Optimized Operation of Large Scale Battery Systems – Experiences, New Opportunities and Big Data

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Abstract

In the decentralized renewable driven electric energy system, economically viable battery systems become increasingly important for providing grid related services. End of 2016 STEAG has successfully started the commercial operation of six 15 MW large scale battery systems which have been incorporated in STEAG's primary control pool. During the commissioning phase extensive effort has been spent in optimizing the operational efficiency of these systems with promising results. However, our one-year operation experience has shown that there is still significant potential for improving the system behavior as well as reducing the aging of the battery cells. On the one hand the potential lies in adapting crucial parameters related to the preprocessing of the primary control power and the SoC management in order to mitigate existing limitations. On the other hand more involved control strategies allow for improving the system behavior by properly considering the specific characteristics of the battery systems. In addition, due to the modular design of the large scale battery systems, big data based approaches are well suited particularly for diagnostic purposes. Apart from giving insights into the operational experience with the large scale battery systems, the contribution of this paper lies in addressing appropriate measures for counteracting existing limitations and discussing their impact on the system behavior. In addition, latest experiences and test results with respect to grid forming and black start capability of a selected battery system will be presented. Finally, first results are shown on how big data based approaches are capable of properly supporting the diagnosis of the battery condition.

1 Introduction

The German energy turnaround focusing on wind and solar energy changes the energy supply in Germany drastically. However, due to its weather dependency, power produced by wind and sun is subjected to strong variations and forecast uncertainties and is fed into the grid independently of the current consumption. As a result electrical grids have to increasingly manage unusual load situations.

Today, conventional power plants are still the backbone of a reliable energy supply. However, challenging requirements on their flexibility and low energy prices lead to a strong economic pressure. In addition, there are ongoing political discussions covering a quicker phase out of the power generation by coal-fired power plants. Considering this scenario, the central question is how to ensure a reliable energy supply with acceptable quality and costs.

Battery systems are often considered to be the „missing link“. Globally, they are gaining more and more attention as a proper means for a reliable energy supply. One of the most evolved storage technologies in the market is the lithium ion technology which was developed originally in the area of smartphones, notebooks and e-mobility. It is already used today successfully in the energy industry and is considered as a "proven technology". Today, the demand for this technology for energy-economic applications is already very high and, besides, will grow in future globally. Due to its specific characteristics the lithium ion technology is particularly suitable for fulfilling the performance requirements of frequency control / primary control.

Since 2009, STEAG deals with large scale battery systems, starting – together with partners – with the research project “Lithium-Ion-Electricity-Storage-System” (LESSY). With investing in the large scale battery systems STEAG went new and innovative ways and has realized one of the worldwide biggest battery system projects within less than a year without funding. Since November 2016, STEAG successfully operates large scale battery systems in six locations in Germany with in total 90 MW which is exclusively offered in the primary control market [1].

Optimization of operation

During the commissioning phase extensive effort has been spent in optimizing the operational efficiency of the large scale battery systems. However, our one-year operation experience has shown that there is still significant potential for improving the system behavior as well as reducing the aging of the battery cells. On the one hand the potential lies in adapting crucial parameters related to the SoC management in order to mitigate existing limitations. On the other hand more involved control strategies allow for improving the system behavior by properly taking the specific characteristics of the battery systems into account [2].

Black start capability as an ancillary service

Public infrastructure and industrial production units are dependent on emergency power generators. In order to restore the energy supply autonomously after a widespread power outage, power plants with black start capability are required. The main feature of these units is that they can be started without external energy. By means of these units other supply-relevant power plants are activated and the electrical grid is restored gradually. Particularly running water, pumped storage, compressed air storage or gas power plants are suitable for fulfilling this task.

At the Völklingen Fenne site, STEAG operates a gas turbine in addition to hard coal-fired units as well as one of its six large scale battery systems. In addition to providing primary control power, the battery system at Völklingen site is designed for providing black start and island network formation. Recently, the black start of the gas turbine using the power island provided by the battery system was successfully tested.

Big data based approaches

Large scale batteries are complex systems which produce huge amounts of data. In order to maintain optimum operating conditions and efficiency it is important to identify abnormal behavior within this data as early as possible. However, the sheer quantity of available information makes a detailed, manual monitoring of the system nearly impossible.

Recently the development of Big Data and Machine Learning technologies and their introduction into the industry within the Internet of Things has made technologies available which allows detecting anomalies in large sets of data by means of advanced algorithms. Machine Learning comprises algorithms which automatically recognize and analyze correlations in the data and which use these as a basis to make predictions ("predictive analytics") or to detect recurrent patterns („Advanced Pattern Recognition") [3]. These procedures have been successfully used e.g. in speech recognition or in autonomous vehicles. They play an important role in many business models: Wizards like Siri (Apple) or Cortana

(Mircrosoft), advertising like Google AdWords, "recommendation engines" as with Amazon are some examples.

STEAG has long term experiences in applying these methods to enable predictive maintenance in power generation [4]. On this basis the potential of applying these methods to large scale battery systems has been evaluated.

The remainder of this paper is organized as follows: Section 2 introduces STEAG's large scale battery systems as well as our operational experience. In Section 3, optimization measures and simulation results related to the SoC management are addressed. Section 4 deals with latest experiences and test results with respect to grid forming and black start capabilities by means of large scale battery systems. Finally, in Section 5 first results are shown on how big data based approaches are capable of properly supporting the diagnosis of the battery condition.

2 Large Scale Battery System

2.1 Configuration

STEAG currently operates six almost identical large scale battery systems, which differ only slightly due to the local technical infrastructure and the specific grid conditions. Due to the modular design and the arrangement of the technology in 40-foot cargo containers, a quick realization of the entire project could be achieved.

Each battery system has a total power of 15 MW and a capacity of more than 20 MWh. To achieve this capacity, ten battery containers were installed. Each container consists of AC/DC converters and battery banks. Each of these battery banks has parallel connected battery racks with serially connected modules. With a capacity of 1,5 MW per storage unit, the total power is 15 MW. For the bidirectional connection to the 10 kV grid, two battery containers are combined to form a 3 MW unit, symmetrically constructed and connected via a common three-winding transformer. In order to prevent overheating of the lithium NCM battery cells and the installed converter, cooling systems are provided for each 3 MW unit, which guarantee a constant internal temperature of the container of 23 °C, ± 5 °C.

In addition to the ten storage units, each battery system has an additional control unit, which is housed in a separate container. The control unit carries out the main control functions as well as the frequency measurement and processes the safety signals of the fire alarm and emergency stop systems of the battery containers.

2.2 Operational experience

The first year of operation has proven that the large scale battery systems of STEAG can be successfully operated both commercially and physically. The units show a very good technical availability and meet all requirements of the German TSOs for providing primary control power particularly fulfilling the so called 30-min criterion [4] [5].

Apart from providing primary control power it could be validated that the large scale battery systems can, alternatively, be properly used for several other tasks like load shifting, provision of reactive power, black start capability and compensation of intermittent power generation by renewables like wind and sun.

3 Optimization of SoC management

3.1 Main goal and description of the SoC control loop

In order to optimize the technical and commercial operation of the large scale battery systems several measure have been identified two of which, focusing the optimization of the SoC management, will be discussed next:

- Reduction of lead time (delay) for activation of SoC management power
- Implementation of a better suited control strategy.

The main purpose of the SoC management optimization lies in reducing energy costs as well as reducing the degradation of the battery cells by reducing the overall SoC management power and energy, respectively.

The effect of these measures on the performance of the battery systems has been investigated by means of simulations using MATLAB/Simulink. The model of the battery system has been validated with real plant data showing a very good accuracy [2].

The structure of SoC management of the battery system is shown in Figure 1. The aim of the SoC management controller is to keep the battery SoC in a surrounding of the SoC set-point meeting the 30-min criterion at any time of normal operation [4]. The output of the controller is the SoC management power which has to be delayed by minimum 15 minutes according to [5]. The primary control power which depends on the frequency deviation (preprocessed by means of dead band and droop) and the SoC management power are summed up to get the actual charging power of the batteries affecting the SoC accordingly. In fact the primary control power can be considered as a disturbance affecting the SoC control of the battery. The overfulfillment serves as another measure for SoC management [5] but the effect is rather minor. Hence, in the following the effect of overfulfillment is considered to be negligible.

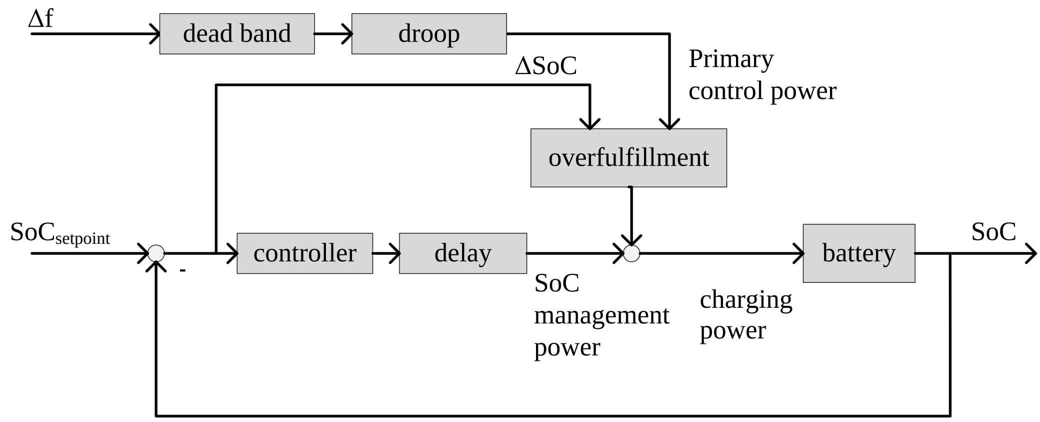

Figure 1: Structure of SoC management

For the following investigation different frequency profiles, each covering a single day, have been considered as exemplarily shown in Figure 2. The figure on the left-hand side shows the frequency profile of the 1st of January 2017 which is considered to be relatively normal with an average frequency of 50 mHz. In the middle plot, showing the frequency profile of the 20th of April 2017, the average frequency is the same but the standard deviation is increased. On the right-hand side the figure illustrates the frequency profile of the 10th of January 2017 where a severe frequency deviation is lasting several hours.

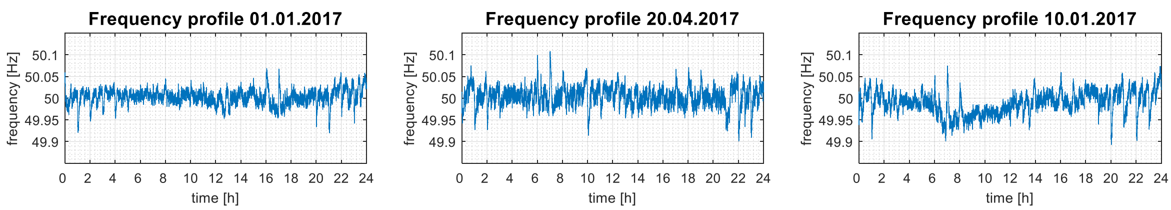

Figure 2: Frequency profiles considered

Figure 3 shows the behavior of the battery model subject the frequency on 10th of January. As depicted in the upper plot the large time period of low frequency (starting around 6:00 AM) results in a long period where primary control power (blue curve) is delivered to the grid. Consequently, the SoC decreases (lower plot). In order to stabilize the SoC, SoC management power is activated by the controller (orange curve in the upper plot) keeping the SoC in its admissible bounds defined by the 30-min criterion (represented by the dashed lines in the lower plot). Due to the long period of a negative frequency deviation, the SoC management power is kept several hours at its limit of 3,75 MW which is the minimum requirement for the maximum SoC management power to be provided according to [4].

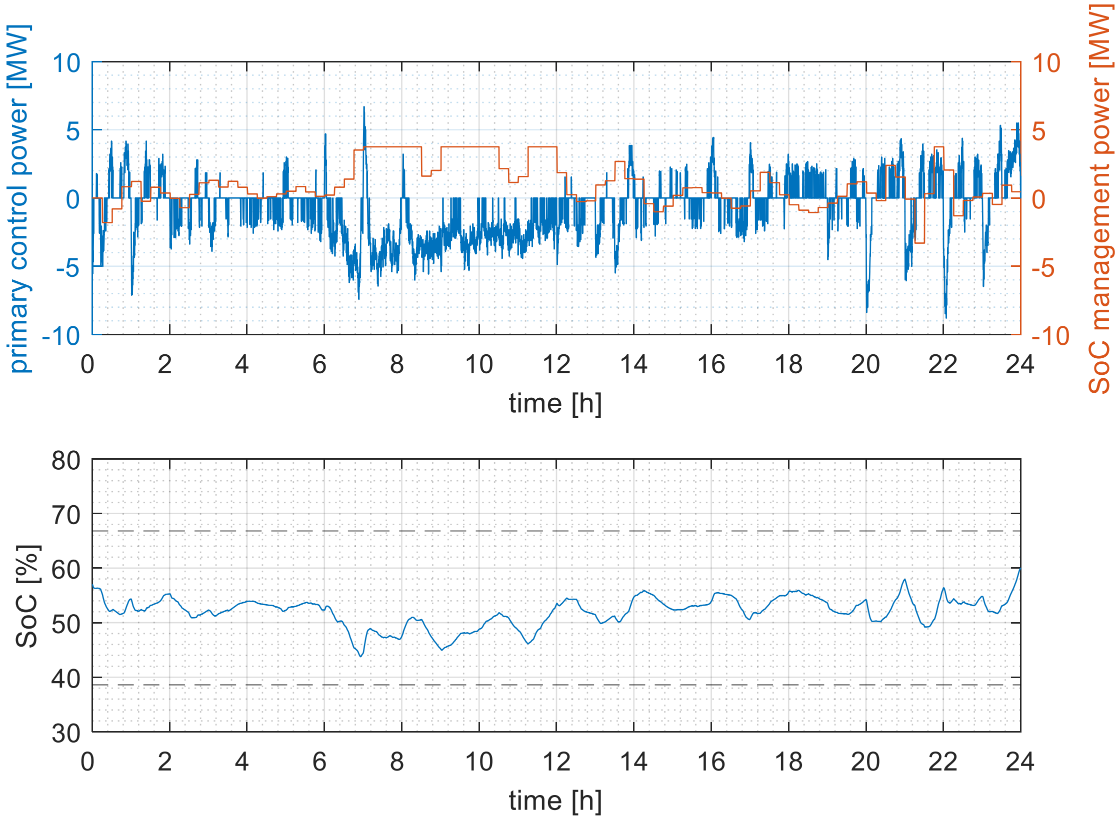

Figure 3: Battery / SoC behavior on 10.01.2017

3.2 Reduction of lead time

Since the primary control power, acting as a disturbance on the system, is relatively large compared to the maximum control power provided by the SoC management, a big challenge of the system is given by the large lead time / delay of minimum 15 minutes (see [5]). However, since the lead time of the intraday market has been reduced to 5 minutes [6], a reduction of the delay in the SoC control seems reasonable.

In Figure 4, the trajectories of the SoC management power with a lead time of 15 min and 5 min for the 1st of January are compared. The characteristics of both profiles are similar which is due to the dominating influence of the primary control power but, in general, the power provided with only 5 min lead time is comparably less, since the system can react quicker to the strongly varying primary control power. Consequently, the SoC management power more rarely adversely affects the system behavior.

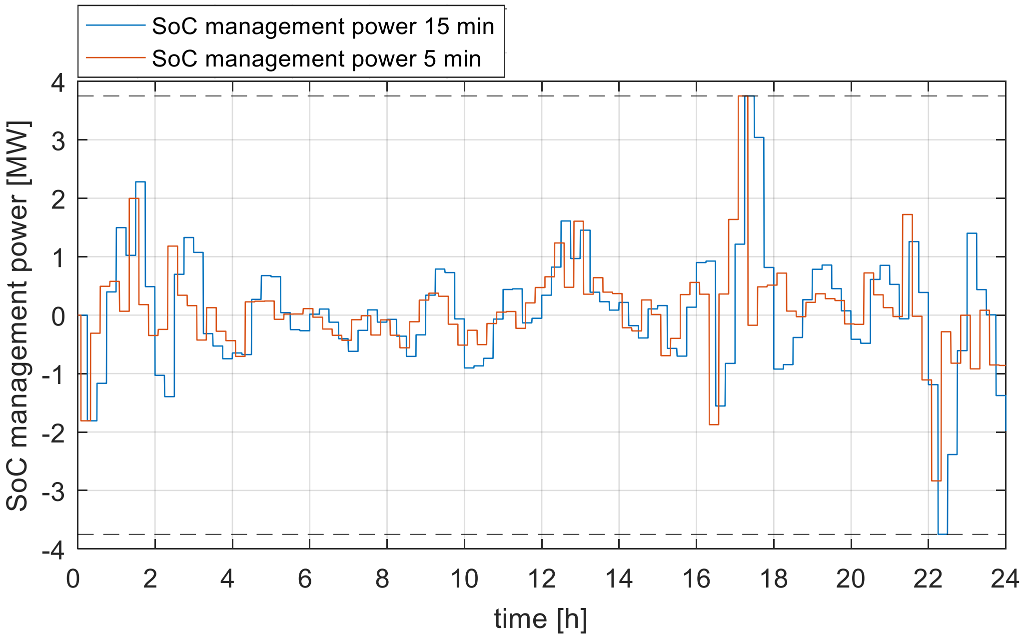

Figure 4: SoC management power profile on 01.01.2017 for delay of 15 min and 5 min

Table 1: Saving potential by means of reduced lead time

	SoC management energy 15 min [MWh]	SoC management energy 5 min [MWh]	difference [%]
Frequency profile 01.01.2017	9,13	7,89	-13,55
Frequency profile 20.04.2017	12,69	10,40	-18,03
Frequency profile 10.01.2017	24,37	23,77	-2,46

Table 1 highlights the saving potential for the different frequency profiles considered. It turns out that with up to 20% the energy saving potential is higher at normal days compared to the rather extreme frequency profile on 10th of January (only 2,5%). This becomes obvious by considering the fact that a strong frequency deviation in a single direction keeps the SoC management power in its bounds for a long period of time severely degrading the positive effect of the lead time reduction.

3.3 Smith-predictor

The Smith-predictor is a control strategy explicitly facing systems with severe delays / dead times [7]. Hence, it might be well suited for improving the system performance of the large-scale battery system.

As shown in Figure 5, the concept of the Smith-predictor includes the parallel connection of the real system with delay and a model of the battery system. The model consists of a delay-free and a delay-affected part. The path without delay basically predicts the output of the actual system. Using this information the controller is able to react to a potential control error even before the actual error occurs. As a result, a better control quality can be achieved and even a higher controller gain can be selected. The outer feedback loop becomes active only if the output of the model differs from that of the real system due to disturbances or model uncertainties which leads to proper robustness properties of this scheme.

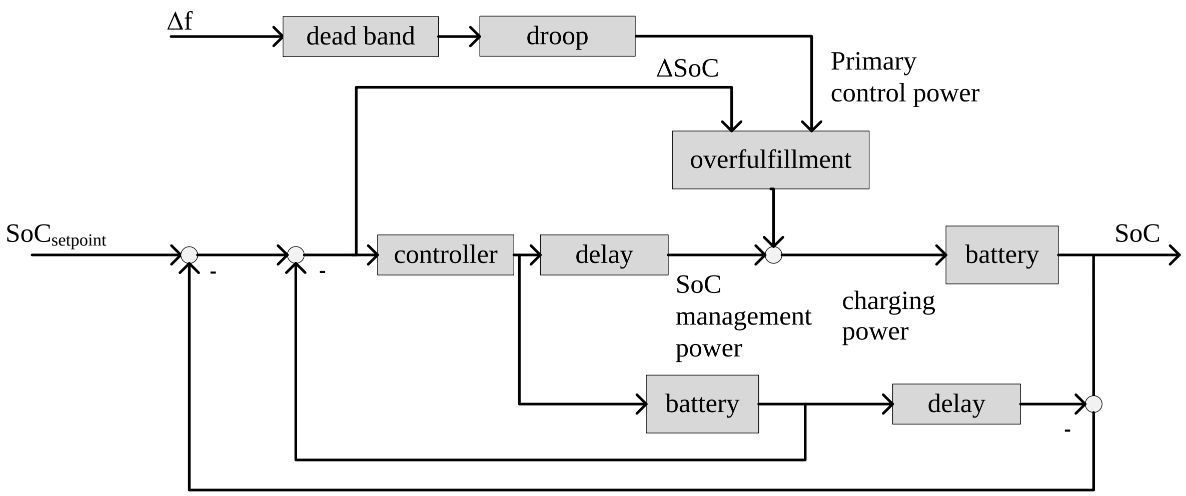

Figure 5: Smith-predictor

The Smith-predictor is generally capable of keeping the control error smaller compared to the existing control implementation and, consequently, less SoC management power is required. The advantages of the Smith-predictor likewise appear particularly by considering frequency profiles with frequent changes between positive and negative primary control power as shown in Figure 6. For the 1st of January 2017 it is clearly illustrated that almost always the SoC management power using the Smith-predictor (orange curve) is significant lower compared to the use of the existing controller (blue curve).

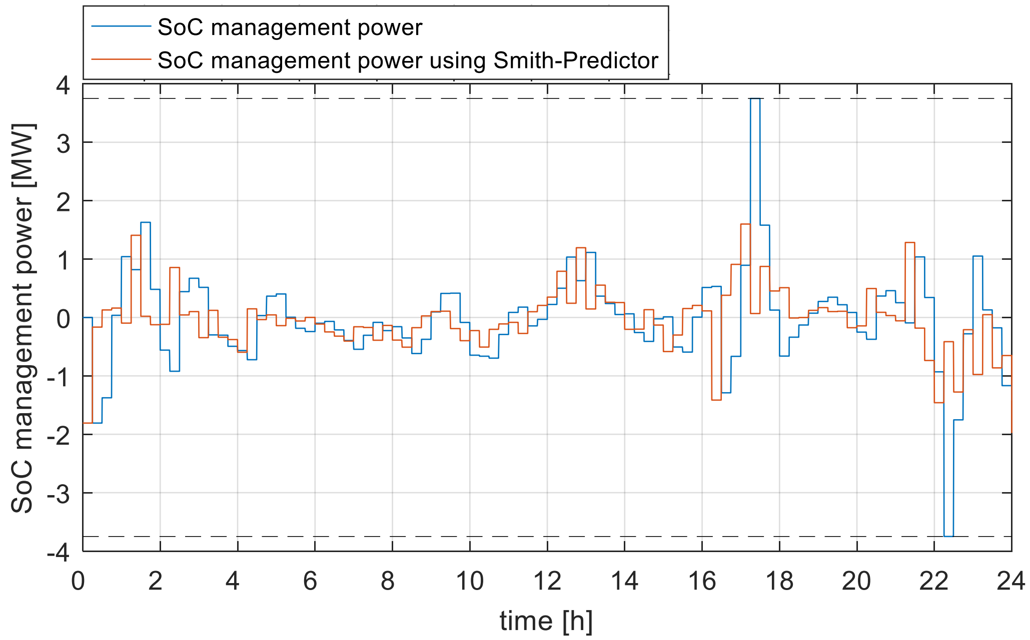

Figure 6: SoC management power profile on 01.01.2017 with existing control implementation and with Smith-predictor

Table 2 summarizes the main findings. On an average day, the adapted control concept can achieve energy savings of up to 30%. In extreme cases, for the same reason as discussed in the previous section, the reduction of the required SoC management energy is generally less.

Table 2: Saving potential by means of Smith-predictor

	SoC management energy [MWh]	SoC management energy using Smith-Predictor [MWh]	difference [%]
Frequency profile 01.01.2017	8,99	7,40	-17,71
Frequency profile 20.04.2017	13,20	9,30	-29,52
Frequency profile 10.01.2017	24,36	23,39	-4,00

In general, considering the measures discussed in this section, it can be observed that the saving potential in terms of SoC management power / energy particularly depends on the disturbance, i.e. the characteristics of the frequency profile. Especially given a frequency profile with a frequent change between positive and negative primary control power, significant energy savings can be achieved.

4 Grid forming and black start capabilities

Picture 1: STEAG's large scale battery system at Völklingen-Fenne site

The transmission system operators have developed black-start concepts for grid restoration in coordination with distribution system operators and power plant operators in case of black-outs of the electrical grid. In such a case, the transmission system operators rely on power plants with black start capability. Small grids of generators and consumers will be formed and gradually connected to larger sub-grids.

The STEAG site in Völklingen-Fenne provides a very good starting point for the reconstruction of the electrical grid, because in addition to the coal-fired power plant, the site also includes a gas turbine and a large scale battery system. Both the battery storage and the gas turbine are connected to the 10 kV auxiliary power supply of the coal unit. Considering black start, the large scale battery system has been equipped with additional black start functionalities. In addition to parallel grid operation, an island grid can be formed via the inverters of the battery storage. This means that the battery storage system does not require an external voltage at the main connections but is capable of forming this grid independently as well as generating the frequency of 50 Hz. The energy stored in the battery is used to energize the 10 kV auxiliary power supply of the coal unit and to feed the gas turbine's auxiliary power. In the next step, the gas turbine is accelerated to ignition speed via a static starting device. When this speed is reached, the fuel is ignited and the gas turbine is further accelerated up to 3000 rpm, the synchronous speed. The gas turbine is then synchronized to the island grid of the battery system and afterwards the battery is replaced. Up to this point, the black start has been already successfully tested and the performance of the large scale battery system was validated.

Consequently, the full power of the gas turbine is available for starting the coal-fired unit which includes starting large consumers such as feed water pumps or fans. Thus, the coal-fired power plant can be started up and can be used as a larger island to build up the public electrical grid.

Considering the implementation of the black start capability, the special challenge was, for example, the handling of inrush currents of transformers due to the comparatively weak grid formed by the battery inverters. In addition, the analog control of the static starting device and excitation system had to be adapted to the changed start sequence.

With this approach, STEAG can now offer transmission system operators an additional ancillary service. This also holds for industrial companies which rely on a stable network which can be quickly rebuilt if necessary. The solution presented is particularly interesting for operators of gas turbine power plants who can integrate large scale battery systems into their systems for providing black start capability.

5 Big data based diagnosis

5.1 Machine Learning for Anomaly Detection

Part of the success of "BigData" technologies and of the "Internet of Things" is due to the advances in "Machine Learning". Machine Learning refers to algorithms that "learn" from existing data the normal behavior of a system by identifying correlations in the data. These algorithms perform that task automatically without the need of additional input from expert knowledge. Once the data based model of the system behavior is built, it can be used for prediction in order to support decision making. The mathematics on which these methods are based on is well known and has been under constant development for decades. However, the recent dramatic increase of the available computational power made commercial applications feasible and boosted the further development.

STEAG has adopted this technology and has applied it to the early detection of abnormal behavior and faults in power generation units [8] [9]. In a first step data is gathered from a DCS or SCADA for a period of time where the considered component (or even the entire plant) is known to be in good condition. The data will not vary independently but due the physical properties of the components and the process there will be correlations. Machine Learning can then, in a second step, be applied to identify these dependencies automatically and to learn, how the data are related in normal condition of the component or plant. Once this data based model of the plant behavior is available, it is used in a third step to calculate expected values for the DCS or SCADA measurements. Due to measurement uncertainties and unavoidable model errors actual and predicted values are never identical. Thus, algorithms known from the statistical process control methodology have to be applied in a forth step to check, if the observed deviations between actual and predicted value are within the expected range or if they are significantly increased. The actual vs. predicted comparison with the subsequent significance testing is applied online with a given frequency (once a day, once every hour …), so that the anomaly detection early and reliably identifies those measurements that show unusual behavior. With this information the operation or maintenance engineers can take proactive action to keep the component in the most efficient condition and to avoid unplanned outages.

A tool that enables this progress is deep learning, an algorithm that has boosted the progress of many AI (artificial intelligence) applications. Speech recognition and picture processing for robotic technologies are among solutions that benefited from this development. Deep learning is an application of neural networks. However it uses network topologies which utilize a high number of hidden layers and complex training algorithms. A special implementation of deep learning that is most valuable for anomaly detection in plant data are deep autoencoders.

A deep autoencoder (see Figure 7) is a neural network which is trained to map the inputs to themselves. So, e.g., in case of plant data all the input will be all the available measurements for the water / steam cycle and the output will be a reference value for each of the measurements. An autoencoder has a symmetrical topology in the hidden layers with a "constriction" in the center layer. That prevents the training algorithm from simply "memorizing" the data but forces a generalization. It will automatically identify a number of key features (corresponding to the number of neurons in the center hidden layer) and learns the relationship between these key features and the input data. In our example of the power plant data from the water steam cycle this topology will force the autoencoder to learn that there is a small number of key features that fully describe the operating condition of the plant, such as load, ambient temperature, certain extractions and others. It will further learn how the DCS measurements depend on these features during the training period.

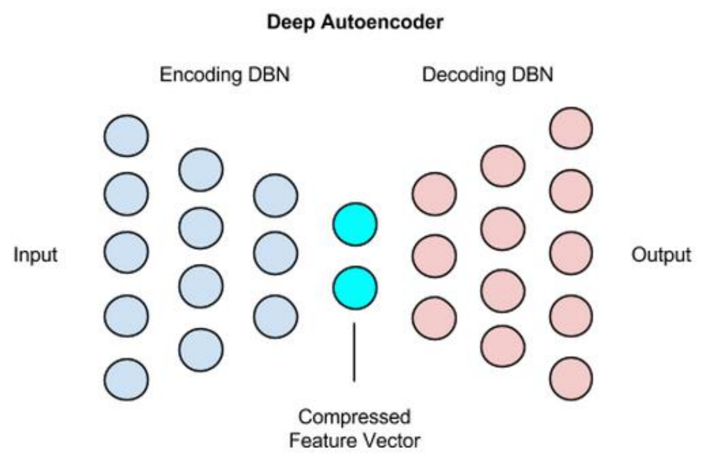

Figure 7: Structure of a deep autoencoder

Once the autoencoder is trained, online measurements from the DCS can be propagated through the neural network and the result will be the expected values which all the measurements would have under the given operating conditions (if the plant is in the same condition as in the reference (training) period). If there are significant deviations between measured and expected values an anomaly is detected in the online data. This anomaly will give an early warning for changes in component health condition and will be a valuable input for predictive maintenance and performance optimization.

A few years ago this approach would have been beyond the scope of affordable hardware if applied to real life DCS / SCADA data. Today it is in the reach of powerful workstations.

5.2 Diagnosis of large scale battery systems

The tool proposed in the previous section – already proven for conventional power plants and wind turbines – has been applied to STEAG's large scale battery system [10].

The measurements of the currents (…CE..) of the racks in a battery group together with the voltages (FE…) and temperatures (FT….) of the modules of one rack within one group have been selected for monitoring using hourly data. A period of 8 weeks immediately after commissioning of the battery system was identified as reference period with good condition. The machine learning was applied to identity the independent key features of the dataset and to learn how the measurements depend on the key features. After the reference period the model generated was applied in an aposteriori analysis to the SCADA data. For each set of measurement the model returns a set of predictions. The difference between actual and predicted measurements was tested on statistically significant deviations. For each measurement it is counted how often the algorithm regards its value as abnormal within a given time-bucket. The heat-map depicted in Figure 8 visualizes the results.

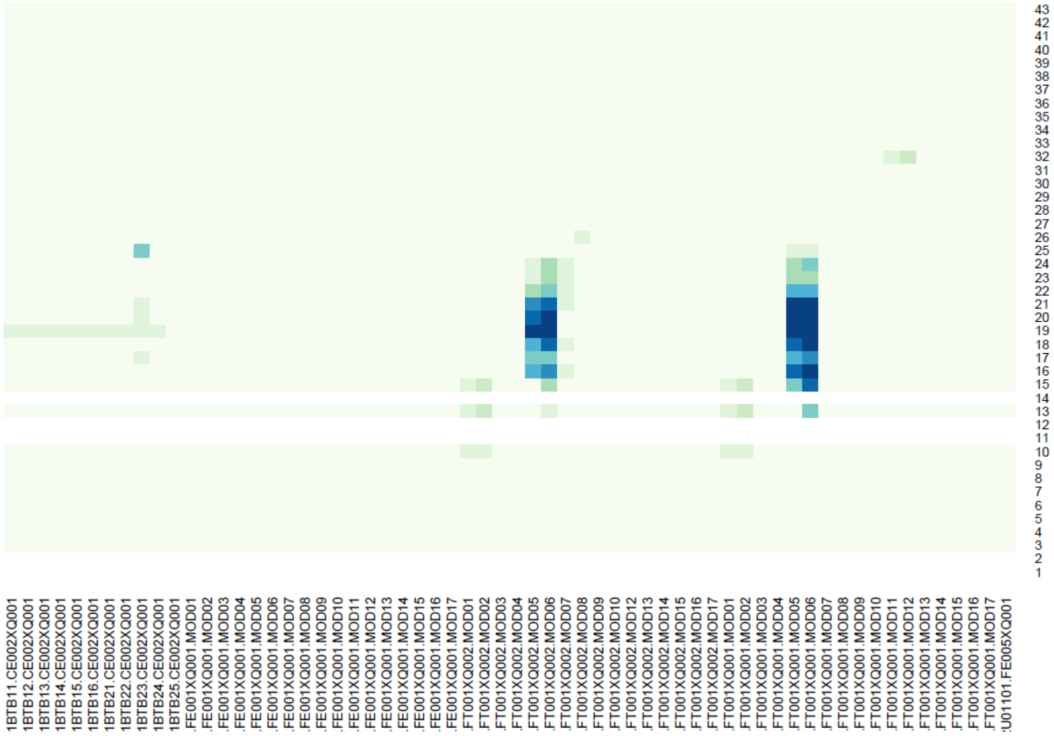

Figure 8: Anomalies in the battery data

Each column in the graph corresponds to a measurement, each row to a time bucket (here: week) starting after commissioning. The color indicates how often the behavior of a given measurement was classified as significantly abnormal: light blue means never, dark blue means permanently. There are obvious temperature anomalies for two modules (5, 6) and a corresponding conspicuousness in the current of the rack (23). These anomalies are in line with the service history of the battery, i.e. temperature anomalies in the rack 23 at position of module 5. After replacing the abnormal module in week 25 the anomalies are removed.

Further investigation will clarify if the anomalies starting in week 15 are early warnings for this fault. However, the above results give strong evidence that an online application of the anomaly detection would have enabled proactive action and, thus, would have avoided a major fault.

6 Conclusions

STEAG's operation experience with in total six large scale battery systems has shown that these systems can be operated successfully both technically and commercially. However, the system behavior can further be optimized by adapting the SoC management of the system. Two measures have been proposed, namely the reduction of lead time as well as the implementation of a more involved control strategy. Both approaches show that significant savings in terms of electrical energy used for the SoC management can be achieved. In addition, large scale battery systems can be used for further ancillary services, such as black-start capability, which in coordination with a gas turbine has been successfully implemented by STEAG in Völklingen-Fenne. Finally, due to their modular design large scale battery systems are well suited for big data based diagnosis approaches. Promising results for detecting anomalies in the battery behavior have been shown by applying an approach using deep learning by means of neural networks.

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