared to the original load profile. The surplus PV energy is primarily charged into the battery during the day. The curtailment losses amount to 6.7% (peak-shaving 8.0% and rule based approach 10.7%) in the sample week. At the weekend, the batteries are actively discharged into the grid to temporarily store as much PV energy as possible on the following day. In order to relief the grid, the feed-in takes place with low power.

Table 3. Results of the annual simulation

	Rule-based	**Peak-shaving**	**Peak-shaving**	**Peak-shaving**	**MPC-DP**	**MPC-DP**	**MPC-DP**
PV forecast	-	Perfect	Commercial	CSI-envelope	Perfect	Commercial	CSI-envelope
k_{ss} in %	52.7	52.3	51.6	51.5	52.1	50.0	50.5
k_{sc} in %	53.6	53.2	52.5	52.3	53.1	50.9	51.4
k_{ct} in %	12.7	9.6	10.2	10.3	7.9	9.1	9.0
k_{ec} in T€	37.8	36.2	36.5	36.6	30.4	33.7	33.9
$k_{cycl,HE}$	166	160	152	150	246	226	235
$k_{cycl,HP}$	173	171	165	165	265	248	261
$k_{P,red}$ in %	13.5	13.5	13.5	13.5	28.7	22.0	22.1
$E_{feed\text{-}in}$ in MWh	336	371	372	373	389	399	394
E_{import} in MWh	473	477	484	485	479	500	495

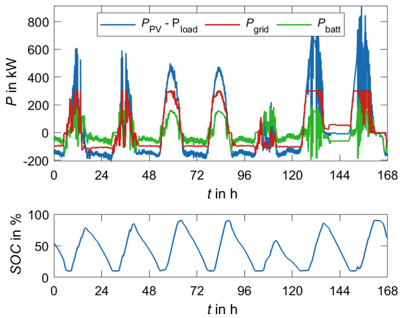

Fig. 6. Power and SOC profiles of an example week.

4.4.2 Results of the Annual Simulation

The results of the annual simulation are listed in Table 3. The first three columns show the results of the reference methods. One reference method is a simple rule-based approach, which maximizes only the self-consumption of solar energy. If there is more PV power available than the consumer demand and the battery is not fully charged, the energy is stored. If the consumption is higher than the PV power, the load is supplied by the battery. The second reference approach additionally relieves the grid by reducing the maximum feed-in power at midday and obtain a fully charged battery in the evening (peak-shaving). Even though both approaches are not able to account for several objectives, they give a first indication in the comparison of the technical performance criteria.

At 50.5%, the degree of self-sufficiency is only about 1.6% below the best value of the MPC-DP. The rule-based approach reaches the overall maximum of self-sufficiency (52.7%) and also self-consumption (53.6%). Analyzing the curtailment losses, it becomes clear that MPC-DP can reduce even further compared to peak-shaving. The reason for this is the active discharge of surplus power into the grid in the early morning hour. This also leads to the increased feed-in of PV energy into the grid. This is contrasted by the greater utilization of the high energy and high power battery, which is particularly noticeable in a higher full cycle number. With ideal PV forecast, a reduction of the reference power (15-min average) by 28.7% is possible and under real conditions by 22.0%. With regard to the evaluation criteria, the influence of the forecast (commercial or csi-envelope) used is negligible for the peak-shaving approach as well as for the MPC-DP concept. For the electricity prices and remunerations utilized, the costs are 33.7 T€ for MPC-DP, 37.8 T€ for rule-based and 36.5 T€ for peak-shaving.

5 Conclusion

This paper presented current research results of the HYBAT project, which is developing an innovative hybrid lithium-ion battery storage solution, consisting of high energy and high power batteries, 1500 V based power electronics, an integrated thermal management, and a multi objective optimizing energy management system with an online condition monitoring. The interesting application fields: self-consumption optimization in industry and commerce, capacity-firming in a renewable energy park and buffer storage for electric vehicle charging stations are introduced and the functionality of suitable energy management concepts is described. The results of the simulation based investigations of the case study point out that the developed MPC-DP energy management reduces the maximum power imported from the grid, increases the utilization of PV-energy and reduces curtailment losses in comparison to a rule based and a peak-shaving approach. Moreover, for the selected scenario with the MPC-DP energy management the energy costs can be reduced round about 8% in comparison to the peak-shaving and 10% to the rule based approach. Current research is focusing on the development, investigation and experimental testing of the online condition monitoring and as well as the testing of the energy management concept under real conditions at a demonstrator of the HYBAT system.

Acknowledgments. The presented paper is based on the results of the research project "HYBAT – Hybrid lithium-ion battery storage solution with 1500 V system technology, innovative thermal management and optimized system management", supported by the Federal Ministry of economic affairs and Climate action (funding code: 03EI3009C).

Federal Ministry
for Economic Affairs
and Climate Action

References

1. F. Ausfelder, F.D. Drake, B. Erlach, M. Fischedick, H.M. Henning, C.P. Kost, et al., Sektorkopplung - Untersuchungen und Überlegungen zur Entwicklung eines integrierten Energiesystems, 2017. ISBN: 978-3-9817048-9-1.
2. D.M. Rastler, Electricity energy storage technology options: a white paper primer on applications, costs and benefits, Electric Power Research Institute, 2010.
3. J. Eyer, G. Corey, Energy storage for the electricity grid: Benefits and market potential assessment guide, Sandia National Laboratories, 2010.
4. G. Fitzgerald, J. Mandel, J. Morris, T. Hervé, The economics of battery energy storage: how multi-use, customer-sited batteries deliver the most services and value to customers and the grid, Rocky Mountain Institute, 2015.
5. W. Zander, et al., dena-Netzflexstudie – Optimierter Einsatz von Speichern für Netz und Marktanwendungen in der Stromversorgung, Deutsche Energie-Agentur GmbH (dena), 2017.
6. S. Englberger, A. Jossen, H. Hesse, Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications, Cell Reports Physical Science, vol. 1(11), 2020. DOI: https://doi.org/10.1016/j.xcrp.2020.100238
7. Y. Shi, B. Xu, D. Wang, B. Zhang, Using Battery Storage for Peak Shaving and Frequency Regulation: Joint Optimization for Superlinear Gains, IEEE Transactions on Power Systems, vol. 33(3), 2018. DOI: https://doi.org/10.1109/TPWRS.2017.2749512.
8. T. Bocklisch, Hybrid energy storage approach for renewable energy applications, Journal of Energy Storage, vol. 8(1), pp. 311–319, 2016. DOI: https://doi.org/10.1016/j.est.2016.01.004
9. T. Bocklisch, L. Graube, W. Hofmann, Modular DC/DC-converter concept for a multi-storage hybrid system, Conference on Power Conversion and Intelligent Motion - PCIM, Nuremberg, 2006. ISBN: 3-928643-43-6.
10. M. Paulitschke, T. Bocklisch, M. Böttiger, Sizing Algorithm for a PV-battery-H2-hybrid System Employing Particle Swarm Optimization, Energy Procedia, vol. 73, pp. 154-162, 2015. DOI: https://doi.org/10.1016/j.egypro.2015.07.664
11. R. Gelleschus, M. Böttiger, T. Bocklisch, Optimization-Based Control Concept with Feed-in and Demand Peak Shaving for a PV Battery Heat Pump Heat Storage System, Energies, vol. 12(11), 2019. DOI: https://doi.org/10.3390/en12112098
12. M. Kersic, T. Bocklisch, M. Böttiger, L. Gerlach, Coordination Mechanism for PV Battery Systems with Local Optimizing Energy Management, Energies, vol. 13(3), 2020. DOI: https://doi.org/10.3390/en13030611
13. C. Weyers, T. Bocklisch, Simulation-based investigation of energy management concepts for fuel cell – battery – hybrid energy storage systems in mobile applications, Energy Procedia, vol. 155, pp. 295-308, 2018. DOI: https://doi.org/10.1016/j.egypro.2018.11.048.
14. C. Romaus, Selbstoptimierende Betriebsstrategien für ein hybrides Energiespeichersystemaus Batterien und Doppelschichtkondensatoren, Dissertation, Universität, 2013.
15. R. Wegmann, Betriebsstrategien und Potentialbewertung hybrider Batteriespeichersysteme in Elektrofahrzeugen. Dissertation, RWTH Aachen University, 2018.
16. K. Ettihir, L. Boulon, and K. Agbossou. Optimization-based energy management strategy for a fuel cell/battery hybrid power system. Applied Energy, 163:142, 2016. DOI: https://doi.org/10.1016/j.apenergy.2015.10.176
17. T. Thien, H. Axelsen, M. Merten, D.U. Sauer, Energy management of stationary hybrid battery energy storage systems using the example of a real-world 5 MW hybrid battery storage project in Germany, Journal of Energy Storage, vol. 51, 2022. DOI: https://doi.org/10.1016/j.est.2022.104257

18. HanseWerk AG, Hrsg.: SmartRegion Pellworm 2.0: Energiewende und Batteriespeicher - Wirtschaftlichkeit im Test, Ergebnisse der 2. Phase des Forschungsprojektes, 2018.
19. S. Nicolai, P. Bretschneider, D. Westermann, Hierarchische Speichereinsatzoptimierung. Mit einem Realisierungsbeispiel auf der Insel Pellworm, in: at-Automatisierungstechnik, vol. 62(5), pp. 364-374, 2014. DOI: https://doi.org/10.1515/auto-2013-1076
20. T. Thien, H. Axelsen, M. Merten, D.U. Sauer, Energy management of stationary hybrid battery energy storage systems using the example of a real-world 5 MW hybrid battery storage project in Germany, Journal of Energy Storage, Volume 51, 2022. DOI: https://doi.org/10.1016/j.est.2022.104257
21. Robert Bosch GmbH, Doppelbatterie für den Stromspeicher Braderup – Große Flexibilität im Umgang mit Windstrom, 2014.
22. A. Serpi, M. Porru, A. Damiano, An optimal power and energy management by hybrid energy storage systems in microgrids, Energies, 2017. DOI: https://doi.org/10.3390/en1011190
23. A. Nottrott, J. Kleissl, B. Washom, Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems, Renewable Energy, vol. 55, pp. 230–240, 2013. DOI: https://doi.org/10.1016/j.renene.2012.12.036
24. A. Zeh, R. Witzmann, Operational Strategies for Battery Storage Systems in Low-voltage Distribution Grids to Limit the Feed-in Power of Roof-mounted Solar Power Systems, Energy Procedia, vol. 46, pp. 114–123, 2014, ISBN: 978-3-8007-4121-2.
25. Y. Riesen, C. Ballif, N. Wyrsch, Control algorithm for a residential photovoltaic system with storage, Applied Energy, vol. 202, pp. 78–87, 2017. DOI: https://doi.org/10.1016/j.apenergy.2017.05.016
26. R. Basmadjian, Optimized Charging of PV-Batteries for Households Using Real-Time Pricing Scheme, A Model and Heuristics-Based Implementation, Electronics, vol. 9(1), pp. 113, 2020. DOI: https://doi.org/10.3390/electronics9010113
27. L. Tziovani, P. Kolios, L. Hadjidemetriou, E. Kyriakides, Energy scheduling in non-residential buildings integrating battery storage and renewable solutions, Proceedings of the IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, 2018. DOI: https://doi.org/10.1109/ENERGYCON.2018.8398738.
28. M. Förstl, D. Azuatalam, A. Chapman, G. Verbič, A. Jossen, H. Hesse, Assessment of residential battery storage systems and operation strategies considering battery aging, Int. J. Energy Res., vol. 44, pages 718–731, 2020
29. R. Hollinger, Gepoolte PV-Heimspeicher zur Bereitstellung von Primärregelleistung, Dissertation an der TU Braunschweig, 2018.
30. J. Marchgraber and W. Gawlik, Dynamic Prioritization of Functions during Real-Time Multi-Use Operation of Battery Energy Storage Systems, Energies, vol. 14, Art. no. 3, 2021. DOI: https://doi.org/10.3390/en14030655
31. Y. Shi, B. Xu, D. Wang, and B. Zhang, Using Battery Storage for Peak Shaving and Frequency Regulation: Joint Optimization for Superlinear Gains, IEEE Transactions on Power Systems, vol. 33, Art. no. 3, 2018
32. S.A. Abdelrazek and S. Kamalasadan, Integrated PV Capacity Firming and Energy Time Shift Battery Energy Storage Management Using Energy-Oriented Optimization, IEEE Transactions on Industry Applications, 2016. DOI: https://doi.org/10.1109/TIA.2016.2531639
33. M.D. Robles, J.-S. Kim, H. Song, Capacity Firming for Wind Generation using One-Step Model Predictive Control and Battery Energy Storage System, 2017. DOI: https://doi.org/10.5370/JEET.2017.12.5.2043
34. A.S. Hintz, K. Rajashekara, R. Prasanna, Controller for combined peak-load shaving and capacity firming utilizing multiple energy storage units in a microgrid, 2016. DOI: https://doi.org/10.1109/ECCE.2016.7854974

35. A. Saez-de-Ibarra, V.I. Herrera, A. Milo et. al, Management Strategy for Market Participation of Photovoltaic Power Plants Including Storage Systems, IEEE Transactions on Industry Applications 2016. DOI: https://doi.org/10.1109/TIA.2016.2585090
36. D. Kler, A. Zabetian Hosseini, S. Varghese, C. Sun und G. Joos, A Rule Based EMS for Fast Charging Station with CHIL Implementation, in 2020 IEEE Energy Conversion Congress and Exposition (ECCE), Detroit, MI, USA, 2020. DOI: https://doi.org/10.1109/ECCE44975.2020.9235380
37. R. Ghotge, Y. Snow, S. Farahani, Z. Lukszo und A. van Wijk, Optimized Scheduling of EV Charging in Solar Parking Lots for Local Peak Reduction under EV Demand Uncertainty, Energies, Jg. 13, Nr. 5, S. 1275, 2020
38. M.O. Badawy und Y. Sozer, Power Flow Management of a Grid Tied PV-Battery System for Electric Vehicles Charging, IEEE Transactions on Industry Applications, Jg. 53, Nr. 2, S. 1347–1357, 2017. DOI: https://doi.org/10.1109/TIA.2016.2633526
39. F. Moya, J. Torres-Moreno und J. Álvarez, Optimal Model for Energy Management Strategy in Smart Building with Energy Storage Systems and Electric Vehicles, Energies, Jg. 13, Nr. 14, S. 3605, 2020. DOI: https://doi.org/10.3390/en13143605
40. H.E. Oliveira Farias et al., Combined Framework with Heuristic Programming and Rule-Based Strategies for Scheduling and Real Time Operation in Electric Vehicle Charging Stations, Energies, Jg. 14, Nr. 5, S. 1370, 2021
41. F. Hafiz, D. Lubkeman, I. Husain, P. Fajri, Energy storage management strategy based on dynamic programming and optimal sizing of pv panel-storage ca-pacity for a residential system, In proceedings of the 2018 IEEE/PES Transmission and Distribution Conference and Exposition, Denver, USA, 2018. DOI: https://doi.org/10.1109/TDC.2018.8440251
42. B. Jeddi, Y. Mishra, G. Ledwich, Dynamic programming based home energy management unit incorporating PVs and batteries, proceedings of the IEEE Power & Energy Society General Meeting, Chicago, USA, 2017. DOI: https://doi.org/10.1109/PESGM.2017.8273925
43. L.N. An, T. Quoc-Tuan, Optimal energy management for grid connected microgrid by using dynamic programming method, IEEE Power & Energy Society General Meeting, Eindhoven, Netherlands, 2015. DOI: https://doi.org/10.1109/PTC.2015.7232678
44. I. Ranaweera, O.M. Midtgård, Optimization of operational cost for a grid-supporting PV system with battery storage, Renewable Energy, vol. 88, pp. 262–72, 2016. DOI: https://doi.org/10.1016/j.renene.2015.11.044
45. R. Bellman, Dynamic programming, Princeton, University Press, 1957. ISBN: 069107951X
46. J. Bergner, Untersuchungen zu prognosebasierten Betriebsstrategien für PV-Speichersysteme, Bachelorarbeit an der HTW Berlin, 2014.
47. M.E. Raoufat, B. Asghari, R.K. Sharma, Model predictive BESS control for demand charge management and pv-utilization improvement, proceedings of the Conference on Innovative Smart Grid Technology (ISGT), Washington, DC, 2018. DOI: https://doi.org/10.1109/ISGT.2018.8403403
48. Di Cao et al., Deep Reinforcement Learning Based Approach for Optimal Power Flow of Distribution Networks Embedded with Renewable Energy and Storage Devices, Journal of Modern Power Systems and Clean Energy (Volume 9, Issue 5, September 2021), 2021
49. Y. Gao, J. Li, and M. Hong, Machine Learning Based Optimization Model for energy Management of Energy Storage System for Large Industrial Park, Processes 2021, 9, 825, 2021. DOI: https://doi.org/10.3390/pr9050825
50. L. Desportes, I. Fijalkow, and P. Anrdy, Deep Reinforcement Learning for Hybrid Energy Storage Systems: Balancing Lead and Hydrogen Storage, Energies, 14, 4706, 2021. DOI:
51. M. Böttiger, M. Paulitschke, T. Bocklisch, Systematic experimental pulse test investigation for parameter identification of an equivalent based lithium-ion battery model, Energy Procedia, vol. 135, pp. 337-346, 2017. DOI: https://doi.org/10.1016/j.egypro.2017.09.525

52. J. Schmalstieg, S. Käbitz, M. Ecker, D.U. Sauer, A holistic aging model for Li(NiMnCo)O2 based 18650 lithium-ion batteries, Journal of Power Sources, vol. 257, pp. 325-334, 2014. DOI: https://doi.org/10.1016/j.jpowsour.2014.02.012
53. M. Böttiger, Multikriteriell optimierendes Betriebsführungsverfahren für PV-Batteriespeichersysteme, Dissertation, TU Dresden, 2020. online: https://nbn-resolving.org/urn:nbn:de:bsz:14-qucosa2-714006.
54. M. Bauer, M. Muehlbauer, O. Bohlen, M.A. Danzer, J. Lygeros, Power flow in heterogeneous battery systems, Journal of Energy Storage, vol. 25(3), 2019
55. M. Böttiger, R. Beyer, P. Steinhorst, R. Gelleschus, OptiStore - Entwicklung eines innovativen Eigenverbrauchssystems auf Basis einer modularen Stromrichter-Lithium-Ionen-Batterie-Einheit zur optimalen Nutzung regenerativer Energiequellen im gewerblichen und industriellen Sektor, Schlussbericht, 2019. DOI: https://doi.org/10.2314/KXP:1698832125