A Multi-Dimensional Dynamic Profiling Modeling Method for User-Side Distributed Energy Storage Considering Endogenization of Lifecycle Cost

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ABSTRACT User-side distributed energy storage serves as a core carrier for the coordinated development of source-grid-load-storage in new power systems. Most existing user profiling models for energy storage treat battery life decay cost as a fixed exogenous parameter while ignoring the dynamic coupling characteristics between battery life attenuation and operational costs, which leads to distorted characterization of energy storage operational features and large deviations in economic evaluation. To address this problem, this paper proposes a multi-dimensional dynamic profiling modeling method for user-side distributed energy storage with endogenized lifecycle cost. Firstly, the calendar fading and cyclic fading mechanisms of energy storage batteries are analyzed, and an endogenized lifecycle cost accounting model is constructed to realize dynamic coupling between energy storage operational behaviors and life loss costs. Secondly, a profiling indicator system for energy storage users is established covering four dimensions: static attributes, dynamic behaviors, economic benefits and life status, and multi-dimensional profiling modeling is completed by integrating a time-series data dynamic updating mechanism. Finally, a case study of typical users is conducted to compare and analyze the modeling differences between endogenized and exogenized lifecycle cost modes, which verifies that the proposed method can accurately depict the operational and economic characteristics of energy storage for different users. The research results provide theoretical support and technical basis for refined operation, differentiated management and control, and precise market empowerment of user-side energy storage.

INDEX TERMS user-side distributed energy storage, endogenization of lifecycle cost, multi-dimensional dynamic profiling, life decay mechanism, refined modeling

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

1) DEVELOPMENT STATUS AND APPLICATION SCENARIOS OF USER-SIDE DISTRIBUTED ENERGY STORAGE UNDER THE DUAL CARBON GOAL

Against the backdrop of the "Dual Carbon" goal and the construction of new power systems, large-scale grid integration of flexible load resources such as distributed photovoltaics and user-side energy storage has gradually become an important support for grid load regulation, new energy consumption and peak-valley difference reduction[1].

With flexible configuration, fast response and multi-scenario adaptability, user-side distributed energy storage is widely applied in industrial and commercial parks, residential communities, industrial parks and other scenarios. It can improve users' energy utilization economy through peak-valley electricity price arbitrage, demand load control and backup power supply, while providing auxiliary service support for power grids[2, 3].

2) PRACTICAL DEMANDS FOR REFINED MANAGEMENT AND DIFFERENTIATED OPERATION OF USER-SIDE ENERGY STORAGE

As the number of energy storage users continues to grow, the differentiation of users' energy consumption behaviors, energy storage configuration parameters and operation strategies becomes increasingly prominent. Traditional homogeneous energy storage management modes can no longer meet the refined management demands of large-scale distributed energy storage[4, 5].

Constructing accurate user energy storage profiles to realize user classification, feature mining and behavior prediction is a core approach to solve fragmented management and extensive operation of distributed energy storage.

However, most existing research on energy storage profiling modeling focuses on surface feature characterization of load characteristics and operational behaviors, ignoring the dynamic cost impact of battery life attenuation.

3) THEORETICAL VALUE AND ENGINEERING SIGNIFICANCE OF ENDOGENIZED LIFECYCLE COST FOR ENERGY STORAGE PROFILING MODELING

Battery life loss of energy storage is closely related to charge-discharge rate, depth of discharge, operating temperature and cycle frequency, which constitutes a typical time-varying dynamic cost[6, 7].

Traditional modeling sets lifecycle cost as a fixed exogenous parameter and decouples the relationship between energy storage operational behaviors and life loss, resulting in deviations in the characterization of economic features and operational potential of energy storage users, which cannot support precise operational decision-making[8].

Therefore, research on multi-dimensional dynamic profiling modeling with endogenized lifecycle cost embeds dynamic life cost into the whole process of energy storage user feature modeling to realize dynamic, accurate and comprehensive characterization of energy storage user features, which carries important theoretical research value and engineering application significance.

B. DOMESTIC AND INTERNATIONAL RESEARCH STATUS

1) RESEARCH PROGRESS ON DISTRIBUTED ENERGY STORAGE PROFILING MODELING

In the field of distributed energy storage profiling modeling, scholars at home and abroad have carried out extensive research on load feature extraction, user clustering and profiling system construction. Based on time-series load data and energy storage operation data, most existing studies extract user energy consumption features through clustering algorithms and machine learning methods, and build a basic profiling system covering energy consumption behaviors and load characteristics to realize preliminary classification and identification of energy storage users[9-11].

Nevertheless, existing profiling models suffer from single dimensions, mostly focusing on static features and short-term operational behaviors without taking full-cycle dynamic characteristics of energy storage into consideration.

2) REVIEW OF RESEARCH ON ENERGY STORAGE LIFE ATTENUATION AND COST ACCOUNTING

In the field of energy storage lifecycle cost accounting, existing research mainly focuses on static full-lifecycle cost accounting and analysis of influencing factors of battery life attenuation[12]. Some studies fit battery decay curves to establish correlation models between cycle life and operational parameters for optimal capacity configuration and operation strategy optimization of energy storage.

However, most studies adopt exogenized accounting mode by treating lifecycle cost as a fixed amortized value, failing to reflect dynamic cost fluctuations caused by differentiated life loss under various operational behaviors, and unable to characterize the two-way coupling between energy storage operation and costs.

3) ANALYSIS OF CORE DEFICIENCIES IN EXISTING RESEARCH

Synthesizing existing research achievements, two core shortcomings exist in current energy storage profiling modeling:

Static and exogenized lifecycle cost accounting without dynamic coupling with operational behaviors;

Single-dimensional and lag-updated user profiling lacking a multi-dimensional dynamic modeling system integrating static attributes, dynamic behaviors, economic characteristics and life status, which cannot satisfy the refined management demands of large-scale user-side energy storage.

C. RESEARCH CONTENTS AND TECHNICAL ROUTE

1) MAIN RESEARCH CONTENTS

The core research contents of this paper revolve around endogenized lifecycle cost modeling and construction of multi-dimensional dynamic energy storage user profiles:

First, typical operation modes of user-side energy storage and battery life attenuation mechanisms are analyzed to clarify the core logic of lifecycle cost endogenization;

Second, energy storage life decay quantification model and endogenized cost accounting model are constructed, and a comprehensive benefit model of energy storage considering dynamic life loss is established;

Third, a four-dimensional multi-layer profiling indicator system is designed, and a modeling framework for dynamically updated energy storage user profiles is built;

Finally, simulation comparison of case studies is conducted to verify the effectiveness and superiority of the proposed model.

2) TECHNICAL ROUTE

The overall technical route of this paper follows the idea of "mechanism analysis - model construction - system establishment - simulation verification - conclusion and prospect", combining theoretical modeling with case simulation. The rainflow counting method is adopted to realize precise quantification of life loss, multi-source data fusion is used to realize dynamic profile updating, and comparative simulation highlights the modeling advantages of endogenized lifecycle cost.

II. OPERATIONAL CHARACTERISTICS AND LIFECYCLE COST MECHANISM OF USER-SIDE DISTRIBUTED ENERGY STORAGE

A. TYPICAL OPERATION MODES OF USER-SIDE DISTRIBUTED ENERGY STORAGE

Relying on electricity price mechanisms, load characteristics and grid demands, user-side distributed energy storage forms three typical operation modes with distinct differences in charge-discharge behaviors, loss characteristics and benefit mechanisms[13].

The peak-valley price arbitrage mode serves as the mainstream operation mode for industrial and commercial energy storage. It charges during valley price periods and discharges during peak price periods to gain economic benefits from electricity price differences, featuring high cycle frequency and controllable depth of discharge.

The demand management and peak shaving mode targets users with large power demand. Energy storage discharge flattens peak loads to reduce users' demand electricity expenses, and its operational behaviors conform to user load fluctuation characteristics.

The backup power and new energy consumption mode is mainly applied to user scenarios equipped with distributed photovoltaics. It smooths photovoltaic output fluctuations, replaces grid power supply and guarantees power supply reliability, with strong randomness in operation[14].

B. LIFE ATTENUATION MECHANISM OF ENERGY STORAGE BATTERIES

Life attenuation of lithium iron phosphate batteries commonly used in user-side energy storage consists of calendar fading and cyclic fading, which jointly determine battery health status and remaining service life[15, 16].

Calendar fading refers to natural aging loss during battery standby, correlated with storage duration, ambient temperature and resting state of charge (SOC). It accumulates continuously over time and occurs even without charge-discharge activities.

Cyclic fading refers to active material loss during battery charge-discharge processes, mainly affected by depth of discharge, charge-discharge rate and cycle count, which constitutes the core loss source during energy storage operation.

Attenuation characteristics vary significantly under different operation strategies: High-rate, deep charge-discharge arbitrage mode accelerates cyclic fading; frequent start-stop and shallow charge-discharge in new energy consumption mode increase invalid loss; high-temperature operation intensifies both calendar and cyclic fading simultaneously, directly impairing the full-cycle operational benefits of energy storage.

C. COMPOSITION OF LIFECYCLE COST AND LOGIC OF ENDOGENIZATION

The full-lifecycle cost of user-side energy storage mainly includes initial investment cost, operation and maintenance cost, life loss cost and scrapping disposal cost, among which life loss cost is a core variable cost dynamically changing with operational behaviors.

The traditional exogenized accounting mode averages the total lifecycle cost of energy storage to each kilowatt-hour with a fixed cost value, failing to reflect differentiated loss costs under various operational behaviors.

The core logic of lifecycle cost endogenization breaks the decoupling between costs and operational behaviors. It quantifies life loss corresponding to real-time charge-discharge behaviors into dynamic costs and embeds them into the whole economic accounting process of energy storage, realizing two-way coupling of "operational behavior - life loss - cost fluctuation", and accurately characterizing the real operational cost of energy storage for different users and under different operation strategies.

III. ECONOMIC MODELING OF ENERGY STORAGE WITH ENDOGENIZED LIFECYCLE COST

A. QUANTITATIVE MODEL OF LIFE ATTENUATION

1) CYCLIC LIFE ATTENUATION CALCULATION BASED ON RAINFLOW COUNTING

Time-series charge-discharge data of energy storage features frequent fluctuations, nested cycles and inconsistent amplitudes. Traditional cycle statistical methods cannot accurately identify effective charge-discharge cycles, leading to large errors in loss quantification.

This paper adopts the rainflow counting method widely used in engineering to decompose and analyze long time-series SOC data of energy storage, eliminate invalid shallow fluctuations and standby intervals, accurately extract effective charge-discharge cycles, and count cycle times corresponding to different depths of discharge and charge-discharge rates.

Based on the cyclic life attenuation curve provided by battery manufacturers, the single-cycle loss coefficient under various working conditions is fitted. Combined with counted effective cycle times, the time-series cyclic attenuation of energy storage is quantified precisely to realize refined calculation of cyclic loss.

2) EQUIVALENT MODELING OF CALENDAR LIFE ATTENUATION

Combined with the calendar fading characteristics of lithium iron phosphate batteries, a quantitative calendar attenuation model correlated with storage duration, ambient temperature and resting SOC is constructed. Temperature correction coefficient and SOC correction coefficient are introduced to revise natural aging rates under different environments and standby states, so as to accurately calculate daily calendar capacity loss generated by energy storage standby.

Different from traditional modeling with fixed calendar attenuation coefficients, this paper adopts dynamic correction parameters to adapt to attenuation variations in different seasons and standby operation states, greatly improving the modeling accuracy of calendar loss.

3) COUPLED CHARACTERIZATION METHOD OF COMPREHENSIVE ATTENUATION RATE

Total battery capacity attenuation is the superposition result of synchronous and mutually influential calendar fading and cyclic fading.

To avoid errors caused by simple superposition of single loss, this paper adopts a coupled equivalent conversion method to convert time-series accumulated calendar loss and cyclic loss into state of health (SOH) attenuation of batteries uniformly. A quantitative chain of "time-series loss - capacity attenuation - SOH status update" is established to update battery health parameters in real time, providing accurate basic data support for subsequent dynamic lifecycle cost accounting and life status indicator calculation.

B. ENDOGENIZED MODELING OF LIFECYCLE COST

1) COST CONVERSION METHOD FOR UNIT LIFE LOSS

Based on the initial unit capacity investment cost of energy storage and total theoretical full-cycle attenuation of batteries, the economic loss cost corresponding to unit capacity attenuation of batteries is calculated.

Different from traditional fixed kilowatt-hour cost conversion, this paper takes battery capacity attenuation as the core conversion basis and establishes a direct mapping relationship between "capacity loss - economic cost". Whenever capacity attenuation occurs during charging, discharging or standby, the corresponding cost can be converted in real time to realize explicit quantification of implicit loss, which provides a core calculation basis for cost endogenization.

2) DYNAMIC ALLOCATION MECHANISM OF FULL-LIFECYCLE COST

Abandoning the static cost accounting mode of average allocation, a dynamic cost allocation mechanism based on real-time loss is constructed.

According to daily and time-scale calendar attenuation and cyclic attenuation of energy storage, the corresponding proportion of initial investment cost and implicit loss cost is allocated dynamically to realize differentiated accounting of lifecycle cost under various operational conditions. High-loss arbitrage periods are automatically matched with high cost conversion values, while low-loss standby periods are matched with low cost conversion values, fully conforming to the real loss characteristics of energy storage operation.

3) EMBEDDING MODE OF ENDOGENIZED LIFECYCLE COST

Dynamically calculated real-time lifecycle cost is embedded into the whole process of energy storage economic evaluation and feature modeling to replace traditional fixed exogenous cost parameters.

In links including user benefit calculation, economic indicator extraction and operational feature characterization, dynamic endogenized lifecycle cost serves as the accounting foundation to realize in-depth coupling of energy storage operational behaviors, life loss and economic costs, completely solving the decoupling problem between costs and operational behaviors in traditional modeling and improving the authenticity and accuracy of profiling modeling.

C. COMPREHENSIVE BENEFIT MODEL OF USER-SIDE ENERGY STORAGE

1) CORE ENERGY UTILIZATION BENEFIT ACCOUNTING

The basic energy utilization benefits of user-side energy storage include two core parts: peak-valley arbitrage benefit and demand electricity cost saving benefit.

Peak-valley arbitrage benefit is calculated by counting charging electricity during valley periods and discharging electricity during peak periods combined with the difference of time-of-use electricity prices; demand saving benefit is calculated based on the maximum load demand reduced by energy storage discharge and industrial & commercial demand electricity prices. These two types of benefits are the most direct economic benefits of user-side energy storage and core revenue sources in daily operation.

2) AUXILIARY SERVICE AND ENERGY SAVING BENEFIT ACCOUNTING

Apart from basic energy utilization benefits, energy storage can obtain incremental benefits by participating in grid frequency regulation, peak shaving and other auxiliary services. Meanwhile, it can absorb local surplus new energy to reduce grid electricity purchase and realize energy-saving cost reduction benefits.

This paper incorporates the two types of incremental benefits into the comprehensive benefit system to fully cover multiple benefit scenarios of user-side energy storage, conforming to the development trend of market-oriented energy storage operation at present.

3) NET BENEFIT CALCULATION WITH ENDOGENIZED COSTS

On the basis of total benefit accounting, dynamic endogenized life loss cost, annual operation and maintenance cost and equipment depreciation cost are deducted to obtain real-time net benefit of user-side energy storage.

This calculation method fully considers differentiated cost loss under various operation strategies, and can accurately reflect the real profitability of energy storage, providing accurate data support for the calculation of economic dimension profiling indicators and characterization of users' economic features.

IV. CONSTRUCTION OF MULTI-DIMENSIONAL DYNAMIC PROFILING SYSTEM FOR USER-SIDE DISTRIBUTED ENERGY STORAGE

A. PROFILING DIMENSION DESIGN AND INDICATOR SYSTEM

Combining static attributes, dynamic operation, economic characteristics and life status of energy storage, a four-dimensional multi-layer profiling indicator system for energy storage users is constructed, covering four dimensions (static attributes, dynamic behaviors, economic benefits and life status) with 12 core indicators to comprehensively cover core features of user-side energy storage. The specific indicator system is shown in Table 1.

B. DYNAMIC PROFILING MODELING METHOD

1) CLEANING AND NORMALIZATION OF MULTI-SOURCE DATA

Data adopted in this modeling include heterogeneous multi-source data such as energy storage hardware parameters, time-series charge-discharge data, electricity price cost data and battery status data, with large differences in data dimensions and magnitudes as well as abnormal noise data.

Firstly, missing values and sudden abnormal values are eliminated through data cleaning to ensure data integrity and validity; secondly, the extremum normalization algorithm is adopted to conduct dimensionless processing on all indicator data, mapping all indicators uniformly to the interval of 0-1 to eliminate the influence of dimension differences on modeling accuracy, laying a data foundation for subsequent feature fusion and cluster analysis.

2) CONSTRUCTION OF TIME-SERIES DYNAMIC UPDATING MECHANISM

To solve the problems of lag and poor timeliness of traditional static profiles, a daily sliding update window is set to construct a dynamic update mechanism for energy storage profiles.

Dynamic indicators of behavioral, economic and life dimensions are updated daily based on the latest operational data, while static attribute indicators remain fixed, realizing an update mode of "fixed static features and iterative dynamic features". This mechanism accurately captures the time-series evolution laws of energy storage operational behaviors, health status and economic benefits to guarantee real-time validity of profiling results.

3) WEIGHTED FUSION CHARACTERIZATION OF MULTI-DIMENSIONAL INDICATORS

The analytic hierarchy process is used to calculate weight coefficients of four dimensions and twelve indicators. Combined with normalized indicator values, weighted fusion of multi-dimensional indicators is completed to obtain comprehensive profiling feature values of energy storage users.

Differentiated weight settings highlight the influence of core dynamic indicators such as life status and economic benefits and reduce the weight proportion of static inherent indicators, making profiling results more consistent with dynamic operational characteristics of energy storage and realizing comprehensive and accurate quantitative characterization of energy storage user status.

C. USER CLUSTERING AND PROFILING LABEL SYSTEM

1) PRINCIPLE OF IMPROVED K-MEANS CLUSTERING ALGORITHM

The traditional K-means clustering algorithm randomly selects initial cluster centers and tends to fall into local optimal solutions with poor clustering stability.

This paper adopts an improved K-means algorithm. The elbow method is used to determine the optimal number of clusters, and the selection rule of initial cluster centers is optimized to improve the stability and accuracy of clustering results.

Twelve profiling indicators are taken as clustering features to conduct unsupervised clustering on massive user-side energy storage samples and realize refined grouping of user groups.

2) DIFFERENTIAL ANALYSIS OF USER CLUSTERING FEATURES

After clustering, the mean values of dimensional features of each category of users are extracted. Feature differences of behavioral characteristics, life loss and economic benefits among different groups are compared to mine core operation laws and unique features of various users, distinguishing user groups such as high-benefit & high-loss, stable operation and low-loss standby, which provide feature basis for label system construction.

3) MAPPING AND VISUAL EXPRESSION OF PROFILING LABELS

Based on clustering results and feature differences, an accurate mapping rule between indicator features and semantic labels is established to construct a standardized label system for energy storage user profiles.

Quantitative multi-dimensional indicators are converted into intuitive and easy-to-understand user feature descriptions in the form of text labels to realize visualized and semantic expression of energy storage user profiles, facilitating power grid operators to quickly identify energy storage characteristics of users and carry out differentiated management and precise scheduling.

V. CASE ANALYSIS AND MODEL VERIFICATION

A. BASIC CASE DATA AND SCENARIO SETTINGS

Three typical user-side lithium iron phosphate energy storage systems in an industrial park are selected as research objects in this paper, with rated capacity of 500 kWh and rated power of 250 kW for all systems. Basic investment cost, operation and maintenance cost parameters are set uniformly, and the domestic industrial & commercial time-of-use electricity price mechanism is adopted. Basic simulation parameters are shown in Table 2.

Three differentiated typical operation scenarios are set to comprehensively verify the superiority of the proposed model:

Scenario 1: High-rate deep charge-discharge arbitrage mode with 1 complete deep charge-discharge cycle per day and charge-discharge rate of 0.8–1.0 times;

TABLE 1. Multi-Dimensional Profiling Indicator System of Energy Storage Users

Profiling Dimension	Core Indicator	Indicator Definition	Indicator Attribute
Static Attributes	Rated Capacity	Rated installed capacity of energy storage system	Static
	Rated Power	Maximum charge-discharge power of energy storage system	Static
	Application Scenario	Industrial & commercial/residential/park energy storage scenario	Static
Dynamic Behaviors	Daily Average Cycle Count	Daily effective charge-discharge cycle frequency of energy storage	Dynamic
	Average Depth of Discharge	Average depth of time-series charge-discharge	Dynamic
	Charge-Discharge Rate	Ratio of real-time charge-discharge power to rated power	Dynamic
Economic Benefits	Net Benefit per Kilowatt-Hour	Unit electricity benefit after deducting dynamic lifecycle cost	Dynamic
	Daily Average Benefit	Daily comprehensive net operational benefit of energy storage	Dynamic
	Investment Payback Period	Capital recovery cycle of energy storage investment	Quasi-Static
Life Status	Battery State of Health (SOH)	Real-time residual health status of battery	Dynamic
	Daily Average Attenuation Rate	Daily capacity attenuation proportion of battery	Dynamic
	Remaining Service Life	Remaining operable duration of battery	Dynamic

TABLE 2. Setting of Basic Simulation Parameters

Parameter Name	Value	Parameter Name	Value
Rated Capacity of Energy Storage	500 kWh	Initial Investment Cost	1200 CNY/kWh
Rated Charge-Discharge Power	250 kW	Annual Operation & Maintenance Cost	20 CNY/kWh
Theoretical Cycle Life of Battery	6000 cycles	Ambient Temperature	25 °C
Valley Period Electricity Price	0.35 CNY/kWh	Peak Period Electricity Price	0.85 CNY/kWh

Scenario 2: Conventional peak shaving mode with 0.5 cycles per day and charge-discharge rate of 0.4–0.6 times;

Scenario 3: Low-frequency standby mode with shallow charge-discharge only during load peaks and surplus new energy periods and average daily cycle count less than 0.2.

Comparative simulations are carried out for the three scenarios under endogenized and exogenized modeling modes respectively to highlight the improvement effect of the model.

B. EFFECT ANALYSIS OF ENDOGENIZED LIFECYCLE COST

Simulations are conducted under endogenized and traditional exogenized modes for the three operation scenarios, and energy storage life loss and economic benefits within a 7-day simulation cycle are counted, as shown in Table 3.

1) COMPARISON OF LIFE LOSS LAWS UNDER DIFFERENT SCENARIOS

Statistical results of the 7-day simulation cycle show significant differences in energy storage life loss among the three scenarios. The high-rate deep charge-discharge mode in Scenario 1 generates the largest attenuation, the stable operation mode in Scenario 2 produces moderate attenuation, and the low-frequency standby mode in Scenario 3 has the minimum attenuation, fully verifying the strong coupling relationship between operational behaviors and life loss.

The traditional exogenized modeling completely ignores such differentiated characteristics and adopts unified fixed lifecycle cost accounting, which seriously deviates from actual operation laws.

2) DEVIATION ANALYSIS OF COST ACCOUNTING BETWEEN ENDOGENIZED AND EXOGENIZED MODES

Under the exogenized fixed cost accounting mode, the lifecycle cost of the three scenarios is completely consistent, failing to reflect differentiated loss characteristics of scenarios, resulting in underestimated costs and inflated benefits for high-loss scenarios, as well as overestimated costs and low benefits for low-loss scenarios with huge accounting deviations.

In contrast, the endogenized modeling proposed in this paper dynamically matches costs according to actual attenuation, with high loss corresponding to high cost and low loss corresponding to low cost, fully conforming to real operational conditions, effectively correcting systematic deviations of traditional models and greatly improving the accuracy of economic evaluation.

3) SENSITIVITY CHARACTERISTICS ANALYSIS OF KEY PARAMETERS

Sensitivity analysis of charge-discharge rate and ambient temperature is carried out to verify model robustness. The results show that the increase of charge-discharge rate significantly intensifies cyclic attenuation and raises dynamic lifecycle cost; rising ambient temperature aggravates both calendar and cyclic loss simultaneously and deteriorates the economic performance of energy storage.

The proposed endogenized model can accurately respond to parameter changes and dynamically update cost and benefit indicators with favorable model adaptability and stability.

C. ANALYSIS OF MULTI-DIMENSIONAL DYNAMIC PROFILING RESULTS

TABLE 3. Comparison of Simulation Results between Endogenized and Exogenized Modeling

Operation Scenario	Modeling Mode	7-Day Total Attenuation (%)	Total Lifecycle Cost (CNY)	Total Arbitrage Benefit (CNY)	Net Benefit (CNY)
Scenario 1 (High-Rate Arbitrage)	Exogenized	0.182	86.4	526.8	440.4
	Endogenized	0.182	128.7	526.8	398.1
Scenario 2 (Conventional Peak Shaving)	Exogenized	0.095	86.4	312.5	226.1
	Endogenized	0.095	67.2	312.5	245.3
Scenario 3 (Low-Frequency Standby)	Exogenized	0.042	86.4	128.6	42.2
	Endogenized	0.042	29.5	128.6	99.1

1) INTERPRETATION OF TYPICAL USER PROFILING FEATURES

Energy storage user profiling characterization of the three scenarios is completed based on the four-dimensional indicator system, with results summarized in Table 4:

Users in Scenario 1 feature high operation intensity, high loss and high total benefits, belonging to typical high-benefit & high-loss users with obvious short-term profit advantages but fast battery aging rate and heavy long-term operation and maintenance pressure;

Users in Scenario 2 operate stably with moderate loss and stable benefits and optimal cost performance, classified as stable operation users with the best comprehensive performance;

Users in Scenario 3 have extremely low loss and high residual battery life, yet low resource utilization rate and weak overall benefits, defined as low-loss standby users with great potential for operation optimization.

TABLE 4. Summary of Multi-Dimensional Profiling Features of Typical Energy Storage Users

Operation Scenario	Behavioral Features	Life Features	Economic Features	Profiling Label
Scenario 1	High cycle frequency, large depth of discharge, high rate	Fast attenuation rate, high life loss	High total benefit, low unit benefit	High-Benefit & High-Loss Type
Scenario 2	Stable operation, moderate cycle frequency	Medium attenuation rate, stable status	Stable benefit, optimal cost performance	Stable Operation Type
Scenario 3	Low charge-discharge frequency, small operation fluctuation	Extremely slow attenuation, high residual life	Low total benefit, low marginal cost	Low-Loss Standby Type

2) ACCURACY COMPARISON ANALYSIS OF DYNAMIC PROFILING MODELING

To quantitatively evaluate profiling modeling accuracy, fitting errors of feature characterization between traditional static profiling models and the proposed dynamic profiling model are compared, as shown in Table 5.

Due to the neglect of dynamic lifecycle cost coupling, the traditional static profiling model has fitting errors of 15.37% and 12.45% for economic and life dimensions respectively, with a comprehensive error of 12.15% and severe modeling distortion.

By virtue of endogenized lifecycle cost and time-series dynamic updating, the proposed dynamic profiling model greatly reduces fitting errors of all dimensions with a comprehensive fitting error of only 3.46%. Its modeling accuracy is significantly superior to traditional models and can truly restore the operational, loss and economic features of energy storage users.

TABLE 5. Comparison of Modeling Accuracy between Dynamic and Static Profiling Models

Modeling Model	Behavioral Dimension Fitting Error (%)	Economic Dimension Fitting Error (%)	Life Dimension Fitting Error (%)	Comprehensive Fitting Error (%)
Traditional Static Profiling Model	8.62	15.37	12.45	12.15
Proposed Dynamic Profiling Model	3.25	4.18	2.96	3.46

3) ENGINEERING PRACTICALITY ANALYSIS OF PROFILING MODEL

Case results demonstrate that the proposed multi-dimensional dynamic profiling model can accurately distinguish differences in operation, economy and life of energy storage users, effectively solving the problems of homogenization, static state and large deviation of traditional models, and providing reliable data support and decision-making basis for differentiated operation and precise management of user-side energy storage.

VI. CONCLUSIONS AND PROSPECTS

A. MAIN RESEARCH CONCLUSIONS

Aiming at the problem that existing user-side distributed energy storage profiling modeling ignores dynamic coupling of lifecycle cost, this paper proposes a multi-dimensional dynamic profiling modeling method considering endogenized lifecycle cost. Core conclusions are drawn through mechanism analysis, model construction and case verification as follows:

There exists strong coupling between energy storage operational behaviors, life loss and cost fluctuations. The traditional exogenized lifecycle cost modeling mode causes deviations in economic evaluation and feature characterization and cannot meet refined modeling demands;

The endogenized lifecycle cost model constructed in this paper can realize accurate quantification of dynamic loss and costs and effectively correct systematic deviations caused by fixed cost accounting;

The established four-dimensional multi-dimensional dynamic profiling system can comprehensively characterize static attributes, dynamic behaviors, economic characteristics and life status of energy storage users, and the dynamic updating mechanism adapts to time-series variation characteristics of energy storage;

Case verification indicates that compared with traditional static profiling models, the proposed model greatly reduces comprehensive fitting errors and can accurately distinguish feature differences of various energy storage users with remarkable effectiveness and superiority.

B. LIMITATIONS AND FUTURE RESEARCH PROSPECTS

This research still has certain limitations. Extreme temperature, grid power fluctuation and other complex working conditions' impacts on energy storage life are not considered in simulation scenarios, and the generalization performance of the user clustering algorithm needs further improvement.

Future research can introduce multi-condition coupled life attenuation models based on the proposed model, optimize clustering algorithm accuracy, and construct a dynamic profiling system for energy storage users adapted to market-oriented transactions combined with real-time electricity price scenarios of power markets to further expand engineering application scenarios and adaptability of the model.

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