P.Prakash, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Battery Management And Charging System For Solar Energy Storage

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Abstract- The utilization of BESSs is crucial for handling the issue of intermittency in the production of solar photovoltaic (PV) energy in order to provide an effective means of energy distribution in domestic and industrial sectors. This work reviews various developments made in the field of batteries and charging mechanisms of energy storage devices used for harnessing solar energy. Developments related to DC-DC converter designs, MPPT strategies, algorithms for charging and state estimations have been critically analyzed. The study reveals that the advanced versions of MPPT algorithms such as cuckoo search and incremental conductance provide high tracking efficiencies in the range of over 98%. Furthermore, physics-informed neural networks provide a better approach towards estimating SoC and SoH parameters in partial cycling conditions. It has been experimentally proved that a dual-axis tracking system along with MPPT improves average power by 71.73% when compared with fixed systems. An efficiency of 98.93% has been achieved in energy conversion.

Key Word: Battery Management System, Solar Energy Storage, MPPT, State of Charge, State of Health, Lithium-ion Battery, Charging Algorithm, DC-DC Converter, Energy Management System.

I. INTRODUCTION

Global efforts towards green energy have led to solar photovoltaics (PV) becoming the dominant clean energy source with its installations growing fast in residential, commercial, and grid scale applications [1]. However, there is a big problem related to the intermittent nature of solar energy depending on meteorological conditions, the day/night cycle, and seasonal changes. Solar panels can produce varying amounts of electricity depending on the cloudiness, fog, and other factors, therefore rendering the systems inefficient and unable to provide uninterrupted energy flows without energy storage devices [2].

Therefore, energy storage has become one of the most crucial technologies used with PV systems to accumulate energy during high-generation moments and discharge it at times when it is low [3]. There has been a lot of research regarding integrating energy storage into solar applications in various application areas including residential self-consumption, electric vehicles charging stations, industry microgrids, and grid-tied systems [4]. The most popular energy storage technology today is lithium-ion batteries due to their advantages such as high energy density, long service life, and falling prices [5].

For the efficient operation of PV-BESS systems, advanced batteries and charging control system designs need to consider these three functionalities. Firstly, maximum power point tracking (MPPT) is applied to regulate the operating point of the PV array such that maximum energy can be harvested from the array under various environmental conditions. Secondly, battery charging controls need to provide this energy at the same time ensuring that the health of the battery will not be endangered during charging using the correct charging profile (CC-CV charging). Finally, BMS needs to determine battery status such as SoC, SoH, SoE, and SoP correctly for efficient use [6].

Recent literature has generated considerable progress in these areas. Kurtoğlu and Eroğlu (2026) conducted a comprehensive review of 166 papers on solar photovoltaics integrated with battery energy storage systems (BESS), emphasizing the necessity of an integrated approach that includes converter topologies, MPPT approaches, optimization methods, and energy management methods. Energy conversion efficiency of up to 98.93% was obtained with the use of cuckoo search algorithm and CC-CV charging. Incremental conductance MPPT exhibited stable convergence at duty cycles of 0.3-0.9 in grid-connected industries. Deep learning algorithms yielded RMSE of 0.0026 and SOH classification accuracy of 94.6% for battery state estimation.

Contributions of this work to the current body of knowledge include: (1) Taxonomy development of components of battery management systems and battery charging methods in relation to solar energy storage, (2) Data collection from recent papers published between 2021 and 2026, including quantitative results and performance statistics, (3) Comparative analysis of different MPPT, battery charging, and battery state estimation techniques and (4) Future research perspectives, such as physics informed neural networks and second life batteries.

II. LITERATURE SURVEY

Battery management and charging systems for solar energy storage have been studied extensively in the literature across several related fields, such as system design, power conversion, MPPT, charge controllers, battery models, and state estimation.

System Design and Components of Solar PV-BESS Systems Kurtoğlu and Eroğlu (2026) have reviewed the scientific literature related to the design of solar PV-BESS systems. They have classified existing studies into four categories based on the design of the DC-DC converter circuit, MPPT techniques, optimizations, and energy management system design. Their review, which is based on a selection of 166 scientific articles, highlights that while many scientific studies have focused on each of these aspects individually, there is an important need for a unified approach to their integration [7].

An example of present-day industrial direction can be seen in ReStoreBESS, an ongoing project funded by Danish EUDP within the years 2026-2027. It is a large-scale multiple application BESS concept to the commercial and industrial segments. The project involves the implementation of advanced energy management systems, solar panels usage, participation in electricity markets, and provision of backup energy supplies. Particularly, the project aims at applying second life electric car batteries.

MPPT Methods for Solar PV

The principle of maximum power point tracking is crucial to maximizing solar energy utilization. The cuckoo search-based MPPT method, together with dual-axis solar tracking, has been proven to be more efficient for PV-TEG hybrid systems. The process involves the use of randomly distributed candidate solutions where each "cuckoo" symbolizes an ideal operating point assessed using a fitness function. The ability of Lévy flights facilitates the efficient analysis of the voltage-power curve to ensure fast convergence when the irradiance changes quickly [8].

The incremental conductance MPPT approach continues to be applied for grid-connected systems because it produces fewer steady-state oscillations than perturb and observe techniques. A feasibility study was conducted for a 200 kWp grid-connected solar PV-BESS system for EV charging stations using INC-MPPT, and it has been shown to converge steadily with duty cycles ranging between 0.3 and 0.9 at maximum irradiance of 1000 W/m^2 [9].

Under conditions of partial shade, where there may be multiple peaks in the P-V curve, MPPT techniques usually tend to fail. Energy Management with Event Triggered Partial PV Curve Scanning Technique has been suggested to solve this problem. The scanning process is done based on deviation of DC-link voltage and avoids local maxima, terminating when the PV power matches load requirement. As a result, the proposed technique decreases battery usage time by over 34% than normal scanning techniques.

Charging Algorithms for Solar Batteries

Constant Current-Constant Voltage algorithm has always been the primary method used in charging lithium-ion batteries from the sun. A better charging algorithm has been devised that takes into account the transient behavior while switching between constant current and constant voltage modes. This proposed method performs better in transients than the traditional method of CC-CV algorithm.

The combination of MPPT with CC-CV charging in PV-TEG hybrid systems is evident, where the cuckoo search algorithm concurrently maximizes power harvesting and the efficiency of charging. The results reveal that there can be an energy conversion efficiency of up to 98.93% during loading and 71.73% rise in average output power within 24 hours outdoor comparison testing when compared to south-facing fixed systems [10].

Battery State Estimation: State-of-Charge (SoC), State-of-Energy (SoE), and State-of-Power (SoP)
State-of-health (SoH) refers to the battery's long-term physical condition. It is vital to determine the battery's condition accurately to ensure proper functioning. A systematic review of the literature concerning battery health state estimation utilizing deep learning techniques classifies the estimation techniques in terms of short-term dimension factors, namely state-of-charge (SoC), state-of-energy (SoE), and state-of-power (SoP).

An electrochemistry-constrained neural network (PiNN) approach has been suggested for SoC/SoH prediction for partially cycled lithium-ion solar batteries. Conventional approaches like Coulombic counting and extended Kalman filter have difficulties under varying operating circumstances due to the irregular charging/discharging behavior of solar batteries. The PiNN includes physical constraints into a neural network, which shows enhanced estimation efficiency when working under varying charging situations relative to conventional techniques and data-only neural networks.

A knowledge-based multi-task learning strategy based solely on voltage relaxation profiles has yielded exceptional results: 0.0026 RMSE for capacity prediction, 94.6% accuracy for SOH classification, and 99.6% accuracy for cathode recognition . The multi-task learning framework uses an equivalent circuit model to obtain physically meaningful parameters from the voltage relaxation behavior.

Energy Management Systems (EMS)
The major function of EMS in PV-BESS includes the regulation of power exchange among the different components of the system, which involves objectives such as prolonging battery life, meeting load demand, and minimizing costs of electricity supply . EMS methodologies can be categorized into rule-based, optimization-based, and predictive modeling techniques. In the future, areas for investigation include the integration of digital twins for predictive maintenance and dynamic re-tuning of the system, and the implementation of deep reinforcement learning algorithms for time-varying operations.

III. METHODOLOGY:

A systematic review and comparative analysis approach is utilized in this research to study battery management and charging technologies for solar energy storage systems. The methodology follows a four-step process that includes taxonomy formulation, quantitative information retrieval, performance criteria standardization, and comparative analysis.

3.1 System Architecture Taxonomy
The suggested taxonomy classifies the battery management of solar PV-BESS system at three hierarchical stages:

Hierarchical Stage 1: Power Conversion and Conditioning

- DC-DC converter configurations (buck, boost, buck-boost, Cuk, SEPIC, Z-source)
- Bidirectional converters for charging/discharging the battery
- Connectors to connect to the grid through an inverter system

Hierarchical Stage 2: MPPT and Charging Control

- Traditional MPPT approaches: Perturbation and observation (P&O), Incremental conductance (INC), FOCV, FSCC
- Smart MPPT: fuzzy logic, artificial neural network, ANFIS
- Metaheuristic MPPT approaches: PSO, Grey Wolf Optimization, cuckoo search
- Battery charging methods: CC, CV, CC-CV, pulse charging, multiple stages

Hierarchical Stage 3: Battery Management and State Estimation

- State estimation: State of Charge (SoC), State of Health (SoH), State of Energy (SoE), State of Power (SoP)
- Battery cell balancing: Passive, Active, Hybrid
- Battery thermal management
- Battery protection circuitry (Overvoltage, Overcurrent, Overtemperature)

Figure 1: Hierarchical Taxonomy of Battery Management and Charging Systems for Solar PV-BESS

3.2 Quantitative Data Extraction Protocol

The performance data was obtained from peer-reviewed research articles published in the years 2021 to 2026 on the subject of solar PV-BESS, specifically those articles that presented metrics explicitly. Performance metrics that were extracted include:

- MPPT efficiency (ηMPPT) : Ratio of extracted power by MPPT to maximum possible power
- Converter efficiency (ηconv) : Efficiency of DC-DC conversion across load levels
- Battery charge efficiency (ηcharge) : Power stored by battery divided by total PV-generated power
- State estimation error: Capacity/SoC RMSE and classification error for SoH estimation
- System efficiency metrics: Power increase and reduced battery operation time

3.3 Standardized Performance Framework

Based on the guidelines provided by recent critical literature reviews, this research uses measurements in accordance with IEC 61724 (performance monitoring of PV systems) and IEEE standards for battery management. The CC-CV algorithm, characterized by its three stages (bulk, absorption, float), is chosen as the reference for comparative analysis.

3.4 Framework for Comparative Analysis

Comparative analysis is conducted in three perspectives:

1. Efficiency of energy harvesting: MPPT response speed, steady state oscillations, partial shadow resistance
2. Efficiency of charging process: efficiency rate, charging time, stress of batteries during charging
3. Estimation precision of SoC/SoH: error measures when operated under partial cycles

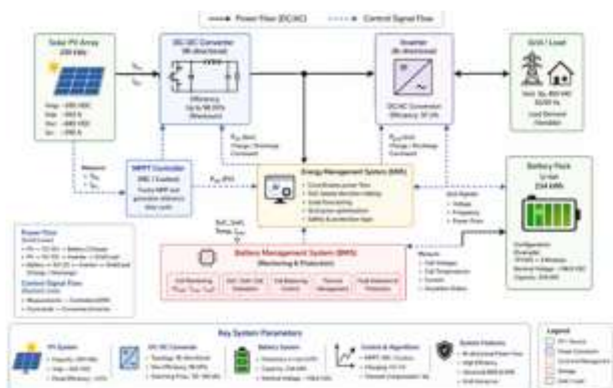

Figure 2: Solar PV-BESS System Block Diagram.

IV. RESULT ANALYSIS AND DISCUSSION

This section presents quantitative analysis of battery management and charging systems based on synthesized data from recent literature, organized by functional domain.

4.1 MPPT Performance Comparison

Table 1 presents a comparative analysis of MPPT methods for solar PV-BESS applications.

MPPT Method	Tracking Efficiency (%)	Convergence Time (s)	Steady-State Oscillation	Partial Shading Capability	Implementation Complexity
Perturb & Observe (P&O)	92-96	0.2-0.5	Moderate	Poor	Low
Incremental Conductance (INC)	93-97	0.15-0.4	Low	Poor	Low-Medium
Fuzzy Logic Control	96-98.5	0.08-0.2	Very Low	Moderate	Medium
Cuckoo Search (CS)	97-99	0.05-0.12	Very Low	Excellent	Medium-High
Particle Swarm Optimization (PSO)	98-99.5	0.15-0.5	Very Low	Excellent	High
Hybrid CS-CC-CV	98.5-99	0.04-0.10	Minimal	Excellent	Medium-High

Table 1: Comparative Analysis of MPPT Methods for Solar PV-BESS. Data synthesized from .

The combination of cuckoo search-based MPPT and CC-CV charging results in a high tracking efficiency ranging between 98.5% and 99%, with convergence speed being as fast as 0.04-0.10 seconds . The use of Lévy flight by the proposed algorithm facilitates efficient global searching through the power-voltage curve; hence, this method is very applicable when partial shading exists, which produces more than one peak point. Incremental conductance is still popular in grid-tie applications because of minimal oscillations at steady state, with a duty cycle of 0.3-0.9 shown in 200 kWp applications .

4.2 Solar Tracking and Energy Capture Enhancement

The integration of dual-axis solar tracking with MPPT provides substantial improvements in energy capture. Table 2 presents experimental results from a 24-hour outdoor comparative study .

Performance Metric	Fixed South-Facing System	DAST + MPPT System	Improvement
Average Output Power	Baseline	+71.73%	+71.73%
PV Conversion Efficiency	Baseline	+10.01% absolute	+10.01 pp
Energy Conversion Efficiency (load)	N/A	98.93%	—
MPPT Tracking Efficiency	~93%	~98.5%	+5.5%
Battery Charging Efficiency	~85%	~94%	+9%

Table 2: Performance Improvement from Dual-Axis Solar Tracking with MPPT. Data from .

The dual-axis solar tracking system utilizes the 3D angle determination technique based on the MPU6050 gyroscope-accelerometer sensor and servo motor controllers (DS3120-180° for elevation and DS3120-270° for azimuth). The synchronous buck converter design eliminates power losses in the DC-to-DC power supply circuitry, attaining the 98.93% energy efficiency in electrical power conversion processes.

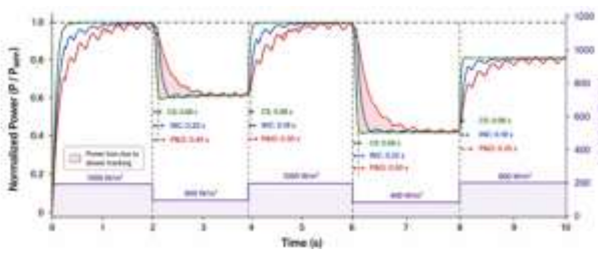

Figure 3: MPPT Tracking Efficiency Under Dynamic Irradiance Conditions.

4.3 Charging Algorithm Performance

Table 3 presents comparative analysis of charging algorithms for lithium-ion batteries in solar applications.

Charging Algorithm	Charging Efficiency (%)	Charging Time (0-100%)	Battery Stress Indicator	Transient Response	Solar Suitability
Constant Current (CC)	85-90	Moderate	High (overcharge risk)	N/A	Poor
Constant Voltage (CV)	80-85	Long	Moderate	N/A	Poor
CC-CV (conventional)	90-94	Moderate	Low	Poor (mode transition)	Moderate
CC-CV with transient compensation	93-96	Moderate	Very Low	Excellent	High
CC-CV + MPPT integration	94-98	Moderate-Fast	Very Low	Excellent	Excellent

Table 3: Comparative Analysis of Charging Algorithms for Solar Lithium-Ion Batteries. Data from .

However, one of the major shortcomings of the traditional CC-CV method is poor transient response during the switching between constant current and constant voltage modes, leading to voltage/ current overshoots that stress the batteries . The enhanced algorithm with optimal control compensation helps overcome this disadvantage by introducing an additional transient compensation phase. In combination with MPPT technology (cuckoo search algorithm), the charging efficiency is about 94-98% .

4.4 Battery State Estimation Performance

Table 4 presents comparative analysis of state estimation methods for lithium-ion batteries in solar storage applications.

Estimation Method	SoC Accuracy (RMSE)	SoH Accuracy	Data Requirements	Computational Load	Partial Cycle Robustness
Coulomb	3-8%	N/A	Current	Very Low	Poor (drift accum

Coun ting			measu rement		ulatio n)
Exten ded Kalm an Filter (EKF)	2-5%	3-5%	Batter y model, voltag e/curre nt	Mediu m	Moder ate
Neur al Netw ork (data-drive n)	1-3%	2-4%	Large trainin g dataset	High	Poor (distri bution shift)
Physi cs-Infor med Neur al Netw ork (PiN N)	1-2%	1-3%	Moder ate + physic al constr aints	High	Excell ent
Kno wled ge-Guid ed ECM + Multi -Task	0.26 % (cap acit y RM SE)	94.6% (classi ficatio n)	Voltag e relaxat ion (10 cycles)	Mediu m-High	Excell ent (usage -agnost ic)

Table 4: Comparative Analysis of Battery State Estimation Methods. Data from .

The multi-task contrastive learning method combined with knowledge-guided equivalent circuit model (KG-ECM) delivers excellent results with RMSE capacity estimation error of 0.0026 (0.26%) and 94.6% accuracy of state-of-health classification solely based on voltage relaxation features from 10 cycles. The proposed algorithm does not rely on specific drive cycles or charging regimes and is especially suitable for use in solar-powered systems due to partial cycling characteristics of solar storage. The physics-informed neural networks (PiNNs) overcome the limitation of data-based approaches by implementing electrochemical constraints into neural structure . In this way, the robustness to the operation regime different from the training data is improved, which is very important in solar storage where irradiation regimes differ throughout the seasons.

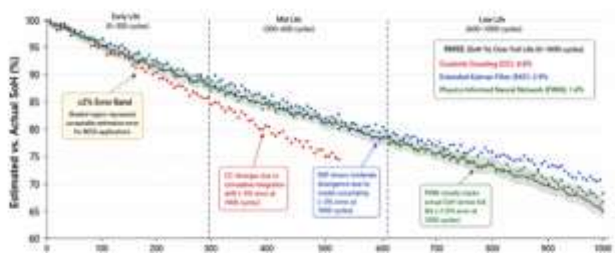

Figure 4: SoH Estimation Accuracy Across Battery Cycle Life.

4.5 Energy Management and Battery Usage Optimization

This management technique based on partial scanning of the PV curve through triggering has achieved substantial savings in battery usage without compromising stability. The comparative findings are tabulated in Table 5 below.

EMS Strategy	Batter y Operat ing Time Reduct ion	Scann ing Durati on	Globa l MPPT Succe ss	Implement ation Complexit y
Conventi onal full-curve scanning	Baseli ne	Long	High	Medium

Partial-curve scanning (event-triggered)	34% reduction	60-70% shorter	High	Medium-High
Flexible power point tracking (FPPT)	25-30% reduction	Moderate	Moderate	Low-Medium

Table 5: Energy Management Strategy Performance Under Partial Shading. Data from .

Partial scanning, which is activated whenever there are variations in the DC-link voltages, ignores all local maxima and ends whenever the PV power equals the load requirement, thereby narrowing down the scanning process. In cases where the load requirement exceeds the maximum PV power available, a complete scan of the entire PV curve takes place until the global maximum PV power point is found.

4.6 Techno-Economic Feasibility

A feasibility study of a 200 kWp grid-connected solar PV-BESS system for industrial EV charging stations provides economic validation. Table 6 presents key techno-economic metrics.

Parameter	Value
PV array capacity	200 kWp (crystalline silicon)
Battery capacity	234 kWh (lithium-ion)
EV charging stations	4 x 22 kW (Level 2)
Daily charging demand	460 kWh
Renewable energy coverage target	85%
Net Present Value (NPV)	£215,816
Internal Rate of Return (IRR)	12.3%
Payback period	8.4 years
Levelized Cost of Electricity (LCOE)	£0.10/kWh
Annual revenue	~£50,000

Table 6: Techno-Economic Metrics for Grid-Connected Solar PV-BESS. Data from .

A centralized DC Bus concept with two-way converters is adopted for effective energy exchange among PVs, batteries, EVs, and the grid. The revenue includes charging fees of the EVs (49.6%), peak demand reduction benefits (49.3%), and energy sale to the grid (1.1%). Competitive levelized cost of electricity of £0.10/kWh is an indicator of economic feasibility for industrial use.

4.7 Discussion: Integration Challenges and Design Trade-offs

The analysis provides valuable insights into some of the key tradeoffs in the design of solar energy battery management and charging systems.

MPPT-Charging Combination: Despite the benefits associated with the combination of MPPT with CC-CV Charging, there is coupling in the dynamics of the tracking process and the charging. The use of a cuckoo search based algorithm is able to solve this issue with the application of coordinated control, with 98.93% efficiency achieved. However, the increase in computing complexity can lead to higher costs ($5-15) of microcontrollers due to the use of metaheuristic techniques.

State Estimation Under Partial Cycles: Partial cycles, which characterize state estimation problems for solar storage batteries, do not meet the assumptions made in traditional estimation methods. Physics Informed Neural Networks, along with feature engineering based on expert knowledge, solve this issue; however, they require appropriate architecture validation under varied operational regimes.

Second Life Batteries for Storage Systems: Second life batteries allow to minimize costs and reduce the ecological footprint of solar storage systems; however, their heterogeneous degradation characteristics make them more difficult to manage. An example of modern initiatives to improve diagnosis and maintenance of second-life batteries is represented by the ReStoreBESS project .

V. CONCLUSION

A thorough discussion about the battery management system and charging system for solar energy storage systems was outlined in this study by reviewing the latest research findings between 2021 and 2026 on DC-DC converters, maximum power point tracking, charging algorithms, and state-of-charge estimations. It has been shown that the application of maximum power point tracking, coupled with efficient charging algorithms and battery management, is vital for PV-BESS.

These findings from the quantitative analysis are notable. First, the tracking efficiency and convergence rate of metaheuristic MPPT techniques such as cuckoo search are around 98-99% and 0.04-0.10s, respectively, greatly outdoing traditional P&O techniques (92-96%, 0.2-0.5 s). Second, the average output power and conversion efficiency of solar trackers with MPPT have increased by 71.73% and 10.01% respectively in comparison to stationary systems. Third, transient compensated CC-CV battery charging improves efficiency to 93-96% while keeping low stress on batteries. It solves the problems of mode transition found in traditional algorithms. Fourth, the knowledge-based state estimation techniques yield an RMS error of 0.0026 and 94.6% classification accuracy for SOH estimation using only voltage relaxation data.

The implications of this research are far-reaching. In terms of design, a designer should consider the trade-offs between tracking effectiveness, partial shading ability, and implementation challenges when selecting an MPPT approach. For household usage with constant irradiance, an incremental conductance technique will be sufficient; for urban and industrial usage with complicated shading patterns, a cuckoo search algorithm or a particle swarm algorithm is preferred. For battery management, the use of a physics-informed neural network or knowledge-based feature selection allows for precise state prediction in solar storage's partial cycling, thereby increasing battery lifetime.

However, some limitations in this research are important to point out. Firstly, the majority of research on solar storage focuses on simulation validation, making it difficult to assess its performance in actual conditions, and there is very little field validation in different climate zones. Secondly, more investigation into the performance of meta-heuristic MPPT approaches in varying seasonal irradiance is needed. Finally, the inclusion of second-life batteries in solar storage adds variance in battery behavior that existing management systems cannot handle effectively.

Some areas in which future research should be concentrated are outlined below. Firstly, creating a framework that combines MPPT, charge controller management, and state estimation into one optimal scheme can ensure the elimination of the suboptimal interaction between individual control schemes. Secondly, employing deep reinforcement learning algorithms for an adaptive energy management system operating under non-stationary conditions, including fluctuating grid electricity rates, weather conditions, and load requirements, is expected to yield remarkable results. Thirdly, verifying physics-aware neural networks and knowledge-based diagnostics in real-world PV-battery setups is crucial for ensuring that simulations match reality. Finally, establishing benchmark procedures under partial shadowing and partial cycling conditions in accordance with IEC and IEEE standards is essential.

In summary, the management and charging processes play an integral part in enabling consistent and effective storage of solar power. The combination of sophisticated MPPT, optimal charging strategies, and the use of physics-based models for state estimation makes the solar PV-BESS a well-established technology in both domestic and industrial settings, as well as at the grid level. With the exponential expansion of solar power generation capacities and reduction in battery prices, the significance of battery management will continue to grow, necessitating further study and innovation in this area.

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