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Cooperative Application of Onboard Energy Storage and Stationary Energy Storage in Rail Transit Based on Genetic Algorithm

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Abstract: The transition towards environmentally friendly transportation solutions has prompted a focused exploration of energy-saving technologies within railway transit systems. Energy Storage Systems (ESS) in railway transit for Regenerative Braking Energy (RBE) recovery has gained prominence in pursuing sustainable transportation solutions. To achieve the dual-objective optimization of energy saving and investment, this paper proposes the collaborative operation of Onboard Energy-Storage Systems (OESS) and Stationary Energy-Storage Systems (SESS). In the meantime, Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is applied to optimize the ESS capacity and reduce its redundancy. The simulation is programmed in MATLAB. The results show that the corporation of OESS and SESS offers superior benefits (70 kWh energy saving within 30 min operation) compared to using SESS alone. Moreover, the OESS plays a significant role, emphasizing its significance in saving energy and investment, therefore presenting a win–win scenario. It is recommended that the capacity of OESS be designed to be two to three times that of SESS. The findings contribute to the ongoing efforts in developing more sustainable and energy-efficient transportation solutions, with implications for the railway industry's investment and broader initiatives in energy saving for sustainable urban mobility.

Keywords: rail transit; ESS; SESS; OESS; SMES; Lithium-ion battery; regenerative braking; NSGA-II; energy recovery; energy management

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Citation: Kong, D.; Miyatake, M. Cooperative Application of Onboard Energy Storage and Stationary Energy Storage in Rail Transit Based on Genetic Algorithm. *Energies* **2024**, *17*, 1426. https://doi.org/10.3390/en17061426

Academic Editors: Artur Kierzkowski, Tomasz Kisiel, Franciszek Restel, Tomasz Nowakowski, Agnieszka A. Tubis, Anna Jodejko-Pietruczuk and Mateusz Zając

Received: 7 February 2024
Revised: 4 March 2024
Accepted: 11 March 2024
Published: 15 March 2024

1. Introduction

This research aims to achieve multi-objective optimization of energy consumption and cost in rail transit by coordinating OESS's and SESS's capacity. Therefore, NSGA-II is applied and works well, as expected.

In general, the pantograph-catenary is the primary energy supply for a train's operation in rail transit [1,2]. To improve the diversity and stability of energy supply in emergencies, renewable energy sources like photovoltaic power have also been introduced in rail transit [3]. On the other hand, as a supplement to the primary energy supply system, one key area of focus is the recovery and efficient utilization of RBE in railway transit by ESS. Regarding the construction of ESS, there are three types: power-density ESS, energy-density ESS, and hybrid energy-storage systems (HESS). The rated output power divided by the storage device's volume yields the power density (W/kg or W/liter). Power-density ESS like SMES and supercapacitors appropriate for high discharge current have quick response power quality applications. Similarly, stored energy divided by the volume refers to the energy density (Wh/kg or Wh/liter). Energy-density ESS like Li-ion holds higher energy density than conventional batteries, excelling in space reduction, mobility increase, and operating time extension [4]. Ratniyomchai introduced the application of ESS in electrified railways, especially batteries, flywheels, electric double-layer capacitors, and HESS. The storage and reuse of RBE is managed by energy-storage devices depending on the purpose of each system [5,6]. By lowering the frequency of battery charge and discharge and controlling battery peak current, Li introduced HESS with Superconducting Magnetic Energy Storage (SMES) and batteries in electric buses, extending battery life [7].

The efficient management and storage of energy have become integral to sustainability goals. In general, according to the allocation of ESS, there are also three types: SESS, OESS, and both. Unlike OESS, SESS is not confined to the train itself but is distributed strategically along the railway network. SESS plays a crucial role in capturing and storing the excess energy generated during regenerative braking events to improve efficiency and reliability in urban rail systems [8]. Lamedica demonstrates the utilization of Particle Swarm Optimization (PSO) in developing an optimal siting and sizing methodology for designing a SESS tailored for railway lines and maximizing the investment's financial return [9]. On the other hand, Andres Ovalle proposed the optimal energy storage sizing formulation, taking the characteristics of different modern battery and supercapacitor technologies into account, and the objective function to minimize the trade-off between energy-storage capacity and charging rates based on a real-time simulation [10]. At the same time, Dupré developed a methodology that divides installation into stages with different budgets and periods to obtain optimum installation of ESSs in a railway line, balancing energy saving and profit [11]. Also, simulations in different conditions managed by different algorithms have been conducted by many authors, all of which prove that installing SESS will lead to energy saving for the railway system [12–16]. Also, real examples have been commercially applied around the world [17–20]. This paper proposes the utilization of a hybrid energy-storage system (HESS) combining SMES and conventional batteries in rail transit.

SMES is a high-power-density energy-storage technology that relies on the principle of superconducting magnets. SMES takes advantage of the unique properties of superconducting materials, which exhibit zero resistance at low temperatures. A strong magnetic field is generated by passing an electric current through a superconducting coil, allowing for the storage of electrical energy. In addition, it exhibits a fast response in milliseconds. It is mainly applied for network stability applications [21,22]. While in rail transit, thanks to its unique characteristics, SMES is well-suited for recovering the intermittent and random nature of RBE. However, the negative impact of strong magnetic fields on the environment and their high cost are the main obstacles to deploying SMES devices.

Lithium-ion battery (LIB) presents a rechargeable characteristic. Electrical energy is stored and released through the embedding and de-embedding of lithium ions in its chemical reactions. This innovative technology has gained widespread adoption, positioning itself as one of the most prevalent energy-storage solutions available in commercial markets today. On the other hand, the high-energy-density characteristic distinguishes Lithium-ion batteries (LIBs) from SMES, which allows them to store more electrical energy in a light and small form. Consequently, LIB has become the preferred energy-storage technology for electric vehicles and mobile devices. Furthermore, successful commercialization and significant global investments have led to a considerable reduction in its cost. Although LIBs offer high energy density, they can still be relatively heavy compared to alternative ESS technologies like ultracapacitors [4]. In railway transit applications, weight directly impacts energy consumption and vehicle performance.

By utilizing a combination of several energy-storage technologies, the HESS system effectively delivers and controls energy. The two complementary technologies that constitute HESS's core are LIB and SMES. While LIB is distinguished by its high energy density and wide applicability, SMES is recognized for its quick reaction in milliseconds, exceptional power density of up to 2000 W/kg, and extended life expectancy. The HESS system may efficiently utilize the advantages of both LIB and SMES to accomplish efficient energy delivery and storage. Meanwhile, SMES can be regarded as a buffer for temporary energy storage to reduce the load of the battery, thus reducing the energy exchange frequency of the battery and extending its lifespan. One challenge is the specification of power-density ESS and energy-density ESS. Integrating both effectively requires careful design. In the meantime, higher capacity does not always lead to more significant energy savings [23]. Optimal sizing is crucial.

A consistent power-supply infrastructure is frequently absent in remote or isolated regions. Under such circumstances, trains may face challenges relying directly on an external power source. OESS serves as a solution, enabling trains to provide energy independently in areas lacking power supply. OESS enables trains to capture RBE immediately and store it in real time. It also allows the train to utilize this energy as soon as needed. Batteries and supercapacitors are commonly applied in OESS [24]. However, it is regarded that high input and output power models are only sometimes feasible for battery energy systems to operate at [25]. In the meantime, OESS introduces an extra burden on the train along with more energy consumption [26,27]. In addition, the converter is a massive burden on driving range and design as well [28]. Ahmad proposed a chopper topology that reduces mass and volume with high chopper efficiency [29]. Miyatake investigated electric double-layer capacitors as an OESS due to their high energy density. A mathematical model is formulated using a widely applicable optimization technique known as sequential quadratic programming, which can determine optimal acceleration/deceleration and current commands at each sampling point, maintaining fixed transfer time and distance [30]. Wu introduced OESS with on-route constraints to model the real-world scenario. Based on the proposed MILP model, degradation of the OESS influences discharge/charge strategy, and the energy consumption is reduced by 11.6% with the introduction of OESS recovering RBE [31]. González-Gil considered Lithium-ion battery (LIB) and nickel-metal hydride (NiMH) batteries as viable options for OESS [8]. In addition, Pulazza proposed that the energy transmission congestion resulting from renewable energy can be managed by installing OESS, which proves the advantage of the installation of OESS [32]. Similarly, different types of OESS are also applied in commercial operation [33–39].

On the other hand, the application of OESS improves the efficiency of train power delivery because the energy does not need to be delivered through the catenary to a SESS but is embedded directly in the train itself. It is important to note that this does not mean that SESS is useless. Combination applications of SESS and OESS are usually installed in smart grids, microgrids, wind farms, etc. [25,40,41]. The cooperation between SESS and OESS is just part of this paper's proposal. They can work together to optimize the recovery and utilization of RBE throughout the rail transit system. OESS can capture energy quickly on the train, while SESS can distribute stored energy more evenly throughout the rail network to be shared and utilized when needed. Considering that the weight of OESS influences the energy consumption of the train, LIB is adopted as OESS. From a cost–benefit perspective, due to the introduction of OESS, the quantity and capacity of all the SESSs will be decreased, compared with the case only equipped with SESS [42], leading to substantial gains in energy savings and electricity cost reduction [43].

Besides the concern of SESS and OESS, capacity optimization of ESS is of great significance. Pang applied NSGA-II to address the capacity configuration of Energy-Storage Systems (ESS) in rail transit, considering two objectives: minimizing braking resistor energy consumption and configuration cost [44]. Similarly, Mundra also takes advantage of NSGA-II, achieving dual-objective optimization for the peak-to-average ratio of the total energy demand and electricity usage charge in smart grid [45]. On the other hand, Qayyum adopted PSO to minimize the nano grid energy trading cost while meeting energy demand [46]. Meanwhile, Li utilized Improved Particle Swarm Optimization (IPSO) to balance system economy and stability in the distribution grid [47]. On the other hand, to enhance the coordination between Transit-Oriented Development (TOD) and station-area land use in developing a potential city transit, Pishro employed Multiple Linear Regression (MLR) to establish Node–Place–Ridership–Time (NPRT) equations. This approach surpasses the accuracy of the earlier Node–Place (NP) and Node–Place–Ridership (NPR) models, delivering more precise outcomes [48]. Similarly, Pishro develops eight Multiple Linear Regression (MLR) equations for each hub by combining mathematical techniques and machine learning. It yields valuable insights that guide decision-making and facilitate the development of transportation systems [49]. Boukerche proposed machine-learning (ML)-based methods for building traffic-prediction models that are less restrictive to the prediction task as they require less prior knowledge of the relationships between different traffic modes and can better fit the nonlinear features in the traffic data [50]. Hitachi created and implemented an AI-driven hybrid railway traffic-management system to aid in the automation of the intricate process of planning train schedules [51]. Essien suggested a novel urban traffic-prediction model using deep learning. The model integrates insights from tweets along with traffic and weather data to enhance accuracy and reliability in predicting urban traffic patterns [52].

All in all, this paper adopts HESS configuration as SESS, combining high-power-density ESS, SMES, and high-energy-density ESS, LIB. To explore the combination of SESS and OESS in rail transit energy management, OESS utilizes LIB. To optimize the ESS capacity, minimize redundancy, and balance trade-offs between multi-objectives, cost, and energy consumption, NSGA-II is applied [53]. This is because of its ability to achieve a notably enhanced distribution of solutions and improved convergence closer to the Pareto-optimal front across various problem scenarios. The Parallel Computing Toolbox has been introduced to save computation time.

2. Methodology

2.1. Topology

A practical simulation of the SESS in rail transit involves designing a specific network configuration, as depicted in Figure 1. In this setup, three trains with OESS travel from Station A to Station E, while another three trains with OESS travel in the opposite direction, from Station E to Station A. The entire operation adheres to a predefined timetable, outlined in Figure 2. There are two substations strategically placed along the railway line. Each substation is equipped with a SESS comprising a SMES and a set of LIBs in parallel.

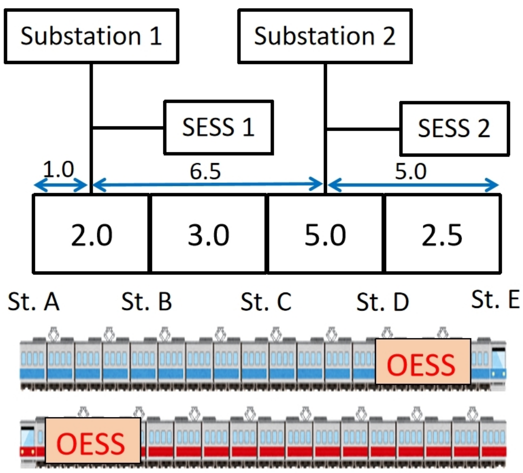

Figure 1. Topology of the Railway.

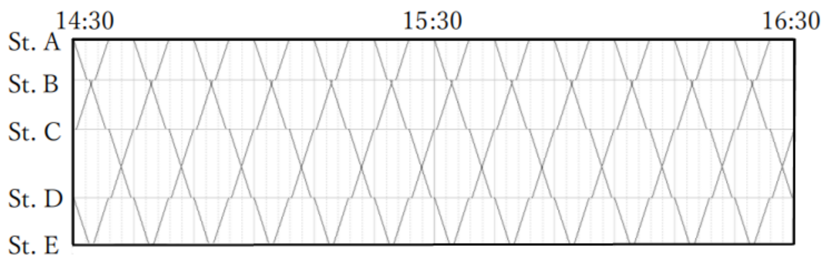

Figure 2. Timetable.

The simulation encompasses modeling the feeding system, trains, and substations. It is worth mentioning that the feeding system presents the connected nodes adopting the term "tie nodes". This approach offers a significant benefit as it eliminates the necessity for a comprehensive modification of the circuit topology whenever there is a change in the feeding system, as depicted in Figure 3. The tie nodes can make the different node voltages identical to connect the feeders for different directions under the substations. This technique enables simple modeling of feeding circuits and avoids using the conductance matrix. On the other hand, the train model is constructed by voltage, current, and notch. The notch simulates a driver's or Automatic Train Operation's (ATO) command to accelerate or decelerate. The whole operation is based on a timetable. In the meantime, the substation model is represented by current and voltage. It is detailed in Reference [54].

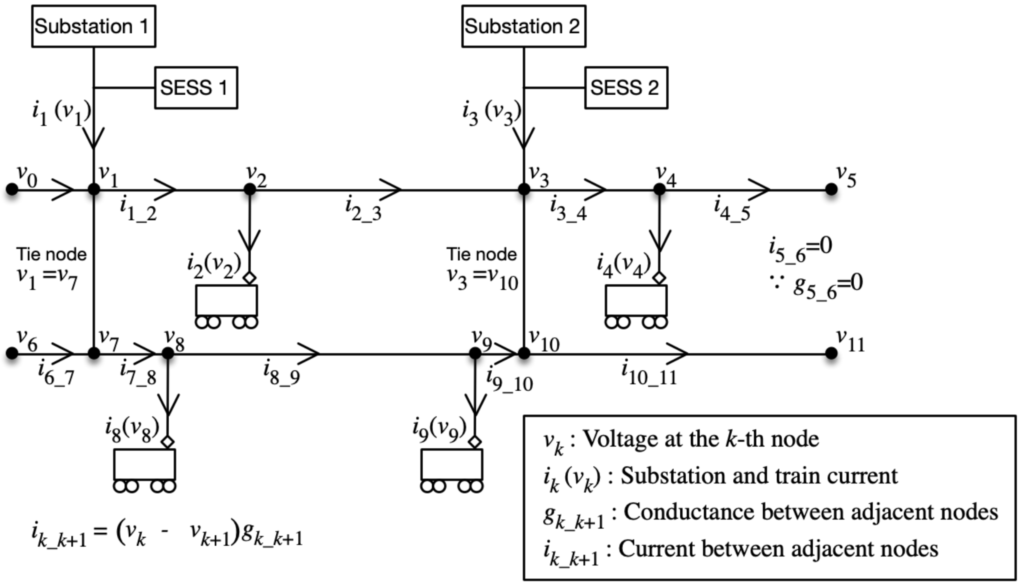

Figure 3. Circuit Topology.

2.2. NSGA-II

Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is a multi-objective optimization algorithm for solving problems with multiple objective functions. It is an extension of the genetic algorithm that aims to find a non-dominated (non-inferior) solution in the objective space and form a Pareto front, i.e., no other solution can outperform this set of solutions on all objectives. Meanwhile, the fast non-dominated sorting approach is introduced with significant improvement over the complexity of other algorithms in the same category. On the other hand, by incorporating elitism, NSGA-II ensures that the best solutions are carried over to the next generation, improving the convergence towards the true Pareto-optimal front [53].

The operation of NSGA-II follows the flowchart Figure 4. First, a set of potential solutions to the optimization problem is generated. These solutions are usually represented as chromosomes in a genetic algorithm context. Then, for each solution in the population, the objective functions are calculated, which evaluate how 'fit' or 'good' the solution is. Next, the best solutions from the current population to parents are selected to create a new generation of solutions. Crossover combines two parents to produce children for the next generation. Mutation introduces random changes to some of the children to maintain genetic diversity. Finally, the algorithm selects the best solutions based on their fitness, and these become the new population for the next iteration until there is no significant improvement between generations or when a satisfactory solution is found. However, NSGA-II also meets some challenges. In this paper, SESS and OESS capacity allocation are the solutions. To further optimize the energy management of the transportation system and discover the balance between investment and energy consumption, NSGA-II is applied. NSGA-II involves sorting individuals based on non-domination, with a time complexity of O(MN^2), where N is the population size, and M is the number of objectives. This can become computationally expensive for large populations or high-dimensional problems. In the meantime, storing and maintaining the non-dominated fronts over generations can increase memory usage. Therefore, a server equipped with high computation ability and large RAM is of great necessity. On the other hand, the algorithm aims to discover and maintain a diverse set of solutions that approximate the entire Pareto front. However, due to the complexity of the search space and the inherent characteristics of the optimization problem, the algorithm might converge to or focus on specific regions of the Pareto front, forming what is known as local Pareto fronts [55]. One solution combines multiple algorithm runs with different random seeds or initial conditions. The ensemble of runs can provide more comprehensive coverage of the Pareto front, reducing the risk of converging to local Pareto fronts.

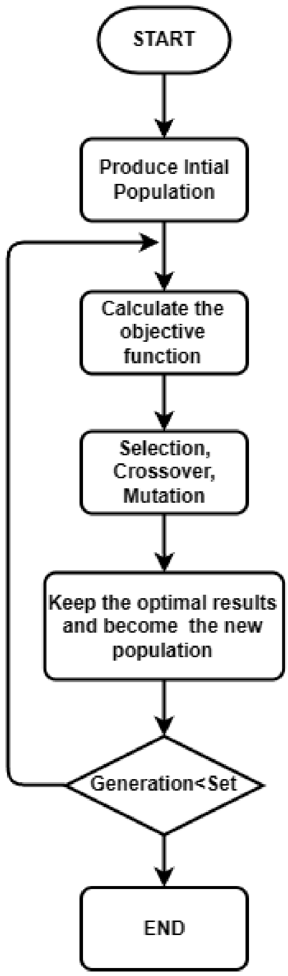

Figure 4. Flowchart of NSGA-II.

The objective function F consists of two sub-objectives: cost minimum (represented by $f1$) and energy consumption minimum (represented by $f2$), shown in Equation (1). In Equation (2), the composition of cost function $f1$ is associated with the number of battery modules in each SESS (K_i) and each OESS (K_p), as well as the fixed costs for different components like SMES ($cost_{sc}$), DCDC converters ($cost_{dcdc}$), battery ($cost_{bt}$), and the cost of electricity ($cost_e$). On the other hand, the sub-objective ($f2$) is a measure of the total energy consumption aggregating the energy supplied across substation (E_{sub}), SESS (E_{sess}), and OESS (E_{oess}) associated with the train system. The energy supplied by the substation is mainly for the train's operation. The energy supplied from SESS and OESS is calculated by the difference in energy capacity between the beginning and end of the operation, shown in

Equations (3) and (4). In addition, the cost of electricity is based on the energy consumption in all substations, as shown in Equation (5).

$$Objective \quad : \quad F(K_i, K_p, E_{sub}, E_{sess}, E_{oess}) \quad = \quad [f_1(K_i, K_p), f_2(E_{sub}, E_{sess}, E_{oess})] \tag{1}$$

$$Sub-Objective : \begin{cases} f_1(K_i, K_p) = \sum_{i=1}^{N}(cost_{sc} + 2 \times cost_{dcdc} + cost_{bt} \times K_i + cost_e) \\ \qquad + \sum_{p=1}^{M}(cost_{bt} \times K_p) \\ \\ f_2(E_{sub}, E_{sess}, E_{oess}) = E_{sub} + E_{sess} + E_{oess} \end{cases} \tag{2}$$

$$E_{sess} = \sum_{i=1}^{N}(Esinitial_i - Esend_i) \tag{3}$$

$$E_{oess} = \sum_{p=1}^{M}(Eoinitial_p - Eoend_p) \tag{4}$$

$$cost_{alle} = E_{sub} \times cost_e \tag{5}$$

K_i: Amount of battery modules in SESS i
K_p: Amount of battery modules in OESS p
i: Order of substations
p: Order of trains
E_{sub}: Energy consumption in all substations
E_{sess}: Energy consumption in all SESS
$Esinitial_i$: Energy stored in SESS i in the beginning
$Esend_i$: Energy stored in SESS i in the end
E_{oess}: Energy consumption in all OESS
$Eoinitial_p$: Energy stored in OESS p in the beginning
$Eoend_p$: Energy stored in OESS p in the end
N: Amount of substations
$cost_{sc}$: Cost of SMES
$cost_{dcdc}$: Cost of DCDC converter
$cost_{bt}$: Cost of a battery module
$cost_{alle}$: Total electricity fee
$cost_e$: Cost of electricity fee per kWh
M: Quantity of trains

Table 1 outlines the predetermined parameters on which the algorithm runs.

Table 1. NSGA-II Parameter Settings.

Setting	Value
Amount of Population	30
Amount of Variable	5
Variable Range	[1100]
Iteration Count	40
Selection Strategy	Binary Tournament
Crossover Strategy	Simulated Binary
Crossover Factor	20
Crossover Probability	100%
Mutation Strategy	Polynomial
Mutation Factor	20
Mutation Probability	20%

Table 2 [56], Tables 3 and 4 provide specifics of the predetermined parameters for train, costs, SESS, and OESS. Specifically, the operating period is set at 30 min, from 2 p.m. to

2:30 p.m., under the timetable outlined in Figure 2. This timetable dictates when trains travel between stations, ensuring that the simulation accurately reflects the timing and scheduling constraints of an actual railway system. Within 30 min of simulation, three trains with OESS travel from Station A to Station E, while another three trains with OESS operate in the reverse way. The schedule influences the operation of these substations, as they must manage the energy flow to and from the trains according to their arrival and departure times. These parameters play a crucial role in the simulation, influencing the capacity allocation, cost assessment, and energy consumption within the specified time frame.

Table 2. Specifications for Train.

Setting	Value
Mass	310.4 (tons)
Occupant Capacity	60%
Braking Mechanism	Regenerative braking
Terminal velocity in Constant Torque	50 (km/h)
Terminal velocity in Constant Output	80 (km/h)
Max Acceleration Rate	2.5 (km/h/s)
Max Deceleration Rate	3 (km/h/s)
Nominal Voltage	1500 (V)
Max Regenerative Current	3000 (A)
Starting/Cutoff Voltages for Regenerative Current Restriction	1750 (V), 1800 (V)

Table 3. Initial Investment.

Expenditure	Value
SMES Module	50,000,000 (JPY) [57]
Battery Module	645,337 (JPY)
DCDC Converter Module	4,302,250 (JPY)
Electricity Cost	15.65 (JPY/kWh) [58]

Table 4. Specifications for SESS and OESS.

Setting	Value
Inductance of SMES (L)	0.1 (H)
Maximum Superconductor Current Limit (Isc_max)	3000 (A)
Initial Superconductor Current (Isc)	2625 (A)
Minimum Superconductor Current Limit (Isc_min)	2250 (A)
DCDC Converter Efficiency	95%
Battery Output Power (P)	500 (W)
Battery Capacity	10 (Ah)
Initial Battery State of Charge (SOC)	50%
SOC Limit	30–80%

It is worth mentioning that the deceleration corresponds to a stop in the power supply to the motors. However, as the train continues to move with inertia, the axle reacts on the motor rotor to produce an induced current due to electromagnetic induction, i.e., the motor becomes a generator. At the same time, the torque generated by the rotation of the drive motor acts on the wheels to slow down the vehicle, which is called regenerative braking [59]. Utilizing the electrical energy generated by electromagnetic induction is called regenerative braking energy recovery. In the meantime, due to the regenerative energy output, the pantograph voltage increases. To avoid unpredictable damage to the catenary-connected appliances, which cannot withstand voltages exceeding the rated value, the regenerative current restriction is conducted in accordance with the catenary voltage, shown in Figure 5 and Table 2. In addition, the RBE is first consumed by auxiliary applications. If the auxiliary application cannot consume all RBE, then the OESS stores most of the RBE to power the train in the next acceleration. The excess RBE that OESS cannot store transmits and stores in nearby SESS. Calculation of the distance between the train and SESS induces the nearest SESS. By sizing capacity and allocating priority of OESS and SESS based on the train's energy demand and operational state, utilization of RBE is fully optimized, energy consumption decreases, and the system's economic benefit is enhanced.

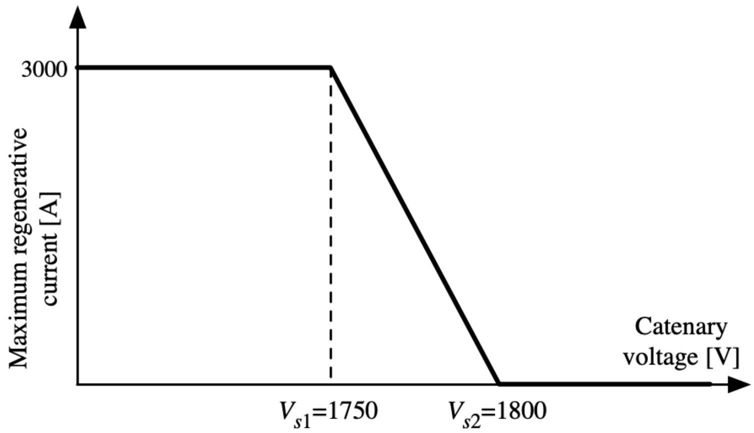

Figure 5. Regenerative Current Output Control.

3. Results and Discussion

In this study, MATLAB is employed as the simulation tool for modeling rail transit scenarios. Meanwhile, the Parallel Computing Toolbox and a server equipped with an AMD Ryzen Threadripper 3970X 32-Core CPU and 64 GB of RAM are applied to save simulation time. The cases under examination are categorized into five parts.

3.1. Case A

Neither SESS nor OESS is introduced into the rail transit system in Case A. The topology is depicted in Figure 6, and the predefined parameters for substations, trains, and capital costs are detailed in Tables 2–4. The operation period is 30 min from 14:00 to 14:30, according to the timetable shown in Figure 2. The simulation results are shown in Figure 7 and Table 5. The cost only consists of the electricity fee.

Table 5. Case A: Simulation Result of Railway System without ESS.

Energy Consumption	Cost	Capacity of All SESSs	Capacity of All OESSs
1196.28 (kWh)	18721.84 (JPY)	0 (kWh)	0 (kWh)

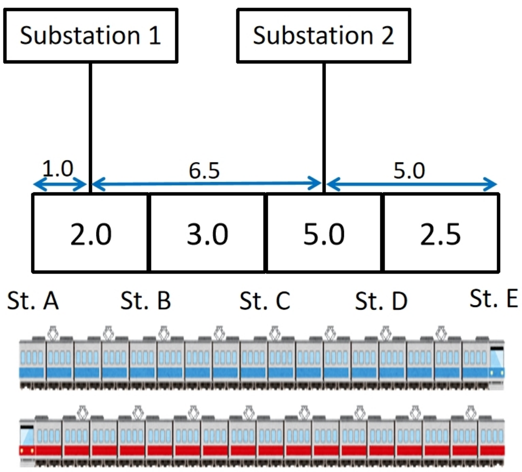

Figure 6. Topology of the Railway without ESS.

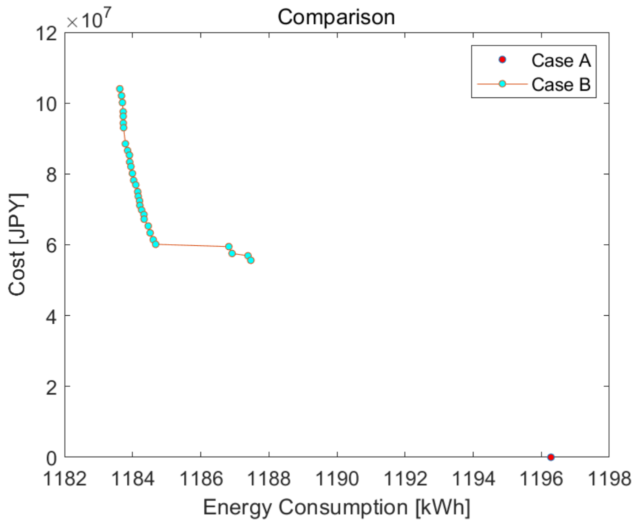

Figure 7. Cases Comparison: A and B.

3.2. Case B

In Case B, only SESS is integrated, and the capacity of all LIBs is tailored through customization using NSGA-II. The energy consumption varies from 1183.63 to 1187.47 kWh. The cost varies from 1.04×10^8 to 5.56×10^7 JPY. They are shown in Figure 7. On the other hand, the capacity distribution is depicted in Figure 8. Clearly, with the integration of SESS, the more the investment increases, the more energy is saved. However, energy savings are not apparent with a double investment. It was analyzed that there was a transmission loss from the regenerative braking device to SESS. At the same time, the SMES's capacity is fixed and limited due to its complicated construction to optimize its capacity.

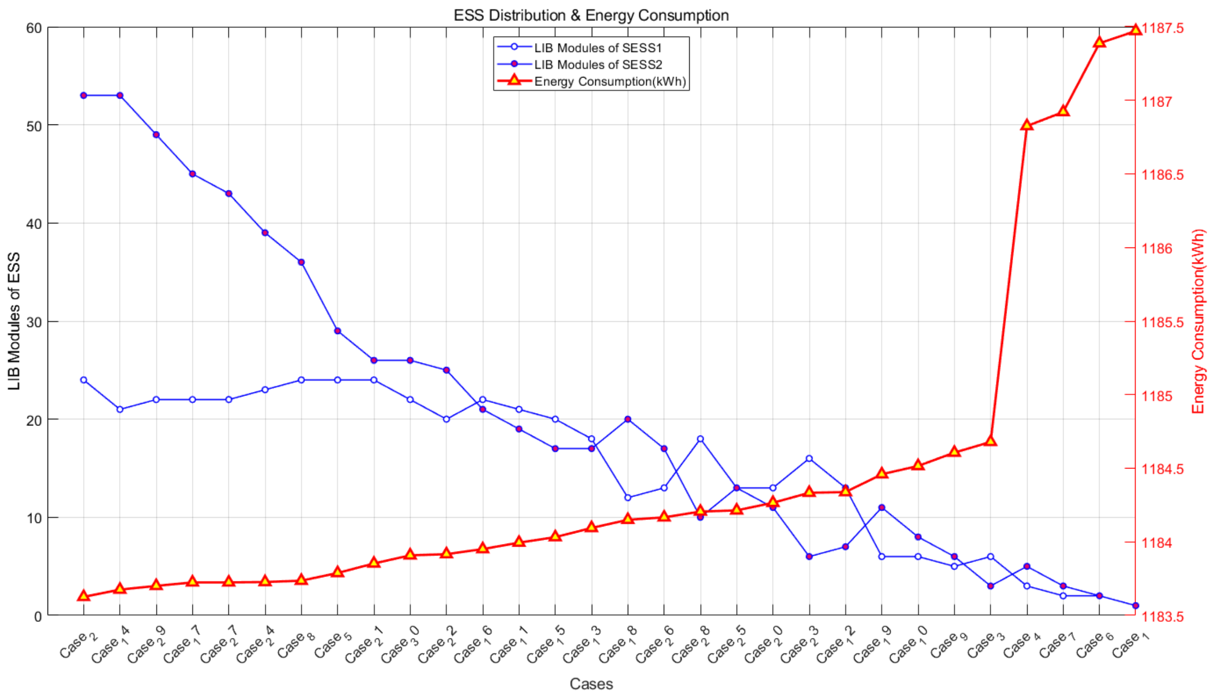

Figure 8. Case B: Capacity Distribution and Energy Consumption.

3.3. Case C

In Case C, both SESS and OESS are implemented in rail transit. Simultaneously, the capacities of LIBs for both SESS and OESS are optimized for uniformity through NSGA-II. Energy consumption varies from 1054.72 to 1111.30 kWh. And the cost varies from

1.84×10^9 to 5.94×10^7 JPY. They are depicted in Figure 9. Meanwhile, the relationship between capacity distribution and energy consumption is presented in Figure 10. Compared with case B, with the introduction of OESS, there is approximately 76.2 kWh of energy saving when the investment is around 5.94×10^7 JPY. And with more investment increases, there are further energy savings.

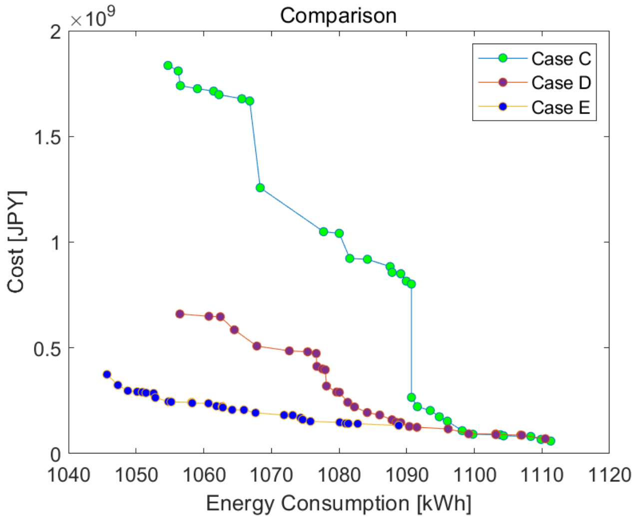

Figure 9. Pareto front cases comparison: C,D,E.

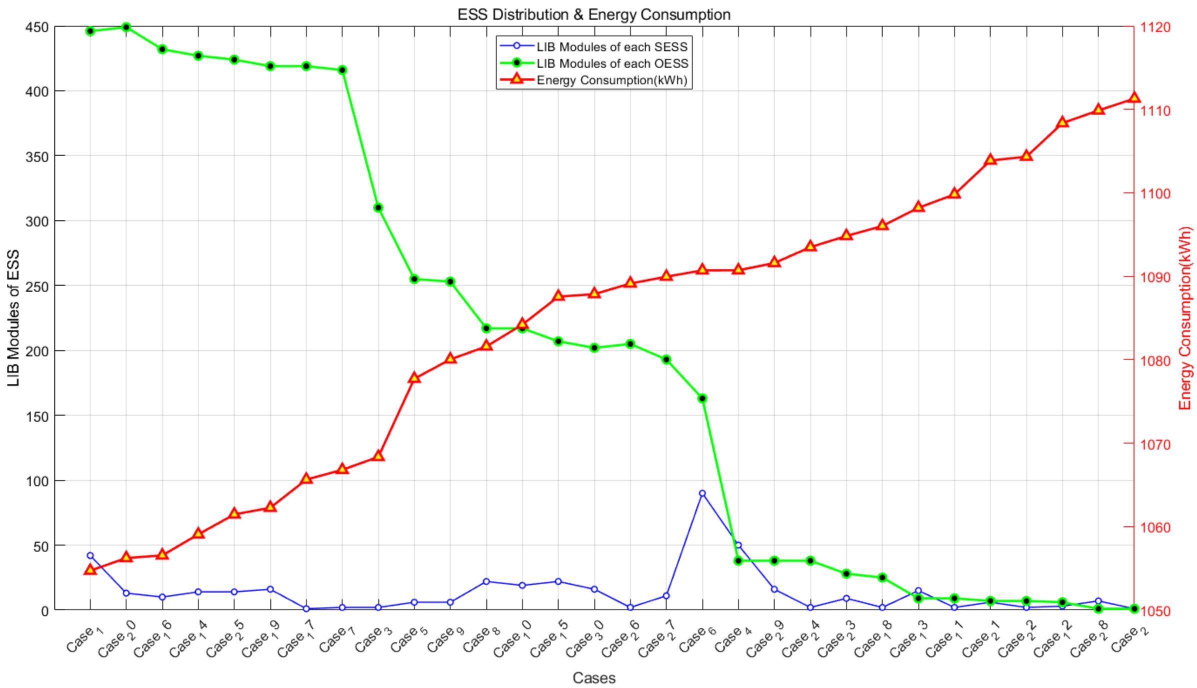

Figure 10. Case C: Capacity Distribution and Energy Consumption.

3.4. Case D

In Case D, both SESS and OESS are installed. However, due to the difficulty of equipment manufacturing, the SESS capacities may vary between stations, while OESS capacities remain uniform across all trains. Consequently, only SESS LIB capacities undergo customization, while OESS LIB capacities are optimized for uniformity. Energy consumption varies from 1056.48 to 1110.50 kWh. And the cost varies from 6.60×10^8 to 7.05×10^7 JPY. They are depicted inFigure 9. Simultaneously, the relationship between capacity distribution and energy consumption is presented in Figure 11.

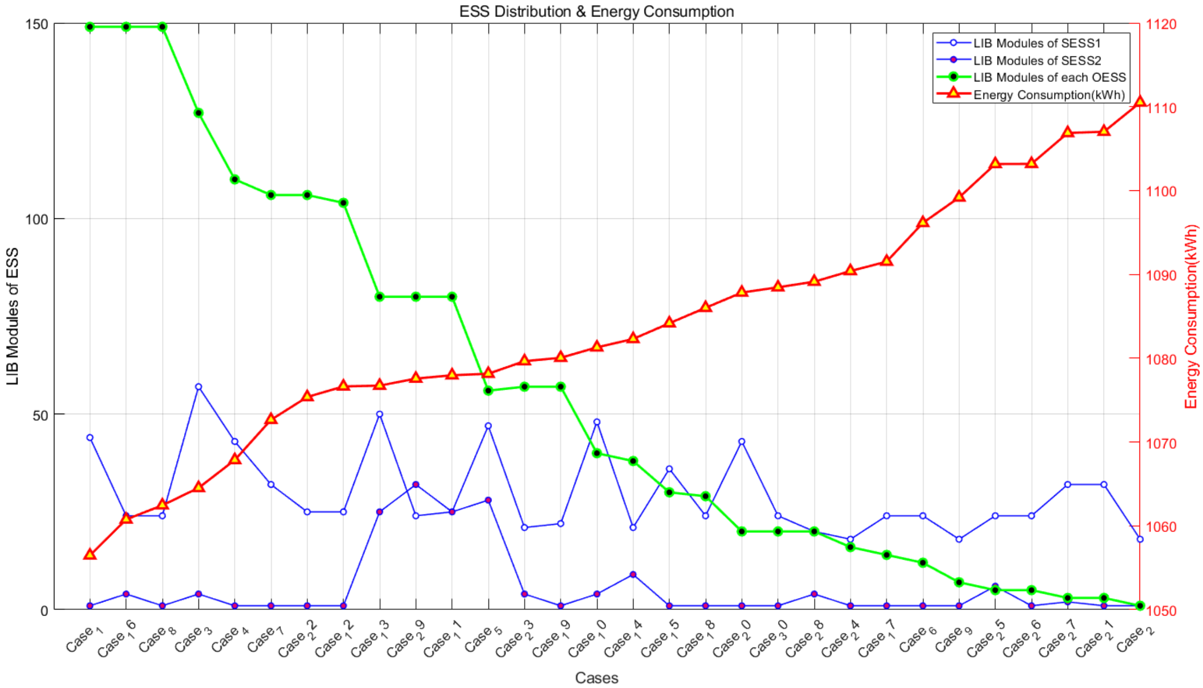

Figure 11. Case D: Capacity Distribution and Energy Consumption.

3.5. Case E

In Case E, similarly, both SESS and OESS are installed, but as a comparison, the capacities of LIBs for both SESS and OESS undergo customization using NSGA-II. Energy consumption varies from 1045.70 to 1088.83 kWh. And the cost varies from 3.74×10^8 to 1.33×10^8 JPY shown in Figure 9. On the other hand, the relationship between capacity distribution and energy consumption is presented in Figure 12. With the application of SESS and OESS, energy consumption decreased. It is noticeable that compared with OESS, the capacities of SESSs vary relatively flat in different cases. It further proves that the capacities of OESSs play a significant role in saving energy and investment.

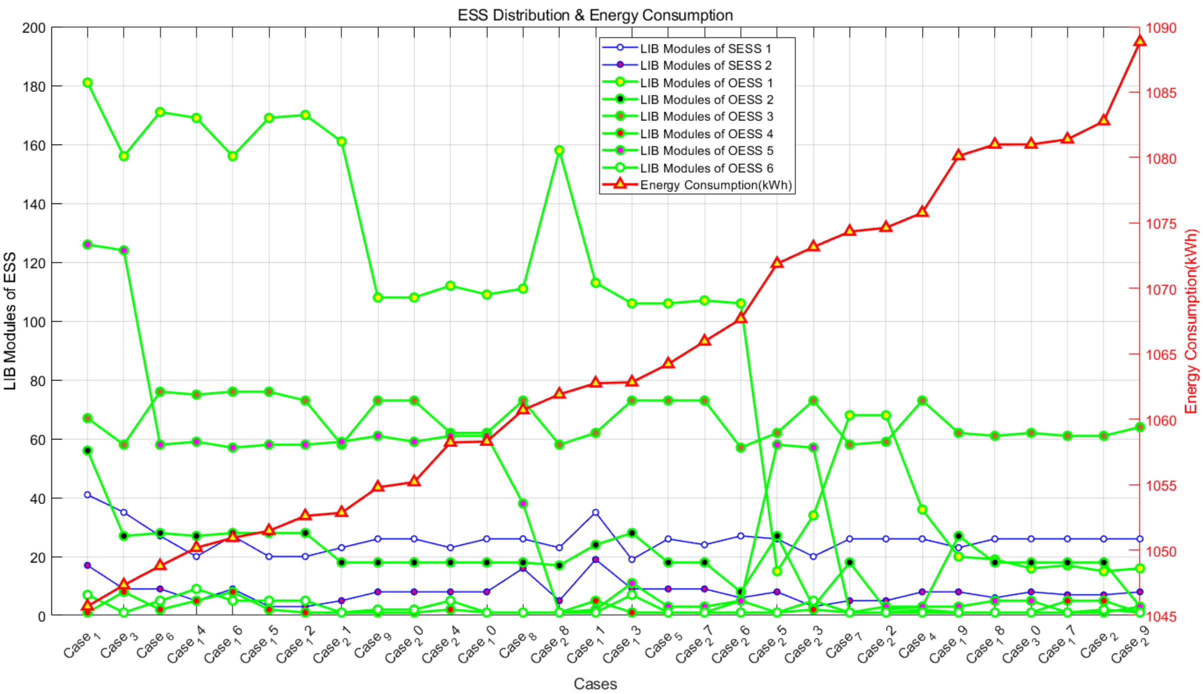

Figure 12. Case E: Capacity Distribution and Energy Consumption.

3.6. Cases Comparison

Table 6 summarizes the case comparison in configuration, impact on energy saving, and cost. As illustrated in 3.2 Case B, introducing SESS (Capacity Customization) has a limited impact on energy saving. On the contrary, the cost increased significantly, which is not a beneficial solution for rail transit construction.

Table 6. Cases Configuration and Impact Comparison.

Case	Configuration	Impact on Energy Saving	Impact on Cost
A	No SESS or OESS	Baseline for comparison	Baseline for comparison
B	Only SESS integrated	Limited energy savings	Increased due to SESS investment
C	SESS and OESS with uniform capacities	Notable energy savings	Highest cost suggesting redundancy
D	SESS with customized capacities and uniform OESS	Notable energy savings	A balance in cost
E	SESS and OESS with customized capacities	Notable energy savings	Lowest cost. Not practical in manufacturing train

Comparing Cases C, D, and E reveals that including OESS alleviates the rail transit's reliance on SESS capacity for energy management. Moreover, despite the increased investment, more energy savings are achieved compared to Case B. It is noteworthy that when energy consumption is similar in Cases C, D, and E, Case E incurs the highest cost among the three. This suggests potential redundancy in the Energy-Storage Systems (ESS) capacity. Conversely, Case D, which pragmatically optimized SESS and OESS capacity, presents a more reasonable outcome.

Moreover, the depicted Figure 13 demonstrates that with the introduction of the utilization rate of RBE into energy-cost Pareto front of Case D, as cost rises, the utilization rate of RBE also increases in a trend, therefore promoting efficient energy management. Additionally, Figure 11 represents the SESS1, SESS2, and OESS's capacity proportion in each optimal non-dominated solution of Case D, named Case 1 to Case 30. It is clear that the capacity of SESS1 and SESS2 have a minimal impact on the RBE utilization rate. Instead, the OESS predominantly plays a crucial role in recovering RBE. Therefore, by optimizing the capacities and configurations of SESS and OESS, rail transit systems can significantly reduce energy consumption and operational costs. In particular, the uniform capacity of each OESS should be two to three times the average capacity of each SESS.

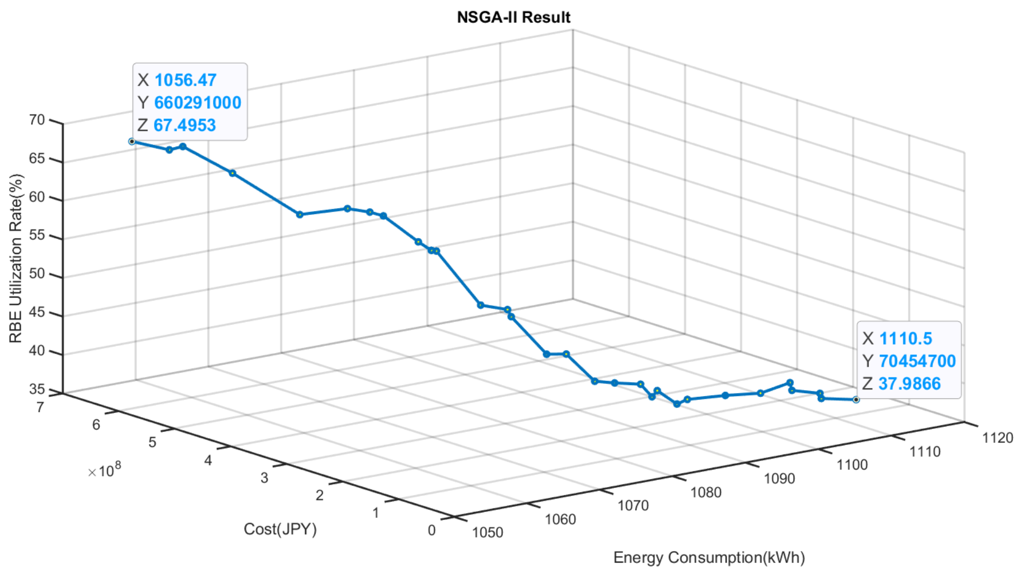

Figure 13. Case D: Cost Energy Regenerative Braking Energy Utilization rate.

4. Conclusions

Through the capacity optimization of LIB using NSGA-II, the integration of SESS proves effective in recovering RBE. Nearly 30 kWh is saved within 30 min of operation. In the meantime, the HESS configuration of SESS, combining SMES and LIB, ensures rapid response and high power exchange while providing a relatively large energy storage capacity to store regenerative braking energy. Furthermore, the collaborative implementation of both SESS and OESS emerges as a superior strategy for recycling. This approach not only achieves significant energy savings (approximately 100 kWh) but also demonstrates a mutually beneficial outcome for both energy consumption and investment efficiency within 30 min of operation.

Particularly noteworthy is the vital role played by OESS in this integrated system. The capacity of OESS is recommended to be two to three times that of SESS. The OESS emphasizes its significance in realizing a win–win scenario for optimizing energy consumption and investments in the rail transit system.

5. Possible Directions for Future Studies

The findings of our study on the coordination of SESS and OESS in rail transit for achieving multi-objective optimization in energy and cost suggest several promising avenues for future research. In this section, we outline challenges and potential directions for further investigation based on the insights gained from our study.

5.1. Optimization of SMES Capacity

Unlike conventional battery-based ESS, SMES presents unique challenges due to its complexity. A possible exploration is optimizing SMES's capacity within the rail transit operations. By delving deeper into determining optimal SMES capacity parameters, researchers can refine energy management strategies and maximize cost savings. Future studies could employ advanced optimization techniques to systematically evaluate the impact of varying SMES capacities on system performance metrics, such as energy efficiency and operational costs.

5.2. Application and Comparison of Different Energy-Storage Systems (ESSs)

Comparative studies involving diverse Energy-Storage Systems (ESSs) offer another avenue for exploration. By evaluating the performance of different ESS technologies, such as lithium-ion batteries, flywheels, and compressed air energy storage, researchers can identify the most suitable solutions for specific rail transit applications. Future research could involve comprehensive assessments of each ESS type under varying operating conditions, considering factors such as energy capacity, response time, and lifecycle costs. Furthermore, conducting sensitivity analyses and scenario-based simulations can provide valuable insights into the robustness and resilience of different ESS technologies in real-world deployment scenarios.

5.3. Validation Experiment

Validation experiments represent a critical step toward confirming the efficacy and feasibility of proposed coordination strategies in practical settings. Future research efforts could focus on conducting field trials and pilot implementations to empirically validate the performance of the developed models and methodologies. Researchers can gain access to real-world data and infrastructure by collaborating with industry partners and transit agencies, facilitating the validation process.

Author Contributions: Conceptualization, D.K. and M.M.; methodology, D.K.; software, D.K.; validation, D.K. and M.M.; formal analysis, D.K.; investigation, D.K.; resources, D.K. and M.M.; data curation, D.K.; writing—original draft preparation, D.K.; writing—review and editing, M.M.; visualization, D.K.; supervision, M.M.; project administration, D.K.; funding acquisition, M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is contained within the article.

Acknowledgments: The authors would like to thank all the colleagues in Miyatake's laboratory for their kind help.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RBE	Regenerative Braking Energy
ESS	Onboard Energy-Storage Systems
ESS	Stationary Energy-Storage Systems
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
HESS	Hybrid Energy-Storage Systems
SMES	Superconducting Magnetic Energy Storage
PSO	Particle Swarm Optimization
LIB	Lithium-ion Battery
NiMH	Nickel-Metal Hydride
IPSO	Improved Particle Swarm Optimization
ATO	Automatic Train Operation
L	Inductance
Isc	Initial Current in Superconductor
Isc_max	Upper Limit of Current
Isc_min	Lower Limit of Current
SOC	Initial State of Charge for Battery
K_i	Quantity of battery modules in each SESS
K_p	Quantity of battery modules in each OESS
i	Order of substations
p	Order of trains
E_{sub}	Energy consumption in all substations
E_{sess}	Energy consumption in all SESS
$Esinitial_i$	Energy stored in SESS i in the beginning
$Esend_i$	Energy stored in SESS i in the end
E_{oess}	Energy consumption in all OESS
$Eoinitial_p$	Energy stored in OESS p in the beginning
$Eoend_p$	Energy stored in OESS p in the end
N	Quantity of substations
$cost_{sc}$	Cost of SMES
$cost_{dcdc}$	Cost of DCDC converter
$cost_{bt}$	Cost of battery per module
$cost_{alle}$	All cost of electricity fee
$cost_e$	Cost of electricity fee per kWh
M	Quantity of trains

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