Carbon-Aware Optimal Power Flow Considering the Carbon Footprint of Carbon Capture Power Plants

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***Abstract*—Decarbonizing power systems requires not only controlling direct emissions from generation but also accounting for indirect emissions embedded in the carbon footprint of low-carbon technologies. Existing carbon-aware optimal power flow (OPF) models typically consider only the direct emissions of carbon capture power plants (CCPPs), thereby underestimating their actual carbon impact and potentially misguiding dispatch decisions. This paper proposes a carbon-aware OPF formulation that explicitly incorporates the full carbon footprint of CCPPs, including both direct and indirect emissions from capture, compression, transport, and storage processes. The model enhances carbon awareness on both the supply and demand sides through a carbon emission flow-based representation of nodal and system-level carbon intensities. Case studies on a modified IEEE 39-bus system show that neglecting indirect emissions leads to an underestimation of up to 25.24% of CCPP emissions, while the proposed model achieves a reduction of up to 7.42% in total system emissions under identical system settings.**

***Index Terms*—Carbon Footprint, Carbon Emission Flow, Carbon Capture Power Plant, Carbon-Aware Optimal Power Flow, Low-Carbon Dispatch**

I. Introduction

The power system is a major source of greenhouse gas emissions, with electricity generation alone contributing 13,800 million tons of CO_2 in 2024, the highest among all sectors [1]. Consequently, decarbonizing power system operation has become an urgent global priority.

Carbon Capture and Storage (CCS) technologies, particularly Carbon Capture Power Plants (CCPPs), provide an effective pathway for reducing emissions from fossil fuel-based electricity generation [2]. Compared with conventional thermal units, CCPPs can reduce direct carbon emissions by up to 90% [2], and their integration into power system dispatch has been investigated to support system-level decarbonization [3]. However, in practical operation, captured CO_2 must be transported and permanently stored in geological formations [4]. The electricity consumption associated with these downstream processes introduces indirect carbon emissions that are often overlooked, leading to an underestimation of the actual carbon impact of CCPPs, i.e., their carbon footprint.

Carbon footprint characterizes the total greenhouse gas emissions associated with an activity or technology, including both direct and indirect emissions, and is typically expressed in CO_2 equivalents [5], [6]. It encompasses direct emissions from owned or controlled sources (Scope 1), indirect emissions from purchased energy consumption (Scope 2), and emissions along the value chain (Scope 3) [6]. For CCPPs, Scope 1 mainly corresponds to uncaptured CO_2 released during power generation, while Scope 2 and Scope 3 emissions primarily arise from electricity consumption during CO_2 transport and geological storage. Therefore, carbon accounting based solely on direct emissions fails to capture the full carbon footprint of CCPPs.

Carbon awareness is fundamental to low-carbon power system operation and has received increasing attention in recent years. The Carbon Emission Flow (CEF) theory, for example, attributes direct emissions from generation units to electricity consumption at the load side based on power flow relationships, enabling carbon-aware electricity consumption [8]. Carbon-aware quantification has also been explored for flexible resources such as electric vehicles [9]. However, existing carbon-aware OPF formulations predominantly rely on direct emissions only. From a carbon footprint perspective, awareness of indirect emissions beyond direct stack emissions remains largely unexplored, making it difficult to accurately perceive the carbon impact of individual system components.

To address this gap, this paper, as illustrated in Fig. 1, first establishes a carbon footprint calculation method for CCPPs that explicitly accounts for both direct and indirect emissions. Based on this formulation, a carbon-aware Optimal Power Flow (OPF) model incorporating carbon footprint considerations is developed, enabling footprint-based carbon awareness on both the supply and demand sides of power system operation.

II. Operation and Carbon Footprint of CCPPs

This section models CCPP operation and carbon footprint for dispatch. It first introduces the energy penalty that links gross generation, capture-related auxiliary consumption, and net grid injection, and then formulates the CCPP carbon footprint by combining direct emissions from uncaptured CO_2 with indirect emissions from CO_2 compression, transport, and geological storage. These models will be incorporated into the carbon-aware OPF in Section III.

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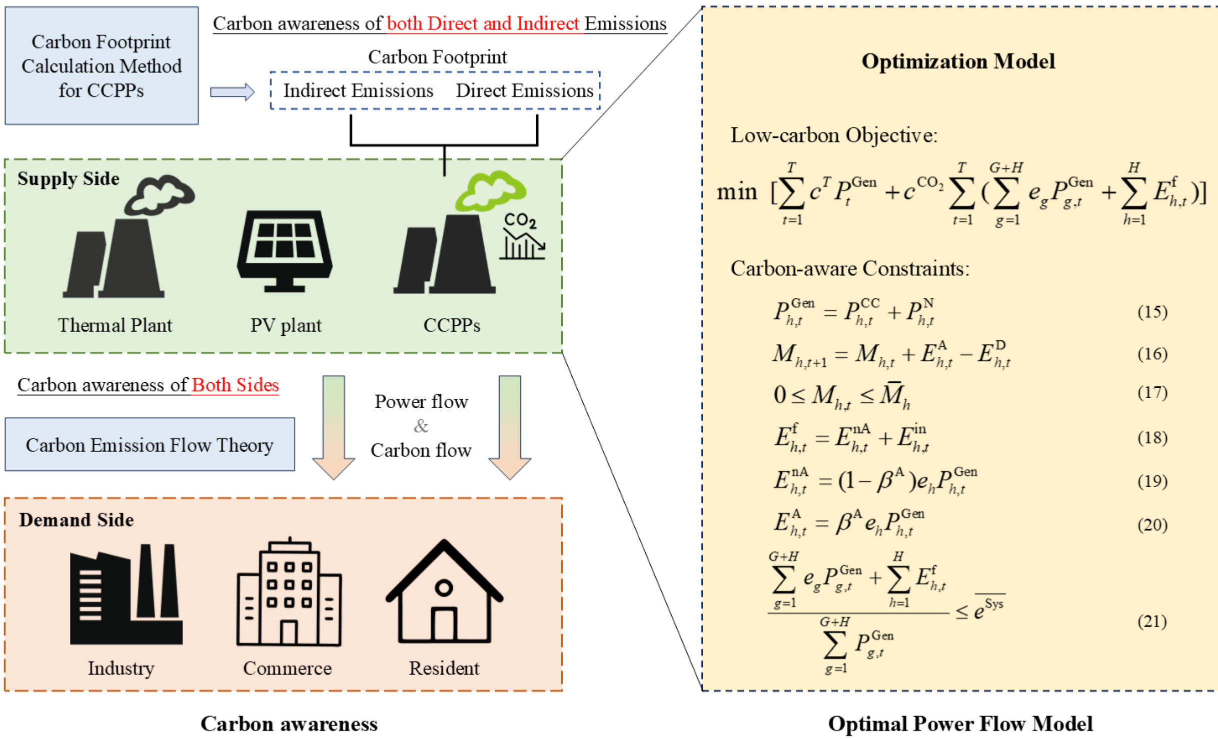

Fig. 1. The proposed framework.

A. *CCPP Power Output*

The energy penalty in a CCPP refers to the incremental energy consumed by the carbon capture system, which reduces the plant's net power output:

$$P^{\text{Gen}} = P^{\text{CC}} + P^{\text{N}} \tag{1}$$

where P^{Gen} is the gross power generation of the CCPP. P^{CC} is the power consumption of the carbon capture system in the CCPP. P^{N} is the net power generation of the CCPP, which is injected into the grid.

CO_2 capture system has three main components: the absorber, the stripper and the compressor. According to research, P^{CC} is composed of a constant part P_0^{CC} and three variable parts which vary linearly with the operating level of the three components [10].

$$P^{\text{CC}} = P_0^{\text{CC}} + P^{\text{A}} + P^{\text{D}} + P^{\text{C}} \tag{2}$$

$$P^{\text{A}} = \lambda^{\text{A}} E^{\text{A}} \tag{3}$$

$$P^{\text{D}} = \lambda^{\text{D}} E^{\text{D}} \tag{4}$$

$$P^{\text{C}} = \lambda^{\text{C}} E^{\text{C}} \tag{5}$$

where P_0^{CC} is the basic power consumption of the carbon capture system in CCPPs. P^{A} is the operating power consumption of the absorber, determined by E^{A} which denotes the amount of absorbed CO_2. λ^{A} is the ratio of power consumption to absorbed CO_2. Similarly, P^{D} is the power consumption for stripper desorption, while P^{C} is the power consumption for compressor compression.

In a CCPP, usually two solvent storage tanks are set between the absorber and the stripper to store the solvent containing CO_2 and the solvent for absorption; therefore, the operating levels of the absorber and the stripper are not necessarily equivalent. The solvent storage tanks are modeled in part III. The CO_2 stripped from the solvent is instantly compressed, so we have:

$$E_t^{\text{D}} = E_t^{\text{C}} \tag{6}$$

After capture, the compressed CO_2 is transported to suitable sites for permanent geological storage.

B. *CCPP Carbon Footprint*

Technically, not all CO_2 produced can be captured; a fixed fraction is directly emitted into the air [10]. Thus, we have

$$E_t^{\text{nA}} = (1 - \beta^{\text{A}}) E_t^{\text{G}}, \tag{7}$$

where E_t^{nA} is CO_2 not absorbed and emitted directly into the air and β^{A} denotes the CO_2 capture rate, which is roughly in the range of 85%–95% [2].

In addition, a CCPP indirectly results in carbon emission by consuming electrical power in the transport process and the storage process. The electricity consumed for the two processes, along with the resulting indirect carbon emissions, is entirely attributed to the CCPP. Whether direct or indirect, these emissions have an equivalent impact on climate change. Therefore, they are also included in the CCPP's carbon footprint. Indirect carbon emissions E^{id} can be expressed as

$$E^{\text{id}} = E^{\text{ct}} + E^{\text{cs}} \tag{8}$$

$$E^{\mathrm{ct}} = d^{\mathrm{ct}} \lambda^{\mathrm{ct}} D^{\mathrm{ct}} E^{\mathrm{e}} \tag{9}$$

$$E^{\mathrm{cs}} = \lambda^{\mathrm{cs}} D^{\mathrm{cs}} E^{\mathrm{e}} \tag{10}$$

$$E^{\mathrm{A}} = D^{\mathrm{ct}} = D^{\mathrm{cs}} \tag{11}$$

where E^{ct} and E^{cs} are indirect carbon emissions caused by consuming electrical energy in the transport and geological storage process individually, and D^{ct} and D^{cs} are the CO_2 transported and geological stored individually. d^{ct} is CO_2 transport distance by pipelines. E^{e} is the average carbon emission intensity for the region, in units of tCO_2/MWh.

Compared to traditional carbon accounting methods, the carbon footprint better reflects the carbon emission caused by CCPPs. In this paper, we use the carbon footprint to replace direct carbon emissions when calculating the carbon emission E^{f} and the carbon emission intensity of CCPPs e^{f}:

$$E^{\mathrm{f}} = E^{\mathrm{nA}} + E^{\mathrm{in}} \tag{12}$$

$$e^{\mathrm{f}} = \frac{E^{\mathrm{f}}}{P^{\mathrm{N}}} \tag{13}$$

III. Carbon-Aware Optimal Power Flow

This paper proposes a carbon-aware OPF model, employing the CEF methodology to calculate Nodal Carbon Intensities (NCIs) on the basis of Direct Current OPF (DCOPF) model. By incorporating carbon intensity constraints into the model, it better simulates the operation of the power system under carbon intensity control, thereby promoting deep decarbonization of the power system. NCIs are treated as decision variables, with CEF-based equations included as equality constraints to enable demand-side carbon awareness. This approach enables control over the carbon emission intensity of electricity consumption behavior on the demand side.

A. Objective Function

The objective function of the proposed model is to minimize operating costs, consisting of both power generation costs and carbon footprint costs on the generation side. The carbon footprint of thermal power plants represents direct carbon emissions from thermal power generation units, while the carbon footprint of CCPPs has already been analyzed in Part II. In this paper, the carbon price P^{CO_2} is fixed, and the carbon footprint cost is linearly proportional to the quantity of carbon footprint. The objective function is:

$$\min \left[\sum_{t=1}^{T} c^T P_t^{\mathrm{Gen}} + c^{\mathrm{CO_2}} \sum_{t=1}^{T} \left(\sum_{g=1}^{G+H} e_g P_{g,t}^{\mathrm{Gen}} + \sum_{h=1}^{H} E_{h,t}^{\mathrm{f}}\right)\right] \tag{14}$$

where c is the matrix of power generation costs, P_t^{Gen} is the matrix of gross power generation at time t. T is the number of time intervals. G and H is the number of non-CCPP power units and CCPP units individually. In this paper, non-CCPP power units include both thermal units and sustainable energies. $P_{g,t}^{\mathrm{Gen}}$ is the gross power generation of the g-th unit at time t. e_g is the carbon intensity the of g-th non-CCPP unit.

B. Constraints

In addition to system power balancing constraints, power generation constraints, power flow constraints, ramping constraints, the proposed carbon-aware OPF model additionally includes the following constraints:

1) Energy penalty constraints:

Derived from (1)-(5), the energy penalty constrains can be expressed as

$$P_{h,t}^{\mathrm{Gen}} = P_{h,t}^{\mathrm{CC}} + P_{h,t}^{\mathrm{N}} \tag{15}$$

which is in the form of power.

2) Constraints of the CCPP solvent tanks:

One of the solvent tank is used to store the CO_2-rich solution containing a large amount of CO_2 after the absorption process. As this CO_2-rich solution is subsequently transferred to the stripper for desorption, the volume of solution in the CO_2-rich solvent tank decreases. The other solvent tank is used to store the solvent ready for absorption. In this paper, the volume of CO_2-rich solution is expressed using the mass of its CO_2 content, thereby eliminating the need for conversion calculations. For the solvent tank containing the CO_2-rich solution, we have:

$$M_{h,t+1} = M_{h,t} + E_{h,t}^{\mathrm{A}} - E_{h,t}^{\mathrm{D}} \tag{16}$$

where $M_{h,t}$ is the mass of absorbed CO_2 in h-th CCPP's solvent tank at time t, while $\overline{M}_h$ is the maximum mass limit of absorbed CO_2 in h-th CCPP's solvent tank.

Post-combustion flue gas contains substantial amounts of CO_2, making it impractical to design a solution storage tank with sufficiently large capacity. Therefore, the volume of the CO_2-rich solution within the storage tank must be limited [3]:

$$0 \leq M_{h,t} \leq \overline{M}_h \tag{17}$$

When the CO_2-rich solution tank satisfies the constraints, constraints of the other solvent tank are naturally satisfied.

3) Carbon footprint constraints of CCPPs:

Carbon footprint constraints of CCPPs calculate the carbon footprint of CCPPs, encompassing both direct carbon emissions resulting from CO_2 generated by the CCPP units that cannot be fully captured, and indirect carbon emissions caused by electricity consumption during pipeline transport and geological storage processes. The constraints are:

$$E_{h,t}^{\mathrm{f}} = E_{h,t}^{\mathrm{nA}} + E_{h,t}^{\mathrm{in}} \tag{18}$$

$$E_{h,t}^{\mathrm{nA}} = (1 - \beta^{\mathrm{A}}) e_h P_{h,t}^{\mathrm{Gen}} \tag{19}$$

$$E_{h,t}^{\mathrm{A}} = \beta^{\mathrm{A}} e_h P_{h,t}^{\mathrm{Gen}} \tag{20}$$

and (8)-(11). e_h is the carbon intensity of h-th CCPP unit.

It is worth noting that although indirect emissions do not occur immediately, they are included in the carbon footprint generated at that time in this paper.

4) Carbon intensity constraints: Carbon intensity constraints have different forms, such as nodal carbon intensity constraints, system carbon intensity constraints and so on.

The CEF-based calculation method [8], as well as power flow direction reconstruction [11], is used to calculate NCIs in this model. Note that NCIs are treated as decision variables so that constraints on NCIs can be incorporated.

The system carbon intensity constraint can be the upper bound constraint on the system carbon intensity, which requires sufficient clean energy power output in the perspective of generation side. The system carbon intensity constraint can be expressed as:

$$\frac{\sum_{g=1}^{G+H} e_g P_{g,t}^{\mathrm{Gen}} + \sum_{h=1}^{H} E_{h,t}^{\mathrm{f}}}{\sum_{g=1}^{G+H} P_{g,t}^{\mathrm{Gen}}} \leq \overline{e^{\mathrm{Sys}}} \tag{21}$$

where $\overline{e^{\mathrm{Sys}}}$ is the upper limit of the system carbon intensity.

In the actual operation of power systems, both the total carbon emissions and the carbon intensity are controlled. In this model, the carbon emissions control is already incorporated into the design of the objective function, while the control of carbon intensity is achieved through the constraint (21).

IV. Case Studies

The proposed model was tested on a modified IEEE 39-bus system, as shown in Fig. 2, implemented in MATLAB R2023a and solved by Gurobi 10.0.3 on a PC with an Intel Core i5-11300H @3.1GHz.

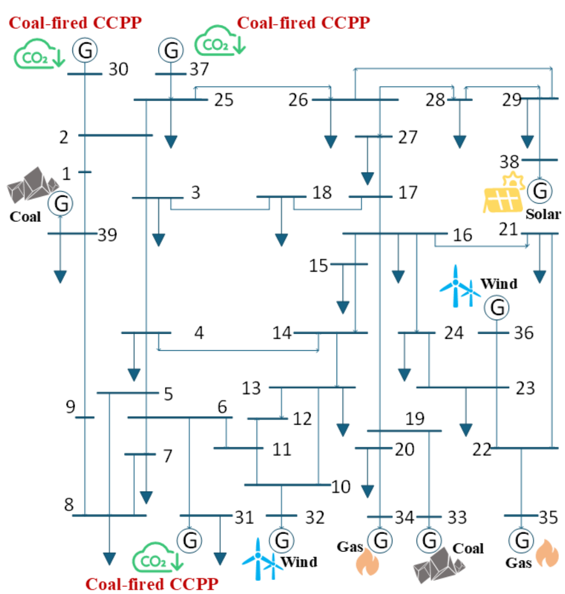

Fig. 2. Modified IEEE 39-bus system with 3 CCPPs.

A. Experimental Setup

Three sets of experiments were conducted to demonstrate the effectiveness of the method. Each set contained 10 generating units, including 1, 2, and 3 coal-fired CCPPs, respectively, and 2 wind power plants and 1 solar power plant. The upper limits of system carbon intensity were set as 0.4, 0.3 and 0.25 tCO_2/MWh respectively, while NCIs were not constrained in any set. The parameters for the generation units, loads and transmission lines are referenced from PGlib [12] and PGlib-CO_2 [13]. Wind and photovoltaic data and load profiles come from real operating data from Elia [14].

TABLE I
PARAMETERS OF THE CCPPs

Parameter	Value
P_0^{CC}	20 (MW)
β^{A}	0.9
λ^{A}	0.02 (MWh/tCO_2)
λ^{D}	0.26 (MWh/tCO_2)
λ^{C}	0.12 (MWh/tCO_2)
d^{ct}	50 (km)
λ^{ct}	1.3 (kWh/tCO_2*km)
λ^{cs}	10 (kWh/tCO_2)
E^{e}	0.5 (tCO_2/MWh)

All CCPPs are equipped with solvent storage tanks, and the captured CO_2 is transported to suitable sites and geologically stored. Parameters related to the CCPPs and their carbon footprints are shown in Table I. The CO_2 price is set as 30\$/tCO_2. The time period is 24 hours and the basic time interval is 1 hour. For comparison, a baseline model accounting for only direct emissions in the calculation of NCIs and the system carbon intensity was established in each set of experiments

Moreover, computational performance with and without NCI calculation and carbon constraints was tested in the case with three CCPPs.

B. Experimental Results

As shown in Table II, the proposed model increased total costs but reduced carbon footprints by up to 7.42% compared to the baseline.

The reduction in carbon footprint, as well as the increase in the total cost, stems directly from adjustments to the power generation mix. As shown, under the carbon constraint, coal-fired units reduce their output while gas-fired units increase theirs, leading to a higher proportion of low-carbon power generation and a more expensive cost.

In the baseline model, only direct carbon emissions are included and subject to the carbon intensity constraint. This results in the system's carbon emissions appearing not to exceed the carbon intensity cap, while in fact, from a carbon footprint perspective, they have already exceeded it. In other words, if the carbon footprint of the CCPPs is not accounted

TABLE II
COST AND CARBON RESULTS OF THREE SETS OF EXPERIMENTS (UNIT:K\$)

Case	Model	Coal	Gas	System	Carbon(t)	Reduced by
1 CCPP	Proposed	2402	5883	2.24×10^6	33055	2.26%
	Baseline	2625	5252	2.20×10^6	33821	
2 CCPPs	Proposed	943	6821	2.23×10^6	24791	4.77%
	Baseline	1305	5798	2.16×10^6	26033	
3 CCPPs	Proposed	555	5275	2.12×10^6	20659	7.42%
	Baseline	1038	3911	2.03×10^6	22315	

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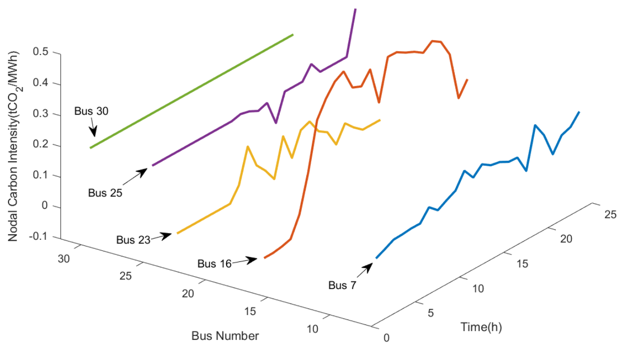

Fig. 3. Nodal carbon intensity of selected nodes (3 CCPPs).

TABLE III
DIRECT EMISSION AND CARBON FOOTPRINT OF CCPPS

	Direct Emission	Carbon Footprint	Underestimation
1 CCPP	2270.1t	3036.3t	25.23%
2 CCPPs	3680.2t	4922.3t	25.24%
3 CCPPs	4960.1t	6561.9t	24.41%

for within the model, the actual carbon emissions caused by the CCPPs will be underestimated. This conclusion applies not only to CCPPs but also to the carbon footprints of other components in the power system.

In addition, the proposed model calculated the NCIs at each point in time, as shown in Fig. 3.

Through NCIs and their variations, we can trace the carbon footprint on the supply side caused by electricity consumption on the demand side. Unlike conventional carbon emission intensity in CEF theory that only considered direct emissions, the model proposed in this paper extends the concept of demand-side carbon intensity to that of carbon footprint rather than direct emissions. This allows better attribution of carbon responsibility on the demand side or carbon control policies.

The comparison of CCPPs' carbon footprint and direct carbon emissions is shown in Table III. From a carbon footprint perspective, carbon emissions caused by CCPPs increased by up to 33.75%. This means that if we do not measure CCPP's actual carbon emissions using the carbon footprint method, 25.24% of these emissions would be overlooked.

The original intent of CCPPs was to reduce carbon emissions, and this has been achieved by cutting direct emissions by over 90%. However, the resulting increase in indirect emissions is rarely discussed. Although for CCPPs, according to the results, the reduction in direct emissions far outweighs the increase in indirect emissions, this may not hold true for the next technology claiming to reduce carbon emissions.

TABLE IV
COMPUTATIONAL PERFORMANCE OF THE CASE WITH THREE CCPPS

NCI calculation	Carbon constraints	Solving time (s)
✓	✓	26.22
✓	×	25.91
×	✓	/
×	×	0.50

Results of the computational performance tests are shown in Table IV. As shown, the solving time of the proposed model is far more than that without considering CO_2, which is primarily due to NCI calculation. In this model, in order to make NCIs potentially controllable, NCIs and calculation variables are defined as decision variables rather than post-solution quantities, and constraints are used to express NCI calculation formulation. As a result, NCI calculation is naturally decision model solution rather than matrix operation, leading to a much slower solving time.

V. CONCLUSION

In this paper, after accounting for the carbon footprint of CCPPs, a carbon-aware OPF model is proposed. Indirect carbon emissions from transport and geological storage processes in CCPPs are also included in carbon emission costs and NCI calculation, enabling carbon awareness of both supply and demand sides. The effectiveness of the proposed model is verified through a comparative analysis of direct emissions and carbon footprints at both the CCPP and the system levels.

Future work could assess scalability of this model on larger systems. And on the basis of carbon awareness, CCPPs with solvent storage could be leveraged to increase renewable penetration, thereby deepening power system decarbonization.

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