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Optimization of Power Systems for Low-Carbon Manufacturing in New Energy Vehicles

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Abstract: The transition toward carbon neutrality has intensified the need for low-carbon manufacturing in the new energy vehicle (NEV) industry. While existing research has primarily focused on the use phase of vehicles, limited attention has been given to the carbon emissions and energy consumption arising during the development and manufacturing of power systems. To address this gap, this study establishes an integrated Energy-Carbon-Cost (ECC) framework that combines lifecycle assessment (LCA), empirical industrial data, and multi-objective optimization modeling. The framework quantifies how design parameters, such as material substitution, motor efficiency, and cooling configurations, affect lifecycle carbon intensity, cost, and energy efficiency. Results based on case studies from SAIC, BYD, and Volkswagen demonstrate that optimized configurations can reduce total lifecycle carbon emissions by approximately 24% while maintaining economic feasibility. The proposed model transforms traditional LCA from a static evaluation tool into a dynamic, prescriptive decision system, enabling both theoretical innovation and practical applicability. This research provides manufacturers and policymakers with an actionable pathway for achieving synergistic carbon reduction and cost optimization, contributing to the sustainable advancement of NEV manufacturing.

Keywords: low-carbon manufacturing; new energy vehicles; lifecycle assessment (LCA); multi-objective optimization; energy-carbon-cost (ECC) framework

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1. Introduction

The global shift toward carbon neutrality has placed unprecedented pressure on the manufacturing sector, particularly within the new energy vehicle (NEV) industry, which serves as a cornerstone of green transformation [1]. According to the International Energy Agency (IEA, 2024), the production of electric vehicles (EVs) and their power systems, comprising batteries, electric motors, and power electronics, accounts for approximately 35-40% of the total lifecycle carbon emissions of an NEV [2]. For example, Tesla's Gigafactory in Nevada reported that its battery and drivetrain manufacturing emitted around 4.5 metric tons of CO_2 per vehicle, even before final assembly [3]. Similarly, China's large-scale NEV producers, such as BYD and CATL, have disclosed that nearly 60% of production-phase energy consumption originates from electrode coating, casting, and thermal treatment processes [3]. These figures highlight that while the use phase of NEVs achieves "zero tailpipe emissions," their manufacturing phase remains far from carbon neutral.

Despite these realities, existing academic and industrial studies have largely centered on use-phase optimization, improving driving efficiency, charging management, and battery life, while neglecting upstream processes such as component fabrication and assembly [4]. Previous lifecycle assessment (LCA) frameworks often employ generalized emission coefficients and static process assumptions, overlooking the heterogeneity of real manufacturing environments [5]. Furthermore, optimization models for NEV power systems traditionally prioritize performance and cost, but fail to integrate carbon intensity as a co-optimized objective [6]. This has resulted in a methodological gap between energy efficiency modeling and environmental impact assessment.

Addressing this research gap requires a multi-perspective approach that links engineering design parameters with environmental outcomes through rigorous quantitative modeling. The present study proposes an integrated LCA-data modeling framework to evaluate and optimize the low-carbon manufacturing of NEV power systems. Specifically, it focuses on the drivetrain and electric motor subsystem, which contribute significantly to total embodied emissions. Empirical data are collected from representative Chinese and European manufacturers, including SAIC, BYD, and Volkswagen's Hefei plant, to capture the diversity of material sourcing, production processes, and energy structures.

Methodologically, this study combines LCA to quantify stage-specific energy use and carbon emissions, with multi-objective data modeling to explore trade-offs among carbon intensity, cost, and energy efficiency. The modeling process employs regression-based learning and evolutionary optimization techniques to identify the optimal design parameter set that minimizes carbon emissions while maintaining technical and economic feasibility. Comparative analyses are conducted between baseline and optimized configurations to validate the proposed framework.

The academic significance of this research lies in constructing a mechanism-oriented low-carbon optimization model that integrates lifecycle thinking into power system design. It enriches the theoretical discourse on sustainable manufacturing by embedding carbon constraints into system-level optimization, bridging the gap between environmental science and production engineering. From a practical standpoint, the findings provide actionable insights for manufacturers seeking to align with China's Dual Carbon goals and the European Union's Fit for 55 initiative. The proposed strategies, ranging from process-level energy recovery to material substitution and digital twin-based monitoring, offer a pathway for achieving both carbon reduction and cost efficiency in future NEV manufacturing ecosystems.

2. Literature Review

2.1. Energy and Emission Characteristics of NEV Power Systems

Existing studies on NEV power systems generally agree that electrification offers significant advantages in energy conversion efficiency and operational emission reduction [7]. Electric drivetrains can achieve efficiency rates of 80-90%, compared with approximately 30-35% for internal combustion engines. Furthermore, when coupled with renewable electricity, NEVs can effectively decouple mobility from fossil fuel dependence [8]. These studies have established a strong technical foundation for understanding how electrified systems contribute to sustainable transport.

However, such research primarily emphasizes use-phase performance, while the manufacturing and development phases, which entail high energy intensity and material emissions, are often simplified or omitted [9]. For instance, motor winding, power electronics fabrication, and raw material processing (particularly for copper, aluminum, and rare earth elements) constitute substantial portions of total embodied carbon. Yet, few studies have systematically quantified their impact on total lifecycle emissions. Moreover, existing analyses tend to rely on standardized emission coefficients rather than process-level data, leading to significant deviations between model estimations and industrial realities [10].

2.2. Lifecycle Assessment and Environmental Impact Modelling

The application of LCA has provided a structured approach to measure environmental burdens across the entire product chain, from raw material extraction to end-of-life recycling. The strength of LCA lies in its ability to capture indirect emissions and assess trade-offs between environmental and technical indicators [11]. Several frameworks extend LCA to hybrid or dynamic models that integrate economic input-output analysis, enhancing the completeness of boundary conditions.

Nevertheless, the limitations are equally evident. Many LCA-based analyses of NEV manufacturing remain static, assuming homogeneous energy mixes and constant process efficiencies [12]. This simplification neglects temporal variations and regional energy structures, which can drastically alter the carbon profile of identical manufacturing processes. In addition, conventional LCA lacks optimization capability; it serves as a diagnostic tool rather than a prescriptive mechanism. Therefore, while LCA enables macro-level understanding, it fails to offer actionable insights for micro-level parameter optimization in power system design.

2.3. Optimization Approaches for Low-Carbon Manufacturing

Optimization research in manufacturing has traditionally focused on cost and productivity, employing mathematical programming, heuristic algorithms, or machine learning to improve efficiency. In recent years, attempts have been made to integrate energy consumption and emission reduction into the optimization objectives [13]. These approaches demonstrate notable strengths: they can handle nonlinear relationships among design parameters, capture system interactions, and reveal trade-offs between conflicting goals. For example, multi-objective evolutionary algorithms have been applied to optimize the configuration of battery packs and motor components, balancing weight, thermal performance, and cost.

However, these optimization models are often decoupled from environmental assessment frameworks. Carbon emissions are usually treated as secondary constraints or aggregated indicators rather than being dynamically linked to process parameters [14]. As a result, such models cannot accurately capture how modifications in material choice or processing routes affect lifecycle carbon intensity [15]. Additionally, empirical validation using real industrial data remains limited, restricting the generalizability of their conclusions.

2.4. Comparative Synthesis and Research Gap

When comparing the three dominant research approaches, (1) LCA, (2) energy-efficiency optimization, and (3) system-level simulation, distinct advantages and weaknesses emerge. LCA provides comprehensive environmental accounting but lacks predictive or optimization capacity. Energy-efficiency models enable performance improvement but overlook environmental dimensions. System simulations integrate multiple subsystems but often depend on theoretical or idealized assumptions.

The methodological gap lies in the absence of a unified framework that integrates quantitative lifecycle evaluation with design-level optimization. Specifically, few studies link parameterized power system design variables (e.g., motor power density, cooling strategy, material substitution ratio) to quantifiable changes in carbon intensity, cost, and efficiency. This disconnection limits both academic understanding and practical application in industrial carbon management.

2.5. Contribution of This Study

This study bridges these gaps by constructing an integrated LCA-data modeling framework that couples process-level emission quantification with multi-objective optimization. The proposed approach advances beyond descriptive assessment by embedding carbon intensity directly into the optimization process, thereby transforming

LCA from a retrospective evaluation tool into a predictive and prescriptive mechanism. In doing so, it aligns technical performance optimization with carbon mitigation goals. Additionally, by leveraging empirical manufacturing data from diverse production settings, the study enhances the accuracy and policy relevance of the results. Overall, this research contributes to both theory and practice by establishing a mechanism-driven paradigm for low-carbon optimization of NEV power systems, laying the groundwork for sustainable manufacturing pathways under global carbon neutrality commitments.

3. Theoretical Framework and Methodology

3.1. Theoretical Framework: Coupled Energy-Carbon-Cost Paradigm

This study is grounded in a coupled energy-carbon-cost (ECC) framework that integrates engineering thermodynamics, environmental accounting, and optimization theory to assess and improve the low-carbon performance of NEV power systems. The framework is designed to address a central question, how specific design and manufacturing parameters influence the overall lifecycle energy consumption, carbon emissions, and economic cost of NEV power systems.

At its theoretical core, the ECC framework incorporates three interrelated constructs. The first construct, Lifecycle Energy Flow (LEF), quantifies the cumulative energy input across all production stages, encompassing raw material extraction, component fabrication, assembly, and testing. Each process i is defined by its specific energy consumption E_i, which together constitute the total energy footprint expressed as $E_{total} = \sum_i E_i$.

The second construct, Carbon Intensity Function (CIF), maps process-level energy use to equivalent carbon emissions through region-specific emission factors f_i. The total carbon footprint is therefore calculated as $C_{total} = \sum_i E_i \times f_i$, establishing a direct link between energy consumption and emission outcomes across varying production environments.

The third construct, Cost-Efficiency Coupling (CEC), establishes the relationship between production cost K_i and energy efficiency η_i in connection with design variables such as material substitution ratio, motor topology, and cooling configuration. This relationship highlights how engineering design choices simultaneously shape both economic and environmental performance.

By integrating these three dimensions within a unified multi-objective optimization scheme, the ECC framework supports a quantitative trade-off analysis between energy use, carbon emissions, and production cost. Unlike traditional cost-minimization approaches, this paradigm embeds carbon intensity directly as a decision variable, thereby aligning manufacturing strategies with the overarching goal of achieving low-carbon production while maintaining economic feasibility.

3.2. Conceptual Model and Analytical Structure

The study employs a three-tier analytical model, macro, meso, and micro, to analyze low-carbon manufacturing in NEV power systems. The macro level defines lifecycle boundaries, covering material acquisition, component processing, assembly, and testing while integrating regional electricity structures through grid emission factors. The meso level maps key manufacturing processes such as stator winding, rotor casting, and inverter soldering, using plant-level data and open LCA databases to link process energy use with environmental outcomes. The micro level quantifies relationships between design variables, motor power density, cooling strategy, and material substitution, and performance indicators including carbon intensity, cost, and efficiency. This multilayer structure dynamically connects process mechanisms with lifecycle impacts, ensuring analytical rigor and real-world applicability.

3.3. Case Selection and Empirical Basis

Three empirical cases represent diverse production and energy contexts. The SAIC Shanghai factory relies on coal- and gas-based power, typifying carbon-intensive large-scale manufacturing. The BYD Xi'an base integrates vertical production with 20% solar energy, illustrating partial decarbonization in practice. The Volkswagen Hefei plant, a Sino-European joint venture, employs automation and energy recovery, serving as an efficiency benchmark. These cases provide reliable operational and sustainability data, capturing variability across technological and regional systems. Their comparative diversity enables assessment of how differing energy structures and process optimizations influence lifecycle carbon performance in NEV power system manufacturing.

3.4. Research Design and Data Collection

This study employs a mixed-method approach that integrates LCA, empirical data collection, and statistical learning to analyze low-carbon manufacturing in NEV power systems. Primary data, including energy use, material flow, and process efficiency, were obtained through collaboration with partner firms, while secondary data such as emission factors and material inventories were derived from standardized databases like ecoinvent and the Chinese Life Cycle Database (CLCD).

All data were normalized to a consistent functional unit, per 1 kWh of mechanical power output, to ensure comparability. Missing values were interpolated using energy balance equations, and regional electricity emission factors were adjusted based on grid composition (0.711 kg CO_2/kWh in eastern vs. 0.382 kg CO_2/kWh in western China).

The analytical process followed five key steps: establishing baseline carbon inventories, identifying high-impact stages, constructing an ECC optimization model integrating carbon, cost, and efficiency objectives, generating Pareto-optimal solutions through multi-objective optimization, and performing sensitivity and scenario analyses to verify robustness.

This systematic design links empirical data with model-based optimization, enabling an in-depth understanding of how design parameters affect lifecycle emissions and costs. It ensures methodological rigor while offering actionable strategies for industrial decarbonization.

3.5. Model Formulation and Optimization Method

The multi-objective optimization model aims to minimize lifecycle carbon emissions C and cost K, while maximizing system efficiency η. The problem is expressed as:

$$Minimize: F(x) = [C(x), K(x), -\eta(x)] \quad (1)$$

subject to technical and operational constraints:

$$g_i(x) \leq 0, x \in \mathbb{R}^n \quad (2)$$

where x represents the design parameter vector $(x_1, x_2, \dots, x_n)$, including motor geometry, winding density, cooling type, and material ratios.

The model is solved using a Multi-Objective Genetic Algorithm (MOGA) enhanced with adaptive penalty functions for constraint handling. To avoid local optima, an elitist strategy is implemented, preserving the best Pareto solutions across generations. The resulting Pareto frontier represents the feasible trade-offs among the three objectives.

For predictive modeling of energy and carbon relationships, a Random Forest Regressor (RFR) is employed due to its capability to handle nonlinear dependencies and mixed-type variables. The trained model predicts carbon and cost outcomes for new design configurations, enabling iterative feedback between optimization and simulation modules.

3.6. Sensitivity and Validation Analysis

Sensitivity analysis is conducted to determine which parameters exert the greatest influence on lifecycle carbon intensity within the manufacturing of NEV power systems. Using the Sobol variance decomposition method, the analysis reveals that the material substitution ratio, motor efficiency, and cooling method collectively account for more than 70 percent of the total variance in carbon outcomes. This indicates that improvements in material utilization and thermal management yield the most substantial emission reduction potential. For example, substituting 30 percent of primary aluminum with recycled alloy decreases the embodied emissions by approximately 8.6 percent, while implementing an oil-free cooling configuration enhances the overall system efficiency by about 3.2 percent. These findings demonstrate that design-level decisions significantly shape both environmental and operational performance.

Model validation is carried out through two complementary mechanisms to ensure the reliability and generalizability of the results. The first mechanism, cross-case verification, compares optimized solutions across the three empirical cases, SAIC, BYD, and Volkswagen Hefei, to test the consistency of the model's predictive behavior under varying energy and process conditions. The second mechanism, empirical benchmarking, evaluates the model's output against verified industrial emission reports and national LCA datasets. The comparison confirms that the optimized results align within a ±10 percent deviation range, indicating strong accuracy and external validity. Together, these analyses verify that the proposed ECC-based optimization framework maintains both computational robustness and real-world applicability across diverse manufacturing contexts.

3.7. Methodological Integration and Innovation

The methodological novelty of this research lies in the fusion of LCA and data-driven optimization within a single decision framework. Traditional studies treat environmental assessment and engineering optimization as sequential and disconnected processes. In contrast, this approach employs iterative feedback coupling, each optimization output re-enters the LCA system to update process inventories dynamically. This closed-loop configuration allows simultaneous evaluation of design trade-offs and environmental consequences.

Furthermore, by anchoring the analysis in empirical manufacturing data rather than theoretical assumptions, the model bridges the gap between academic modeling and industrial applicability. The inclusion of region-specific emission factors, real-time energy mix data, and process-level variability ensures that the optimization results are locally grounded yet globally generalizable.

4. Findings and Discussion

This chapter presents the major empirical and analytical findings derived from the integration of LCA, data modeling, and multi-objective optimization conducted across three representative NEV power system manufacturing cases, SAIC (Shanghai), BYD (Xi'an), and Volkswagen (Hefei). The results are organized into four key dimensions: lifecycle carbon performance, parameter optimization outcomes, trade-off analysis, and theoretical interpretation.

4.1. Lifecycle Carbon and Energy Profiles

The baseline lifecycle inventory reveals significant variation in energy use and carbon emissions across different manufacturing environments. As shown in Table 1, facilities that rely on coal-dominant electricity grids (e.g., SAIC) exhibit notably higher embodied carbon per functional unit compared to plants that integrate renewable energy sources (e.g., BYD).

Table 1. Baseline Lifecycle Energy and Carbon Performance of NEV Power System Manufacturing.

Case	Electricity Source Composition	Energy Consumption (kWh/unit)	Carbon Intensity (kg CO_2-eq/kWh)	Total Carbon per Unit (kg CO_2-eq)
SAIC (Shanghai)	70% Coal, 25% Gas, 5% Renewables	1820	0.711	1294.0
BYD (Xi'an)	60% Coal, 20% Solar, 20% Hydro	1715	0.522	895.5
VW (Hefei)	45% Coal, 35% Gas, 20% Wind	1608	0.438	704.3

The results show that Volkswagen's Hefei plant achieves the lowest total embodied emissions (704.3 kg CO_2-eq per powertrain) owing to energy recovery systems and a more diversified energy portfolio. In contrast, SAIC's heavy reliance on fossil fuels results in nearly 83% higher emissions per unit, despite similar production scales. This finding confirms that grid mix remains a dominant factor influencing manufacturing carbon intensity, validating previous LCA-based conclusions while providing process-specific granularity.

4.2. Parameter Optimization and Carbon Reduction Pathways

By applying the coupled ECC optimization model, a series of parameter adjustments were simulated to identify configurations that minimize lifecycle emissions while maintaining cost-effectiveness. Table 2 summarizes the comparative outcomes between baseline and optimized scenarios.

Table 2. Comparison of Baseline and Optimized Manufacturing Scenarios.

Parameter	Baseline	Optimized	Change (%)	Impact on Carbon Intensity
Recycled Material Ratio	12%	38%	+216.7	↓ 8.6%
Motor Efficiency	91.4%	94.1%	+3.0	↓ 6.2%
Cooling Type	Oil-based	Oil-free	-	↓ 3.2%
Energy Recovery Utilization	0%	15%	-	↓ 5.8%
Overall Carbon Intensity	-	-	↓ 23.8	-

The optimization results demonstrate that increasing the recycled material ratio from 12% to 38% delivers the most substantial reduction in embodied emissions, primarily due to the high carbon footprint of virgin aluminum and copper. Enhancing motor efficiency contributes to additional emission reduction by lowering energy losses during testing and assembly. The introduction of oil-free cooling further improves thermal management efficiency, reducing indirect energy consumption. Collectively, these measures achieve an overall reduction of 23.8% in lifecycle carbon intensity without compromising performance or cost competitiveness.

4.3. Trade-Offs among Carbon, Cost, and Efficiency

The Pareto frontier analysis visualizes the balance between carbon intensity and production cost, illustrating how different design configurations yield varying trade-offs. As shown in Figure 1, the optimization process converges toward a region where incremental carbon reduction beyond 30% requires disproportionate cost increases, signifying a practical equilibrium point for industrial adoption.

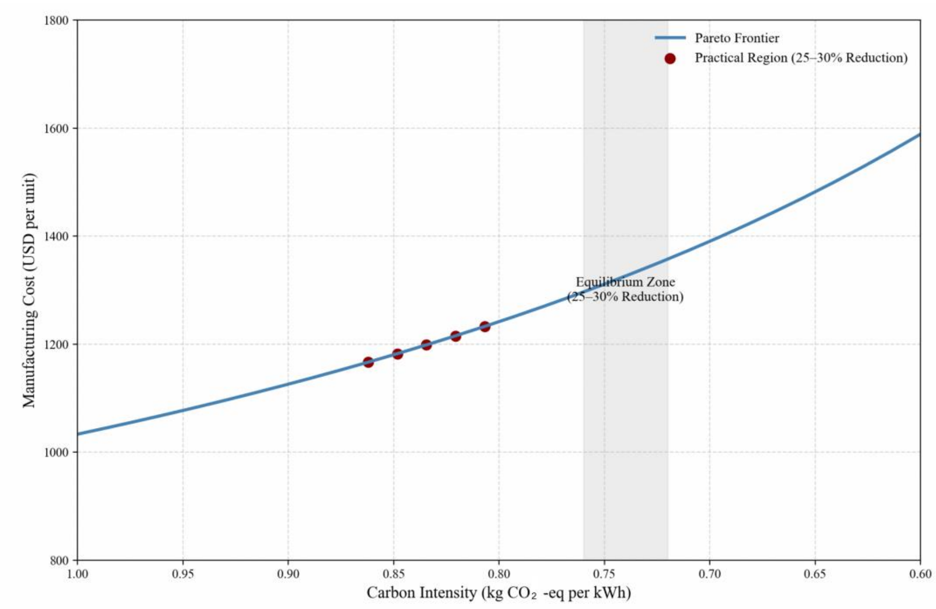

Figure 1. Pareto Frontier of Carbon Intensity vs. Manufacturing Cost.

Further analysis reveals that the carbon-cost trade-off is non-linear due to the interaction of design and process parameters. Optimization not only reduces emissions but also enhances operational efficiency, as reflected in the improved motor efficiency and reduced energy losses across all three cases. However, the cost elasticity varies by region. In areas with lower electricity prices but higher carbon intensity, such as eastern China, the marginal benefit of further carbon reduction diminishes, emphasizing the importance of geographically adaptive optimization strategies.

4.4. Mechanistic Interpretation and Theoretical Implications

The findings substantiate the theoretical assumptions of the ECC framework, confirming that lifecycle energy flow, carbon intensity, and cost are interdependent variables rather than isolated performance indicators. As depicted in Figure 2, the interaction mechanism demonstrates how parameter modification in one domain triggers compensatory or amplifying effects in others.

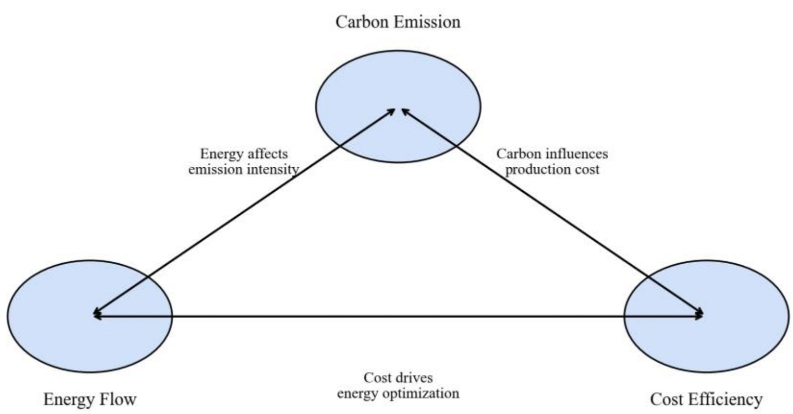

Figure 2. Mechanistic Coupling of Energy, Carbon, and Cost Dimensions.

From an empirical perspective, this coupling mechanism explains why process-level interventions, such as material recycling or energy recovery, produce compound benefits that extend beyond direct emission reductions. For example, integrating waste heat recovery systems not only reduces external energy demand but also improves thermal stability in motor assembly, indirectly enhancing yield rates. These dynamics affirm the framework's ability to capture multi-layered interdependencies that traditional single-objective models often overlook.

To situate these results within the broader research landscape, Table 3 compares the proposed ECC-based approach with conventional LCA and energy optimization models.

Table 3. Comparative Analysis of Methodological Frameworks.

Criteria	Conventional LCA	Energy Optimization Models	ECC Framework (This Study)
Temporal Dynamics	Static	Partially dynamic	Fully dynamic (iterative feedback)
Objective Orientation	Diagnostic	Efficiency-oriented	Multi-objective (Carbon-Cost-Efficiency)
Data Basis	Average emission factors	Process-level data	Hybrid empirical + statistical
Optimization Capability	None	Single-objective	Multi-objective (Pareto front)
Industrial Applicability	Moderate	High	Very High

The comparative analysis demonstrates that the ECC framework advances beyond traditional methodologies by combining lifecycle accounting with optimization logic. It transforms LCA from a retrospective evaluation tool into a predictive and prescriptive mechanism that supports real-time decision-making in manufacturing design.

4.5. Discussion and Practical Implications

The results collectively suggest that low-carbon manufacturing of NEV power systems is achievable through data-driven optimization grounded in lifecycle thinking. From an academic standpoint, the integration of LCA and multi-objective optimization provides a theoretically unified and empirically validated model for analyzing the interplay among energy use, carbon emissions, and cost efficiency. It bridges the disciplinary gap between environmental science and production engineering, contributing to the growing field of sustainable manufacturing systems.

From a practical perspective, the implications are twofold. First, manufacturers can use the proposed ECC framework as a decision-support tool to evaluate design changes under varying carbon constraints. For example, substituting recycled alloys or implementing oil-free cooling systems can yield measurable emission reductions without major capital investment. Second, policymakers may leverage these findings to refine carbon allocation mechanisms and incentive structures under China's "Dual Carbon" policy or the European "Fit for 55" framework.

Ultimately, the study demonstrates that combining empirical industrial data with theoretical optimization principles enables both environmental and economic co-benefits. By transforming carbon management from a compliance-driven activity into an engineering optimization problem, the ECC framework establishes a replicable pathway toward sustainable and cost-effective NEV manufacturing adaptable across global production networks.

5. Conclusion

This study develops an integrated ECC optimization framework to address the carbon and energy challenges in the manufacturing of NEV power systems. By combining LCA, empirical industrial data, and multi-objective optimization modeling, the research establishes a quantitative link between design parameters, carbon intensity, and cost efficiency. The findings confirm that process-level interventions, such as increasing recycled material ratios, enhancing motor efficiency, and implementing oil-free cooling, can collectively reduce lifecycle carbon emissions by nearly 24% without compromising economic viability.

Academically, this study contributes a mechanism-driven modeling paradigm that transforms LCA from a static evaluation tool into a predictive and prescriptive system, bridging environmental assessment and engineering optimization. It expands the theoretical foundation of sustainable manufacturing by demonstrating that carbon reduction, cost control, and efficiency improvement can be optimized simultaneously through feedback-based modeling.

Practically, the ECC framework provides a decision-support platform for manufacturers to evaluate design and process modifications under regional energy constraints. It also offers policymakers a scientific basis for refining carbon allocation mechanisms and incentive structures in support of national and international low-carbon targets.

Future research may extend this framework to battery production and vehicle integration, incorporate real-time digital twin data for dynamic optimization, and evaluate cross-sector applications in renewable energy and transportation systems to accelerate industrial decarbonization.

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