



Analysis on Carbon Peaking Pathways for a Pilot City Based on a Hybrid LEAP Model

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Abstract. The Long-range Energy Alternatives Planning (LEAP) model is widely used for carbon emission forecasting, but its application in regions with limited statistical data remains challenging. This study proposes a hybrid modeling framework that integrates a grey rolling model GM (1,1) with LEAP to improve parameter forecasting accuracy under small-sample conditions. The method is applied to a national carbon peaking pilot city in southwestern China characterized by a tourism-dominated economy and 100% green electricity supply. The grey model generates baseline socioeconomic trajectories (GDP, population, sectoral structure) with a rolling window mechanism, while the LEAP model is customized with five demand sectors, including a dedicated tourism subsector. Three scenarios including Business as Usual (BAU), Energy Efficiency (EF), and Electricity Substitution (ES) are designed to simulate carbon emission pathways to 2030. Results show that the BAU and EF scenarios fail to achieve carbon peaking before 2030, whereas the ES scenario, featuring accelerated electricity substitution and a declining fossil fuel share, keeps emissions consistently below 2020 levels, showing the probability of achieving the goal ahead of schedule. The hybrid approach enhances statistical efficiency and regional relevance, offering a robust tool for carbon pathway analysis in data-limited settings.

Keywords: Carbon peaking; LEAP model; Grey rolling model; Scenario analysis; Pilot city

1 Introduction

As a bottom-up energy system simulation tool, the Long-range Energy Alternatives Planning (LEAP) model plays an essential role in carbon emission forecasting and policy scenario analysis. However, it demands substantial data on activity levels and driving parameters disaggregated by sector and by energy type, which makes it vulnerable when dealing with regions with weak statistical infrastructure, short monitoring series, missing data or inconsistent definitions. For instance, prefecture or city-level analyses in China frequently encounter significant data limitations, including short time series and inconsistent statistical coverage. Several parameter forecasting methods have been applied to embed into LEAP modelling process to improve the reasonableness of

parameter settings and reliability of simulation results [1]. Under such information-poor conditions, grey system theory offers a powerful tool for small-sample forecasting, as it requires as few as four data points to establish a predictive model. The methodological complementarity between these two approaches has attracted increasing scholarly interest. Earlier attempts to couple the models have predominantly adopted a one-way linkage: grey models forecast key macroeconomic variables such as GDP and population, which then serve as scenario inputs for LEAP simulations. Xu et al. used a novel grey rolling model to forecast Chinese greenhouse gas emission and empirical applications show that the proposed model has advantages over the conventional models [2]. A typical approach to integrate the grey model with the LEAP model is to apply the two models in a sequential configuration. Sadri et al. developed a general procedure for long-term energy-environmental planning with grey model and LEAP model for developing countries where required data are usually limited or unavailable and applied the methodology to the transportation sector of Iran [3]. Cao et al. constructed a Grey-Monte Carlo model to predict scenario parameters of the LEAP model and their occurrence probability to improve the simulation accuracy of the LEAP model [4]. Researchers have further refined this framework by incorporating factor decomposition and grey relational analysis to enhance the selection of driving parameters, constructing integrated frameworks like the LMDI-Grey-LEAP or Grey correlation-LEAP pipelines [5].

This study applies a coupled Grey-LEAP modeling framework tailored to a carbon peaking pilot city in China. The grey model generates baseline socioeconomic trajectories under a rolling mechanism, and the LEAP model, whose structure is deliberately designed to reflect the pilot city's industrial and energy profile, simulates carbon emission pathways up to 2030. This integrated approach aims to improve both the statistical efficiency and the regional relevance of emission projections.

2 Methodology

2.1 Grey Rolling Model GM(1,1)

Grey system theory, first proposed by Prof. Deng Julong, is designed for systems with partially known and partially unknown information [6]. The GM(1,1) model, its core forecasting component, transforms a discrete raw sequence into a monotonically increasing accumulated generating sequence (AGO) to dampen randomness and reveal exponential growth patterns.

Let the original non-negative time series be

$$x^{(0)} = \begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \text{ with } n \geq 4.$$

The first-order AGO sequence is

$$x^{(1)} = \begin{bmatrix} x^{(1)}(1) \\ x^{(1)}(2) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}, \text{ where } x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i), k=1,2,\dots,n.$$

A first-order linear differential equation, known as the whitening equation, is then constructed:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b$$

where a is the development coefficient and b is the grey action quantity. The parameters are estimated via the least squares method using background values

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), k=2,3,\dots,n$$

The time response function yields the predicted AGO value:

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}$$

The predicted value of the original series is obtained by inverse AGO:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k).$$

Model accuracy is assessed using the mean absolute percentage error (MAPE), the posterior-variance ratio C , and the small-error probability P .

To enhance adaptability to evolving data patterns, this study adopts a rolling mechanism with a fixed window length of four years. Starting with the earliest four data points to fit the initial model and produce the first forecast, the window subsequently rolls forward by one year, dropping the oldest observation and incorporating the newly forecast value as a quasi-observation, before re-estimating the parameters. This iterative process continues until all target-year forecasts are generated, ensuring the model's responsiveness to recent structural changes.

2.2 LEAP Model Framework

The LEAP model, developed by the Stockholm Environment Institute, is a bottom-up energy-environment accounting tool that simulates energy consumption, transformation, and emissions under user-defined scenarios.

This hybrid LEAP framework thus integrates the statistical parsimony of small-sample forecasting with the technological granularity of bottom-up energy modeling, producing a regionally tailored tool of carbon emission pathway analysis for the pilot city, as shown in Fig.1.

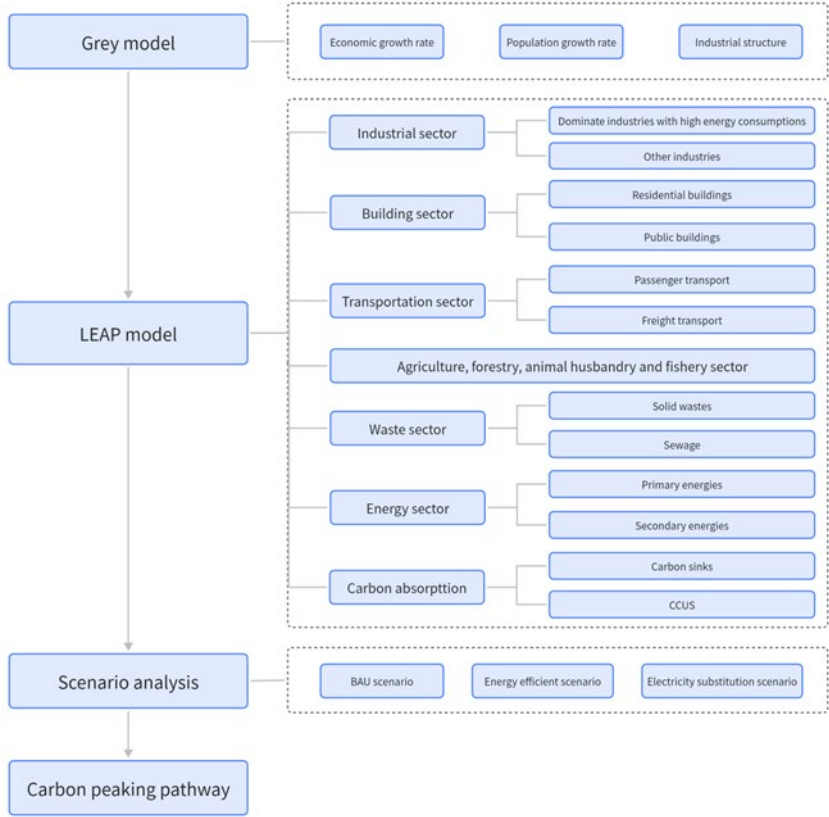


Fig. 1. Flowchart of the hybrid modeling method

2.3 Data and Scenario Design

The object of this study is a city of the national carbon peaking pilots. The pilot city locates in southwestern China and has distinctive characteristics in its energy production structure, which has achieved 100% green electricity generation and supply. Its industrial structure is dominated by the tertiary sector, which has continued to rise since 2021, gradually exceeding 50% of the total. The primary and secondary sectors account for approximately 20% and 28% respectively.

In this study, LEAP is configured to represent the city's distinct socioeconomic and energy profile, characterized by a large service sector anchored in cultural tourism, a significant agricultural base, modest but transitioning industry, and abundant hydro-power resources complemented by growing wind and solar capacity.

The demand side of the pilot city is divided into five sectors: agriculture, industry, commercial and public services, residential, and transportation. The commercial sector is further stratified to include a dedicated tourism-related services subsector (hotels, restaurants, and scenic area operations) to capture the energy footprint of the pilot city's

dominant tourist industry. The residential sector is split into urban and rural households to reflect differing energy use patterns. Transportation covers road freight, road passenger (including tourist buses and private vehicles), and a minor share for rail and aviation. The supply side encompasses electricity generation (hydropower, wind, solar photovoltaic, and a small amount of thermal), heat production, and petroleum refining.

Final energy demand in each subsector is calculated as the product of an activity level and an energy intensity. Activity levels such as agricultural value added, industrial output, commercial floor area, number of households, and the distance that vehicle traveled etc. are driven by socioeconomic variables including GDP, population, and sectoral structure, which are forecast by the rolling grey model described in Section 2.1. Energy intensities are parameterized based on historical trends and technology-specific assumptions and are allowed to evolve over the simulation period to reflect efficiency improvements. Primary energy requirements are determined by the transformation module, accounting for conversion efficiencies and the generation technology mix. Carbon dioxide emissions are estimated using the IPCC Tier 1 method, with fuel-specific emission factors sourced from China's national guidelines and provincial inventories.

This study uses historical energy consumption data from the pilot city covering the period 2020–2024 as the main basis for model construction and scenario forecasting. And The model's prediction period spans from 2026 to 2035, because whether carbon peaking goal has been achieved can only be examined after the target year. Based on calculations from this period, the total carbon emissions from the city's energy sector peaked as early as 2020. With the continuous decline in the share of fossil fuels, this indicates that the pilot city achieved its carbon emissions peak during that period in or even before 2020. This is mainly due to the sustained and significant reduction in output from the ferrous metal smelting and rolling processing industry (primarily steel) and the non-metallic mineral industry, which led to a decrease in both the consumption and share of bituminous coal, while the share of terminal electricity increased substantially. The two show a clear trend of one rising as the other falls. The city's high level of renewable power has enabled this process of electricity substitution to significantly reduce overall carbon emissions. However, changes in energy consumption patterns driven by industrial transformation and upgrading could reverse this peaking trend. Total carbon emissions in 2024 rebounded slightly from the 2023 level. The future trend of total carbon emissions may continue to fluctuate depending on changes in the industrial and energy structures. If the upper limit of these fluctuations remains below the 2020 level, the pilot city can be considered to have moved from the carbon peaking stage toward the carbon neutrality goal. If the upper limit exceeds the 2020 level, then measures must be taken to ensure that the peak occurs before 2030, followed by a stable downward trajectory. Therefore, the scenario analysis in this study is designed to test these two possibilities and to define medium-to-long-term carbon emission targets and pathways. It should also be noted that in 2026, the electrolytic aluminum production capacity in this pilot city will be significantly reduced as planned, and this will be reflected in the energy consumption figures of each scenario.

The study established three scenarios arranged in a sequential progression as described in Table 1. A Business as usual (BAU) scenario projects energy demand and emissions assuming that current development trends and existing policies persist

without major new interventions. Mitigation scenarios incorporate progressive low-carbon measures, such as accelerated electrification in the tourism sector, enhanced renewable energy penetration, and stricter building efficiency standards. All scenarios share identical GDP and population trajectories derived from the grey model to isolate the emission reduction attributable to technological and structural changes from the scale effect of economic growth. The model is calibrated to the year 2024 using the official energy balance of the pilot city, ensuring that simulated fuel consumption and emissions align with observed data. Sensitivity analyses on key drivers and technology assumptions are conducted to evaluate the robustness of the projection outcomes.

Table 1. Settings for scenarios

Scenario	Features
BAU scenario	Economic and industrial development moves forward in line with predictions from grey model. Energy consumption and energy structure developed along existing trends.
EF scenario	Energy efficiency is promoted in a more significant trend compared to BAU scenario.
ES scenario	Extending from the EF scenario, the energy mix exhibits a more low-carbon profile through proactive electricity substitution.

3 Results and discussion

The energy consumptions and carbon emissions of the three scenarios are shown in Fig.2. to Fig. 7.

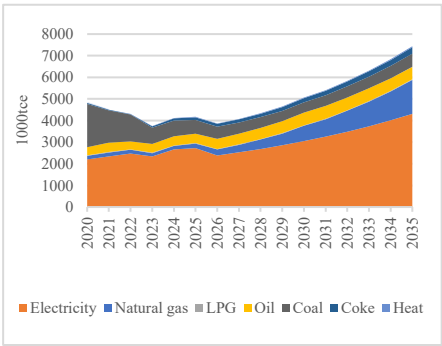


Fig. 2. Energy consumption in BAU scenario

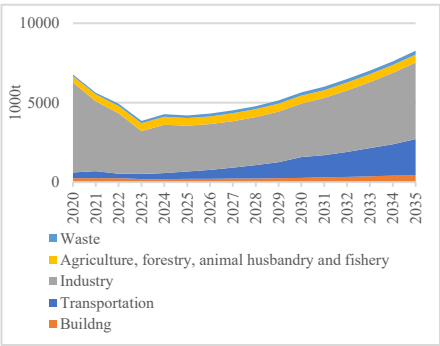


Fig. 3. Carbon emission in BAU scenario

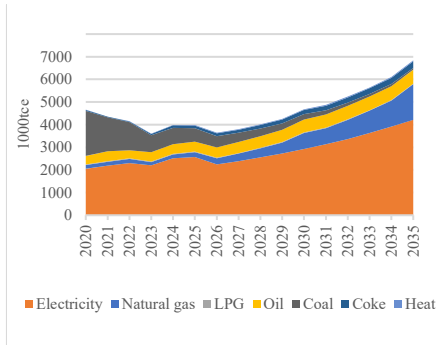


Fig. 4. Energy consumption in EF scenario

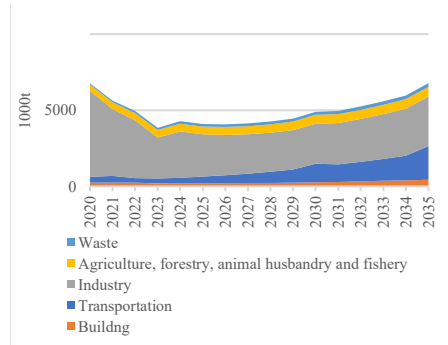


Fig. 5. Carbon emission in EF scenario

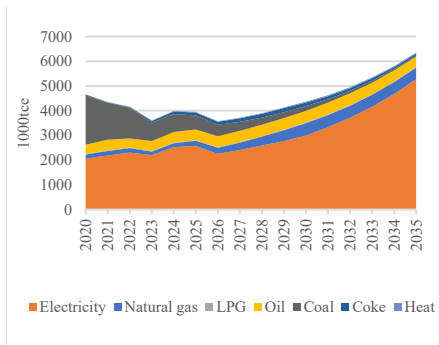


Fig. 6. Energy consumption in ES scenario

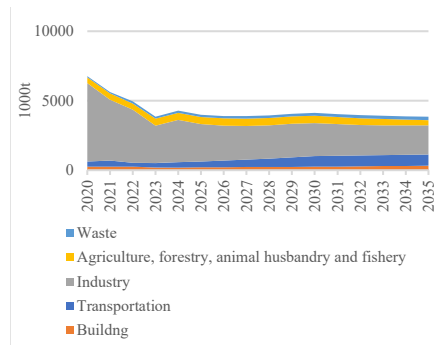


Fig. 7. Carbon emission in ES scenario

In the BAU scenario, total energy consumption continues to grow after 2024 and returns to 2020 levels by 2028. Electricity, after declining in the electrolytic aluminum sector, rebounds and still holds the major share. Among fossil fuels, coal and oil show little change, while natural gas increases significantly, becoming the main source of carbon emission growth. Meanwhile, carbon emissions rise steadily after 2024, returning to the 2020 peak level in 2033, reaching 8.27 million tons in 2035, failing to achieve the goal of carbon peaking before 2030. The industrial sector contributes the most, while sectors such as construction show little growth. The transportation sector, due to increased natural gas consumption, sees a gradually rising share of new carbon emissions.

In the EF scenario, energy consumption growth slows but still increases on a yearly basis, returning to 2020 levels in 2029. Carbon emissions continue to rise but at a more moderate pace than in the BAU scenario, reaching 6.78 million tons in 2035, also failing to peak before 2030. Increased natural gas consumption remains the main driver of emission growth, especially in the transportation sector. Therefore, relying solely on energy saving and efficiency improvements cannot meet the carbon peaking target; it is necessary to accelerate the adjustment of the energy mix and increase the share of green electricity.

In the ES scenario, electricity substitution is intensified, therefore, electricity consumption grows rapidly, and the share of fossil fuels, especially natural gas, declines. Total energy consumption exceeds the 2020 peak after 2030 and continues to rise. However, carbon emissions slowly fluctuate downward after 2024, remaining consistently below 2020 levels, reaching 3.84 million tons in 2035, making it possible to peak carbon emissions before 2030. The industrial sector still contributes the highest emissions, followed by transportation, agriculture (including forestry, animal husbandry, and fishery), construction, and waste.

The scenario results suggest several policy priorities for the pilot city:

First, accelerate electrification in transportation and heating. The ES scenario's success relies on rapid electrification beyond the industrial sector. Policy incentives for electric tourist vehicles, charging infrastructure at scenic spots, and electric heating in commercial buildings could drive this transition.

Second, manage natural gas as a transition fuel carefully. The EF scenario's failure to achieve peaking despite efficiency improvements indicates that natural gas expansion, particularly in transportation, must be constrained or offset by aggressive renewable penetration.

Third, leverage tourism industry decarbonization. The city's tourism-dominated economy offers unique opportunities for green tourism certification, low-carbon hotel standards, and emission reduction through visitor management.

Fourth, prepare for post-peaking pathways. The ES scenario's emissions trajectory suggests the city may achieve peaking long before 2030, but maintaining a downward trend requires continued policy support and monitoring. The rebound observed in 2024 underscores the need for robust institutional mechanisms to prevent backsliding.

4 Conclusions

This study develops a hybrid grey-LEAP modeling framework tailored to a carbon peaking pilot city with limited data and a unique economic structure dominated by tourism and renewable energy. The main conclusions are as follows:

The rolling GM(1,1) model effectively forecasts key socioeconomic drivers using as few as four data points, addressing the data scarcity issue in prefecture-level analyses. The customized LEAP model improves regional relevance.

Under the BAU scenario, total carbon emissions return to the 2020 peak by 2033 and continue rising, failing the 2030 peaking target. The EF scenario slows emission growth but still does not achieve carbon peaking goal before 2030 due to increased natural gas consumption. Only the ES scenario, with aggressive electricity substitution and renewable energy penetration, keeps emissions below 2020 levels throughout the simulation period, showing the possibility of carbon peaking before 2030 is feasible.

Energy efficiency improvements alone are insufficient for carbon peaking; structural adjustments in the energy mix and accelerated electrification which leverages the city's abundant hydropower are essential. The industrial sector remains the largest emission contributor, followed by transportation, which indicates the priority areas for intervention.

The proposed hybrid model demonstrates strong potential for transferring to other data-limited regions. And future work could incorporate feedback loops from LEAP scenarios to grey model parameters and extend the analysis toward carbon neutrality pathways.

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