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Development of an Energy Planning Model Using Temporal Production Simulation and Enhanced NSGA-III

Xiaojun Li[1*], Yilong Ni[1], Shuo Yang[1], Zhuocheng Feng[1], Qiang Liu[1], Jian Qiu[1], Chao Zhang[1]

[1]Information Data Department Guangdong Electric Power Trading Center Co. Ltd., Guangzhou, Guangdong 510000, China

Abstract

This paper presents an innovative model of Energy Planning Model which allows navigating the complexities of modern energy systems. Our model utilizes a combination of Temporal Production Simulation and an Enhanced Non-Dominated Sorting Genetic Algorithm III to address the challenge associated with fluctuating energy demands and renewable sources integration. The model represents a significant advancement in energy planning due to its capacity to simulate energy production and consumption dynamics over time. The unique feature of the model is based on Temporal Production Simulation, meaning that the model is capable of accounting for hourly, daily, and seasonal fluctuations in energy supply and demand. Such temporal sensitivity is crucial for optimization in systems with high percentages of intermittent renewable sources, as existing planning solutions largely ignore such fluctuations. Another component of the model is the Enhanced NSGA-III algorithm that is uniquely tailored for the nature of multi-objective energy planning where one must balance their cost, environmental performance, and reliability. We have developed improvements to NSGAIII to enhance its efficiency when navigating the complex decision space associated with energy planning to reach faster convergence and to explore more optimal solutions. Methodologically, we use a combination of in-depth problem definition approach, advanced simulation, and algorithmic adjustments. We have validated our model against existing models and testing it in various scenarios to illustrate its superior ability to reach optimal energy plans based on efficiency, sustainability, and reliability under various conditions. Overall, through its unique incorporation of the Temporal Production Simulation and an improved optimization algorithm, the Energy Planning Model provides novel insights and practical decision support for policymakers and energy planners developed to reach the optimal sustainable solutions required for the high penetration of renewables.

Keywords: Energy Planning, Temporal Production Simulation, Enhanced NSGA-III, Optimization, Multi-Objective Evolutionary Algorithms

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1. Introduction

Effective planning is an essential aspect of managing energy to ensure sustainability, reliability, and cost-effectiveness. Energy planning is the process of allocating resources in such a way as to satisfy current and future needs, considering factors such as environmental impact, technological innovation, and economic justification. The emphasis on renewable energy sources is explained by the necessity to reduce greenhouse gas emissions and counteract the consequences of climate change. Planning, however, is difficult given the complexity and dynamics of energy systems currently, characterized by the increasing contribution of renewable sources and varying loads. Indeed, a typical energy planning model does not take into account these multi-dimensional dynamics and

*Corresponding author. Email: lixj2024@126.com

constraints. The first limitation is that, generally, only the spatial dimension is considered. This means that the production and consumption of energy are averaged without considering the hourly, daily, or seasonal variation which are typical of the grid mixes and insufficiency related to renewable source fluctuations. In fact, the above-mentioned flaws may lead the planner to take an incorrect decision so that calculating the ideal investments or others on the basis of source's availability. A second flaw is the lack of temporal dimension when modeling many existing patterns. For instance, most models relate the production potential of solar panels with an average insulation pattern during the year. This may not ensure that, in a frame of many days without the sun or insubstantial work during the night, the average insulation should trigger the production.

The Energy Planning Model proposed in this paper is designed to address gaps in existing energy planning approaches by integrating temporal production simulation with an enhanced version of the NSGA-III algorithm [1], [2]. The Energy Planning Model (EPM) is designed to implement a novel perspective on energy planning problems' objectives which captures and optimizes the spatial dynamics of energy production and consumption in concert with many other objectives, using multiple levels of refinement in space and time [3],[4]. It is one of its most significant contributions. The Energy Planning Model (EPM) is designed to provide policymakers and other stakeholders with a better understanding of the temporal trade-offs inherent in energy planning. This correlation, for instance, allows it to analyze the long-term consequences of various energy planning alternatives. The model helps to discover the best set of answers that are resilient to significant variations in the availability of power. Additionally, the EPM contains an enhanced version of the NSGA-III algorithm, which significantly improves its performance by enhancing the optimization process [5]. It assists in locating the best answers while also aiding in the taming of the multi-objective energy planning issue. The Energy Planning Model (EPM) aims to achieve two goals; the use of multiple resolutions in time to blend with the multidimensional spatial resolution and the ability to handle multi-objective optimization times. Since the Energy Planning Model (EPM) achieves these goals, it is reasonable to assume that it will greatly contribute to energy planning in the near future.

2. Literature Review

Energy planning comprises a wide range of methodologies and models, each developed to efficiently and sustainably produce, distribute, and consume energy throughout the spectrum. The traditional models are tasked with the responsibility of single-objective optimization with cost minimization as the primary focus. However, the increasing recognition of the environmental impacts of energy, the deregulation of the energy markets, and the integration of unpredictable renewable energy sources have necessitated the adoption of more sophisticated, multi-objective optimization models [6]. Various factors must be considered, such as economic costs, environmental impacts, system reliability, and social acceptability, in the development of these models. The models have evolved to integrate stochastic elements to address the variability and uncertainty inherent in renewable energy and dynamic models capable of simulating energy systems over time, with optimization algorithms and modeling approaches continuing to advance to cope with the complexity and scale of modern energy systems. Recent academic contributions reveal that methodologies in energy planning have made a tremendous leap due to some advancement, especially by the application of NSGA-II, NSGAIII and other related approaches. Nonetheless, the review identifies gaps for improvement in the future. Distributed Photovoltaic and Battery Energy Storage Systems integration is a contemporary energy planning model that is being given significant weight [8]. A study that applied the NSGA-III algorithm sought a Mult objective joint planning model to minimize the DN cost, voltage fluctuation, and network loss . The results underscore the suitability of NSGA-III for addressing multi-dimensional complex optimization problems for more integrated and efficient energy systems [6].

The steel industry consumes a substantial amount of energy, and a newly developed NSGA-II approach has been employed to formulate energy plans that focus on the two concurrent goals of saving and optimizing consumption reduction [9]. Through the development of a mixed-integer nonlinear planning model to represent the qualities of the energy flow network among the process of steel production, this study has demonstrated how the algorithm efficiently and effectively addresses energy optimization challenges unique to the sector. These two unrelated parallel machine tasks must also be scheduled under changing power costs if the net energy costs of manufacturing are to continue to be the focus. The implementation of the NSGA-II approaches to address the bi-optimal challenge indicates the importance of including setup times that are dependent on the sequence of plans in making important conclusions regarding real-world energy consumption patterns and the ensuing cost reductions [9].

In the expanded application of Integrated Energy Systems, the application of NSGA-II-MOABC, a hybrid algorithm that combines NSGA-II and Multiple Objective Artificial Bee Colony, illustrates the approach's flexibility in optimizing multi-dimensional energy flow [14]. This type of optimization solves scheduling concerns in IES but also enhances overall system output and reliability, emphasizing the increased inclusion of integrative energy plans. Additionally, NSGA-III has played an essential application role in optimizing reactive power application in distribution networks, especially those with a large number of new energy elements such as wind and PV. As demonstrated by this study, the fundamental optimization problems of minimizing voltage offset, minimizing network loss, and ability to quickly resolve the bi-optimal equation are dire need of efficient algorithms, especially with the aspect of a more extensive penetration of renewable energies. Furthermore, the new NSGA-II algorithm has proven efficient in multi-objecting problem solutions in integrated energy [15]. These alternative applications have improved the efficiency of NSGA algorithms, making them more applicable to multiple other novelties and critical emerging energy applications [11].

Moreover, joint optimization models for multi-region integrated energy systems, along with flexible demand response, are essential to prove the capabilities of mixed integer linear programming in energy planning efficiency uplift. These models incorporate planning and operation optimization through several regions and demonstrate how vital flexibility and adaptability for modern energy systems to function effectively. However, NSGA-III and related algorithms have indeed made considerable advancements in the sector, some diverse gaps of current energy planning approaches are still left. One of the most notable is the under consideration of temporal dynamics and uncertainties [10]. NSGA-III, for example, is undoubtedly optimal for multi-objective optimization, but incorporating temporal production simulation provides the potential to significantly increase the accuracy and robustness of energy planning approaches, especially in terms of renewable energy sources, which introduce significant variability. Scalability and computational efficiency gaps must also be addressed. Developing further generations of NSGA-III algorithms that can perform with a reduced computational load but with the prevailing accuracy levels would benefit energy planning in many ways. Finally, more consideration for socio-economic factors would be beneficial. Even though NSGA-III and other multi-objective optimization algorithms have made a significant contribution to the field of energy planning, there is a lot more to develop [12]. Filling the gaps of temporal dynamics, computational efficiency, and holistic socio-economic factor consideration would enable the development of more sustainable, resilient, and equitable energy systems. Energy planning models and strategic positions need to follow the demand and complexity of the expanding world's energy and assure they can help to solve the contemporary and future issues.

3. Proposed Model

To tackle these ever-changing and complex requirements of energy planning, our model offers a fresh perspective through the incorporation of Temporal Production Simulation using the Enhanced NSGA-III Algorithm [13]. This configuration offers a more precise representation of the dynamic nature of energy systems and, as such, allows for a more efficient resolution of multi-objective problems that are inherent in energy planning processes. This results in a more flexible and efficient decision-making process.

3.1. Temporal Production Simulation

This approach recognizes that energy production, storage, distribution, and consumption are profoundly impacted by temporally relevant variables, such as fluctuations in the generation of renewable energy resulting from the weather, the energy required at various times of the day or the season and the usage cycles of energy infrastructure, and others. The temporal aspect of energy systems introduces a level of unpredictability due to the variability associated with renewable energy and demand patterns. For example, solar energy production is predominantly available during sunny midday hours and is null at night, while the presence of wind is more consistent, although the output is largely altered by the weather. Additionally, while energy production may remain constant, demand does not follow the same trends. Energy demand is at its peak in the morning and evening and lowest late at night.

Furthermore, demand trend variations are also observed in temporal intervals such as summer and winter. The Temporal Production Simulation methodology consists of three processes: data collection, modeling, and computational simulation. Initially, historical records of energy production and consumption are studied to determine the trends and correlations. Subsequently, mathematical models that portray the nature of energy production and consumption, as well as storage, are drafted. These models are then employed in computational simulations, which can be altered in various ways to test energy planning scenarios.

3.2. Enhanced NSGA-III Algorithm

The Non- dominated Sorting Genetic Algorithm III is one of the leading algorithms in solving mult objective optimization problems. However, for the purpose of applying it to the specific requirements of energy planning, which involves the temporal nature of energy systems, our approach suggests modifications to the baseline NSGA-III algorithm [2], [3]. The Enhanced NSGA-III Algorithm includes adjustments to enhance the performance of the non-dominated sorting algorithm while working with a multi-dimensional and time-dependent problem, which is characteristic of energy planning. Our approach includes the NSGA III and specific crossovers and mutations based on the features of the temporal nature of production and consumption. In so doing, with the significant search space and a relatively large number of dimensions, the algorithm converges faster and finds high-quality solutions [16]. An important conceptual piece of our model is the integration of the Temporal Production Simulation with the Enhanced NSGA-III Algorithm [4]. This mechanism allows us to perform temporary optimizations, meaning the algorithm can determine the best outcomes over time and it also makes decisions based on how effective such optimal allocation would be across diverse time periods.

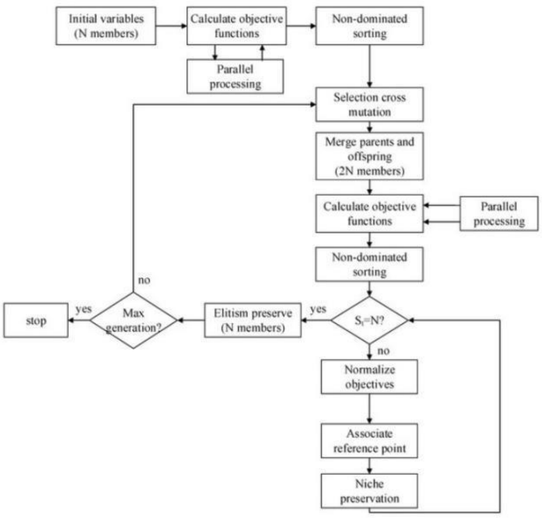

Figure 1. Flow chart of non-dominated sorting genetic algorithm III (NSGA-III)

3.3. Mathematical Model for Energy Planning

In order to model the complexity of energy planning, a multi-objective optimization framework is created in this research study. In this model, three essential aspects of energy planning are combined, including its economic feasibility, environmental impact, and overall system capacity to ensure every individual is supplied [17]. This model must also define the variables that represent decision points within the energy system.

Variables

- P_{gt}: Power generated by source g at time t.
- D_t: Demand at time t.
- C_g: Capacity of generation source g.
- E_t: Emissions at time t.
- S_{gt}: State of generation source g at time t, where 0 is offline and 1 is online.
- I_g: Investment in generation source g.
- B_t: Battery storage level at time t.
- R_{gt}: Renewable energy generated by source g at time t.

3.4. Objective Functions

The model aims to minimize cost and emissions while also maximizing reliability, establishing a multi objective optimization problem with three primary objectives:

$$Minimize\ Z_1 = \sum_g \sum_t (O_g * P_{gt} + I_g * C_g) \quad (1)$$

where O_g represents the operational cost per unit of energy generated by source g.

$$Minimize\ Z_2 = \sum_t E_t \quad (2)$$

E_t might depend on the mix of generation sources utilized at time t.

$$Minimize\ Z_3 = -\sum_t |D_t - \sum_g P_{gt}| \quad (3)$$

Constraints

$$\sum_g P_{gt} = D_t \quad \forall t \quad (4)$$

Demand-Supply Balance: The total power generated must meet the demand at all times.

$$0 \le P_{gt} \le C_g \cdot S_{gt} \quad \forall g,t \quad (5)$$

Generation Capacity Limit: The power generated by each source cannot exceed its capacity.

$$Et \le E_{max}\ \forall t \quad (6)$$

Emissions Constraint: Emissions at any given time must not exceed a specified threshold, reflecting environmental policies or goals.

$$\sum_{g \in Grenewable} R_{gt} \ge \theta \sum_g D_t \quad (7)$$

Renewable Generation Targets: A certain percentage of total generation must come from renewable sources to meet sustainability goals.

$$B_t+1 = B_t + \eta \sum_g (P_{gt} - D_t) \quad \forall t \quad (8)$$

Storage Dynamics: The level of battery storage is affected by the surplus or deficit in generation relative to demand, considering the efficiency of storage.

$$\sum_g I_g \le I\max \quad (9)$$

Investment Constraints: Limitations on the investment for expanding the capacity of different energy sources to ensure financial viability.

This mathematical model for energy planning is designed to optimize across multiple objectives, capturing the trade-offs between cost, environmental impact, and reliability.

4. Methodology

The methodology of the proposed model's implementation and evaluation consists of the following steps. First, the data needed to run the optimization model is collected. In order to apply simulation on the costs, emissions and reliability and to optimize them against each other, data for energy production, demand and pollution rates, and environmental impact studies will be collected [18]. The data collected is mainly used to simulate the energy system, and the inputs collected during this first step are vital to accurately setup the simulation. On the collection of the necessary inputs for this model, these inputs need to be preprocessed to achieve normalization when inputs have different scales. Missing data also needs to be substituted and the whole dataset is segmented before normalization [19]. These preprocessing steps are essential for the preparation of the inputs for the upcoming simulation and optimization. Following preprocessing, the simulation is then set up temporally. The production of energy needs to be simulated over long periods of time to simulate different demand profiles and production capacities to observe the systems behavior. After this simulation is running the optimization process can be applied. The algorithm used is an enhanced NSGA-III [20], where the optimization is aware of the temporal production simulation and the cost, emission and reliability is optimized at the same time. The algorithm is enhanced to want to use to tackle the complexities of the trade-offs encountered in the model of the energy research model.

The next step is post-optimization, where the proposed solutions are evaluated on the effectiveness of optimizing the desired fields, and on feasibility of the investments given the constraints [21]. Sensitivity analyses on key parameters are also performed to assess the model's robustness and flexibility. Finally, Scenario testing is performed. These tests input the model with hypothetical input variations corresponding to different planning objectives [22], [23]. For example, some scenarios might involve varied demand patterns, production constraints, or policy settings. The methodology outlined, ranging from data input to scenario testing, provides a comprehensive strategy for developing and testing an energy planning model suitable for optimization. Each of the methodologies encompasses key activities that must be undertaken for optimal planning.

5. Results and Discussion

The deployment of an enhanced Non-dominated Sorting Genetic Algorithm III for energy system optimization marks a significant advance towards the strategic planning and operational performance of power systems. In that regard, the model's structuring based on temporal dynamics and multi-objective analysis, considering the balance between generation costs, emissions and reliability, offers a more detailed solution to the challenges faced by the contemporary power systems.

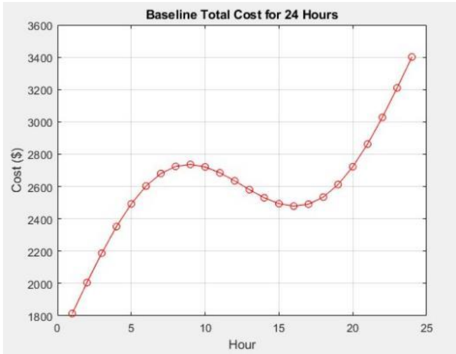

Figure 2. Baseline Scenario Cost for 24-Hours

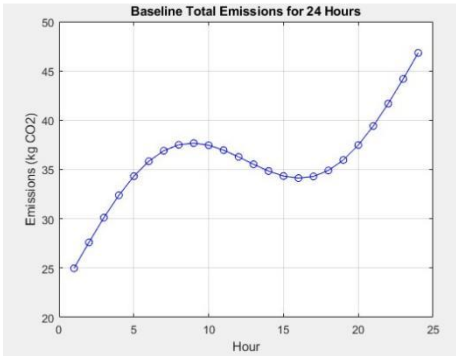

Figure 3. Baseline Scenario Carbon Emissions for 24-Hours

The comparison with the existing models accentuates the enhanced capability of the NSGA-III approach [24] existing generation-based issues reflect a more simplistic generation, focusing on the individual

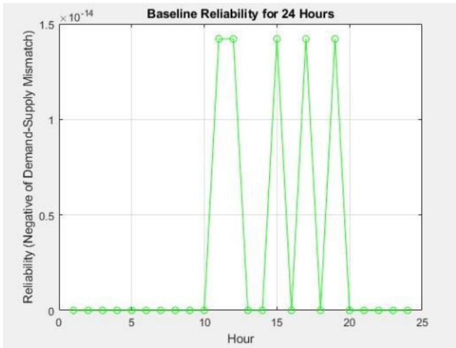

Figure 4. Baseline Scenario Reliability

objective with minimal consideration over time or the environmental and reliability aspect. Instead, the proposed solution dynamically adjusts to the hourly fluctuations, while simultaneously considering the cost, emission and reliability indices. The latter assertion is particularly important in the context of increasing integration of renewable energy sources, calling forward a more sophisticated analysis of the optimal performance [25]. Statistical analysis supports the model, as all optimized scenarios developed in the model show statistical significance over all objectives in comparison with the baseline allocations [26]. The reduction of the system costs and emissions and the increase of the reliability were consistently significant for variations in the demand and generator assets. Thus, the statistical validation not only makes the model robust, but also boundedly rational, adaptable to the realistic operational conditions.

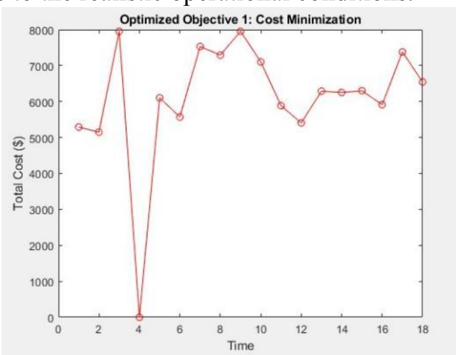

Figure 5. Optimized Results of Cost Minimization

The model outcomes expose its strategic capacity in negotiating the trade-offs of the multi-objective analysis [27], [28]. During the 24-hour allocation period, the model effectively balances system costs and emissions with reliability. Particularly, during the peak hours, the model sufficiently emphasizes the emission reduction capacity at a lower cost, pointing out to the possibility of including more environmentally friendly sources without drawback of the reliability or operation costs.

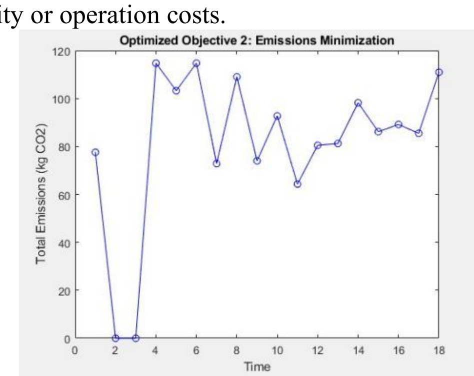

Figure 6. Optimized Results of Emissions Reduction

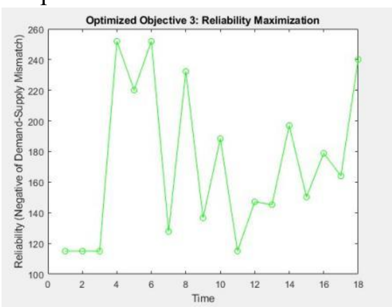

Figure 7. Optimized Results of Enhanced Reliability

Temporal granularity is one of the most critical added features of the model's optimization process to provide profound insights about the operational flows of energy system [29]. The model's ability to change the cost of energy in an hourly manner also enables it to provide information that is very relevant to real-world energy management systems; especially when managing the optimization of the wide extents of renewable energy sources. This variable temporal approach is essential in managing the natural variation found in renewables to counteract the unmanageable deviation and to calculate the human and financial costs of the unanticipated need for resources. However, NSGA-III is a very advanced evolutionary algorithm that is specifically designed to handle multi-objective problems efficiently [30]. It is very good at finding a set of Pareto-optimal solutions that provides the best possible tradeoffs among the competing objectives. By using the algorithm, the code is able to find its way through the complex energy system solution space to arrive at plausible outlets that offer value-based information about the best tradeoff between cost, emissions and reliability.

6. Conclusion

The outcomes of the investigation into energy systems' optimization of such results, conducted with sustainability, economic feasibility, and reliability principles in mind, exceed the typical framework of energy planning. By producing a variety of consistent, non-dominant, and Pareto optimal solutions via the application of the Enhanced Non-dominated Sorting Genetic Algorithm III, the results of the investigation offer novel insights into the delicate balances and potential synergies in the energy domain. The outcomes of the investigation are several, reaching from the demonstration of the capabilities of the NSGA-III algorithm, their realization through practical applications, and the horizon of future technologies and innovations in the realm of energy planning. However, the key outcome of the investigation is the application of the NSGA-III algorithm to discover the optimum solutions for energy systems' complexity. Because this approach is concerned with not only the reduction of costs and the maximum level of emissions reduction but also the extent of failure of the existing supply conditions, the investigation emphasizes economics and planning as multi-layered phenomena. The NSGA-III's capacities to formulate a variety of Pareto optimal solutions allow investigation outcomes to reveal the intricate responses in energy systems' responses. This, in turn, helps policymakers, planners, and industry participants to make better informed decisions.

Overall, the implications of this study for the field of energy planning are profound. In the age when the transition to sustainable energy sources becomes not only a choice but a necessity, the ability to navigate the trade-offs between economic, environmental, and reliability objectives with precision could be a gamechanger. The realization and integration of the NSGAIII algorithm in this field represent a significant leap forward, overcoming the constraints of conventional optimization. By providing a systematic framework for the evaluation of the implications of various energy strategies, the model serves as a bridge between theoretical optimization and the actual implementation. It also creates a system for an integrated evaluation of renewable energy potential, energy distribution efficiency, and novel technological solutions based on sustainable, economic and reliability principles. However, the potential increase of efficacy in this area, suggests multiple paths for further research and development. This may concern the integration of renewable sources in the model and the ways of managing their variability, thus, outlining effective storage and distribution solutions. The other area may involve microgrid and off-grid systems, where the optimization of energy resources is crucial in improving accessibility and independence opportunities.

This research paper offers a valuable addition to the incessant conversation in the field of sustainable energy planning. This study underlines a vision of a future where energy systems are less wasteful and more robust and live up to the demands of environmental preservation and economic viability. As we progress along this path, the finding and discoveries unveiled by this work will undoubtedly become fundamental in an effort to design the energy system of the future, propel further discovery, and stimulate curiosity.

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