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Database-Driven Energy Management in Electric Vehicles

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Abstract

With the growing concern over environmental pollution, there is an increasing demand for sustainable and eco-friendly technologies. Among these, electric vehicles (EVs) have emerged as a promising alternative to conventional fossil-fuel-based transportation. However, as EV adoption accelerates, efficient energy management becomes critical to enhance vehicle performance, extend battery life, and ensure overall system reliability. This research presents a Database-Driven Energy Management System (DBEMS) that leverages real-time data from EV components to facilitate intelligent decision-making and optimization. The proposed system utilizes time-series databases to collect and store dynamic parameters such as battery health, temperature, charge-discharge cycles, and energy consumption patterns. By structuring this data within a robust database framework, the system enables comprehensive analysis and predictive modeling. A comparative study between SQL (Structured Query Language) and NoSQL (Not Only SQL) database architectures is conducted to evaluate their effectiveness in handling large-scale, heterogeneous EV data. The paper discusses the strengths and limitations of each model in terms of scalability, query performance, and data flexibility. Furthermore, the integration of predictive analytics and machine learning techniques within the DBEMS framework is explored to forecast energy demands, detect anomalies, and optimize charging strategies. This approach not only improves operational efficiency but also contributes to the long-term sustainability of EV systems. The findings underscore the importance of data-centric energy management in advancing the next generation of smart electric vehicles..

Keywords: Pollution, electric vehicles, energy management, DBMS, SQL NoSQL, predictive analysis

INTRODUCTION

The increasing global warming has an impending need for us to stop the use of non-renewable resources and reduce carbon emissions. Carbon emissions from vehicles are increasing annually. PM (Particulate matter) is making the air more dangerous. PM 2.5 and PM 10 are causing different diseases. Electric vehicles have been adopted by many countries since their development, creating a positive impact on the environment. Efficient energy management is vital to optimize performance and prolong battery life. Computer science, particularly database technologies, plays a pivotal role in storing, processing, and analyzing the massive volume of data generated by EV systems [1–3].

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Role of Databases in EV Energy Management

Databases form the backbone of modern energy management systems in electric vehicles by efficiently storing, managing, and processing vast amounts of data generated by vehicles, users, and charging infrastructure. The integration of databases enables the extraction of actionable insights, improving energy efficiency, battery life, and user experience [4–6].

Data Sources

Electric vehicles and their ecosystem generate diverse data types from multiple sources:

- *Battery Management Systems (BMS):* The BMS continuously monitors battery parameters such as voltage, current, temperature, state of charge (SoC), and state of health (SoH). These sensor readings are critical for managing battery usage, preventing overcharge/over-discharge, and predicting battery degradation.
- *Vehicle Telematics*: Telematics systems collect data related to vehicle speed, acceleration, braking, GPS location, and route information. This data helps analyze driving patterns, energy consumption trends, and optimize routes for better energy usage [8].
- *Charging stations:* Information about charging station locations, availability, charging speed, and electricity prices are recorded. This enables smart scheduling and cost-efficient charging [9].
- *User Behaviour Data*: User preferences, driving habits, and scheduled trips provide context to tailor energy management strategies. For example, knowing when the user plans to use the vehicle allows pre-conditioning or strategic charging [10].
- *External Data Sources:* Weather conditions, traffic congestion, and grid energy supply data can influence energy management decisions.

Database Types and Structures

Handling this heterogeneous and high-volume data demands specialized database systems:

- *Relational databases (RDBMS)*: Relational databases (RDBMS) are used for structured data such as user profiles, charging session logs, and vehicle maintenance records. These databases support SQL querying, ensuring data integrity and relationships [11].
- *Time-series databases*: Because sensor data like voltage and temperature are continuously recorded over time, time-series databases (e.g., InfluxDB, TimescaleDB) efficiently store and retrieve this data for trend analysis and anomaly detection [12].
- *NoSQL databases*: Unstructured or semi-structured data such as GPS logs or telemetry data can be stored in document-based or key-value NoSQL databases like MongoDB or Cassandra, which offer flexibility and scalability [13].
- *Distributed databases:* To manage data from fleets or multiple geographic regions, distributed databases ensure data availability and fault tolerance.

Database Functions in Energy Management

- *Data collection and storage*: Databases collect and archive real-time data from EV components and infrastructure, forming the historical dataset required for analysis.
- *Data processing and analytics*: Querying capabilities allow real-time and batch processing to identify patterns, such as peak energy usage times, charging habits, and battery health trends [14].
- *Decision support*: Based on processed data, the system recommends optimal charging schedules, routes, and maintenance, thus optimizing energy consumption.
- *Predictive modeling*: Historical data stored in databases feeds machine learning models that predict battery degradation, energy demand, and charging needs [15].
- *Integration with other systems*: Databases enable interoperability between the EV, charging stations, power grids, and cloud services, facilitating energy trading, grid balancing, and user notifications [16].

Importance of Data Quality and Security

Accurate, consistent, and secure data is paramount. Faulty data can lead to poor energy management decisions, while insecure data poses privacy risks. Databases must implement:

- Validation and error-checking mechanisms.
- Encryption and access controls.
- Compliance with data privacy regulations.

ARCHITECTUTRE OF A DATABASE- DRIVEN EV ENERGY MANAGEMENT SYSTEM

The architecture of a database-driven EV energy management system integrates hardware components, data acquisition layers, a centralized database, processing modules, and user interfaces to optimize energy consumption and battery performance in electric vehicles. The system aims to collect, store, analyze, and utilize various data streams to manage energy efficiently [17–20]. Figure 1 illustrates the architecture of a database-driven EV energy management system.

Key Functionalities

Table 1 illustrates the key functions for EV.

Example Workflow

Figure 2 illustrates the workflow of data-driven energy management in EV:

1. Vehicle starts → Sensors collect data → Data is logged into the database.
2. Database triggers analytics → Detects high consumption pattern.
3. System suggests reduced HVAC usage or alternate route.
4. Battery optimization algorithm updates charging strategy.
5. Data loop continues for real-time adaptation and future learning.

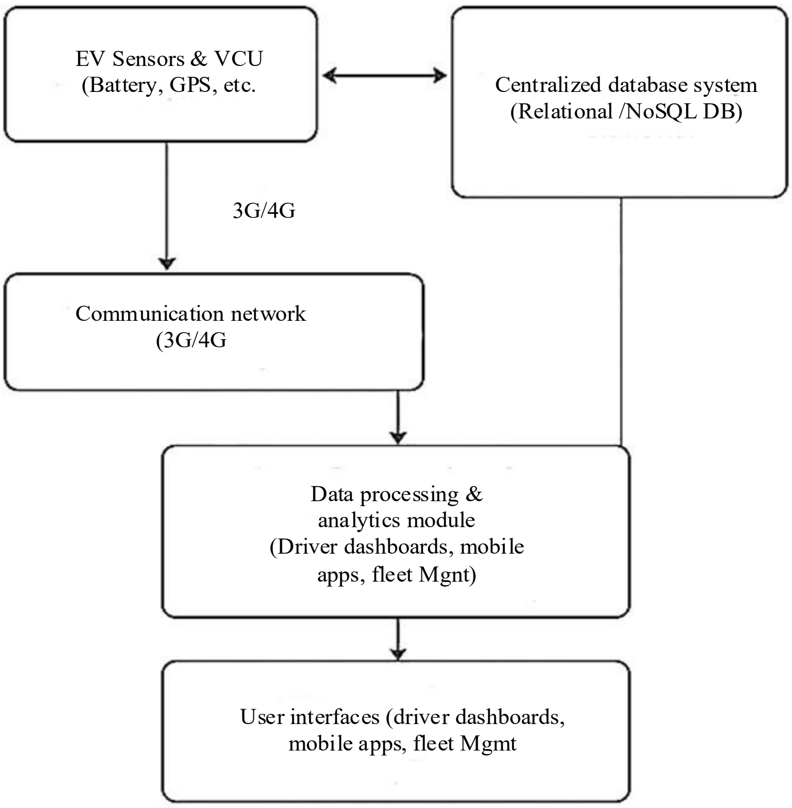

Figure 1. Architectutre of a database-driven EV energy management system.

Table 1. Key functions.

Description	
Energy Optimization	Adjust motor output and HVAC usage dynamically based on driving habits and conditions.
Route Optimization	Choose energy-efficient routes based on historical and live traffic data.
Charging Management	Recommend best charging points and times based on user patterns and grid load.
Battery Health Monitoring	Use historical battery data to forecast degradation and advise on optimal usage.
Driver Behavior Analysis	Suggest driving habits to conserve energy (e.g., accelerationpatterns).

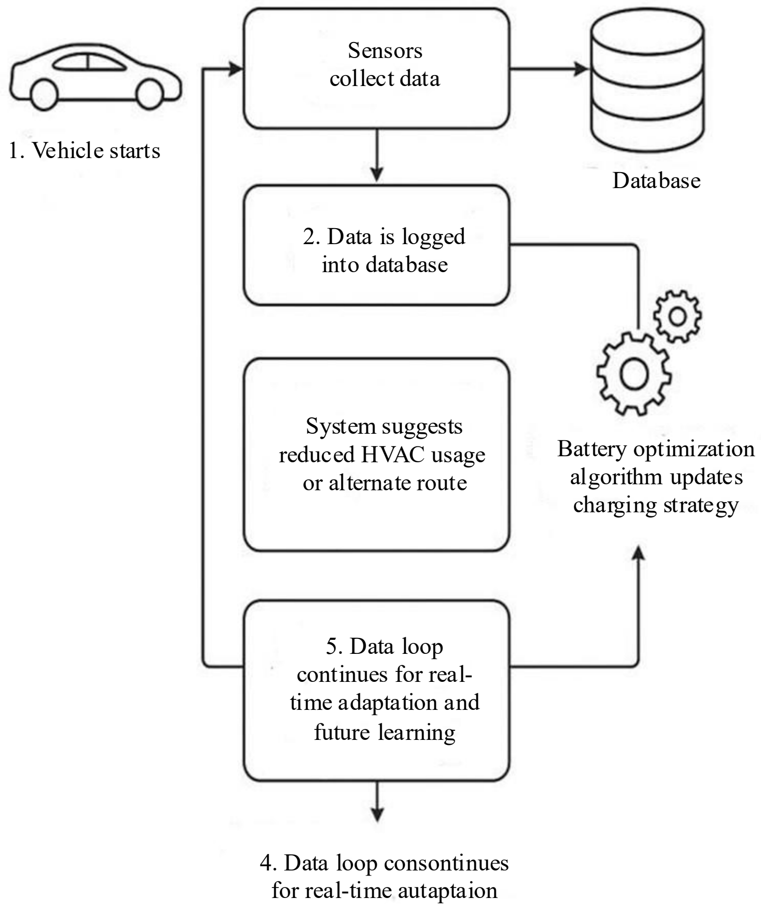

Figure 2. Work flow of data driven energy management in EV.

CHALLENGES AND CONSIDERATIONS

1. Data security and privacy
2. Scalability with real-time data
3. Interoperability with legacy systems
4. Reliability in dynamic driving conditions

FUTURE DIRECTIONS

1. Edge computing for local decision-making
2. Integration with smart grids and V2G (Vehicle-to- Grid)
3. Standardized data models for EVs
4. Autonomous vehicle synergies

CONCLUSION

Database-driven systems significantly enhance energy management in electric vehicles. This paper presents a framework for real-time data collection, storage, and analysis using both SQL and NoSQL models, enabling smarter, data-informed energy decisions in EV systems. Database-driven energy management represents a transformative approach to optimizing the performance and efficiency of electric vehicles (EVs). By systematically collecting, storing, and analyzing real-time and historical data, EV systems can make intelligent decisions that enhance energy efficiency, extend battery life, and improve overall vehicle performance. The integration of databases with machine learning and predictive analytics enables dynamic responses to changing driving conditions, user behavior, and environmental factors. As EV adoption continues to grow, database-centric architectures will play a crucial role in enabling scalable, adaptive, and intelligent energy management solutions. This not only supports individual vehicle efficiency but also contributes to broader goals such as grid integration, sustainability, and smart transportation ecosystems.

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