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Synergistic simulation of carbon benefit optimization and economic benefits of grid investment based on digital twin modeling

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SUMMARY: *This paper constructs a physical model of carbon benefits and economic benefits of grid investment, as well as a virtual mapping relationship model from three levels: direct mapping, computational mapping, and inferential mapping. Based on the minimization of energy consumption cost and considering the constraints of benefit matching degree, the economic co-optimization model is designed. With the maximization of economic benefits as the optimization goal, the virtual model is realized as a closed loop of simulation, evaluation, analysis and co-optimization calculation. With the digital twin model as the framework, carbon emission cost, carbon trading cost, carbon governance cost, and total carbon cost are calculated, and the carbon benefit architecture of power grid equipment is analyzed to achieve the optimization of investment carbon benefit, considering the uncertainty in the process of equipment operation. With the digital twin as the core of the platform, we realize the carbon - economic collaborative deduction, quantitative analysis and management, and the optimal scheme at the level of integrated co-simulation. In the optimal Pareto frontier validation, the digital twin model carbon emission reduction rises from 85.2 tons in 1 million yuan to 1923 tons in 31 million yuan, with a maximum time of 19.5 s, while the particle swarm algorithm and the big data analysis require a maximum time of 38.3 s and 40.7 s. The transmission process emission reduction benefits of the digital twin model, the particle swarm optimization, and the big data analysis for the transmission process in 2024 are 402/104, 239/104t, and 379/104t, which is comprehensively better than the comparison method, and verifies the feasible path to realize the synergistic gain of carbon benefit and economic benefit when the digital twin model is used.*

KEYWORDS: *grid investment carbon benefit; economic benefit; virtual mapping; benefit matching degree; digital twin modeling*

1 Introduction

Along with the new generation of information technology innovation and breakthroughs, data is gradually integrated into industrial innovation and all aspects, and has become a key production factor that is increasingly emphasized by the world's major countries and large enterprises in the era of digital economy. In recent years, Power Grid Corporation, with the strategic goal of building an internationally leading energy Internet enterprise with characteristics, seizes the opportunity of new digital infrastructure construction, focuses on the demand for intelligent, digitalized, and transparent power grids, puts forward the innovative concept of digital twin grid construction, and elaborates on the value of the digital twin grid in the dispatching and operation, equipment management, marketing and operation,

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development planning, integrated energy and other business aspects [1-3]. The introduction of the carbon emission market inevitably increases the generation cost on the generation side and changes the generating unit portfolio scheduling. In addition, the volatility of carbon emission prices exposes the generation and grid segments to greater uncertainty and increases the difficulty of grid planning [4, 5]. In the face of the rise of the worldwide carbon trading market and the deepening of energy conservation and emission reduction, the emergence of factors such as the control of carbon emissions and the volatility of carbon prices will put forward new challenges and requirements for the theoretical modeling and implementation process of grid investment. Through digital transformation, grid companies are expected to build a "digital twin grid" covering the entire process of grid investment and production, and improve economic efficiency. Energy saving and emission reduction is the core element to improve productivity, release the value of assets, promote the transformation of production and operation mode, and realize management and business changes [6, 7].

Literature [8] explores the impact of digital twin based transformation on renewable energy investment decisions and empirically analyzes it to conclude that companies with digital twin technology demonstrate higher accuracy and efficiency in renewable energy investment decisions. Realizing 15% increase in ROI in renewable energy investments, digital twin technology provides actionable insights and guidance for companies on their journey towards digital transformation. Literature [9] investigated the integration of digital twins with the circular economy and the results showed that digital twins have a great potential to improve the economy by enabling economic circularity and overcoming the barriers and challenges of the circular economy. Literature [10] investigated the generalized meaning of digital twin system, available digital twin in power system to define the future power system, there are differences between the power system and the twin digital requirements, and finally derived that the digital twin can be realized through SDTS open source framework. Literature [11] states that digital twin in geospatial technology, the main goal of digital twin is to reduce uncertainty in projects and help in project deployment, sustainable assessment of carbon emissions. The results of the study showed that the digital twin system can be used for urban planning as the urban management system can be improved continuously through the twin digital system and hotspot analysis can be used to assess the high carbon emission areas. Literature [12] investigated the development and application of digital twins in the field of building energy and discussed the background of building information modeling and digital twin technology, which has advantages and challenges in building energy. With optimizing energy efficiency can reduce carbon emissions, digital twin technology provides accuracy and improves management processes for future development. Literature [13] discusses the application of digital twins with advanced digital technologies, under the International Energy Agency pointed out that regenerative technologies such as carbon emissions and smart grids, digital twins and artificial intelligence technologies are vital, digital twins and AI, the power system can learn to varying degrees and have sustainable goals in the power system. Literature [14] explores the integration of digital twin technology, predictive analytics and sustainable project management to enhance global supply chain efficiency, resilience and environmental sustainability, predictive analytics, digital twins can optimize the solution process, reduce carbon footprints, facilitate risk mitigation and resource optimization, can provide supply chain performance, and drive market sustainability.

From the point of view of the existing research results, whether in the study of carbon benefits or economic benefits of grid investment, there is no in-depth consideration of the possible mutual influence of the two, especially the synergistic development between the two. In this paper, we consider the complexity and diversity of the grid operating environment, and establish the interconnection between the physical model and the virtual model from three levels, supported by dynamic data and policy development. Based on the virtual model line-plane double-layer correction method, it reflects the real situation more objectively. Focusing on the grid carbon benefit digital twin, from the perspective of minimizing the cost of energy consumption, we design the interaction mechanism between carbon benefit optimization and economic benefit, and realize the closed-loop iteration between the virtual model and the collaborative optimization calculation. Based on the grid operation structure, the output power, CO_2 emissions, carbon emission cost, carbon trading cost, carbon governance cost, and carbon contingent cost of PV and load are calculated. In order to accurately measure the energy consumption of power equipment, a complete and scientific equipment operation and maintenance cost model is constructed starting from the equipment reliability growth model to optimize the carbon benefits of investment. Eventually establish a system optimization system with digital twin technology as the core, carbon benefit and economic benefit co-simulation and integrated co-simulation level.

2 Optimization of carbon benefits from investments and synergy with economic benefits

2.1 Grid investment benefits

Accurate carbon benefit calculation is the basis for the synergistic development of grid investment and economic benefits, and the operating environment during grid operation is complex, diverse and dynamic [15]. Traditional measurement and analysis models are mostly oriented to the more complex, the lack of real-time information interaction, difficult to accurately describe the carbon benefits, there are limitations in the application of grid investment and economic system development [16]. Based on this, the optimization and synergistic development model of economic benefits based on digital twin system can be constructed on the basis of carbon benefit calculation and economic benefits, supported by dynamic data and policy development [17-19]. Further, from the three levels of direct mapping, computational mapping and inference mapping, the physical model of carbon benefit and economic benefit of grid investment and the mapping relationship model of virtual model are established to realize the interconnection between the physical model and the virtual model. Then, considering the high fidelity demand of the virtual model, combined with the multi-source characteristics of the grid system data, we design the virtual model line-plane double-layer correction method from the real grid operation data and simulation operation data, and the problem description is shown in Fig. 1. Dynamically correct the state of the virtual model in the digital twin system, so that it is close to the real situation, so as to obtain the digital twin simulation data of the grid investment efficiency for economic development synergistic applications.

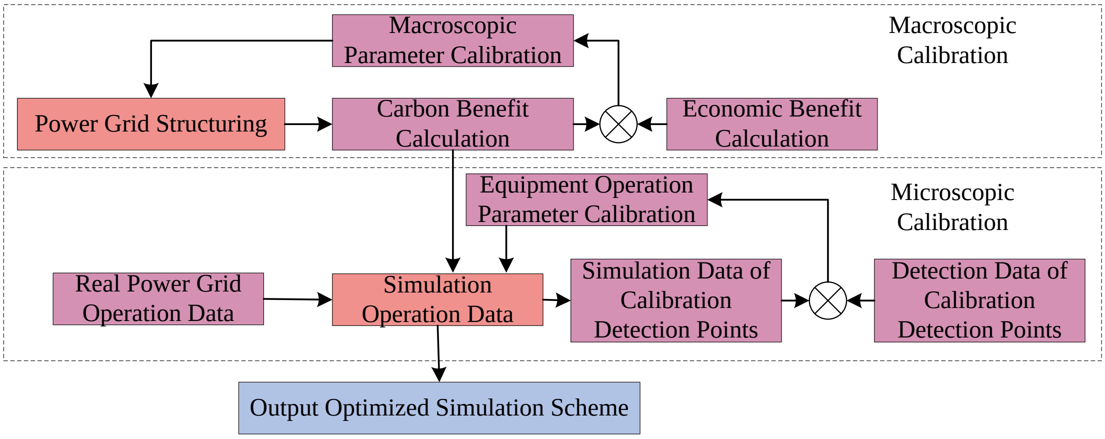


Figure 1: Description of the problem

2.2 Co-optimization

In the traditional research on the synergistic development of investment benefit optimization and economic benefit, due to the unavailability of data such as the grid operation process, the relevant parameters are often idealized and difficult to be adjusted in real time after the formation of the optimization scheme. Based on this, the economic synergistic optimization model can be established by considering the benefit matching degree constraint from the perspective of minimizing the energy consumption cost firstly from the perspective of minimizing the energy consumption cost by making full use of its real operation results as well as the fitting and reproduction of the simulated operation process around the carbon benefit digital twin of the power grid. On this basis, with the maximization of economic benefits as the optimization objective, a variety of optimization schemes are constructed by constraining the conditions of real-time energy consumption, maximum energy consumption minimum energy consumption, etc., and furthermore, the synergistic optimization model of carbon benefits and economic development is designed and its solution algorithm is studied [20, 21]. The interaction mechanism of carbon benefit optimization and economic benefit is shown in Fig. 2, which realizes the closed-loop iteration of simulation, evaluation, analysis and synergistic optimization calculation of the virtual model.

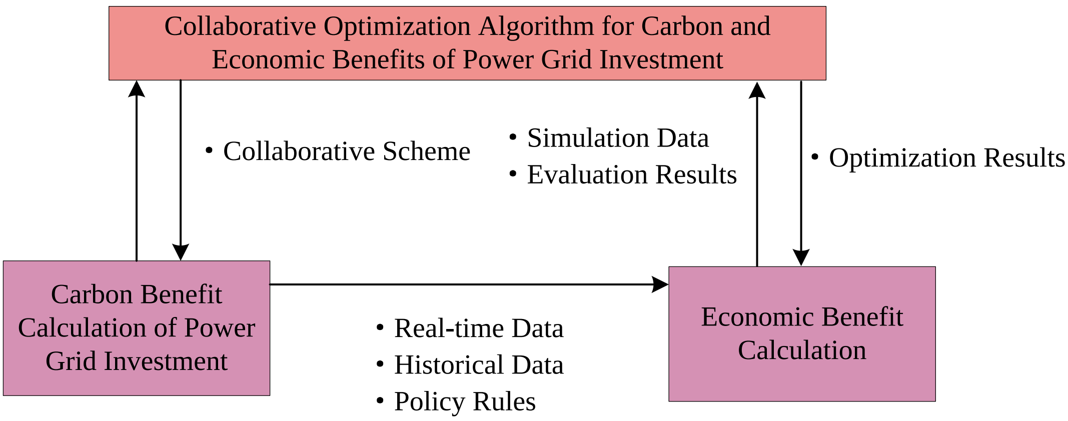


Figure 2: Interaction mechanism between carbon benefit optimization and economic benefits

3 Digital twin grid modeling

3.1 Grid operation structure

Fig. 3 shows the grid operation structure, which contains one conventional diesel generator set, one photovoltaic power unit, one fuel cell unit, one energy storage system unit, and two load users [22, 23]. In this paper, the digital twin model is constructed based on the digital twin model, and the grid operation structure is shown in Fig. 3. The “source” refers to the distributed power source, including diesel generator sets, photovoltaic units and fuel cells. The diesel generator sets are used to simulate the power interaction between the grid and the external grid, and the photovoltaic units and fuel cells supply power to the local loads through the converter. “Load” refers to the load, load 1 is a controllable flexible load and load 2 is a fixed load.

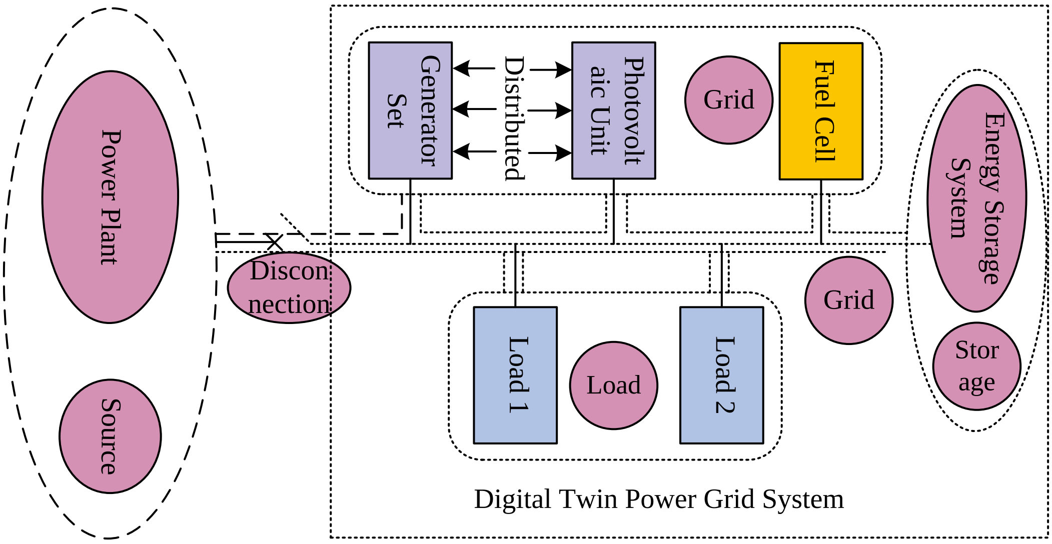


Figure 3: Grid operating structure

Based on the digital twin of the grid operation model construction process, the output power of the PV unit is mainly affected by the standard test conditions of the PV cell, its own performance and the actual conditions of the ambient temperature and light intensity, the output power model of the PV unit as shown in equation (1):

$$P_{pv} = \frac{V_M \times I_M}{V_{OC} \times I_{SC}} \times (I \times S) \times \left[V_{OC} - K_V (T_a + T) \right] \quad (1)$$

where: V_M the point of maximum power voltage, I_M denotes the point of maximum power current, and V_{OC} denotes the open circuit voltage. I_{SC} denotes the short circuit current, I denotes the unit output current, and S denotes the light intensity. K_V denotes the voltage coefficient, T_a denotes the ambient temperature at which it is located, and T denotes the standard temperature.

Load 1 is a controllable flexible load, used for basic scenarios of power consumption, load 2 is a fixed load, used to mold special power consumption. The output power models of loads 1 and 2 are shown below:

$$\begin{cases} P_1 = P_{1N} \times V_1 \times H_1 \\ P_2 = P_{2N} \times V_2 \times H_2 \end{cases} \tag{2}$$

where: P_{1N} denotes the rated power of Load 1, V_1 denotes the operating state of Load 1, and H_1 denotes the operating period of Load 1. P_{2N} denotes the rated power of Load 2, V_2 denotes the operating state of Load 2, and H_2 denotes the operating period of Load 2. When the load is out of operation, $V = 0$, H is the load operation time period, i.e., the sum of the time periods during which the load is continuously operating.

In this paper, the energy storage system based on the digital twin of the power grid is established, which uses the storage battery for power saving, and effectively improves the stability of the microgrid by shaving the peaks and valleys of the microgrid system [24, 25]. The charging and discharging models of the energy storage system are shown in equations (3) and (4), respectively:

$$S_t = S_{t-1} \times (1-\sigma) + P_{t,c} \times \frac{\eta_c}{W_s} \times \Delta t \tag{3}$$

$$S_t = S_{t-1} \times (1-\sigma) + P_{t,d} \times \frac{\eta_c}{W_s} \times \Delta t \tag{4}$$

where: S_t denotes the state of charge at the moment of t, S_{t-1} denotes the state of charge at the moment of $t-1$, σ denotes the rate of self-discharge of the battery, P_t denotes the power of charging and discharging, η denotes the efficiency of the storage charging and discharging, W_s indicates the electrical energy capacity, Δt indicates the unit time interval.

3.2 Carbon Benefit Costing

3.2.1 Carbon emission accounting

Fuel combustion emissions involved in the grid are mainly CO_2 emissions resulting from the full combustion of fuel with oxygen in combustion equipment. There:

$$f = \sum_{i=1}^{n} \left(AD_i \times EF_i \right) \tag{5}$$

where: f represents CO_2 emissions due to fuel combustion in tons. EF_i represents the CO_2 emission coefficient of the i type of fuel in tons/gigajoule, AD_i represents the intensity of the activity of the i type of fuel in gigajoules, and i represents the fuel type.

Electricity consumption of enterprises usually comes from purchasing electricity from external sources, utilizing solar energy to generate electricity, and generating electricity from waste heat in the production process of enterprises. Among them, the CO_2 emission coefficients of solar power generation and waste heat power generation can be regarded as 0 because they are effective utilization of resources. Therefore, it is only necessary to account for the CO_2 emissions generated by the production chain corresponding to the purchase of electricity by the enterprise from outside, with the following formula:

$$e = AD \times EF \tag{6}$$

where e represents the CO_2 emissions of the enterprise due to electricity production in tons, EF represents the CO_2 emission factor of the annual average electricity supply in tons/kW-hr, and AD represents the amount of power purchased by the firm in kW-hr [26].

3.2.2 Accounting models for total carbon costs

According to the above relevant carbon cost classification criteria, the total carbon cost (TC) includes carbon emission cost C_1, carbon trading cost C_2, carbon governance cost C_3, and carbon contingent cost C_4, and the cost is attributed in accordance with the calculations of Eq. (7) to Eq. (11) respectively [27, 28]. The calculation methods are as follows:

$$C_1 = \sum_{i=1}^{n} C_{1,i} = \sum \left(EIC_i + WEIV_i \right) \tag{7}$$

$$EIC_i = PC_i + NC_i \tag{8}$$

$$PC_i = \frac{f_i + e_i + m_i + p_i}{P_c + N_c} \times P_c \tag{9}$$

$$NC_i = \frac{f_i + e_i + m_i + p_i}{P_c + N_c} \times N_c \tag{10}$$

$$WEIV_i = \sum_{i=1,\, j=1}^{m,n} WEI_{ij} \times UEIV_{ij} \tag{11}$$

where C_1 represents the cost of carbon emissions, EIC_1 is the internal cost of carbon emissions for the ith process or node, PC_i is the internal flow cost of carbon emissions for the ith process or node, NC_i is the internal loss cost of carbon emissions for the ith process or node, f_i is the carbon emission due to fuel combustion of the ith process or node. e_i is the carbon emissions due to purchasing electricity from external sources for the i process or node, m_i is the carbon emissions due to the use of energy as a raw material for the i process or node, p_i is the carbon emissions due to the industrial production process for the i process or node, P_c is the i process or node of positive product elemental carbon value, and N_c is the negative product elemental carbon value of the ith process or node. $WEIV_i$ is the external damage cost of carbon emissions of the ith process or node, and WEI_{ij} is the jth type of environmentally impacting waste emissions of the ith process or node. UEV_{ij} is the unit external damage cost of the jth waste of the ith process or node. Also:

$$C_2 = \left(E - Quo \right) \times P - exp \tag{12}$$

where C_2 denotes the carbon trading cost/million yuan, E denotes the carbon emission/million tons, Quo denotes the initial allocated carbon quota/ton, P denotes the carbon emission right price, million yuan/ton, and *exp* is the trading cost. Where C_2 is positive when carbon emissions are greater than carbon allowances, and negative vice versa, there is:

$$C_3 = \sum_{i=1}^{3} C_{3,i} \tag{13}$$

where C_3 denotes the cost of carbon governance, $C_{3,1}$ denotes the cost of carbon prevention, $C_{3,2}$ denotes the cost of carbon control, and $C_{3,3}$ denotes the cost of carbon recovery.

$$C_4 = \sum_{i=1}^{2} C_{4,i} \tag{14}$$

$$C_{4,1} = E \times Tax \tag{15}$$

where C_4 denotes the contingent cost of carbon, $C_{4,1}$ denotes the carbon tax, $C_{4,2}$ denotes the penalty, E denotes the carbon emissions per 10,000 tons, and Tax denotes the amount of tax per unit of emissions.

These four types of carbon costs are calculated separately and then summed up to get the total carbon cost:

$$TC = C_1 + C_2 + C_3 + C_4 \tag{16}$$

where TC denotes the total cost of carbon. By allocating C_2, C_3, C_4 proportionally against the carbon emissions E_i of each production process or node, the explicit carbon cost can be apportioned to each production process, thus refining the recognition, accounting, and reporting of carbon investment costs.

3.3 Optimization of investment benefits

In the process of optimizing the carbon benefits of grid investment, one of the key problems to be solved is to be able to scientifically, reasonably and accurately estimate the energy consumption of power equipment. Uncertainty in the process of equipment operation determines the difficulty of estimating cost inputs at a later stage. This paper starts from the equipment reliability growth model, and constructs a complete and scientific equipment operation and maintenance cost model through the quantitative reliability index of equipment. The carbon benefit architecture of power grid equipment is shown in Fig. 4. In this paper, taking into account the characteristics of power equipment such as high reliability requirements and high cost of punishment after failure, the cost of failure is added to the benefit decision of power equipment. By analyzing the carbon benefit architecture of power grid equipment in order to achieve the optimization of investment carbon benefit, it lays the foundation for the subsequent synergy between carbon benefit and economic benefit based on digital twin.

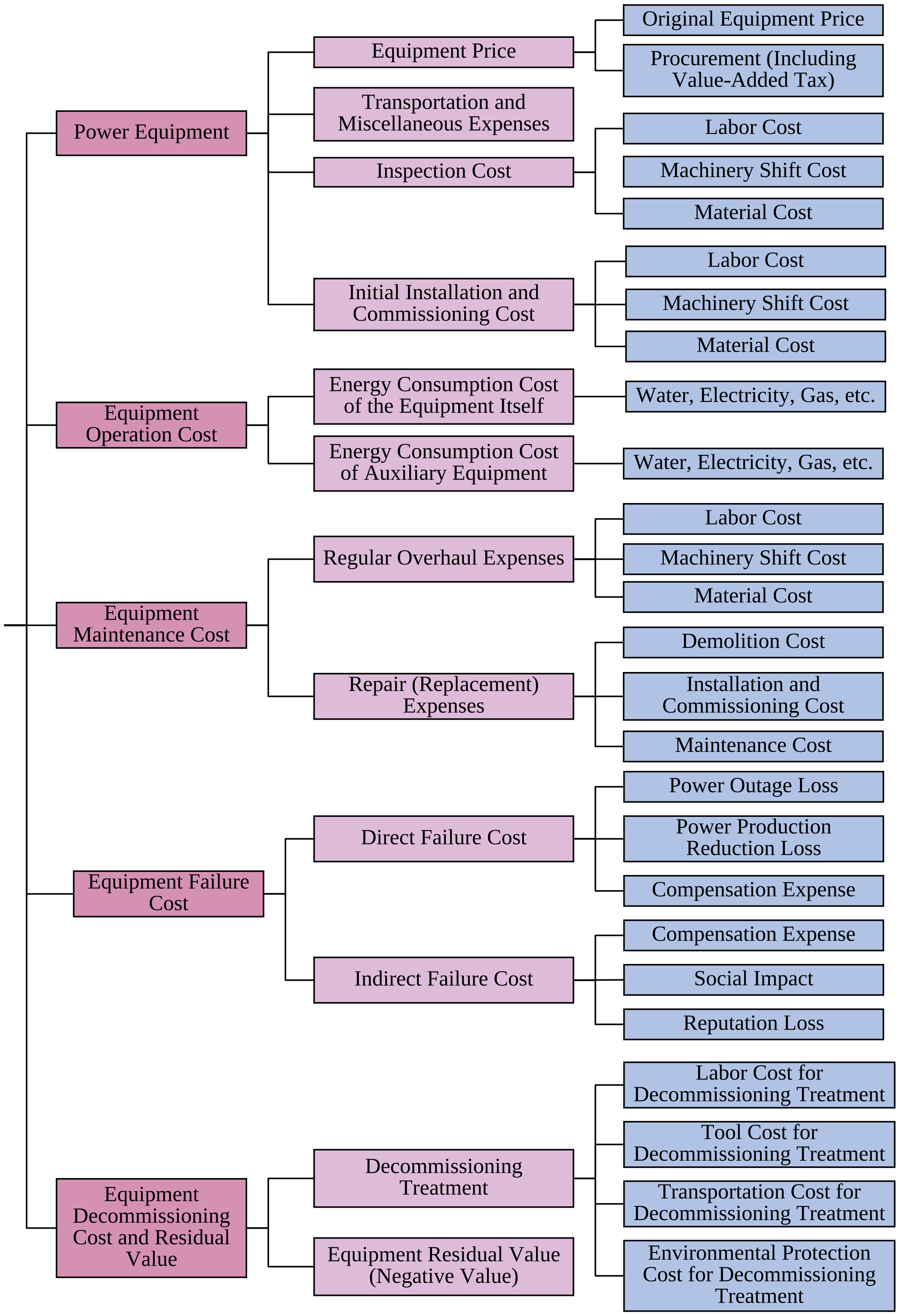


Figure 4: Carbon Benefits Architecture for Grid Equipment

3.4 Synergies between carbon and economic benefits

With the grid digital twin model as the core, the above grid operation structure, carbon emission accounting, and total carbon cost accounting can form an integrated platform, and the carbon benefit and economic benefit synergistic platform is shown in Figure 5. The core technology is the grid digital twin, which realizes carbon benefit assessment, rule management, model application, and post-assessment at the carbon benefit and economic benefit co-simulation level [29]. At the level of integrated co-simulation, it realizes carbon - economic co-extrapolation, quantitative analysis and management, as well as program evaluation [30].

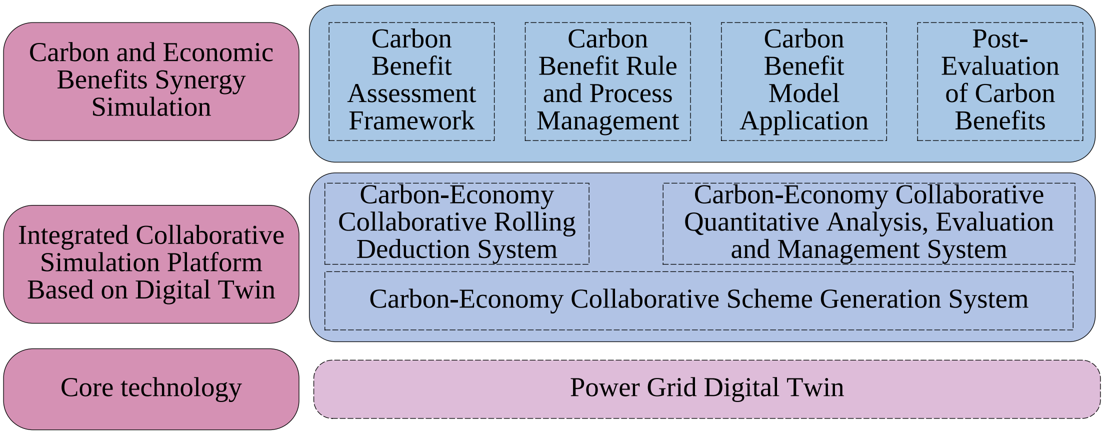


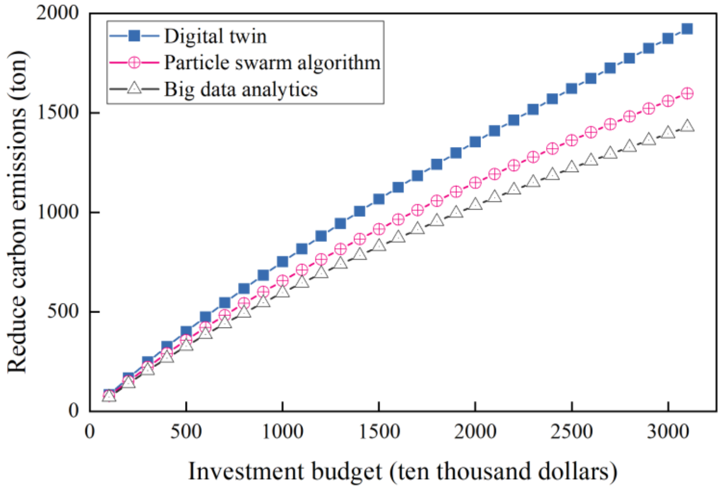
Figure 5: Platform for synergies between carbon and economic benefits

4 Carbon-Economic Benefits Co-simulation Based on Digital Twin Modeling

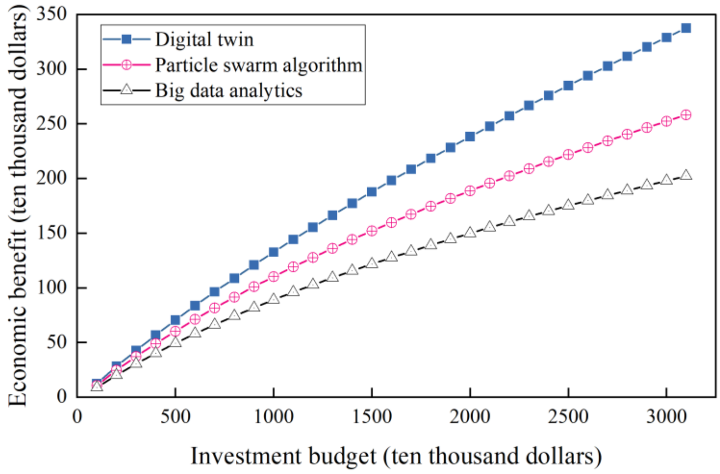
4.1 Comparison of Pareto frontiers

In this section, a related simulation study is conducted to validate the performance of the proposed digital twin model for collaborative grid carbon investment optimization and economic efficiency. The simulation model is based on an IEEE 30-node system, which contains distributed CCHP stations and wind turbines. The distributed energy sources are connected through the 30-node grid, so the test system can be used as an integrated energy system for the grid. In the multi-objective optimization process, one objective represents the interest of the grid and the other objective represents the interest of the regional CCHP units, and these two not objectives conflict with each other.

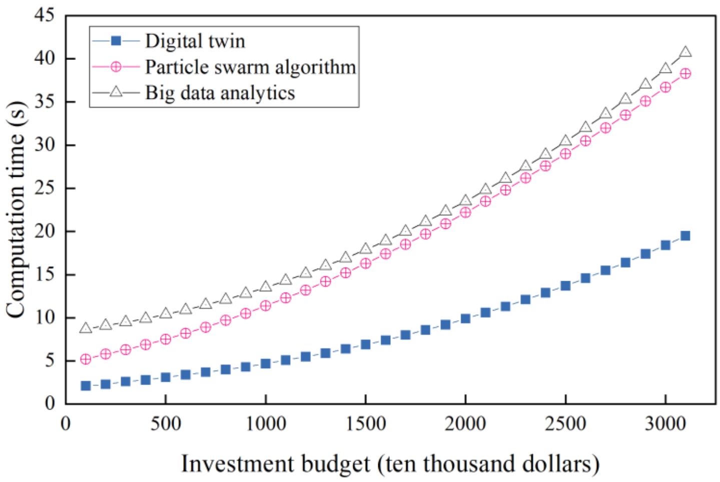
Fig. 6 shows the comparison of optimal Pareto frontiers, Fig. 6(a) shows the investment budget and carbon emission reduction, with the increase of the investment budget, the digital twin carbon emission reduction rises from 85.2 tons at 1 million yuan to 1923 tons at 31 million yuan, and the particle swarm algorithm and the big data analysis algorithm carbon emission reduction at an investment budget of 31 million yuan is 1598.2 tons and 1428.6 tons, respectively, and the digital twin carbon benefit is is better. Figure 6(b) shows the investment budget and economic benefits, the digital twin model economic benefits increased from 125,000 yuan to 3,375,000 yuan, the economic benefits are more obvious. The investment budget calculation time is shown in Fig. 6(c), and the digital twin model still shows the best performance, with a maximum time of 19.5 s, while the particle swarm algorithm and big data analysis have a maximum time of 38.3 s and 40.7 s. The results show that the application of the proposed digital twin model synergistic grid carbon investment optimization and economic benefits is better than particle swarm algorithm and big data analysis.



(a) Investment budgets and carbon reduction



(b) Investment budgets and economic benefits



(c) Investment budget calculation time

Figure 6: Optimal Pareto Frontier Comparison

4.2 Comparison of optimal investment programs

After calculating using each model and algorithm, the optimized configuration scheme is shown in Table 1. The digital twin model is configured with the least number of units in the PV, WG, GS, BS and SC devices, and in the case of the BS, the digital twin model requires only 230 units, while the particle swarm algorithm and the big data analysis require 540 and 289 units. Particle swarm algorithm and big data analytics have lower energy savings than digital twin model due to more inputs of renewable energy generation devices and storage devices than digital twin model.

Table 1: Optimized Configuration Scenarios

Equipment Type	Digital twin models/units	Particle swarm algorithm/units	Big Data Analytics/units
Photovoltaic System (PV)	276,124,202,175	370,250,429,306	309,189,292,301
Wind Generator (WG)	1,3,6,2	1,4,8,3	1,5,7,4
Gas Generator Set (GS)	4,1,3,3	2,1,2,2	4,2,2,3
Battery Storage System (BS)	230	540	289
Supercapacitor Storage System (SC)	148	907	856

For ease of calculation, government subsidies have been subtracted from the investment costs. Table 2 shows the cost of the planning scheme, the digital twin model spends the least on investment, low carbon, penalty and total cost, with a total cost of 236,506,000,000 yuan, and the particle swarm algorithm and big data analysis have a total cost of 411,474,000,000 yuan and 517,135,000,000 yuan. It can be seen that due to the reduction of the total cost, the capacity of the grid for renewable energy generation is increased, thus promoting economic efficiency.

Table 2: Planning program costs

Programmatic	Investment cost/million dollars	Low carbon cost/$10,000	Penalty costs/$10,000	Total cost/million dollars
Digital twin models	125235	82531	28740	236506
Particle swarm algorithm	284256	91520	35698	411474
Big Data Analytics	375854	101025	40256	517135

4.3 Carbon reduction calculations

Preliminary calculation of low-carbon benefits brought by the development of grid technology through relevant models and methods, the results of carbon emission reduction benefits are shown in Table 3. The digital twin model is effective in user energy saving and clean power emission reduction, and the benefits in 2024 are $5980/10^4$t and $5123/10^4$t respectively. It shows that the grid should continue to vigorously develop carbon investment and actively develop new energy according to its resource conditions and construction basis. In addition, the transmission process emission reduction benefits of the digital twin model in 2023 and 2024 are $389/10^4$t and $402/10^4$t, although the fluctuation is small. However, compared with particle swarm optimization $211/10^4$t and $239/10^4$t, and big data analysis 36010^4t and $379/10^4$t, the effect is significant. Therefore, there is a direct relationship between the carbon benefits of grid investment and economic benefits. If the grid low-carbon strategy continues to develop and the digital twin model can be widely promoted and applied, the role of carbon benefit optimization and economic synergy will be rapidly highlighted.

Table 3: Calculation results of carbon emission reduction benefits

Carbon reduction benefits /10^4t	Digital twin models		Particle swarm algorithm		Big Data Analytics	
	2023	2024	2023	2024	2023	2024
Clean Power	4928	5123	3451	4236	4163	4231
Transmission Process	389	402	211	239	360	379
User Energy Savings	4589	5980	4025	4144	4205	4502
Node Voltage	205	362	184	200	145	167

4.4 Impact of investment costs on carbon emissions

The relationship between total cost and total emission is shown in Fig. 7. When the total cost is 125.2 million yuan-168.9 million yuan, the carbon emission decreases from 5800 kilotons/CO_2 year to 500 kilotons/CO_2 year, showing a decreasing trend. When the total cost is 142.31 million yuan - 193 million yuan, the carbon emission decreases from 5000 kilotons/CO_2 year to 50 kilotons/CO_2 year, with obvious reduction effect. When the total cost is 158.9 million yuan, the carbon emission is 3800 kt/CO_2 year, until the total cost is 217.6 million yuan, the total emission is 0. This means that zero carbon emission can be realized under the high cost constraint. It shows that under the digital twin model, the carbon trading price affects the grid carbon efficiency investment, and the higher the price, the more attention will be paid to emission reduction to realize the synergistic development with the economy.

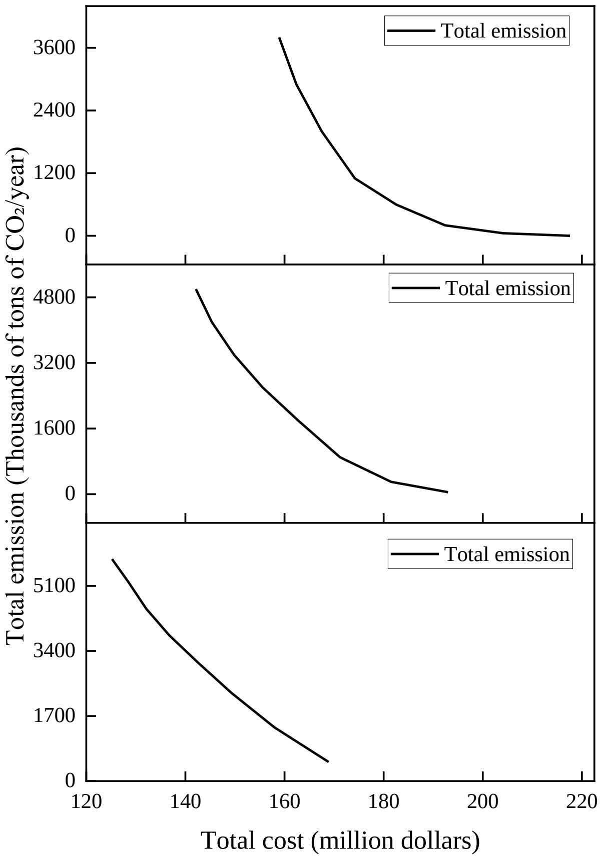


Figure 7: Relationship between total costs and total emissions

5 Conclusion

In this study, the optimization of carbon benefit and synergistic development model of economic benefit of grid investment is constructed with digital twin as the core technology, and the simulation results are as follows:

(1) The Pareto frontier comparison shows that as the investment budget increases, the better the carbon reduction effect. When the investment budget is 31 million yuan, the digital twin model is 1923 tons, and the particle swarm algorithm and big data analysis algorithm are 1598.2 tons and 1428.6 tons. The economic benefit of the digital twin model increases from 125,000 tons to 3,375,000 tons, and the maximum time is 19.5s, and the digital twin model has better synergy performance.

(2) The digital twin model configuration BS for example needs 230 units, while particle swarm algorithm and big data analysis need 540 units and 289 units, proving that the model can realize accurate investment.

(3) The calculation of low-carbon benefits shows that the emission reduction benefits of the digital twin model in the transmission process in 2023 and 2024 are $389/10^4$t and $402/10^4$t, particle swarm optimization is $211/10^4$t and $239/10^4$t, and the big data analysis is 360 10^4t and $379/10^4$t, which verifies the significance of the synergistic effect of the digital twin model.

(4) The results of the relationship between total cost and total emission show that when the total cost is 217.6 hundred yuan in dollars, the total emission is zero, indicating that zero carbon emission can be realized under high cost constraints.

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References

[1] Zhaoyun, Z., & Linjun, L. (2022). Application status and prospects of digital twin technology in distribution grid. *Energy Reports,* 8, 14170-14182.

[2] Bai, H., & Wang, Y. (2022). Digital power grid based on digital twin: Definition, structure and key technologies. *Energy Reports,* 8, 390-397.

[3] Madubuike, O. C., Anumba, C. J., & Khallaf, R. (2022). A review of digital twin applications in construction. *Journal of Information Technology in Construction,* 27.

[4] Jordaan, S. M., Xu, Q., & Hobbs, B. F. (2020). Grid-scale life cycle greenhouse gas implications of renewable, storage, and carbon pricing options. *Environmental Science & Technology,* 54(17), 10435-10445.

[5] Yang, C., He, B., Liao, H., Ruan, J., & Zhao, J. (2022). Price-based low-carbon demand response considering the conduction of carbon emission costs in smart grids. *Frontiers in Energy Research*, 10, 959786.

[6] Hanafy, W. A., Bostandoost, R., Bashir, N., Irwin, D., Hajiesmaili, M., & Shenoy, P. (2024). The war of the efficiencies: Understanding the tension between carbon and energy optimization. *ACM SIGENERGY Energy Informatics Review*, 4(3), 87-93.

[7] Di Bella, A., Canti, F., Prina, M. G., Casalicchio, V., Manzolini, G., & Sparber, W. (2024). Power system investment optimization to identify carbon neutrality scenarios for Italy. *Environmental Research: Energy,* 1(3), 035001.

[8] Cao, M., Song, W., & Xu, Y. (2024). Research on the impact of enterprise digital transformation based on digital twin technology on renewable energy investment decisions. *Energy Informatics*, 7(1), 142.

[9] Meng, X., Das, S., & Meng, J. (2023). Integration of digital twin and circular economy in the construction industry. *Sustainability*, 15(17), 13186.

[10] Song, Z., Hackl, C. M., Anand, A., Thommessen, A., Petzschmann, J., Kamel, O., ... & Hauptmann, S. (2023). Digital twins for the future power system: An overview and a future perspective. *Sustainability,* 15(6), 5259.

[11] Park, J., & Yang, B. (2020). GIS-enabled digital twin system for sustainable evaluation of carbon emissions: A case study of Jeonju city, south Korea. *Sustainability,* 12(21), 9186.

[12] Xu, W., & Liu, S. (2024). Novel economic models for advancing urban energy management and transition: Simulation of urban energy system in digital twin. *Sustainable Cities and Society*, 101, 105154.

[13] Ranawaka, A., Alahakoon, D., Sun, Y., & Hewapathirana, K. (2024). Leveraging the Synergy of Digital Twins and Artificial Intelligence for Sustainable Power Grids: A Scoping Review. *Energies,* 17(21), 5342.

[14] Enyejo, J. O., Fajana, O. P., Jok, I. S., Ihejirika, C. J., Awotiwon, B. O., & Olola, T. M. (2024). Digital twin technology, predictive analytics, and sustainable project management in global supply chains for risk mitigation, optimization, and carbon footprint reduction through green initiatives. *International Journal of Innovative Science and Research Technology*, 9(11), 1344.

[15] Yao, X., Fan, Y., Zhao, F., & Ma, S. C. (2022). Economic and climate benefits of vehicle-to-grid for low-carbon transitions of power systems: A case study of China's 2030 renewable energy target. *Journal of Cleaner Production*, 330, 129833.

[16] Chen, X., Wu, X., & Lee, K. Y. (2021). The mutual benefits of renewables and carbon capture: Achieved by an artificial intelligent scheduling strategy. *Energy Conversion and Management,* 233, 113856.

[17] Kou, G., Dinçer, H., Yüksel, S., & Deveci, M. (2024). Synergistic integration of digital twins and sustainable industrial internet of things for new generation energy investments. *Journal of Advanced Research,* 66, 39-46.

[18] Gao, J., & Huang, H. (2023). Stochastic optimization for energy economics and renewable sources management: A case study of solar energy in digital twin. *Solar Energy,* 262, 111865.

[19] Gejo-García, J., Reschke, J., Gallego-García, S., & García-García, M. (2022). Development of a system dynamics simulation for assessing manufacturing systems

based on the digital twin concept. *Applied sciences,* 12(4), 2095.

[20] Liu, T., Liu, J., Li, Y., & Li, Y. (2024). Balancing the water-carbon trade-off: development of a Bi-level source-grid-load synergistic optimization model for multi-regional electric power system. *Electronics,* 13(3), 516.

[21] Li, F., Wang, D., Liu, D., Yang, S., Sun, K., Liu, Z., ... & Qin, J. (2023). A comprehensive review on energy storage system optimal planning and benefit evaluation methods in smart grids. *Sustainability*, 15(12), 9584.

[22] Varganova, A. V., Khramshin, V. R., & Radionov, A. A. (2022). Improving efficiency of electric energy system and grid operating modes: Review of optimization techniques. *Energies*, 15(19), 7177.

[23] Rosso, R., Wang, X., Liserre, M., Lu, X., & Engelken, S. (2021). Grid-forming converters: Control approaches, grid-synchronization, and future trends—A review. *IEEE Open Journal of Industry Applications*, 2, 93-109.

[24] Calero, F., Cañizares, C. A., Bhattacharya, K., Anierobi, C., Calero, I., de Souza, M. F. Z., ... & Violante, W. (2022). A review of modeling and applications of energy storage systems in power grids. *Proceedings of the IEEE,* 111(7), 806-831.

[25] Faessler, B. (2021). Stationary, second use battery energy storage systems and their applications: A research review. *Energies*, 14(8), 2335.

[26] He, H., Zhou, S., Zhang, L., Zhao, W., & Xiao, X. (2023). Dynamic accounting model and method for carbon emissions on the power grid side. *Energies*, 16(13), 5016.

[27] Aryai, V., & Goldsworthy, M. (2022). Controlling electricity storage to balance electricity costs and greenhouse gas emissions in buildings. *Energy Informatics,* 5(1), 11.

[28] Wen, Y., Chen, Y., Wang, P., Rassol, A., & Xu, S. (2022). Photovoltaic–electric vehicles participating in bidding model of power grid that considers carbon emissions. *Energy reports,* 8, 3847-3855.

[29] Almutairi, Z. A., & Eltamaly, A. M. (2024). Synergistic Effects of Energy Storage Systems and Demand-Side Management in Optimizing Zero-Carbon Smart Grid Systems. *Energies*, 17(22), 5637.

[30] Guo, J., Wu, D., Wang, Y., Wang, L., & Guo, H. (2023). Co-optimization method research and comprehensive benefits analysis of regional integrated energy system. *Applied Energy*, 340, 121034.