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Data-driven State of Health Modeling of Battery Energy Storage Systems Providing Grid Services

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***Abstract*— Battery energy storage system (BESS) is key for future renewable energy systems, as it can provide various grid support functionalities, facilitate the participation of renewable energy sources in electricity markets, and increase grid stability. However, battery degradation is a major factor hindering the BESS implementation for grid applications. Battery state of health (SOH) is a key performance indicator of the BESS, and data-driven models powered by machine learning techniques are among the most promising solutions for the BESS degradation estimation. In this paper, a novel taxonomy of BESS services is proposed based on battery usage. Besides, the data-driven techniques for battery SOH modeling and data-driven SOH estimation applications for BESS providing grid services are reviewed and discussed. Further, a comprehensive discussion is presented regarding the challenges in the area of data-driven SOH modeling methods for the BESS providing grid services in practical applications.**

Keywords—data-driven model, battery energy storage system, state of health, grid-connected application, battery service

I. INTRODUCTION

The BESS has played an important role in managing the intermittency of renewable generation, supplying power during the blackout period, and other grid support functions. Since the nature of the quick response time and broad power range, BESS has been the most popular component to provide on-grid and off-grid services in the renewable energy system sector [1]–[4]. However, battery degradation is an inevitable issue as the calendar life and cycle life decrease during the project lifetime. The SOH is the key parameter to describe how much energy could the BESS storage, and the definition of SOH is the current amount of energy capacity divided by the specific amount of energy capacity [5]. One way to measure SOH is to run a full cycle to charge and discharge the BESS under a designated standard capacity testing process. Another way is to build the indirective capacity estimation concerning the other measurable parameters such as the voltage, current, temperature, state of charge (SOC), and so on [6].

For BESS in real applications, the full cycle testing for SOH measurement is not applicable on an everyday basis, as the process is time-consuming and damages the lifetime of the BESS by running the process itself. As a result, the indirect capacity estimation of the battery has played a more and more important role in SOH detection [7]. Logically, the condition monitoring of the above-mentioned measurable parameters will be crucial to achieving an accurate SOH estimation.

With the comprehensive and accurate measurement result, degradation modeling is another key factor of battery SOH monitoring. The semi-empirical, chemistry and mechanism-specific models have all proved the potential of lifetime estimation of battery in various applications, but the statistical and data-driven techniques are the most promising method regarding the applicability of the data volume and the scope of battery applications [8]. However, most of the data-driven model has been built by battery cell lifetime testing results, naturally because battery testing is designed to scan various operating conditions and measure the SOH footprint during the dedicated test process, which matches with the giant amount of data required to utilize the versatile data-driven SOH models [6].

Battery testing is happening all over the world, leading by large battery manufacturers, research institutes, and third-party agencies [8]. From our observation, there is much research where data-driven degradation models are built by battery degradation testing results, however, the number of actual cases that reveal data-driven SOH modeling of batteries that provide grid services in the power system is very limited, which means, the data-driven SOH monitoring for grid applications is still under the developing stage. In this circumstance, implementing data-driven degradation models in grid-connected applications is of vital importance to verify the model applicability and reliability. On the other hand, utilizing the on-site condition monitoring data to build or alter the SOH model has attracted attention as it can potentially decrease the cost of battery cell testing and increase the prediction accuracy for specific BESS services.

The structure of the paper is as follows. In Section II, enumeration BESS grid services are discussed based on the proposed novel taxonomy of BESS services. In Section III, we interpret the techniques of data-driven SOH modeling for the battery. In Section IV, we elaborate on the data-driven SOH estimation applications for batteries providing grid services in the aforementioned taxonomy. The discussion and conclusion are given at the end, which summarized our observation of battery degradation modeling and the research needs for further data-driven SOH estimation development.

II. CLASSIFICATION OF BESS SERVICES BASED ON BATTERY USAGE

This work is supported by the Danish project “BOSS: Bornholm smartgrid secured by grid-connected battery systems” co-founded by Danish Energy Technology Development and Demonstration Program (EUDP) contract no.64018-0618.

In this chapter, we enumerate the BESS application focusing mainly on grid-connected services with the purpose of a brief introduction for each kind of service in the proposed novel taxonomy to facilitate the categorization of battery usage and degradation.

A. *Proposed Taxonomy of BESS Services Based on Battery Usage*

There are more than 10 kinds of BESS services in the market, such as energy arbitrage, frequency regulation, V2G, etc., and most of the BESS services are under the nomenclature of business purpose, however, the business purpose provides limited information regarding the battery usage. Furthermore, there are more kinds of services that need to be considered and even some of them can not be precisely named by business purpose. In this condition, it is necessary to propose a simplified nomenclature by battery usage and to have broader coverage and preciser description for battery usage in connection with degradation for different BESS services. Regarding battery usage, two kinds of usage metrics for energy capacity usage are used when estimating degradation, one is by cycle and another is by throughput. We choose to use the "turnover" as the parameter to describe the duty profile of different BESS services. "Turnover" is a dimensionless number, defined as the cumulative discharged ampere-hour (Ah) divided by the original capacity of the battery. The turnover helps better describe the battery usage regardless of the system size and battery current capacity [6]. There are other deterministic parameters monitored during the battery operation, such as the C-rate and temperature, however, the scope of battery usage in our research focuses on the SOC analysis, which roughly explicates the C-rate and ignores the temperature.

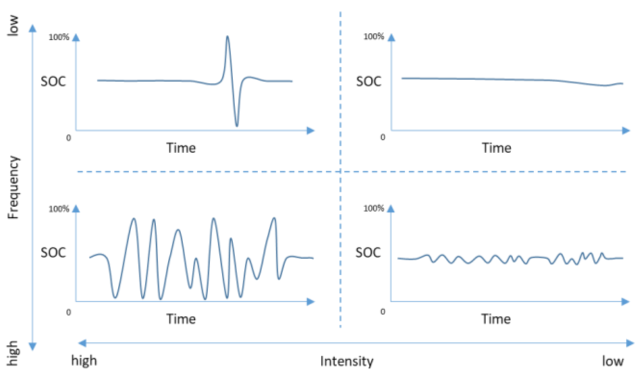

Fig. 1. Illustration of the BESS service categorization from the duty profile of battery cell level

TABLE I. PROPOSED TAXONOMY OF BESS SERVICES

Classification	Application	Explanation
High-frequency & high-intensity usage	Energy arbitrage, behind-the-meter, renewable integration	Fully charge and discharge daily or hourly
High-frequency & low-intensity usage	Frequency regulation, voltage support, power smoothing, secondary supportive duty	Partially charge and discharge daily or hourly
Low-frequency usage	Black start, grid support	Partially charge and discharge weekly or monthly, most of the time standby

In our novel taxonomy, we consider two aspects of the battery usage classification, i.e., the duty intensity and duty frequency. As shown in Fig. 1., the illustration categorizes the BESS services by the SOC variation from the frequency and intensity points of view. In the top of Fig. 1., the low duty frequency category covers the BESS services, where the battery undertakes partially charge and discharge duty on a weekly or monthly basis, and most of the time standby. At the bottom of Fig. 1., there are two kinds of categories for high duty frequency cases, which are high-intensity usage on the left and low-intensity usage on the right. In the high-intensity category, batteries are under heavy-duty cycles intensively for most of the operation time. And low-intensive usage is when the batteries are partially charged and discharged daily or hourly, which means the battery is under frequent shallow duty cycles. In summary, the categorization is made regarding the battery duty profile by evaluating intensity and frequency on battery cell level.

The detailed classification, application, and explanation of our proposed taxonomy of BESS services are summarized in TABLE I. The classification categories include high-frequency & high-intensity usage, high-frequency & low-intensity usage, and low-frequency usage. Since the battery calendar life dominates the low-frequency usage, the usage intensity is not further distinguished in this category. The high-frequency & high-intensity usage class includes the BESS services that the battery fully charges and discharges frequently, such as energy arbitrage, behind-the-meter, and renewable integration. The reason we consider the behind-the-meter usage as high-intensity usage is that the battery size is typically comparatively small and the battery is fully charged and discharged daily or hourly to achieve the designed function. The high frequency & low-intensity usage class covers the BESS services that the battery partially charges and discharges frequently, such as the frequency regulation, voltage support and power smoothing, and some secondary supportive duties. In the end, the low-frequency usage covers the BESS services that the battery is most of the time standby, and partially charges and discharges weekly or monthly, which is related to the black start and grid support applications.

B. *Enumeration of BESS Services*

1) *High-frequency & high-intensity usage*

Here we would like to enumerate the applications of high-frequency & high-intensity usage, which includes energy arbitrage, behind-the-meter, and renewable integration.

The intra- and inter-day power price fluctuation creates the business opportunity of energy arbitrage, which requires charging and buy energy during low price then sell it during the high price period [9].

Although it seems like the most straightforward way to deploy BESS, the cost of battery degradation threatens the business feasibility of this application, normally measured by the levelized cost of storage (LCOS) [10]. It proves that battery condition monitoring and SOH modeling are substantial in real business applications [11].

The behind-the-meter batteries cover the applications when the battery is connected to the customer side and behind the electricity meter of the distribution system operator. It could decrease the electricity bill, in the case of demand charge, time of use (TOU), and also has a synergy with renewable integration applications [12].

The intermittence of renewable energy can to a large extent be controlled, but the prediction and control of long-term and short-term fluctuation are still challenging. Renewable integration covers the battery with a scale from kW to MW. In the case of the hybrid power plant, the multi-renewable combination creates opportunities and threats for energy system management, where effective BESS could contribute to the smoothing function [1]. As the battery utilized under off-grid renewable integration application undertakes a similar duty profile with the on-grid renewable integration and sometimes behind-the-meter cases, from the degradation aspect, the off-grid renewable integration service has naturally been covered in this review work.

2) High-frequency & low-intensity usage

As mentioned before, frequency regulation, voltage support, and second-duty are deemed as high-frequency & low-intensity usage.

In the situation of unbalanced power generation and load demand, the issue of frequency instability appears. Energy resources could provide or withdraw instantaneous active power to support the frequency, which has been named as frequency regulation. Historically, the conventional power generation units such as the gas turbine and hydro turbine provide the frequency regulation service, however, BESS has taken over this service as the superior characteristic of its power input, power output, and response time [2].

The voltage support function happens in the low voltage distribution networks when the voltage drop happens during the peak load period. The BESS can inject and absorb reactive power into/from the grid so that the grid stability and equipment functionality are ensured [13].

When the battery is primarily designed for other purposes such as the electric vehicle and smart building system but has been used for grid-connected applications, we deem this situation as an instance that the grid service is the secondary duty of the battery. Virtual BESS, aggregated BESS, and vehicle to grid (V2G) are under this umbrella. From the use case point of view, the virtual BESS which is composed of a group of distributed energy storage units, such as the batteries from electric vehicles and home energy storage systems, could practice the grid services in the same level of stationary BESS, with the coordination of the aggregator. The total amount of battery installed in the electric vehicle industry is predominantly more than the stationary BESS [14]. Besides the battery degradation of the driving cycle, the V2G service provides miscellaneous grid support functions, which could almost achieve most of the services in the scope of stationary BESS. Frequency regulation provision has been the most popular service of V2G because of the technical readiness and economic feasibility [3], [15].

3) Low-frequency usage

The low-frequency usage covers back-up energy storage applications such as the black start and grid support.

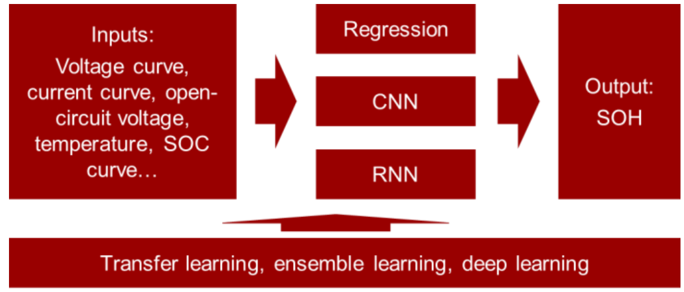

Fig. 2. Process and machine learning techniques for the data-driven model for SOH

Black start is to reinstate the normal grid function by generation assets that can start independently without the grid. This application normally requires a giant size of power capacity but low frequency of usage with low energy capacity usage. It has been observed that the black start service fits to combined with other BESS services and is seldom to be the major reason for depleting battery cycle life [4], [16].

Congestion relief and upgrade deferral are the services categorized by grid support in this paper. Congestion relief sometimes is also known as virtual cable, helps to relieve the transmission network congestion and reduce the overload situation of the peak hours [17]. Upgrade deferral is using BESS to defer the upgrading investment in distribution feeders and transformers.

III. An Overview of Data-driven SOH Modeling for Battery Application

Various data-driven approaches have been implemented in the SOH estimation, using the result of battery cell testings. The battery cell testing results are normally acquired by the tailor-made battery testing process in the designed condition of temperature, C-rate, and duty cycles, with the target of simulating and covering the degradation performance under the upcoming battery use cases. In this section, we have reviewed the contemporary progress of battery degradation modeling, including advanced regression methods, different neural networks, and different training techniques.

The Gaussian process has been used widely for regression problems individually or combined with the neural networks. For instance, an improved Gaussian process regression (GPR) model named deep kernel learning (DKL) combined with dynamic time warping (DTW) algorithm has been used in [18], which makes full use of the information in the voltage curve to avoid a subjective feature extraction [18]. Other regression methods such as the random forest regression and support vector regression have also shown the promising accuracy of the SOH estimation [19], [20].

Both feedforward neural networks (FNN) and recurrent neural networks (RNN) show competency in SOH prediction. For example, a probabilistic neural network (PNN) is used to estimate the SOH of Lithium-Cobalt batteries, indicating that the constant current charging time, the instantaneous voltage drop at the start of discharging and the open-circuit voltage are the key parameters for SOH estimation [21]. As for RNN, the long short-term memory method (LSTM) predominated in cell self-prediction and cross-prediction for degradation and observed to be implemented together with Monte Carlo simulation for probabilistic rest remaining useful life (RUL) prediction [22], [23].

Other machine learning techniques have been used together with above mention neural network structures, to improve the model accuracy, applicability, and efficiency. Transfer learning has been combined with LSTM for reducing the amount of training data, together with fully connect (FC) layers for SOH prediction of the Li-ion battery, where the LSTM is aiming at reducing the noise sensitivity and adjustable FC is set to learn private property from different batteries [24]. Ensemble learning has advantages over avoiding the regionality of training, and able to synthesize the output of s a series of base learners. Combining ensemble learning with the least square support vector machine or extreme learning machine improves the precision and stability of the prediction for SOH [25], [26]. Deep learning techniques have also been used for degradation estimation. An autoencoder-deep learning network (ADNN) is proposed for multiple Li-ion batteries R prediction [27].

As shown in Fig. 2., various measurable parameters are chosen as the input of the neural networks, not only the type of the measurement but also the selected period of the measurement matters for a precious SOH estimation. Different type of data-driven network structure shows competency in different cases, it may worth to try different model and configuration to get the best performance. Transfer learning, ensemble learning, and deep learning all show prospect for SOH prediction, which could be applied in the process of the data-driven model for SOH estimation.

IV. Data-driven SOH Estimation for Batteries Providing Grid Services

As mentioned in the introduction part, the data-driven SOH model applications in grid-connected BESS services are very limited; however, we still find a group of interesting cases and relative research results. We have categorized the selected paper in the classification framework proposed in Section II, which includes the high-frequency & high-intensity usage, high-frequency & low-intensity usage, and low-frequency usage. Not only learning from the real application helps to reduce the cost and time of battery testing, but also the implementation of machine learning techniques in the real grid services can further develop the model accuracy and achieve business benefits. In this section, the review of applications is focusing on the types of grid services, data-driven methods, and data sources.

A. High-Frequency & High-intensity Usage

The energy arbitrage is the most typical high-intensity usage, as the system tends to be fully charged and discharged daily or hourly. The high depth of discharge (DOD) and turnover usage covers the behind-the-meter, renewable integration, and most of the battery testing load profile.

Extreme learning machine algorithm has been used for SOC and SOH prediction for off-grid systems in rural African areas. However, the data used to verify the model is from the NASA-AMES dataset instead of the on-site data from the above-mentioned application [28]. Small-size off-grid solar-battery systems in Africa have been an abundant data source for data-driven battery degradation development, though new challenges appear such as the algorithm, computing power, and data management [29]. With the real data providing by the solar-battery system operator in Africa, the data mining techniques have been applied for SoH estimation of Lead-acid batteries and inferred to other system components [30].

To optimize the tradeoff between battery usage and energy arbitrage revenue, a data-driven method considering variable battery C-rate and efficiencies has been proposed by Sarker et al [31]. Assefi et al. build the degradation model using LSTM followed by a fully-connected network using the real data from behind-the-meter applications [32]. Song et al. proposed an on-line SOH estimation based on the measurement of real operation conditions. Two special degradation features have been put into the relevance vector machine, and the three batteries have been cycled intensively in high-turnover conditions for degradation testing [33]. The high-intensity battery testing results such as CALCE and NASA have been widely used to verify the degradation model in various papers [34], [35].

B. High-Frequency & Low-intensity Usage

The high-frequency & low-intensity category covers the usage that the system is frequently dispatched with shallow charging and discharging duty cycles, where the turnover is low. From the battery cell usage point of view for battery degradation study, the service such as V2G and voltage support is also in this group. It is important to emphasize that low-intensity applications are the most challenging part to estimate battery degradation. Firstly, as the duty profile of the SOC of the battery does not reach the top and bottom, it is hard to have full-cycle battery capacity testing results. Secondly, the battery testing is mostly carried under regular full-cycle tests, the battery degradation SOH estimation under irregular partial low-intensity condition by the data-driven model based on the data from battery testing is much more like an extrapolation problem rather than an interpolation problem.

The data-driven degradation model of LiFePO4/C battery has been validated by data collected from the measurement of short term current pulse test during the battery is offering primary frequency regulation (PFR) service to the grid. The SVR and Non-dominated Sorting Genetic Algorithm II (NSGA-II) have been used for better feature extraction and prediction. However, the overall optimization of BESS service provision and degradation cost is missing in the research of [36].

Using the worldwide light-duty driving test cycle (WLTC) load profiles, the data-driven degradation model purposed with Gaussian process regression capture the relation between real-time SOH and selected condition indicators. Although the WLTC profile is designed to evaluate the real-life EV operation, Khaleghi et al. conclude that the above-mentioned model can predict the SOH regardless of current amplitude and aging pattern, and deems the model as the prerequisite step of real-time predictive-maintenance BMS development, which aligns with machine learning-based optimization of BESS service provision [37]. The least-square support vector machine with a model-based unscented particle filter has been used to have the online joint prediction of SOH and SOC. However, the load pattern of this research could only represent the general operating condition of the EVs, from the authors' point of view, instead of the grid-connected stationary battery [38]. The V2G service provided by a fleet of EVs is deemed as a low-intensity application from the battery usage point of view. A neural network-based SOH estimation for Li-ion battery has been introduced, comparing with another method based on fuzzy logic control, and both of the techniques require early-stage characterization monitoring. The neural network built by nonlinear AutoRegressive with eXogenous inputs model confines estimation errors under 5 % before the end of the lifetime [39].

The Gaussian Process framework has been implemented to estimate the state of health of Li-ion batteries under calendar aging and cycle aging, with the ability to learn from in-field battery operation data. Different training method has experimented and high prediction accuracy has been achieved with the utilization of a small number of test sets. The integrated model is planned to be used to assess the battery degradation performance such as the EV driving load and renewable smoothing [40]. Ma et al. implemented the cycle life testing of eight commercial NMC cells, under 4 different SOC ranges, which is under 20%, 40%, 40%, and 100% of DOD, after that, a recursive least squared method with forgetting factor based on the correlation between SOH and open-circuit voltage changes was employed to estimate the degradation under different duty profile types [41]. Another data-driven battery degradation model has been used for all-electric ships using a similar battery cycle lifetime test for 3 groups of duty cycle, which is under 20%, 40%, and 100% DOD with 50% mean SOC [42].

C. *Low-frequency Usage*

The low-frequency services cover the usage like black start, grid support, and back-up applications. As the battery turnover and usage rate are so low that the calendar life will dominate battery degradation instead of cycle life.

Wang et al. use the deep learning-based model to estimate the remaining lifetime of the battery in the base station with a 1.5-year dataset of the cellular service provider, where the battery was design to handle the power outage situations as a back-up system [43]. Liu et al. investigated calendar-aging data from nine storage cases to build a Gaussian process regression model with automatic relevance termination kernel for accurate calendar life prediction under various working conditions of BESS [44]. And they carried out another study to compare the electrochemical model, semi-empirical model, and data-driven model for calendar aging prediction [45]. Another holistic data-driven battery degradation model based on Gaussian process regression built by Lucu et al. considers both calendar and cycling life, can learn from the real operation data progressively, and achieved accurate remaining useful life predictions [46].

V. Discussion

Although there is a very limited number of investigations on data-driven SOH modeling in the grid-connected BESS, we have seen great progress on the precise data-driven model for the prediction of SOH, various attempts for machine learning techniques implementing in the SOH related topics, and using the field data for mode training. After the classification and review work, some thoughts and discussion are given as follows.

A. *Need for better Data Sharing Platforms for More Accurate SOH Estimation*

The battery SOH modeling has been widely researched, and different models such as the physical model, empirical model, and data-driven model have been extensively discussed. Besides, battery testing has been carried out in different kinds of set-ups all over the world. However, it is urgently needed that we have a better data-sharing environment to drive the success of the battery data-driven model. Data-driven models built by battery testing results from several cells could barely convince others of accurate predicting ability for multifarious real use cases. To be fair, the current data-driven models in academia are using the battery testing data to predict the battery testing results, most of the time even to predict the battery performance in the same group of testing. The model built by testing data may have very limited capability to predict the battery SOH in real applications e.g., the grid-connected applications mentioned in this paper.

B. *Need for Real SOH Data Related to the BESS Providing Different Grid Services*

There are two kinds of data related to the battery SOH, i.e., the standard battery cell testing data and the SOH measured based on the real operation of BESS providing grid services. There is a lack of research comparing the similarity and differences between these two kinds of data. From our point of view, the battery testing data are simplified, well-monitored application data. Naturally and crucially, the real SOH value is recorded during the battery test, and plays as the key input for model training. However, the real SOH value is hard to be measured in the real case. For example, during an application like frequency regulation, there is no chance to measure the current SOH as the SOC is hovering around. And another important point is that the battery testing by designated standard battery testing process upsets the original duty profile of the application, which causes extra battery degradation in short term and long term. In addition, there is limited research to implement or transfer the data-driven SOH model from one configuration to another, e.g., from the testing based model to the real application model, from one battery chemistry to another chemistry, from one group of battery cell production to another group of cell production.

C. *Need for Classification of BESS Services According to the Battery Usage Patterns*

There is a need to better categorize the BESS services and their duty profiles. Although we purpose a brief taxonomy regarding the intensity and frequency of the usage, the detailed pattern of each application still needs to be explored and matching with the performance of different battery technologies, for further optimization of SOH. Also, service stacking and its impact on battery degradation have not been thoroughly investigated, yet it is also a hot topic to pursue better revenue for the BESS. The way to combine the services, which is to satisfy the service simultaneously or arrange the service one by one by the schedule, will also influence the battery SOH modeling.

Challenges including estimation of instantaneous SOH and prediction of further SOH under future usage patterns could be settled at a certain level with the help of machine learning techniques [29]. Furthermore, the future SOH prediction under prospective usage is much more difficult and the current research is very limited, which will be hopefully prompted by a deeper understanding of the BESS service pattern.

VI. Conclusion

In this paper, using our proposed novel taxonomy, we reviewed the grid services of the BESS, the data-driven approach for the SOH estimation, and the data-driven SOH estimation cases for the BESS providing grid services. Based on our observations, a comprehensive discussion was given regarding the key points of the SOH degradation modeling in real applications. According to our investigations, most of the data-driven SOH models have been built and verified by battery testing data, but have not been implemented in real grid applications. Therefore, most of the data-driven models only represent the degradation performance of the same testing setup. As the complexity of duty profile increases prominently between testing and real applications, the model built from testing data could barely transfer to the real applications. Besides, degradation models may not be able to estimate SOH accurately for other battery chemistries or even a different manufacturer. Among other challenges like the barrier of data sharing, data accuracy, and conflict of commercial interests, the limitations may defer the process of data-driven SOH model development powered by machine learning. As a result, implementing data-driven SOH models for real applications, diving into the duty profile analysis of services, and developing accurate SOH models in various situations such as service stacking, data deficiency, and transfer learning should be considered as keys for future research in the area.

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