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SPECIAL SECTION

Processing and analysis of trolleybus traction data using LINQ technology

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Abstract. The paper presents the processing and analysis of the recorded trolleybus data using the LINQ (Language Integrated Query) software technology. The trolleybus data acquisition system collects a huge amount of electromechanical data in real time during vehicle operation. These data are used for the analysis in post-processing mode. In this paper, data processing was performed to assess the technical condition of trolleybus batteries. Selected standard query operators of the LINQ technology were implemented in the Windows Presentation Foundation (WPF) application to process the data and to determine the charge and energy stored in the battery. The LINQ technology proved to be useful for analyzing large amounts of data recorded from trolleybuses.

Keywords: trolleybuses; traction batteries; exploitation and maintaining.

1. INTRODUCTION

Data acquisition systems in modern trolleybuses record several dozen parameters in real time according to multi-objective planning of electric bus systems in cities with trolleybus infrastructure networks [1]. From the energy efficiency point of view of an electric vehicle (EV), the essential data package recorded from a trolleybus equipped with a battery contains the following parameters:

- Time – full date/time pattern;
- Vehicle ID – usually an integer number;
- Input drive energy [kWh];
- Energy recovered from drive [kWh];
- Input vehicle energy [kWh];
- Energy recovered from vehicle [kWh];
- Battery mode – vehicle fed from battery (bool variable);
- Catenary mode – vehicle fed from catenary (bool variable);
- Distance travelled [km];
- Internal and external temperature
- Velocity [km/h];
- Latitude and Longitude;
- On/Off passenger space heating;
- Battery charge status (SOC) [%];
- Catenary voltage [V] and catenary current [A];
- Battery voltage [V] and battery current [A];
- Min and Max battery temperature.

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The way of data sampling depends on the energy management system installed in the electric vehicle [2]. Two methods are typically used to sample data from electric vehicles. In the first method, a constant distance step is used, while the second one makes use of a constant time step when the vehicle is stopped and a varying speed-dependent time step when the vehicle is in motion.

The amount of recorded data per hour or per day depends on several factors, including data resolution (analogue signals), data sampling, and data recording format (binary or text). For the recorded data listed in the first paragraph of this section and the variable time step, the amount of data is equal to about 10 MB per day while the text format is considered. The data used in this work for processing and analysis were obtained from a company providing public transport services in northern Poland. The data, arranged in tables, are saved in files with a specific signature and archived on dedicated servers, thus creating the database resources.

Data processing can be performed using several dedicated software programmes. The Structured Query Language (SQL) is commonly used for this purpose. It is a relatively simple language, designed specifically for accessing, processing, and modifying information in relational databases. SQL (invented in 1974) is still a universal language of data, used in practically all technologies that process data and create complex reports.

Other programming tools for processing and analysis of database resources were developed as well. One such programming tool is the Language Integrated Query (LINQ). Com pared to SQL, LINQ is simpler, more productive, and higher-level [3–5]. However, there are no papers describing in detail the application of LINQ technology in the processing and analysis of traction data from an electric vehicle.

Section 2 briefly presents the LINQ technology and the types of query operators used to process records from the trolleybus data table. In Section 3, selected data regarding one-day trolleybus operation are shown and discussed, while Section 4 presents selected query expressions to perform filtering, ordering, grouping, and selecting operations on trolleybus data sources. These queries are intended to provide results that describe the current health of the traction battery.

The novelty of this work is demonstrating the suitability of LINQ technology for formulating a query interface for processing database tables including trolleybus-recorded data with a minimum of programming code.

2. BIG DATA APPLICATIONS IN BATTERY MANAGEMENT SYSTEMS

Many case studies of Big Data (BD) applications in battery management systems (BMS), including intelligent BMS systems and complex battery modeling, have been already published. Battery life estimation is usually determined using different battery degradation models. These models can be classified into three main groups as described in [6–8]: 1) Model-based approach (MBA), 2) Data-driven approach (DDA), and 3) Hybrid approach (HA).

Model-based approaches are developed taking into account electrochemical phenomena and they use a combination of algebraic and/or differential equations or empirical equations. The following techniques are used in MBA: equivalent circuit models [9, 10], electrochemical models [11], and empirical models [12].

Data-driven approaches are developed taking into account a lot of data gathered in the laboratory through large-scale testing under various aging conditions. The DDA approach (usually known as black-box models) uses statistical theories [13] or machine learning techniques [14] to develop a model from measured data.

Hybrid approaches are developed based on a combination of MBA and DDA models [15, 16]. The advantage of this combination is better performance and accuracy.

Various concepts for data analysis by the EV battery management system (BMS) are presented and tested [17–19]. The most advanced concepts are based on a layered structure of BMS: data sources layer, data acquisition layer, and data analytics layer.

The data sources are usually Big Data collections stored in databases. These sources include structured data such as traditional databases (SQL, mySQL, MongoDB, etc.) as document-based databases, semi-structured data such as BMS monitoring logs, and unstructured data.

The data acquisition layer is responsible for collecting data from several sensors and measurement systems of EVs and transmitting them using several communication protocols, taking into account the data format, size, and sampling.

The core task of data analytics is data processing and analysis. The data analytics layer includes batch processing using various Big Data analytics frameworks. Analytics frameworks considered for implementation in BMS are:

- Apache Hadoop [20] – an open-source framework for distributed processing and Big Data storage built on Hadoop Distributed File System.
- Apache MapReduce [21] – a distributed execution framework that simplifies data processing on large clusters by breaking tasks into parallel processing steps (invented by Google). It implements Map (input, filter, and sort datasets) and Reduce (perform summary operation) approach.
- Apache Spark [22] – a fast, open-source data-processing framework for machine learning and AI applications, supported by the largest open-source community in big data. Spark can be a standalone solution or run with Hadoop. It is used for real-time data processing.

The frameworks mentioned above have great potential in analyzing EV data, but there are further challenges to be addressed both now and in the future:

- Expensive and complicated hardware and software infrastructure implementing the functions of the mentioned layered model – Big Data BMS using cloud-based infrastructure.
- BMS data protection to ensure user data privacy using encryption and provide cybersecurity.
- System reliability in the event of missing or incorrect data and unreliability in some conditions.
- Open-source Big Data for BMSs is necessary for users, developers, and researchers to effectively work on improving BMS to minimize battery degradation.

LINQ technology can be implemented in each framework implementing intelligent and accurate BMS.

3. LINQ TECHNOLOGY – CAPABILITIES

A query in LINQ technology is an expression that retrieves data from a data source. All LINQ query operations include a sequence of three distinct actions [23]:

- Obtaining the data source;
- Creating the query;
- Executing the query.

The data source is a set of tables formulated as: XML documents, SQL databases, .NET collections, and any other format when a LINQ provider is available. The query specifies what results to retrieve from the data tables or database sources. Query execution means that the data source is read, and the operation is performed once in a more productive way. Table 1 classifies selected standard query operator methods implemented in LINQ technology according to their method of execution.

Some of these operators (aggregation, conversion, grouping, and selection) were used in this work to process and analyze the trolleybus data. LINQ technology facilitates the extension of the functionality of standard queries, which can be done by developing LINQ extension methods. In this work, some LINQ extension methods were developed to determine the time intervals of battery charging states and the amount of charge or energy delivered to the battery. All LINQ queries were developed in the Windows Foundation Presentation application using C# language.

Table 1
Standard query operator methods of LINQ technology

Operator type	Operator name
Aggregation	Aggregate, Average, Count, Max, Min, Sum
Conversion	ToArray, ToDictionary, ToList, ToLookup, ToSequence
Equality	EqualAll
Generation	Empty, Range, Repeat
Grouping	GroupBy, GroupJoin, Join
Serialization	OrderBy, ThenBy, Reverse
Division	Skip, SkipWhile, Take, TakeWhen
Constraint	Where
Selection	Select, SelectMany
Fixing	Concat, Distinct, Except, Intersect, Union

4. SELECTED WAVEFORMS – ONE-DAY TROLLEYBUS OPERATION

The presentation of waveforms for a one-day trolleybus operation is justified due to the quasi-repeatable timetable. This section presents selected waveforms recorded by the data acquisition system of trolleybus number 3088 in the period from 2016 to 2022.

The analyzed trolleybus is equipped with lithium-ion modules with cell configuration 12S2P. The traction battery consists of two parallel-connected blocks, each with a 168S2P configuration. The nominal voltage and the nominal capacity of the battery are 613 V and 62 Ah, respectively, while the cut-off voltage and the charge voltage at 100% SOC are 420 V and 689 V, respectively.

Due to the large number of waveforms obtained, they were grouped, and only selected data (representative of all recorded data) are presented here in the following order:

- Input drive energy, regenerative drive energy, input vehicle energy, and regenerative vehicle energy recorded on 2016/07/01 – Fig. 1.

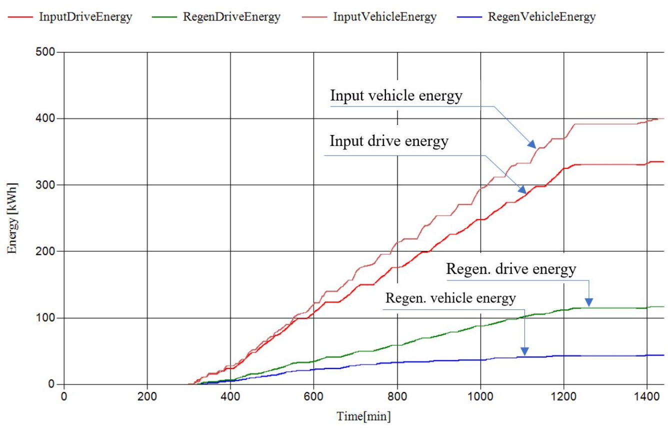

Fig. 1. Waveforms of selected trolleybus per day data: input drive energy (red), input vehicle energy (purple), regenerative vehicle energy (blue), regenerative drive energy (green)

- Battery mode of operation, catenary mode of operation, distance travelled by the vehicle, and velocity recorded on 2016/07/01 – Fig. 2. The battery and catenary modes are binary values, but for clarity, the catenary mode was assigned the value of 110, while the battery mode was assigned the value of 90.
- Battery status, battery voltage, and battery current recorded on 2016/07/01 – Fig. 3.

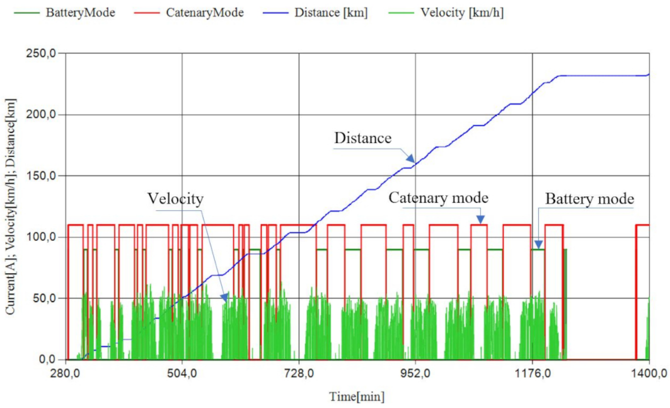

Fig. 2. Waveforms of selected trolleybus per day data: battery mode of operation (green), catenary mode of operation (red), distance travelled by the vehicle (blue), velocity (green)

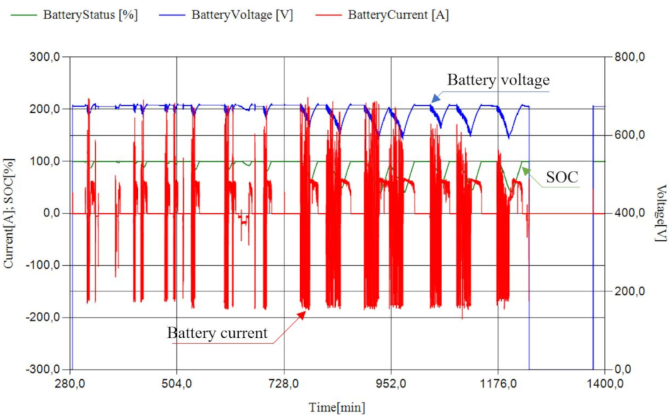

Fig. 3. Waveforms of selected trolleybus per day data: battery status, battery voltage, and buttery current

Comments and notes regarding these waveforms are as follows:

- The energy consumed by this trolleybus per day from the catenary is about 400 kWh.
- The energy returned to the grid by this vehicle is about 50 kWh per day.
- The distance travelled by this vehicle is about 235 km.
- The maximum speed is about 50 km/h.
- The vehicle drive system is energized alternately from the catenary system ("Catenary mode" – charge mode) and the battery ("Battery mode" – discharge mode). The number of charging/discharging cycles per day in most cases is between 10 and 20. The discharge rate depends upon several factors

such as trolleybus load, temperature gradient, surface inclination, terrain, vehicle speed, and also tire pressure [24].
- In the motoring operating mode of the drive system, the battery currents have negative values (energy is taken from the battery) and the extremum value is about −180 A.
- The battery voltage drops significantly from 670 V to 600 V in the battery mode of operation.

5. LINQ QUERY EXPRESSIONS FOR DATA PROCESSING

There are several methods to assess the technical condition of a traction battery [25–27]. The optimal operation of a traction battery managed by an energy storage management system is usually predictive and based on the knowledge SOC of the battery [28, 29].

In this work, the technical condition of the batteries is assessed based on the analysis of many years of data recorded every day of trolleybus operation – historical data. The main goal, however, is to test the usability of the LINQ technology in processing traction data from a trolleybus.

Taking into account the well-known fact that the dynamics of the battery charging state depend on the loss of capacity, the authors decided to specifically analyze the "Catenary mode" states of trolleybus operation. In this mode, the battery is charged with a current depending on the SOC value of the traction battery. It was assumed that the dynamics of the state of charge depend on the loss of battery capacity.

The procedure for processing the trolleybus database using LINQ is as follows:
- Opening a one-day data file and writing data to the memory collection.
- Running the appropriate LINQ query for the memory collection to obtain a group of collections representing the data for the catenary mode only. Each collection has battery charging states (current flows into the battery) and non-charging states (current equal to zero).
- Running the appropriate LINQ query for each item of the collection to select data for the charging state only (positive current flowing into the battery).
- Performing the calculations to determine a set of parameters describing the amount of charge and energy delivered to the battery. In this work two criteria were taken into account for the determination of the delivered charge and energy:
  - SOC criterion – $SOC \in \langle SOC_1, SOC_2 \rangle$.
  - Voltage criterion – $U_{\text{batt}} \in \langle U_1, U_2 \rangle$.
- In the SOC criterion, the charge and energy are determined in the SOC range between SOC_1 and SOC_2, while in the Voltage criterion, they are determined in the U_{batt} range between U_1 and U_2.
- Saving the parameters as metadata to compare them with the same parameters determined in the next procedure.

Windows Presentation Foundation software was developed in the Microsoft Visual Studio Environment to implement the above procedure.

In this work, the same operating temperature of the traction battery was not considered in the SOC criterion and the voltage criterion. The analyzed trolleybus is equipped with a battery cooling system. The set of sensors measures the temperature at several points of the traction battery. However, the temperature acquisition to the database concerns only extreme values – minimum and maximum. The preferred working temperature range for Lithium-Ion batteries, according to studies on their thermal efficiency, is between 25°C and 40°C [30, 31]. The temperature waveforms shown in Fig. 4 and Fig. 6 show that the maximum temperature exceeds 40°C, but this value, as already mentioned, does not apply to all battery cells. Accurate evaluation of the lithium-ion battery temperature is critical for the battery management system to prevent the battery from overheating [32].

5.1. Opening data files and writing them to memory collection

The table with the recorded one-day trolleybus data has one field (column) to identify each record uniquely. This column is **time** and is referred to as a **primary key**. On the other hand, the one-day trolleybus data may have weak relationships with subsequent one-day data – no **foreign key** to relate the records. In this situation, the authors propose to implement batch processing of data files, which means that one-day data files regarding the same trolleybus are automatically and sequentially opened, processed, analyzed, and closed.

The data saved in the memory collection is of List<T> type which supports the generic IEnumerable<T> interface. This means that the collection is a set of data that can have different types (numbers, strings, boolean, images, etc.). This also means that it can be queried with LINQ. In this work, such list collection is named as *inputDataList*.

5.2. Processing data to obtain the group of collections representing data for the catenary mode only

As the first step of this processing, the arrays of times *timesOn*[ ] and *timesOff*[ ] are selected from the "Catenary mode" binary data included in the *inputDataList*. The *timesOn*[ ] array contains the start times, while the *timesOff*[ ] array the end times of the catenary. There is no query in the standard LINQ query library to obtain directly the *timesOn*[ ] and *timesOff*[ ] arrays for the catenary mode. However, LINQ technology allows the development of extended LINQ user methods. It is a new feature that was added in C# 3.0 which allows the user to add new methods (functions) to the existing types without creating a new derived type, recompiling, or otherwise modifying the original type. The extension method named *CatenaryIntervals*( ) for the arrays *timesOn*[ ] and *timesOff*[ ] has been developed by the authors and query to this method is presented in Listing 1.

Listing 1.
```
List<TimeOnOff> catenaryOnOff
      = inputDataList.CatenaryIntervals( );
```

The variable *catenaryOnOff* contains the arrays *timesOn*[] and *timesOff*[]. Once the catenary time intervals are known, a query can be defined to obtain the group of catenary mode collections as shown in Listing 2.

Listing 2.

```
var listCatenaryMode = inputDataList
  .Where(item => ((item.Time >= timeOn[i] && item.Time
<= timeOff[i]));
```

The result of this query is a data collection that meets the condition of data acquisition in catenary mode. A group of such collections is shown in Fig. 4 where the following waveforms are presented:

- Battery status (SOC) as percentage value [%] – left Y-axis;
- Battery voltage [V] – right Y-axis;
- Battery current [A] – left Y-axis;
- Minimum battery temperature [°C] – left Y-axis;
- Maximum battery temperature [°C] – left Y-axis.

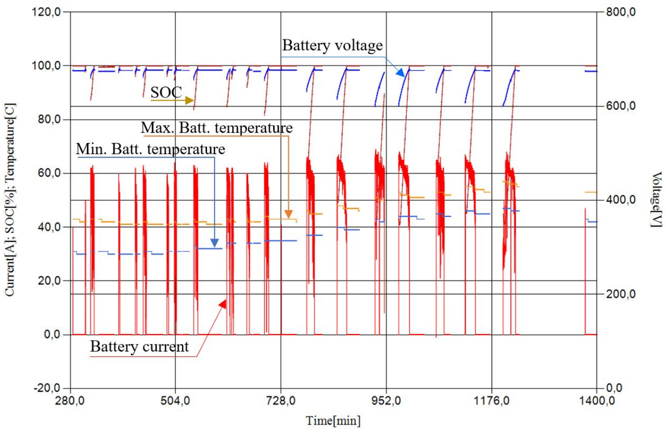

Fig. 4. Waveforms of selected group collections in catenary mode: battery status, battery voltage, battery current, minimum battery temperature, maximum battery temperature

A time window corresponding to a single collection taken from this group is shown in Fig. 5. When the catenary mode is active (turn-on), the system checks the state of battery charge (SOC). If the SOC value is lower than 100%, the system starts the charging process. In this process, the battery current is quasi-constant and has a value of approximately 60 A until the SOC reaches a value of approximately 90%.

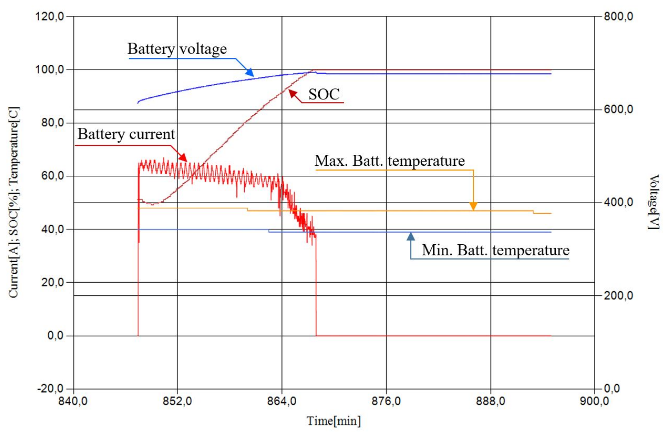

Fig. 5. Time window corresponding to a single collection taken from the group of collections representing catenary mode only

Then the battery current decreases quasi-linearly (from 60 A to 35 A) until the SOC value is close to 100%. When the SOC is very close to 100%, the charging process is stopped. The battery voltage increases quasi-linearly in this process. Typically, the charging state time is shorter than the catenary mode time.

To calculate the charge and energy delivered to the battery during the charging process, only the data collected in the catenary mode with the condition that the battery current is greater than zero is required.

5.3. Processing data to obtain the group of collections representing data for the catenary mode and battery current greater than zero

In this step, the *listCatenaryMode* collection calculated in subsection B is queried at the condition that the battery current is greater than zero. An appropriate LINQ query is shown in Listing 3.

Listing 3.

```
var listChargingStates = listCatenaryMode
  .Where(item => item.BatteryCurrent > 0);
```

The result of this query is a group of data collections that meet the condition of data acquisition in catenary mode at the battery current greater than zero – battery charging state. The waveforms of such collections are shown in Fig. 6. These include: battery status (SOC), battery voltage, battery current, minimum battery temperature, and maximum battery temperature. This group is named “GroupCatenaryCharge”.

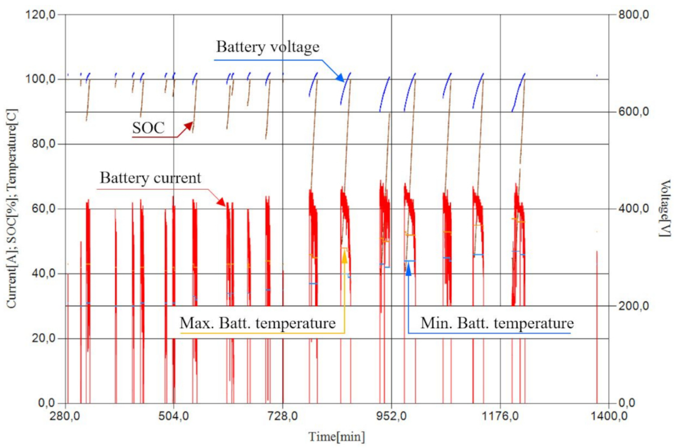

Fig. 6. Waveforms of selected collections in “GroupCatenaryCharge”: battery status, battery voltage, battery current, minimum battery temperature, maximum battery temperature

The time windows for two different single collections taken from “GroupCatenaryCharge” are shown in Fig. 7 and Fig. 8. The difference between the waveforms presented in these two figures is the initial SOC value during the charging process, which is about 50% in Fig. 7 and about 44% in Fig. 8. The charging time in the second case is longer.

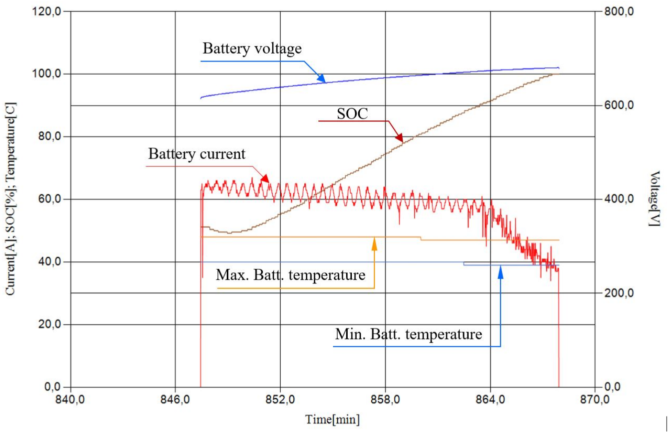

Fig. 7. Time window corresponding to a single collection taken from the group of collections representing catenary mode and charging state at an initial SOC value of 50%

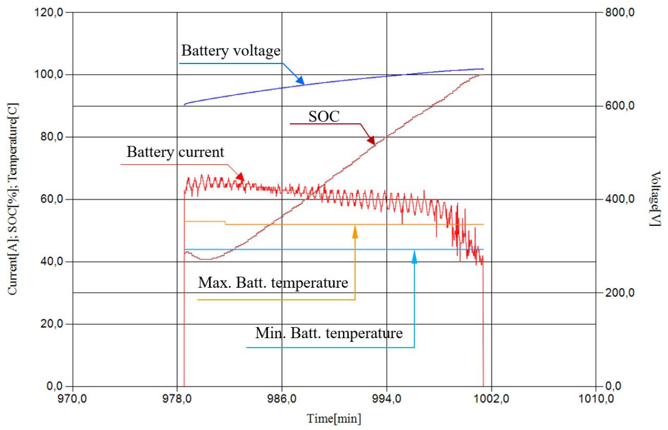

Fig. 8. Time window corresponding to a single collection taken from the group of collections representing catenary mode and charging state at an initial SOC value of 44%

5.4. Charge and energy delivered to the battery during the charging process

The charge Q and the energy W delivered to the battery have been determined for each collection from the "GroupCatenaryCharge". This was done by numerical integration of the following formulas:

$$Q(k) = \int_{t_1(k)}^{t_2(k)} I_{\text{batt}}(k)\,\mathrm{d}t, \tag{1}$$

$$W(k) = \int_{t_1(k)}^{t_2(k)} I_{\text{batt}}(k) U_{\text{batt}}(k)\,\mathrm{d}t, \tag{2}$$

where $I_{\text{batt}}(k)$ and $U_{\text{batt}}(k)$ are the battery current and battery voltage of the k-th collection, respectively; $t_1(k)$ and $t_2(k)$ are the initial time and the final time of the charging process of the k-th collection, respectively.

The trapezoidal formula taking into account a variable time step was implemented. It could be done by a relatively easy algorithm or a LINQ query using aggregate operators.

The amount of charge Q and energy W, the initial and final battery state (percentage value), the initial and final battery voltage, and also the date/time data are saved in an appropriate metadata file related to the analyzed vehicle.

6. COMPARING CHARGE AND ENERGY DELIVERED TO THE BATTERY BASED ON HISTORICAL DATA

This ection presents charge Q and energy W delivered to the battery of trolleybus number 3088 recorded in the period from 2016 to 2022. This comparison was made for both, the SOC criterion and the voltage criterion.

6.1. SOC criterion

In the SOC criterion, for each case in the historical data, the initial SOC battery was chosen to be $SOC_1 = 71\%$, and the final value was assumed as $SOC_2 = 100\%$. The current SOC value was calculated by the vehicle energy management system. The results of Q and W calculations are presented in Fig. 9 and Fig. 10, respectively.

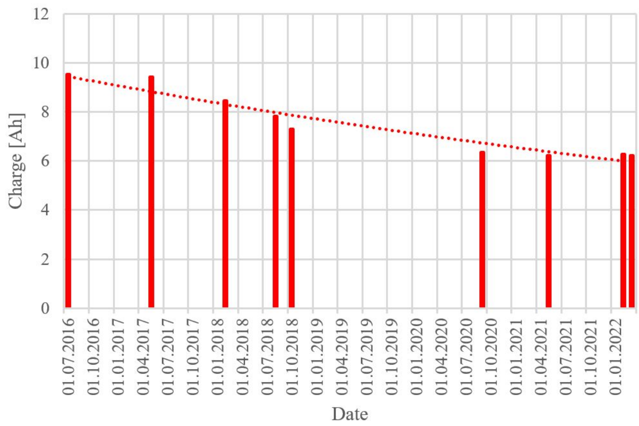

Fig. 9. Charge delivered to the battery at SOC criterion: $SOC \in \langle 71\%, 100\% \rangle$

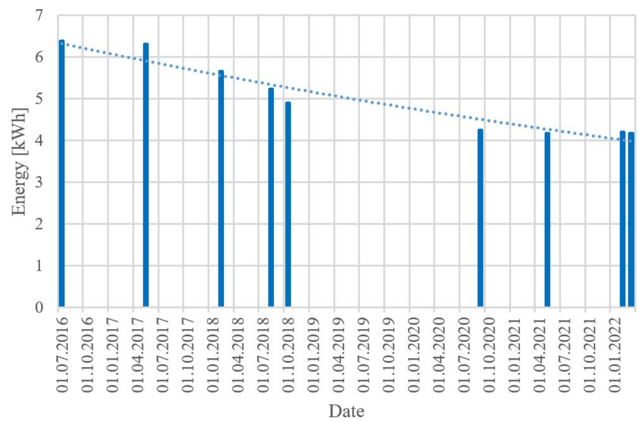

Fig. 10. Energy delivered to the battery at SOC criterion: $SOC \in \langle 71\%, 100\% \rangle$

The presented results show that as the operating time of the traction battery increases, the amount of charge and energy delivered to the battery in the charging process decreases while maintaining the same initial and final SOC of the battery.

6.2. Voltage criterion

In the voltage criterion, for each case in the historical data, the initial battery voltage was chosen to be $U_1 = 643$ V, and the final value was assumed as $U_2 = 680$ V. The results of Q and W calculations for the voltage criterion are presented in Fig. 11 and Fig. 12, respectively.

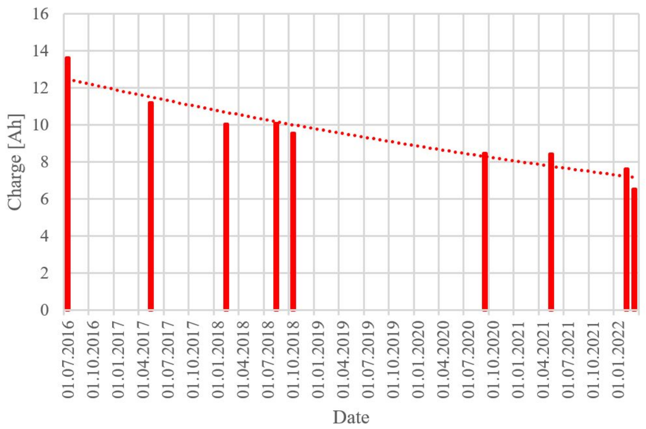

Fig. 11. Charge delivered to the battery at Voltage criterion: $U_{\mathrm{batt}} \in \langle 643\text{ V}, 680\text{ V}\rangle$

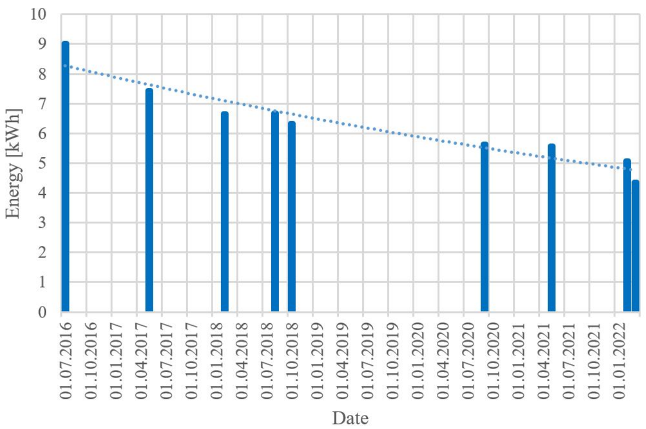

Fig. 12. Energy delivered to the battery at Voltage criterion: $U_{\mathrm{batt}} \in \langle 643\text{ V}, 680\text{ V}\rangle$

As for the SOC criterion, the presented results show that as the operating time of the traction battery increases, the amount of charge and energy delivered to the battery in the charging process decreases while maintaining the same initial and final voltage of the battery.

The next tasks that the authors intend to study include:

- Developing/Refining a computer program for batch processing using LINQ on thousands of historical data stored in database tables.
- Analyzing important battery parameters with statistical analysis tools.
- Determining prediction of traction battery parameter values.

To reduce stress on the traction battery and thus further extend battery life, a hybrid energy storage system can be implemented by integrating supercapacitors [33]. Supercapacitors allow to decrease the load on the battery during sudden power demands and short-term power requirements, which increases energy efficiency.

7. FACTORS AFFECTING BATTERY DEGRADATION

Battery degradation operating in trolleybus is the result of various electrochemical processes occurring inside the battery.

The following degradation mechanisms are observed at the Li-ion battery anode [34]:

- Solid electrolyte interphase/interface (SEI) decomposition and growth [35];
- Blinder decomposition [36];
- Lithium plating [37];
- Corrosion of anode collector;
- Electrode particle cracking (EPC).

The following degradation mechanisms are observed at the Li-ion battery cathode [34]:

- Blinder decomposition;
- Solid permeable interface (SPI) growth;
- Corrosion of cathode collector;
- Electrode particle cracking;
- Structure disordering.

These degradation mechanisms cause undesirable phenomena in the Li-ion battery such as [38]:

- Loss of lithium inventory (LLI);
- Loss of active cathode and anode materials;
- Loss of electrolyte.

The result of these undesirable phenomena is a reduction of the battery capacity and, consequently, a deterioration of the battery state of health (SoH) and remaining useful life (RUL). Several factors influence the mechanism of battery degradation. The most important working conditions that affect the anode domain are [34]:

- High SOC – affects: SEI decomposition/growth; blinder decomposition.
- Low SOC – affects: corrosion of current collector.
- High temperature – affects: SEI decomposition/growth; blinder decomposition; electrode particle cracking.
- Low temperature – affects: lithium platting.
- Time – affects: SEI decomposition/growth.
- Current load – affects: SEI decomposition/growth; corrosion of current collector.
- High charging rate – affects: lithium platting.

The most important working conditions that affect the cathode domain are [34]:

- High SOC – affects: blinder decomposition; solid permeable interface growth.
- Low SOC – affects: corrosion of current collector; transition metal dissolution.

- High temperature – affects: blinder decomposition; solid permeable interface growth.
- Current load – affects: corrosion of current collector; electrode particle cracking; structure disordering.

The maximum SOC value of batteries in the tested trolleybuses was 100%. The maximum SOC value recommended by the Li-ion battery manufacturer is about 80%. Hence, this factor had a significant impact on battery degradation in the tested trolleybuses. It should be noted, however, that after reaching SOC = 100%, the trolleybus immediately switched to battery mode of operation, which caused the SOC value to decrease. The state of SOC = 100% was always very short.

The minimum SOC value in the tested trolleybuses never dropped below 30%. Therefore, this factor had no impact on the battery degradation process.

The traction test battery has several temperature sensors mounted inside the battery housing. Only the minimum ($T_{\min}$) and maximum ($T_{\max}$) temperatures from this set of sensors are recorded by the data acquisition system of the trolleybus BMS. In the summertime (when the outside temperature was around 30°C) the average values recorded by the battery sensors were $\bar{T}_{\min} \approx 40°\text{C}$, $\bar{T}_{\max} \approx 55°\text{C}$. It means that battery cells were not operated at the same temperature. The degradation rate or capacity loss of the battery operated above 45°C is significant [39], hence we can assume that in the summertime the battery cell temperature had a significant impact on battery degradation in tested trolleybuses.

In the wintertime (when the outside temperature was around 0°C) the average values recorded by the battery sensors were $\bar{T}_{\min} \approx 24°\text{C}$, $\bar{T}_{\max} \approx 33°\text{C}$. This temperature has no significant effect on battery degradation.

The charging current value at the catenary mode of operation was about 60 A. The nominal capacity of the battery is C = 62 Ah, hence charging current rate is 1C. At the charging current rate of 1C battery end of life (EOL) is about 3000 charging/discharging cycles [40]. Any value of charging current rate has an impact on the SoH and RUL of the battery, but at 1C rate, it can be assumed that it is not the main factor.

The maximum discharge current (battery mode of trolleybus operation) has been limited to 180 A. It means 3C discharging the current rate. This factor had a significant impact on battery degradation.

8. ASSESSMENT OF BATTERY SOH

The graphs presented in Fig. 9 and Fig. 10 indicate battery degradation because all values of the charge or energy supplied to the battery are obtained with the same SOC range criterion. A simplified formula for calculating the state of health (SoH) from the charge capacity of the battery is given by (3)

$$SoH_{\text{Charge}} = \left(1 - \frac{C_{\text{actual}}}{C_{\text{rated}}}\right) 100\%, \tag{3}$$

where C_{rated} – rated capacity, C_{actual} – actual capacity.

If the actual capacity is not known, it can be estimated using a simplified formula (4)

$$SoH_{\text{Charge}} = \left(1 - \frac{\Delta C_{\text{actual}}}{\Delta C_{\text{initial}}}\right) 100\%, \tag{4}$$

where $\Delta C_{\text{initial}}$ – initial charge increase, ΔC_{actual} – actual charge increase at the same SOC range criterion.

Using results from Fig. 9 and simplified formula (4) SoH_{Charge} equals 65%.

A simplified formula for calculating battery SoH from the energy is given by (5)

$$SoH_{\text{Energy}} = \left(1 - \frac{W_{\text{actual}}}{W_{\text{rated}}}\right) 100\%, \tag{5}$$

where W_{rated} – rated battery energy, W_{actual} – actual energy.

If the actual energy is not known, it can be estimated using a simplified formula (6)

$$SoH_{\text{Energy}} = \left(1 - \frac{\Delta W_{\text{actual}}}{\Delta W_{\text{initial}}}\right) 100\%, \tag{6}$$

the battery has shown that under the same conditions, the dynamics of the battery charging process change as the operating time increases. It is possible to predict the technical condition of the battery based on historical data.

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REFERENCES

[1] C. Iliopoulou, I.X. Tassopoulos, and K. Kepaptsoglou, "Multi-objective planning of electric bus systems in cities with trolleybus infrastructure networks," *Sust. Cit. and Soc.*, vol. 103, p. 105227, 2024, doi: 10.1016/j.scs.2024.105227.

[2] A. Jakubowski *et al.*, "Modeling of Electrified Transportation Systems Featuring Multiple Vehicles and Complex Power Supply Layout," *Energies*, vol. 14, p. 8196, 2021, doi: 10.3390/en14248196.

[3] X. Liu, L. Chen, and C. Wan, "LINQ: A framework for location-aware indexing and query processing," *IEEE Trans. Know. Data Eng.*, vol. 27, no. 5, pp. 1288–1300, 2015, doi: 10.1109/TKDE.2014.2365792.

[4] M. Barth and A. Fay, "Efficient use of data exchange formats in engineering projects by means of language integrated queries – Engineers LINQ to XML," in *36th Annu. Conf. on IEEE Ind. Electr. Soc. (IECON 2010)*, 2010, doi: 10.1109/IECON.2010.5675490.

[5] Y. Wang and X. Zhang, "The Research of Multi-source Heterogeneous Data Integration Based on LINQ," in *2012 Int. Conf. on Comp. Sci. and Electr. Eng.*, 2012, doi: 10.1109/ICCSEE.2012.437.

[6] S.M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, "Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility," *J. Power Sources*, vol. 256, pp. 110–124, Jun. 2014, doi: 10.1016/j.jpowsourc.2014.01.085.

[7] L. Wu, X. Fu, and Y. Guan, "Review of the remaining useful life prognostics of vehicle lithium-ion batteries using data-driven methodologies," *Appl. Sci.*, vol. 6, no. 6, p. 166, 2016, doi: 10.3390/app6060166.

[8] A.T. Stamps, C.E. Holland, R.E. White, and E.P. Gatzke, "Analysis of capacity fade in a lithium ion battery," *J. Power Sources*, vol. 150, pp. 229–239, Oct. 2005, doi: 10.1016/j.jpowsourc.2005.02.033.

[9] K. Goebel, B. Saha, A. Saxena, J.R. Celaya, and J.P. Christophersen, "Prognostics in battery health management," *IEEE Instr. Meas. Mag.*, vol. 11, no. 4, pp. 33–40, Aug. 2008, doi: 10.1109/MIM.2008.4579269.

[10] A. Guha, A. Patra, and K.V. Vaisakh, "Remaining useful life estimation of lithium-ion batteries based on the internal resistance growth model," in *Proc. Indian Control Conf.* (ICC), Jan. 2017, pp. 33–38, doi: 10.1109/INDIANCC.2017.7846448.

[11] G. Ning, R.E. White, and B.N. Popov, "A generalized cycle life model of rechargeable Li-ion batteries," *Electrochim. Acta*, vol. 51, no. 10, pp. 2012–2022, 2006, doi: 10.1016/j.electacta.2005.06.033.

[12] K.-H. Tseng, J.-W. Liang, W. Chang, and S.-C. Huang, "Regression models using fully discharged voltage and internal resistance for state of health estimation of lithium-ion batteries," *Energies,* vol. 8, no. 4, pp. 2889–2907, Apr. 2015, doi: 10.3390/en8042889.

[13] W. Gu, Z. Sun, X. Wei, and H. Dai, "A new method of accelerated life testing based on the grey system theory for a model-based lithium-ion battery life evaluation system," *J. Power Sources*, vol. 267, pp. 366–379, Dec. 2014, doi: 10.1016/j.jpowsourc.2014.05.103.

[14] D. Liu, J. Zhou, D. Pan, Y. Peng, and X. Peng, "Lithium-ion battery remaining useful life estimation with an optimized relevance vector machine algorithm with incremental learning," *Measurement*, vol. 63, pp. 143–151, Mar. 2015, doi: 10.1016/j.measurement.2014.11.031.

[15] H. Dong, X. Jin, Y. Lou, and C. Wang, "Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter," *J. Power Sources*, vol. 271, pp. 114–123, Dec. 2014, doi: 10.1016/j.jpowsourc.2014.07.176.

[16] X. Peng, C. Zhang, Y. Yu, and Y. Zhou, "Battery remaining useful life prediction algorithm based on support vector regression and unscented particle filter," in *Proc. IEEE Int. Conf. Prognostics Health Manage*. (ICPHM), Jun. 2016, pp. 1–6, doi: 10.1109/ICPHM.2016.7542844.

[17] Ch.-Ho. Lee and Ch.-Hu. Wu, "A Novel Big Data Modeling Method for Improving Driving Range Estimation of EVs," *IEEE Access*, vol. 3, pp. 1980–1993, October 28, 2015, doi: 10.1109/ACCESS.2015.2492923.

[18] K. Moharm, M. Eltahan, and E. Immonen, "Big Data Driven Battery Management Systems," *2020 2nd Inter. Conf. on Cont. Sys., Math. Model., Autom. and Energy Effic.* (SUMMA), 11–13 Nov. 2020, pp. 987–992, doi: 10.1109/SUMMA50634.2020.9280667.

[19] Z. Wei, K. Liu, X. Liu, Y. Li, L. Du, and F. Gao, "Multilevel Data-Driven Battery Management: From Internal Sensing to Big Data Utilization," *IEEE Trans. Transp. Electrif.*, vol. 9, no. 4, 2023, pp. 4805–4823, doi: 10.1109/TTE.2023.3301990.

[20] D. Borthakur *et al.*, "Apache hadoop goes realtime at facebook," in *Proc. of the 2011 ACMSIGMOD Intern. Conf. on Manag. of data*, 2011, pp. 1071–1080, doi: 10.1145/1989323.1989438.

[21] J. Dean and S. Ghemawat, "MapReduce: a flexible data processing tool," *Commun. ACM*, vol. 53, no. 1, pp. 72–77, 2010, doi: 10.1145/1629175.1629198.

[22] M. Zaharia *et al.*, "Apache spark: a unified engine for big data processing," *Commun. ACM*, vol. 59, no. 11, pp. 56–65, 2016, doi: 10.1145/2934664.

[23] R. Dollinger and K. Thomas, "Using LINQ transformation patterns to evaluate SQL queries," *Fourth Intern. Conf. on the Applic. of Dig. Infor. and Web Tech. (ICADIWT 2011)*. 2011, doi: 10.1109/ICADIWT.2011.6041397.

[24] S. Dhawan, AA. Sabharwal, R. Prasad, S. Shreya, AA. Gupta, and Y. Parvez, "Performance analysis of a lithium-ion battery of an electric vehicle under various driving conditions," *Arch. Thermodyn.*, vol. 44, no. 3, pp. 43–160, 2023, doi: 10.24425/ather.2023.147541.

[25] W. Waag, Ch. Fleischer and D.U. Sauer, "Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles," *J. Power Sources*, vol. 258, p. 321–339, 2014, doi: 10.1016/j.jpowsourc.2014.02.064.

[26] R. Xiong, L. Li, and J. Tian, "Towards a smarter battery management system: A critical review on battery state of health monitoring methods," *J. Power Sources*, vol. 405, pp. 18–29, 2018, doi: 10.1016/j.jpowsourc.2018.10.019.

[27] S. Bhoira, P. Caliandrob, and C. Brivioa, "Impact of V2G service provision on battery life," *J. Energy Storage*, vol. 44, p. 1103178, 2021, doi: 10.1016/j.est.2021.103178.

[28] M. Hallmann, Ch. Wenge, and P. Komarnicki, "Methods for lithium-based battery energy storage SOC estimation, Part I: Overview," *Arch. Electr. Eng.*, vol. 7, no. 1, pp. 139–157, 2022, doi: 10.24425/aee.2022.140202.

[29] M. Hallmann, Ch. Wenge, P. Komarnicki, and S. Balischewski, "Methods for lithium-based battery energy storage SOC estimation, Part II: Application and accuracy," *Arch. Electr. Eng.*, vol. 71, no. 2, pp. 311–323, 2022, doi: 10.24425/aee.2022.140713.

[30] X. Zhang, Z. Li, L. Luo, Y. Fan, and Z. Du, "A review on thermal management of lithium-ion batteries for electric vehicles," *Energy*, vol. 238, p. 121652, 2022, doi: 10.1016/j.energy.2021.121652.

[31] G. Karimi and X. Li, "Thermal management of lithium-ion batteries for electric vehicles," *Int. J. Energy Res.*, vol. 37, pp. 13–24, 2013, doi: 10.1002/er.1956.

[32] A.A. El Baset, A. El Halim, E.H. EI Bayoumi, W. El Khattam, and A.M. Ibrahim, "Implications of lithium-ion cell temperature estimation methods for intelligent battery management and fast charging systems," *Bull. Pol. Acad. Sci. Tech. Sci.*, vol. 72, no. 3, p. e149171, 2024, doi: 10.24425/bpasts.2024.149171.

[33] G. Yuksek and A. Alkaya, "An adaptive energy management approach for battery-supercapacitor hybrid energy storage system," *Bull. Pol. Acad. Sci. Tech. Sci.*, vol. 72, no. 3, p. e149171,2024, doi: 10.24425/bpasts.2024.149171.

[34] C.R. Birkl, M.R. Roberts, E. McTurk, P.G. Bruce, and D.A. Howey, "Degradation diagnostics for lithium-ion cells," *J. Power Sources*, vol. 341, pp. 373–386, Feb. 2017, doi: 10.1016/j.jpowsourc.2016.12.011.

[35] I. Laresgoiti, S. Käbitz, M. Ecker, and D.U. Sauer, "Modeling mechan ical degradation in lithium ion batteries during cycling: Solid electrolyte interphase fracture," *J. Power Sources*, vol. 300, pp. 112–122, Dec. 2015, doi: 10.1016/j.jpowsourc.2015.09.033.

[36] L. Bodenes *et al.*, "Lithium secondary batteries working at very high temperature: Capacity fade and understanding of aging mechanisms," *J. Power Sources*, vol. 236, pp. 265–275, Aug. 2013, doi: 10.1016/j.jpowsourc.2013.02.067.

[37] X. Lin, K. Khosravinia, X. Hu, J. Li, and W. Lu, "Lithium plating mechanism, detection, and mitigation in lithium-ion batteries," *Prog. Energy Combust. Sci.*, vol. 87, p. 100953, Nov. 2021, doi: 10.1016/j.pecs.2021.100953.

[38] M. Dubarry, C. Truchot, and B.Y. Liaw, "Synthesize battery degradation modes via a diagnostic and prognostic model," *J. Power Sources*, vol. 219, pp. 204–216, Dec. 2012, doi: 10.1016/j.jpowsourc.2012.07.016.

[39] F. Leng, C.M. Tan, and M. Pecht, "Effect of temperature on the aging rate of li ion battery operating above room temperature," *Sci. Rep.*, vol. 5, no. 1, pp. 1–12, Aug. 2015, doi: 10.1038/srep12967.

[40] A.S. Mussa *et al.*, "Fast-charging effects on ageing for energy-optimized automotive LiNi1/3Mn1/3Co1/3O2/graphite prismatic lithium-ion cells," *J. Power Sources*, vol. 422, pp. 175–184, May 2019, doi: 10.1016/j.jpowsourc.2019.02.095.