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Application of Grid Carbon Footprint Full Chain Modeling and LCC Assessment in Low Carbon Equipment Selection

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SUMMARY: *This paper addresses the issue of low-carbon equipment selection for power grids under the dual-carbon objective, calculates the carbon emission intensity of users by tracing their power sources and quantities, and the NB-IoT IoT collects data from power grids to realize the collection and monitoring of carbon footprints. Based on the life cycle cost calculation of carbon emissions, with the modeling objective of minimizing the carbon emission penalty cost and equipment construction and installation cost for a typical day of distribution network, substation power constraints, grid constraints, equipment configuration and operation power constraints are set to establish a framework for coordinated optimal configuration. Combined with the theory of internalization of externalities, the marginal integrated cost of equipment selection backup is defined, and the optimized selection of low-carbon equipment is realized with the goal of minimizing the marginal integrated cost. The application results show that the LCC assessment proposed in this paper has the smallest error compared with the LCA assessment result of 30t, and the relative errors of the NB-IoT IoT acquisition system are 1.14%, 1.26%, and 0.58%, and the model accuracy is more. The actual costs of carbon footprint, transformer, photovoltaic inverter, and energy storage equipment are 482,000, 495,000, 502,000, and 476,000 yuan, which are more in line with the actual costs.The average cost of LCC assessment of tariff changes is 6,172,700 yuan, and the average cost of discount rate is 6,285,700 yuan, which is obvious in terms of economic benefits, and it can provide systematic and quantifiable decision-making support for the selection of low-carbon equipment for power grids.*

KEYWORDS: *carbon intensity; NB-IoT IoT; grid carbon footprint; life cycle cost; penalty fee*

1 Introduction

The power grid plays an important and fundamental role in national economic development, and the connotation of the concept of green power should be further deepened with the proposal of the "double carbon" strategic goal and the gradual increase in the construction of the green manufacturing system [1]. From the perspective of reducing carbon emissions, the energy structure of green power should be composed of low carbon emission power generation methods. For example, according to the carbon emission methodology, compared with the baseline scenario, wind power, photovoltaic and other renewable energy generation can generate a certain amount of emission reduction, which is the main form of energy supply to realize the "double carbon" target in the future. From the perspective of energy saving, we should focus on the application of energy-saving technology and energy-saving equipment, and use information technology to effectively control the energy loss in the process of energy

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generation, transmission, distribution, delivery and utilization [2]. From the perspective of environmental protection, electric power should show the source control of environmental pollutant emissions, the technology and management results of end-of-pipe treatment, and highlight the environmental performance of the energy production and use process. From the perspective of ecological design, the development of electric power should reflect the protection of the ecological environment in the links of electric power construction and electric power operation, and pay attention to the maintenance of the ecological balance of the region in which it is located while ensuring the quality of construction and operation and maintenance [3, 4]. From the perspective of resource recycling, the development of electric power should be manifested in the reduction of consumption of production materials, comprehensive utilization of waste, life-extension use of production equipment, and green cycle design of the whole process, etc., in accordance with the requirements of the concept of circular economy, to promote the sustainable development of energy and power enterprises. In addition, it is necessary to discuss the concept of electricity with the help of the full life cycle cost (LCC), data collection, quality assessment and modeling analysis of the whole process of energy production, transmission and distribution, transmission and use, to achieve an organic correlation with the selection of low-carbon equipment [5, 6].

In this paper, we trace the source and quantity of user electricity through the energy transfer chain to calculate its carbon emission intensity, and the NB-IoT software structure contains RTOS and drivers, REE application programs, etc. The trusted framework contains the security domain of the controlling organization, the security domain of the receiving entity, and the application of the runtime environment target. The carbon footprint of the power grid is accounted for according to the magnitude and significance of the carbon footprint change caused by the basic data. Through the selection of typical materials, construction of accounting model, data screening, numerical calculation, application of the results, combined with the data abridgment strategy, the accounting efficiency and accuracy are improved. The carbon footprint accounting kernel is constructed based on life cycle evaluation to quantify the carbon emissions of resources and energy consumption of power equipment in each unit process. An optimization model with the objective of minimizing the carbon emission penalty fee and equipment construction and installation cost on a typical day is established, and multiple types of constraints such as power, current, security, and equipment capacity are systematically integrated. Carbon price is introduced as an explicit external cost, and the marginal integrated cost of equipment standby is defined to integrate the internal cost with the external cost of carbon emission to realize the coordination of economic and low-carbon dual objectives.

2 Literature Review

2.1 Carbon footprint modeling

Bouza, L et al. presented the representation of energy consumption in deep learning models for training engineering, focusing on the use of carbon footprint estimation, pointing out that these tools can only measure the dynamic energy consumption of computing devices, and that further modeling improvements are needed if static energy consumption and environmental impacts are to be studied [7]. Luccioni, A. S et al. quantified the carbon footprint of the BLOOM model throughout its lifecycle in their study, and the empirical study clearly pointed out the difficulty of machine learning models' carbon footprints by extrapolating them through API endpoints that receive real-time query data from users [8]. Lannelongue, L et al. in the context of the continuous development of computers, based on the green algorithm for estimating and recording the carbon footprint of activities, the tool has universal applicability [9].

In summary, at this stage, the research on modeling of carbon footprint estimation still needs to be deepened, and carbon footprint calculation can help to quantify the greenhouse gas emission indicators and enhance the public's low-carbon awareness.

2.2 LCC Assessment

Larsen, V. G et al. reviewed life-cycle costing, life-cycle assessment, social life-cycle assessment, and integration of life-cycle sustainability assessment, and the study pointed out that it is necessary to integrate related methods in the project development stage and design stage, which is important for the sustainable development of circular economy [10]. Kambanou, M. L and Sakao, T developed a corporate guideline based on life cycle costing developed a guide for enterprises, which mainly includes enterprise processes and process standards, to help enterprises implement circular measures to avoid problems such as resource shortage [11]. Liu, J et al. combined life cycle assessment and life cycle costing to study the impacts of waste on environmental modifications in urban renewal and renovation projects to assess the economic outcomes [12].

The above studies provide new ideas for carbon footprint construction and related assessment from both environmental and economic perspectives.

2.3 Low-carbon equipment selection

Liu, X. For the integrated energy system, a low-carbon equipment allocation method considering the whole life cycle carbon emissions and transaction costs is proposed, and a model of “power-heating-cooling” energy supply equipment and integrated energy reserve is constructed. At the same time, a tiered carbon trading market mechanism is introduced to reduce equipment procurement, investment, operation and maintenance costs [13]. Liu, J et al. analyzed eleven low-carbon technologies in four categories and their combinations, provided technological solutions to meet emission reduction targets, and analyzed future development paths based on a technological perspective [14]. Meegahapola, L et al. for safeguarding the stability of the power system, emphasized the importance of safeguarding the stability of the low-carbon power grid, in which power electronic converters, renewable energy resources and distributed energy sources play an important role in this important feel, for safeguarding the stability of the low-carbon power grid is increasingly important [15].

Taking the above studies together, it is necessary at this stage to integrate the grid electrocarbon equipment sizing methodology in order to fully exploit the full benefits in the whole chain of grid operations.

3 Grid Carbon Footprint Full Chain Modeling

3.1 Basic concepts

According to the current state of research on carbon footprint modeling, from the viewpoint of the energy transfer chain, carbon emissions are pooled by the power flow to the consumer, which can characterize the cleanliness of the consumer's power supply. The transfer of carbon emissions in the grid is called carbon flow, which is numerically equal to the product of the power flow and the corresponding power-side carbon emission rate, and is schematically shown in Fig. 1, where the carbon flow can traverse multiple nodes before reaching the load. It can be used for the assessment of the carbon emission intensity of the customer's electricity, which is calculated by tracing the source and quantity of the customer's electricity [16].

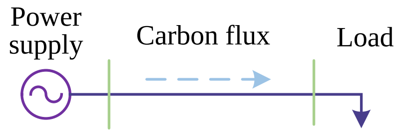


Figure 1: Schematic of carbon flow

3.2 NB-IoT IoT security architecture

NB-IoT is designed to realize the requirements of large connectivity, wide coverage, and low power consumption, etc. The NB-IoT IoT architecture, including modules and service platforms, is shown in Figure 2, which is based on the data requirements of the carbon footprint of the power grid under the goal of "dual-carbon". In terms of hardware, it consists of a highly integrated SoC supporting NB-IoT R13/R14 or higher, ESAM and eSIM supporting AES/3DES and SM1-SM4, or it can be realized by integrating ESAM and eSIM, such as CS18S, the SE-SIM solution launched by China Mobile.

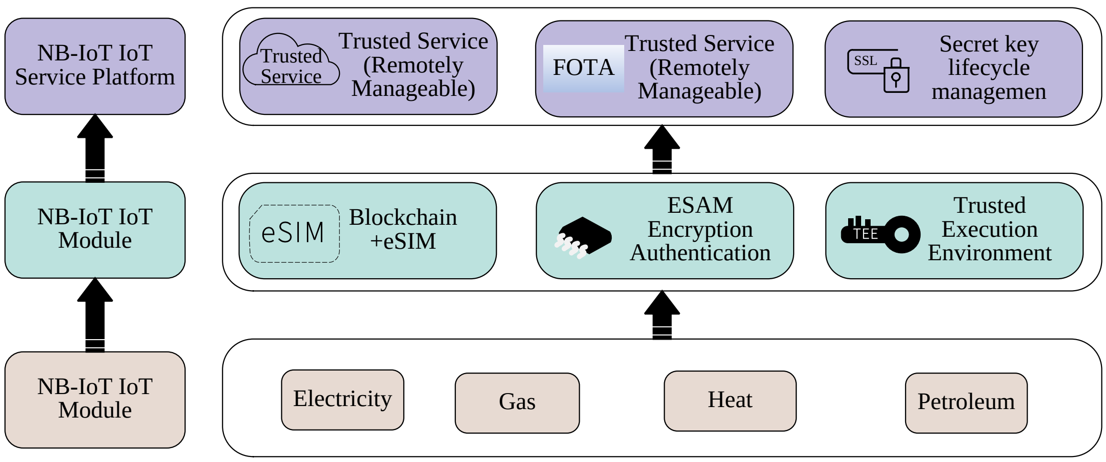
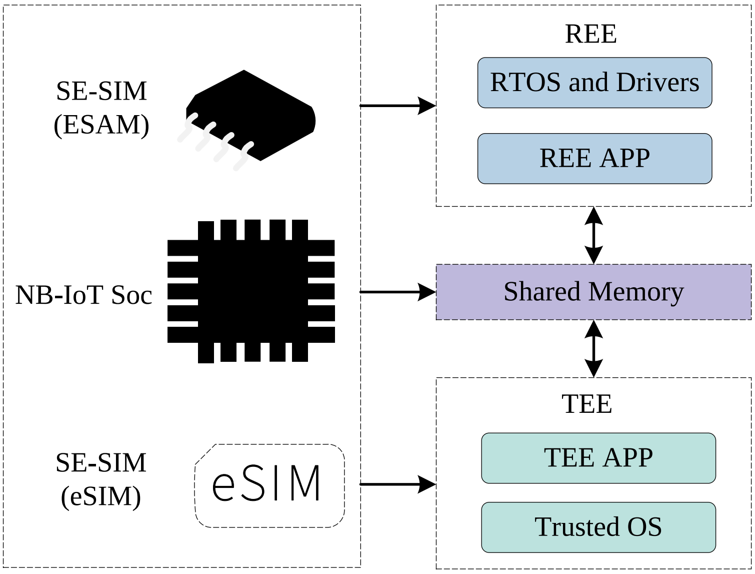
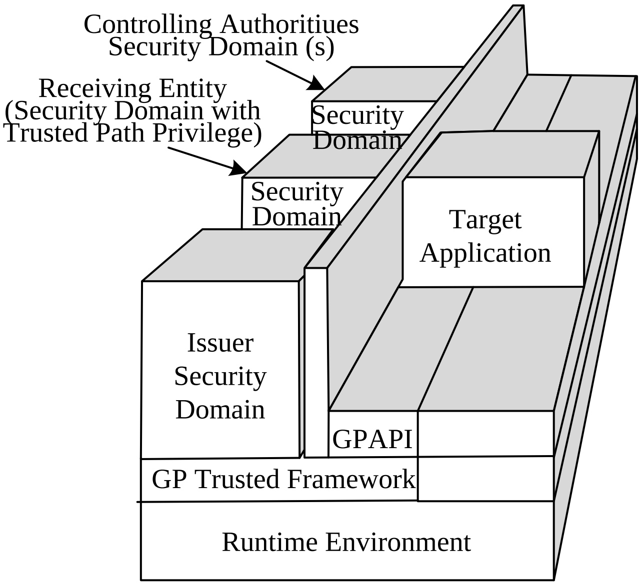


Figure 2: NB IoT IoT Architecture

The IoT module software is shown in Fig. 3, Fig. 3(a) shows the hardware and software structure, and the software structure, based on GlobalPlatform, consists of RTOS and driver, REE application program that contains running in rich execution environment, and trusted OS that runs in trusted execution environment, and trusted APP. Figure 3(b) shows the trusted framework, which contains the security domain of the controlling organization, the security domain of the receiving entity, and the target application of the runtime environment.



(a) Software and hardware structure



(b) Trusted Framework

Figure 3: IoT module software

3.3 Grid Carbon Footprint Accounting

Based on the above NB-loT IoT security architecture, the grid material carbon footprint accounting includes five key steps, typical grid material selection, accounting model construction, data acquisition and screening, numerical calculations, and application of calculation results, and the implementation path of grid carbon footprint accounting is shown in Figure 4. According to the magnitude and significance of the carbon footprint changes caused by the basic data, the data collection target is abbreviated, and the abbreviated data types are determined according to the proportion of different raw and auxiliary materials and different energy types in the carbon footprint of products, combined with the differences in the product data provided by different suppliers.

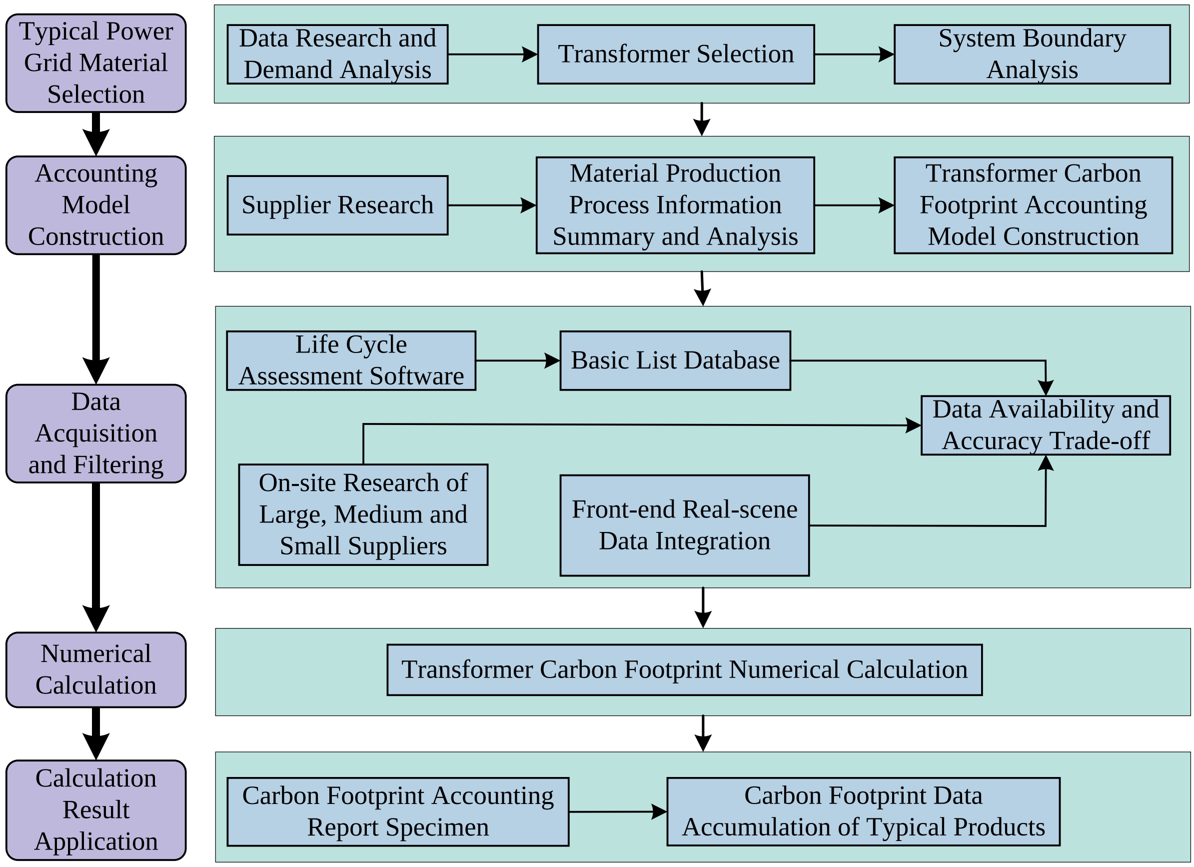


Figure 4: Implementation Path of Carbon Footprint Accounting for Power Grid

4 Full Life Cycle Cost Modeling

4.1 Calculation of carbon emissions

The full chain of carbon footprint calculation is established based on the life cycle cost approach, and the kernel of its accounting model is shown in equation (1):

$$CF = \sum_{j}^{n}\sum_{k}^{n} cf_{jk} = \sum_{j}^{n}\sum_{k}^{n} cf_{jk} \times f_{jk} \tag{1}$$

where: j denotes the unit process of the operation of electric power equipment and its components, and k denotes the type of resources and energy consumed in the unit process of the production of the product and its components. c_{jk} is the carbon footprint of the k type of resources or energy consumed by the j unit process of the operation of the electric power equipment and its components, f_{jk} is the amount of the k type of resources or energy consumed by the j unit process of the operation of the electric power equipment and its components, and CF is the carbon footprint of the power grid.

4.2 Grid Project Life Cycle Stage Classification

4.2.1 Objective function

In this paper, the optimal allocation of multiple equipment siting and capacity is optimized with the modeling objective of minimizing the carbon emission penalty cost and equipment construction and installation cost for a typical day in the distribution network, as shown in Eqs. (2)-(4):

$$\min f = f_{co_2} + f_{ins} \tag{2}$$

$$f_{co_2} = \sum_{i=1}^{T}\left[k_{sub}\eta_{sub}\cdot\sum_{j\in\Omega^{sub}}P_{j,t}^{sub} + \sum_{R\in\{G,F,B\}}\left(k_R\eta_R\cdot\sum_{j\in\Omega^R}P_{j,t}^{R}\right)\right] \tag{3}$$

$$f_{ins} = \sum_{R\in\{G,F,B\}}\left[\frac{\gamma^R\left(1+\gamma^R\right)^{T_L^R}}{\left(1+\gamma^R\right)^{T_L^R}-1}\sum_{j\in\Omega^R}\left(a_0^R u_j^R + a_1^R S_j^R\right)\right] \tag{4}$$

In Eqs. (2)-(4): f_{co_2} is the carbon penalty charge for a typical day in the distribution network, which is determined by the actual output of each type of power generation, carbon footprint coefficients, and the penalty unit price, and the upper and lower labels $R\in\{G,F,B\}$ denote the photovoltaic, wind, and biomass, respectively. η_{sub}、η_R are the whole-life carbon footprint coefficients of the grid and equipment, respectively, k_{sub} and k_R are the unit prices of the carbon penalty cost of the grid and equipment, respectively, and $P_{j,t}^{sub}$、$P_{j,t}^{R}$ are the active output of the substation and each equipment connected to node j at t time period. f_{ins} is the typical daily cost of the equipment throughout the life cycle of the investment and construction costs discounted, γ is the discount rate. T_L is the number of days of the equipment's useful life, a_0 is the fixed installation unit price, which is only related to the number of installations of this equipment, e.g., the cost of power plant construction, bracket transportation and installation. a_1 is the cost that is positively related to the grid-connected capacity, such as photovoltaic panels or wind turbine blades, etc. T is the total number of time slots, which is taken to be 24, and 1h is 1 time slot. u_j^R is a 0-1 variable indicating whether node j accesses a PV/wind/biomass power plant, and the values of 1 and 0 indicate that node j accesses or not, respectively, and it is one of the decision variables for the optimal allocation of the siting and capacity in this paper, and Ω^{sub}、Ω^R is the set of substation, equipment, etc., respectively. access node set.

4.2.2 Constraints

The full life cycle cost model constraints include substation power constraints, grid constraints, equipment configuration and operational power constraints, and the substation output power cannot exceed its upper and lower limit constraints, i.e:

$$\underline{P}_{j,t}^{sub} \le P_{j,t}^{sub} \le \overline{P}_{j,t}^{sub},\quad \forall t,\forall j\in\Omega^{sub} \tag{5}$$

$$\underline{Q}_{j,t}^{sub} \le Q_{j,t}^{sub} \le \overline{Q}_{j,t}^{sub}, \quad \forall t, \forall j \in \Omega^{sub} \tag{6}$$

In equations (5) and (6): $\overline{P}_{j,t}^{sub}$, $\underline{P}_{j,t}^{sub}$ are the upper and lower limits of the active output of the substation to which the node j is connected at the time period of t, respectively; $\overline{Q}_{j,t}^{sub}$, $\underline{Q}_{j,t}^{sub}$ are the upper and lower limits of reactive power output of the substation connected to node t in time period j, respectively.

The grid current constraint is:

$$\sum_{k\in\delta(j)} P_{jk,t} - \sum_{i\in\pi(j)} \left(P_{ij,t} - r_{ij} I_{ij,t}^2\right) = P_{j,t}^G + P_{j,t}^F + P_{j,t}^B + P_{j,t}^{sub} - P_{j,t}^L, \forall_t, \forall_j \in \Omega \tag{7}$$

$$\sum_{k\in\delta(j)} Q_{jk,t} - \sum_{i\in\pi(j)} \left(Q_{ij,t} - x_{ij} I_{ij,t}^2\right) = Q_{j,t}^F + Q_{j,t}^B + Q_{j,t}^{sub} + Q_{j,t}^{sub} - Q_{j,t}^L, \forall_t, \forall_j \in \Omega \tag{8}$$

$$U_{j,t}^2 = U_{i,t}^2 - 2\left(P_{ij,t} r_{ij} + Q_{ij,t} x_{ij}\right) + I_{ij,t}^2 \left(r_{ij}^2 + x_{ij}^2\right), \forall_{ij} \in \Omega^L \tag{9}$$

$$I_{ij,t}^2 = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{U_{i,t}^2}, \forall_t, \forall_{ij} \in \Omega^L \tag{10}$$

In Eqs. (7)-(10), $P_{j,t}$ and $Q_{j,t}$ represent the injected power of node j in time period t, and $\delta(j)$ is the set of all the end nodes of the branch with the first node j. $\pi(j)$ for the end of the node for the branch j of all the first node set, Ω, Ω^L, respectively, node set, branch set, r_{ij}, x_{ij} for the branch j resistance, reactance, $P_{ij,t}$, $Q_{ij,t}$, respectively, t time period branch ij active power, reactive power. $I_{ij,t}$ is the RMS value of current on branch ij in time period t, $U_{ij,t}$ is the RMS value of voltage at node j in time period t, and $P_{j,t}^G$, $P_{j,t}^F$, $P_{j,t}^B$, and $P_{j,t}^{sub}$ are the active injections of photovoltaic power plant, wind power plant, biomass power plant, and transformer substation at node j in time period t, respectively. $Q_{j,t}^F$, $Q_{j,t}^B$ and $Q_{j,t}^{sub}$ are the reactive power injections of wind power plants, biomass power plants and substations at t time period node j, $P_{j,t}^L$ and $Q_{j,t}^L$ are the active and reactive loads at t time period node j, respectively.

Security constraints:

$$P_{ij,t} \le P_{ij}^{\max}, \forall_{ij} \in \Omega^L \tag{11}$$

$$\underline{U}_{j,t}^2 \le U_{j,t}^2 \le \overline{U}_{j,t}^2, \forall_t, \forall_j \in \Omega \tag{12}$$

where: $P_{ij}^{\max}$ is the active upper limit of the branch ij, $\overline{U}_{j,t}^2$, $\underline{U}_{j,t}^2$ denote the upper and lower limits of voltage RMS value of the node j in the time period t, respectively, lower limit.

The equipment configuration capacity constraints:

$$\begin{cases} S_j^R \le S_{j,\max}^R \\ \sum_{j\in\Omega^R} = S_\Sigma^R \\ \sum_{j\in\Omega^R} \mu_j^R \le N_{\max}^R \end{cases} \tag{13}$$

where: S_j^R is the capacity of the node j configured equipment, which is one of the decision variables in this paper. $N_{\max}^R$ is the maximum value of the number of devices of a certain type connected to the distribution network, $S_{j,\max}^R$ is the maximum capacity of node j configured with a certain type of equipment, and S_Σ^R is the total capacity of the distribution network for the various types of equipment planned to be connected to the grid, which is determined by the statistics of the total capacity of the distribution user's report, a known quantity.

Equipment operation power constraints:

$$\begin{cases} P_j^R = S_j^R \tilde{P}_{1,t}^R \\ -P_j^R \tan\varphi^R \le Q_{j,t}^R \le P_{j,t}^R \operatorname{an}\varphi^R \end{cases} \tag{14}$$

where: $\tilde{P}_{1,t}^R$ is the unit-capacity equipment output for the t time period, and is an uncertain random variable. $P_{j,t}^R$ is the actual equipment output, and φ^R is the power factor angle corresponding to the minimum power factor for the safe operation of the equipment.

Based on the above, a model of robust coordination and optimal allocation of grid project distribution based on carbon footprint is developed.

5 Carbon-cost integrated decision-making and equipment selection modeling

5.1 Basic theory of selection

In the low-carbon economy, the introduction of carbon price makes carbon emission an explicit cost, and the decision of equipment selection should be changed to a comprehensive cost decision taking into account this explicit cost [17].

According to the theory of internalization of externalities, carbon emissions can be embedded into the standby offer in the form of external costs, thus effectively connecting the standby market transaction with the carbon emission reduction target. As a result, this paper defines the marginal integrated cost of equipment selection standby as:

$$M_{SC} = M_{PC} + M_{EC} \tag{15}$$

where: M_{SC} is the marginal integrated cost, M_{PC} is the marginal internal cost, M_{EC} is the marginal external cost of the unit, and in this paper, it refers to the carbon emission cost.

Let the unit bidding sequence pair be $(\mathrm{P_r}, P_e, R)$, $\mathrm{P_r}$, P_e are the capacity price and the electricity price, and the two quotes are generally a stepwise incremental curve . From this, we can get $M_{PC} = \mathrm{P_r} + \sum_{m \in M} p_m \cdot P_e$, the electricity cost is an uncertain cost, and the payment depends on the occurrence of accidents, so it should be taken into account the probability of accidents. Capacity costs, on the other hand, are deterministic and are paid to the winning unit regardless of whether an accident occurs or not. The unit standby capacity allocation quantity is the decision variable in this paper, and the optimal allocation quantity can realize the minimum total expected cost of standby, and obviously the capacity cost will be minimized, at this time, in order to prevent the equipment vendor from quoting speculation by decreasing the electricity tariff and increasing the capacity tariff, the low carbon equipment selection can be adopted by the unit's quoted price in the electricity market or the contracted tariff [18, 19].

5.2 Optimum point determination

The key to this paper's comprehensive carbon-cost decision-making and equipment selection lies in the calculation of the marginal carbon emission cost of the unit, and the electric carbon characteristic function of the conventional thermal power unit is:

$$e = \frac{f}{q}\frac{1}{\eta}g \tag{16}$$

where: e for CO_2 emissions, this paper considers the case of combustible fuel mass can be fully combusted, in this case f for the amount of CO_2 emissions per unit of fuel mass, which can be expressed as $f = M_{CO_2}/M$. Where M_{CO_2}, M for the emissions and the grid used fuel mass, q for the unit heating value of fuel mass, η for the unit power generation efficiency, g for the generating power, obviously also represents the unit hourly power generation of the unit.

By the CO_2 molecular weight relationship:

$$M_{CO_2} = \frac{44}{12}M\alpha\% \tag{17}$$

where $\alpha\%$ represents the percent value of base carbon content in the combustion mass, which can be obtained from the power plant medium data. The carbon emission factor of the unit is obtained by combining Eq. (16) and Eq. (17) as:

$$\beta = \frac{de}{dg} = \frac{44}{12}\frac{\alpha\%}{1\eta} \tag{18}$$

The unit of β is kg/Mwh, which can represent the CO_2 micro-increase per unit of power generation under different states of the unit's output level.

As shown in equation (18), the carbon emission factor β for conventional units is related to the unit efficiency β, while β is affected by the unit output level, which in turn is related to the winning bid in the electricity market in that time period, but taking into account that the generation efficiency usually tends to fluctuate within a small range with the change in the unit output level, and the range of variation in the output of the unit that provides standby capacity will not be too large. Therefore, it can be assumed that the unit efficiency is constant in this range, at which time the carbon emission factor can be simplified to a constant, so as to no longer take into account the impact of the output level and reduce the coupling relationship with the electricity market. In summary, the marginal integrated cost of equipment selection standby is obtained as:

$$M_{SC} = \mathrm{P_r} + \sum_{m \in M} p_m \cdot \left(P_e + \lambda\beta\right) \tag{19}$$

where λ is the CO_2 emission target price, the real situation should be taken from the cost of environmental damage caused by each unit of CO2 emissions, it is clear that the cost of carbon emissions should also belong to the cost of uncertainty. Formula (19) can obviously accommodate hydropower, carbon capture and other zero carbon emissions or low emission units, for the use of carbon capture and storage technology units, the capture process will also lead to the unit net external power output decline, capture rate of a certain amount of CO2 external equivalent carbon emission factor does not change with the change in the value of the power, so its marginal carbon emission cost can still be equivalent to a constant.

When the marginal integrated cost of unit standby M_{SC} is equal to its marginal opportunity value M_B, the optimal equipment selection program is obtained:

$$M_B\left(R^*\right) = M_{SC}\left(R^*\right) \tag{20}$$

6 Analysis of the results of the application of low-carbon equipment selection

6.1 Model performance validation

6.1.1 Carbon Footprint Accounting Model Validation

The carbon footprint in the case grid is 1725t, the transformer has the largest carbon footprint of 1320t, followed by the PV inverter 360t, and the carbon footprint of the energy storage equipment is relatively small, 45t. The performance verification of the carbon footprint accounting model is shown in Fig. 5.The LCC assessment method proposed in this paper is closer to the actual value compared to the traditional LCA assessment method, and the LCC assessment is in the energy storage equipment, with the largest error, the The carbon footprint is 42t, compared with the LCA assessment result of 30t, the model accuracy is more.

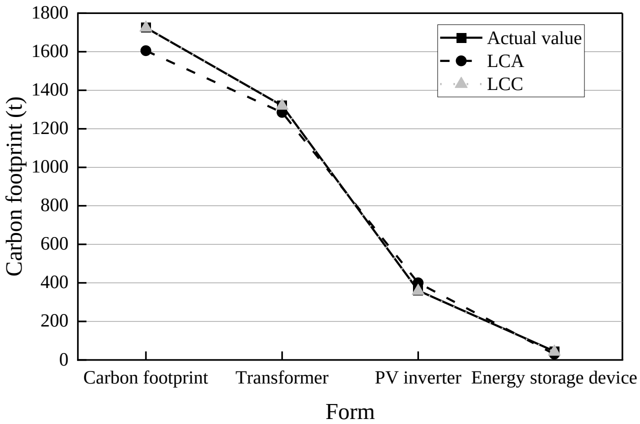


Figure 5: Carbon footprint accounting model performance validation

To validate the system performance of NB-IoT IoT collection of grid data, Table 1 shows the average relative error and absolute error results. It can be seen that the relative errors of all NB-IoT IoT collection systems are 1.14%, 1.26% and 0.58%, while it is even more to achieve the lowest error results, the average absolute error of adaptive collection is only for 14.15/kWh.

Table 1: Mean relative and absolute error results

Power Data Collection Interval	Average relative error	Mean absolute error/kWh
30 minutes	1.14%	36.89
Random Interval	1.26%	42.74
Adaptive Collection	0.58%	14.15

6.1.2 Life cycle cost test

A comparison of the prediction accuracy of the LCC model is shown in Figure 6, which shows that compared with the traditional LCA model, the predicted values of the LCC model are closer to the actual grid equipment costs and the prediction effect is optimal. The actual costs of carbon footprint, transformer, PV inverter, and energy storage equipment are 482,000, 495,000, 502,000, and 476,000 yuan, and the LCC model predicts costs of 471,000, 482,000, 501,000, and 480,000 yuan, which is closer to the actual costs.

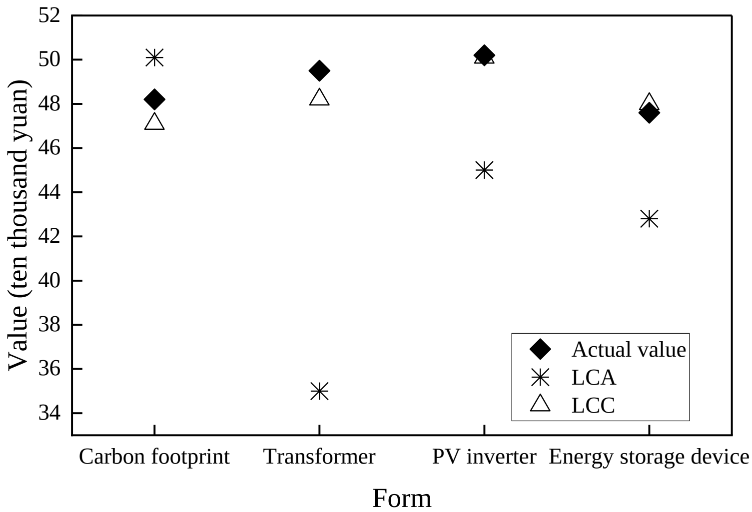


Figure 6: Comparison of LCC Model Prediction Accuracy

By evaluating the carbon footprint of the target grid, the comparison of carbon footprint accounting results is shown in Table 2. It can be seen that the traditional LCA method has the smallest initial investment, but the deviation of the accounting results is larger, and the total cost is 75t higher than the other schemes.The method has more assumptions and is not conducive to the low-carbon management of the grid system. The LCC assessment model constructed in this paper is technically and economically superior, with a carbon footprint deviation of 10t, and the total cost is basically equal in the later stage when the overhaul and fault costs are balanced. The baseline real-time method has the lowest cost in overhaul and failure costs, but the initial investment is close to two times of the other options, and the cash flow pressure in the early stage is large, which is difficult to meet the requirements of the grid system low carbon. In terms of adaptation scoring, the LCC model in this paper has the highest score of 5, followed by the baseline measurement method with 3, and the traditional LCV model has the lowest score of only 2. Therefore, it is further verified that the life cycle cost assessment of the proposed grid carbon footprint model is more adaptive and plays a key role in low-carbon equipment selection.

Table 2: Comparison of carbon footprint accounting results

Comparison projects	Traditional LCA method	This article presents the LCC model	Benchmark measurement method
Initial investment cost (relative value)	1	1.5	2
Static accounting carbon footprint (t)	1650	1735	1750
Operational phase carbon footprint (t)	150	50	30
Total lifecycle carbon footprint (t)	1800	1785	1780
Total carbon footprint deviation (t)	75	10	5
Suitability assessment (1-5 points, 5 points optimal)	2	5	3

6.2 Sensitivity analysis

There is little operational experience in low-carbon equipment selection for power grids, and there are large uncertainties in each link. According to the carbon footprint full chain modeling and accounting characteristics, the impact of the total cost of low-carbon equipment selection by different methods is analyzed in terms of sensitivity by considering the individual changes of three uncertainties: the main transformer failure rate, the feed-in tariff and the discount rate.

6.2.1 Impact of main transformer failure rate

The failure rate of the main transformer of the grid has a direct impact on the cost of equipment selection, and the objective function and constraints are used to calculate the total cost of equipment selection, and the results of the full life cycle comparison are shown in Fig. 7. The end-of-life cost of each redundant configuration transformer is included in its acquisition cost, under the accelerated failure rate curve, the failure cost of the traditional LCA method and the baseline measured method rises to 15.87 and 11.26 million yuan, respectively, and the former rises even more, and the total cost of the LCC is 53.68 and 51.75 million yuan, respectively, which saves 2.02 million yuan, and has a clear advantage, and it is appropriate to prioritize the selection. The sensitivity of failure cost to the change of failure rate in the traditional LCA method is not obvious, and its total cost is still higher than that of LCC.

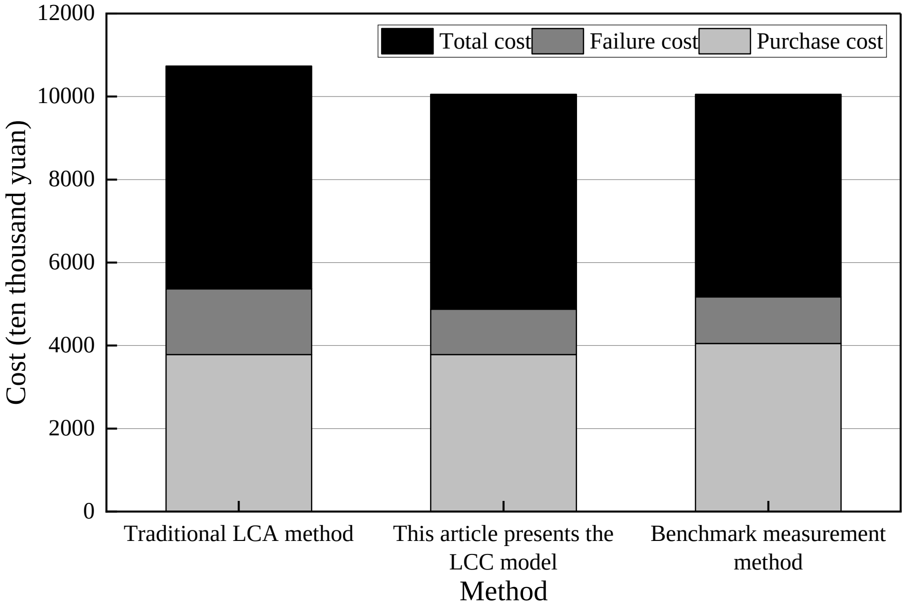
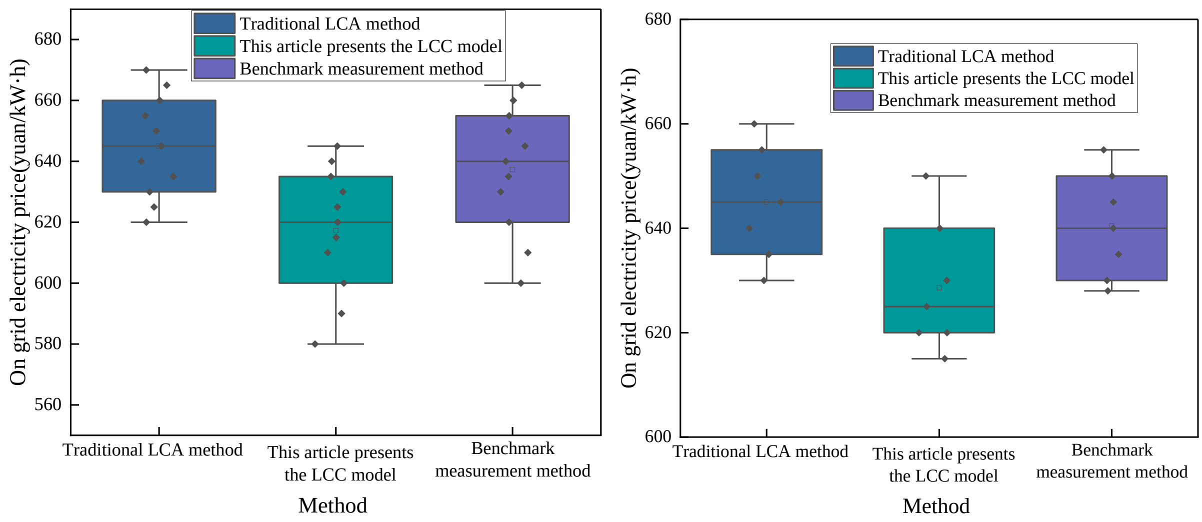


Figure 7: Comparison results of the entire lifecycle

6.2.2 Changes in electricity prices and discount rates

Grid in the low-carbon equipment selection need to consider the time value of money, and the price of electricity and the later operation of the profitability is closely related to the value of the key factors on the results of the calculation of the cost of equipment has a greater impact. Assuming that the price of electricity in the 0.5-1.0 yuan / (kW·h) change, the discount rate change interval of 4%-10%, the price of electricity and the discount rate change as shown in Figure 8. The box in the figure is the change interval, the upper and lower horizontal lines are the maximum and minimum values, the center line is the mean value, and the scatter point is the price distribution. Within the range of the variation interval of the feed-in tariff and discount rate, the total cost of the LCA evaluation method is always higher than that of the LCC evaluation and benchmark actualization method due to the large initial investment cost base, and its relative discount rate changes are relatively smooth because there is no blackout loss. For the LCA evaluation method and the benchmark real measurement method, when the feed-in tariff increases or the discount rate decreases, the total cost of both increases accordingly, but the rate of change is different. Figure 8(a) shows the change in electricity price, and the cost averages 6,172,700 yuan, and the LCC evaluation begins to highlight its economics. The change in discount rate is shown in Figure 8(b), and the total cost of the LCC assessment is significantly better than that of the LCA evaluation method and the baseline actualization method, with an average cost of 6,285,700 yuan, and the economic benefits are obvious.



(a) Changes in electricity prices (b) Change in discount rate

Figure 8: Changes in Electricity Price and Discount Rate

7 Conclusion

Based on the energy transfer chain and NB-IoT IoT architecture, this paper realizes the whole chain modeling of carbon footprint, combines with LCC assessment to realize low-carbon equipment selection, and draws the following main conclusions:

(1) The LCC assessment method proposed in this paper has a large error in the energy storage equipment with a carbon footprint of 42t, but compared to the LCA assessment of 30t, the accuracy is more.The NB-IoT IoT collection system adaptive collection average absolute error is only for 14.15/kWh, which is able to more accurately track the carbon footprint of the power grid.

(2) LCC model carbon footprint, transformer, PV inverter, energy storage equipment predicted cost of 47.1, 48.2, 50.1 and 480,000 yuan, with the smallest gap with the actual cost. the LCC model adaptability score is the highest 5 points, the best adaptability.

(3) The sensitivity analysis shows that the grid main transformer failure rate surges significantly on the traditional LCA method and the baseline actual method, and the cost rises to 15.87 and 11.26 million yuan, and the total cost of LCC saves 2.02 million yuan, which is an obvious advantage. The cost of electricity price changes averaged 6,172,700 yuan, and the total cost of discount rate changes LCC assessment averaged 6,285,700 yuan, with obvious economic benefits.

Future research can further incorporate the power market trading mechanism with multi-timescale dynamic characteristics to enhance the applicability of the model in the complex grid environment.

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