Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 21, No. 2, 2026

Identifying Key Drivers of Natural Gas Demand in Sichuan Province Using a Hierarchical Analysis Framework

Mi Han[1], Xintong Lv[1], Ke Bai[2], Hongbing Li[3, *]

[1]Southwest Petroleum University, Chengdu 610500, China
[2]Cost Center of Southwest Oil & Gas Field Branch, PetroChina, Chengdu 610500, China
[3]Aba Teachers College, Wenchuan County, Sichuan Province 623002, China
[*] Corresponding author

Abstract: Natural gas plays a critical role in the low-carbon energy transition, yet its demand drivers remain insufficiently understood due to complex factor interactions. This study aims to identify and hierarchically classify the key drivers of natural gas demand to better forecasting natural gas demand. Taking Sichuan Province as a case study, we develop an integrated framework combining grey relational analysis, fuzzy DEMATEL, interpretive structural modeling, and MICMAC to examine fourteen candidate factors using data from 2008 to 2023. Results show that all candidate factors have grey relational degrees above 0.82. However, fuzzy DEMATEL reveals that only five factors—population size, technological level, economic development, urbanization, and carbon constraint—are causal drivers, while highly correlated variables such as gas-using population and pipeline length are effect factors. ISM further decomposes the driver system into five hierarchical levels, with population size identified as the root driver, validated by MICMAC. We conclude that statistical association does not equate to causal dominance, and correlation-based variable selection alone is insufficient for natural gas demand forecasting.

Keywords: Natural gas demand; Driver identification; GRA; Fuzzy DEMATEL-ISM; Sichuan Province.

1. Introduction

Natural gas plays a critical role in the low-carbon energy transition[1-2], Now it is widely regarded as a transitional fuel in the low-carbon energy transformation due to its relatively low carbon intensity, high combustion efficiency, and operational flexibility[3-5]. However, its continued expansion may also create risks of carbon lock-in, deeper dependence on gas infrastructure, and delayed substitution by renewable energy[6-9]. Identifying the key drivers of natural gas demand is therefore essential for improving demand forecasting, assessing potential demand peaks, and designing transition policies that balance energy security with carbon mitigation. These issues are particularly important at the provincial level, where resource endowments, industrial structures, infrastructure conditions, and energy-use patterns vary substantially. At the same time, provincial datasets are often characterized by limited sample sizes, strong multicollinearity among variables, and structural shocks induced by energy and climate policies. Accordingly, uncovering the hierarchical structure and causal transmission pathways of the factors influencing provincial natural gas demand remains a critical research challenge.

A growing body of literature has examined the determinants of natural gas demand to improve forecasting accuracy and support policy design. Existing studies have considered a wide range of economic, social, energy-related, environmental, and infrastructure factors. Among economic variables, GDP and industrial structure are widely used [10–11]. Among social variables, urbanization and population size are generally regarded as important factors associated with natural gas demand [12]. Energy-related variables, such as the share of natural gas consumption and the consumption of alternative energy sources, have also received considerable attention [13]. Infrastructure factors, including pipeline length and gas-using population, are frequently incorporated as explanatory variables [14-15]. Despite these advances, several limitations remain. First, most studies focus primarily on examining the degree of association between individual factors and natural gas demand while paying insufficient attention to the interrelationships among the factors themselves. Consequently, the structural interactions, causal directions, and hierarchical transmission pathways within the influencing-factor system remain largely underexplored. Second, factor selection is commonly based on literature frequency or simple correlation analysis, making it difficult to distinguish deep structural drivers from intermediate transmission variables and surface-level response indicators under small-sample provincial conditions. Third, few studies explicitly link driver identification with variable design in forecasting models, which limits the usefulness of identified factors for subsequent scenario simulation and policy analysis.

To address these research gaps, this study develops a multi-stage framework that integrates grey relational analysis (GRA), fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL), interpretive structural modeling (ISM), and Cross-Impact Matrix Multiplication Applied to Classification (MICMAC). These four methods play complementary and sequential roles: GRA screens statistically relevant factors to ensure historical synchronization with natural gas consumption; fuzzy DEMATEL determines causal directions and distinguishes active causal factors from passive effect factors; ISM constructs a multi-level hierarchical structure and reveals the complete transmission pathway from deep-rooted drivers to surface-level responses; and MICMAC independently validates the hierarchical classification through a driving power–dependence diagram. Sichuan Province is selected as the case study because it is both a major natural gas production base in China and a province rich in hydropower and other clean energy resources. This dual feature—abundant gas supply alongside a relatively clean power structure—makes the mechanism of natural gas demand in Sichuan distinct from that in coal-dominated northern provinces, giving the case both theoretical and practical significance.

The main contributions of this study are threefold. First, it proposes an integrated identification framework that combines statistical association, causal direction, hierarchical structure, and driving-dependence classification, reducing the risk of mistaking correlation for causality under small-sample provincial conditions. Second, it reveals the layered transmission mechanism underlying natural gas demand in Sichuan, demonstrating that highly correlated variables such as gas-using population and pipeline length are located in the response layer and should not be treated as independent exogenous drivers. Third, this study establishes an explicit mapping between the identified drivers and forecasting model parameters, providing an operational variable basis for provincial natural gas demand forecasting and low-carbon transition scenario design.

The remainder of this paper is organized as follows. Section 2 describes the methodology and data. Section 3 presents the empirical results. Section 4 discusses the policy implications. Section 5 concludes the study.

2. Methodology

(1) Research framework

This study develops an integrated methodological framework to identify, classify, and hierarchically decompose the key drivers of natural gas demand in Sichuan Province. The framework is designed to address three methodological challenges commonly encountered in provincial energy demand research: limited historical samples, strong interdependence among socioeconomic variables, and the difficulty of distinguishing statistical association from causal driving force.

The research procedure consists of five sequential steps. First, candidate factors are identified through a systematic literature review and refined according to regional characteristics, theoretical relevance, and data availability. Second, grey relational analysis is applied to examine whether measurable candidate factors show sufficient statistical association with historical natural gas consumption. This step serves as a preliminary validity test rather than a causal inference tool. Third, Fuzzy-DEMATEL is used to identify the causal attributes of the candidate factors under uncertainty in expert judgment. Fourth, ISM is employed to construct the hierarchical structure of the natural gas demand driver system, while MICMAC is used to classify factors according to their driving power and dependence. Finally, the identified factors are mapped to variables and parameters in the subsequent forecasting framework, thereby linking driver identification with model construction and scenario design.

This integrated framework combines data-based association testing with expert-based causal structure analysis. Grey relational analysis improves the empirical grounding of factor selection under small-sample conditions, while Fuzzy-DEMATEL, ISM, and MICMAC jointly reveal the causal direction, hierarchical position, and structural role of each factor. In this way, the framework avoids treating all correlated variables as equivalent drivers and provides a more transparent basis for natural gas demand forecasting.

(2) Candidate factor identification

Candidate factor identification is the starting point of the analysis. To ensure that the factor system is theoretically grounded and empirically operable, this study combines literature-based screening, regional contextual analysis, and expert consultation.

First, a systematic review of studies on natural gas demand forecasting and consumption drivers is conducted. The literature search focuses on publications related to natural gas demand, consumption, forecasting, and influencing factors. Frequently used explanatory variables are extracted and grouped into several categories, including economic development, industrial structure, population, urbanization, income and consumption, energy price, energy structure, technological progress, gas supply, and infrastructure conditions. Similar indicators are merged to avoid repeated representation. For example, GDP, economic scale, and regional economic growth are grouped under economic development; energy efficiency, R&D intensity, and technological progress are grouped under technological level; urban population share and urbanization rate are grouped under urbanization.

Second, the initial factor pool is refined according to the characteristics of Sichuan Province. Sichuan is both a major natural gas-producing region and a province with abundant clean electricity resources. Its natural gas demand is influenced not only by economic growth and urbanization, but also by industrial restructuring, gas infrastructure expansion, clean-energy substitution, and carbon constraints. Therefore, the final candidate factor system should reflect both general determinants of natural gas demand and region-specific transition characteristics.

Third, data availability and indicator interpretability are considered. Factors with continuous and comparable historical data are included in the grey relational analysis. Factors that are theoretically important but difficult to measure consistently over the full historical period, such as natural gas price, carbon constraint, and end-use electrification, are retained for causal structure analysis through expert evaluation.

Based on these principles, the study identifies fourteen candidate factors. Eleven factors with continuous historical data are used in grey relational analysis: economic development, industrial structure, technological level, population size, urbanization level, natural gas supply, consumption level, natural gas consumption share, natural gas pipeline length, city-gas investment, and gas-using population. Three additional factors—natural gas price, carbon constraint, and end-use electrification rate—are included in the Fuzzy-DEMATEL-ISM-MICMAC analysis because of their importance for future natural gas demand evolution and low-carbon transition.

(3) Grey relational analysis

Grey relational analysis (GRA) is an important method within grey system theory, suitable for research contexts characterized by limited sample sizes, incomplete system information, complex inter-variable relationships, and difficulty in satisfying the strict assumptions of traditional statistical models. Its fundamental principle is to assess the closeness of the relationship between a reference sequence and comparison sequences by examining the geometric similarity of their curves. If a candidate factor sequence exhibits a temporal trend closer to that of natural gas consumption, the factor is considered to have a higher degree of association with natural gas demand.

In this study exhibits notable grey system characteristics. First, in terms of sample size, this study employs annual data for Sichuan Province from 2008 to 2023, spanning 16 years—a relatively limited sample that is unsuitable for constructing traditional multivariate regression models with numerous explanatory variables. Second, concerning variable relationships, variables such as GDP, urbanization level, population size, gas-using population, and household consumption level may exhibit strong synchronous co-movement. Direct application of conventional regression analysis would likely produce multicollinearity issues, leading to unstable parameter estimates, distorted significance testing, and difficulties in economic interpretation. Third, regarding the research objective, the primary purpose here is to determine whether candidate factors exhibit strong associations with natural gas consumption, rather than to estimate specific elastic coefficients or conduct causal inference. Compared with traditional regression methods, GRA does not require variables to satisfy strict assumptions such as normality or independence, nor does it depend on large-sample conditions. It effectively handles association identification in multi-factor systems under small-sample conditions. Moreover, GRA focuses on the consistency of sequence trend shapes rather than merely examining linear relationships between variables, making it particularly suitable for the preliminary screening of natural gas demand influencing factors in this study.

In this study, natural gas consumption in Sichuan Province is designated as the reference sequence, and the 11 candidate influencing factors are designated as comparison sequences.

Let the reference sequence be:

$$X_0=\{x_0(1),x_0(2),...,x_0(n)\} \quad (1)$$

and the comparison sequences be:

$$X_i=(\{x_i(1),x_i(2),...,x_i(n)\},\ i=1,2，...,11 \quad (2)$$

where X_0 denotes natural gas consumption, X_i denotes the i-th candidate influencing factor, and n denotes the number of sample years.

The calculation procedure consists of six steps.

Step 1: Sequence selection. Based on qualitative analysis of the subject under investigation, one dependent variable and multiple independent variables are selected. The dependent variable forms the reference sequence. $X_0=(x_0(1),x_0(2),\ldots,x_0(n))$, and the independent variables form the comparison sequences $X_i=(x_i(1),x_i(2),\ldots,x_i(n))$

Step 2: Normalization. The collected data span multiple categories—economic, social, energy, and environmental—each with different units and magnitudes. To ensure the accuracy and reliability of subsequent empirical analysis, normalization is required. This study adopts initial-value normalization, whereby each value in a sequence is divided by the first value of that sequence. The normalized values are then used in the subsequent calculations.

Step 3: Difference sequence calculation. After normalization, the absolute difference between the reference sequence and each comparison sequence at each time point is computed as:

$$\Delta i(k)=|X_0(k)-X_i(k)| \quad (3)$$

The absolute differences form the difference sequences. The global maximum and minimum differences are then identified and denoted as $M=max_i min_k \Delta i(k)$。

Step 4: Grey relational coefficient calculation. The grey relational coefficient, which measures the association between the reference and comparison sequences at a specific time point, is computed as:

$$R(k)=\frac{m+\delta M}{\Delta i(k)+\delta M} \quad (4)$$

where δ is conventionally set to 0.5.

Step 5: Grey relational degree calculation. The relational coefficients calculated for each time point are averaged to obtain the grey relational degree, which provides a single scalar measure of the overall association between a comparison sequence and the reference sequence:

$$R_i(k)=\frac{1}{n}\sum_{k=1}^{n}R(k) \quad (5)$$

$i=1,2,...,m;$

Step 6: Result interpretation. After calculating the relational degrees, a larger value indicates a higher degree of similarity between the temporal trajectories of the comparison sequence and the reference sequence, whereas a smaller value indicates lower similarity.

Through the above procedure, the relational degrees between each candidate factor and natural gas consumption in Sichuan Province are obtained and ranked. This ranking provides an empirical basis for subsequent factor screening and causal structure analysis. However, it should be noted that the grey relational degree reflects the closeness of temporal trend similarity rather than the intensity of causal influence in a strict sense. Therefore, the GRA results are used as a preliminary screening and validation step rather than as the final basis for identifying fundamental causal drivers.

(4) Fuzzy-DEMATEL

Although grey relational analysis can identify factors that are statistically associated with natural gas consumption, it cannot determine causal direction among factors. To address this limitation, Fuzzy-DEMATEL is introduced to evaluate the direct and indirect influence relationships among candidate factors.

DEMATEL is suitable for analysing complex systems with interdependent factors. It calculates the degree to which each factor influences and is influenced by other factors, thereby distinguishing cause factors from effect factors. Since expert judgments on inter-factor influence are often uncertain and linguistic in nature, fuzzy set theory is incorporated into DEMATEL to reduce ambiguity.

Experts are asked to evaluate the direct influence of factor (X_i) on factor (X_j) using linguistic scales, such as no influence, very low influence, low influence, high influence, and very high influence. Each linguistic term is represented by a triangular fuzzy number:

$$F_{ijt}=\left(f_{ij},g_{ij},u_{ij}\right),\ 1\leq t\leq 11 \quad (6)$$

where f_{ij}, g_{ij}, and g_{ij} denote the lower, middle, and upper bounds of the fuzzy evaluation. The evaluations from all experts are aggregated to form the fuzzy direct-relation matrix.

A defuzzification procedure is then applied to convert fuzzy numbers into crisp scores, resulting in the initial direct-relation matrix:

$$A=\left[a_{ij}\right]_{n\times n} \tag{7}$$

Where a_{ij} represents the direct influence intensity of factor (i) on factor (j), and (a_{ii}=0).

The direct-relation matrix is normalized as:

$$B=\frac{x_{ij}}{\max\left(\sum_{j=1}^{n} x_{ij}\right)} \tag{8}$$

The total-relation matrix is then calculated as:

$$T=\left(B+B^2+\ldots+B^t\right)=\sum_{t=1}^{\infty} B^t=B\,(I-B)^{-1} \tag{9}$$

where (I) is the identity matrix. The total-relation matrix (T) captures both direct and indirect effects among all factors.

For each factor, the influence degree (D_i) and the influenced degree (C_i) are calculated as:

$$D_i=\sum_{j=1}^{n} x_{ij},\ (i=1,2,\ldots,n) \tag{10}$$

$$C_i=\sum_{j=1}^{n} x_{ji},\ (i=1,2,\ldots,n) \tag{11}$$

The prominence degree and relation degree are then defined as:

$$M_i=D_i+C_i \tag{12}$$

$$R_i=D_i-C_i \tag{13}$$

The prominence degree (M_i) reflects the overall importance of factor (i) in the system, while the relation degree (R_i) indicates its causal attribute. If (R_i), the factor is classified as a cause factor, meaning that it has a stronger active influence on other factors. If (R_i), the factor is classified as an effect factor, meaning that it is mainly influenced by other factors. This classification provides the causal basis for subsequent hierarchical modelling.

3. Data and Case Study

(1) Study Area

Sichuan Province is selected as the case study area because it provides a representative regional context for examining the drivers of natural gas demand under low-carbon transition. As one of China’s major natural gas production bases, Sichuan has a relatively well-developed natural gas supply system and a long history of gas utilization in industrial, residential, and urban public-service sectors. At the same time, the province is also endowed with abundant hydropower resources, which creates favourable conditions for electrification and clean-energy substitution. This dual feature makes Sichuan an appropriate case for analysing the changing role of natural gas in a regional energy system that must balance supply security, coal substitution, end-use electrification, and carbon reduction.

The demand for natural gas in Sichuan is shaped by both general socioeconomic drivers and region-specific energy-system characteristics. Economic growth and industrial activity provide the basic demand scale, while population size, urbanization, and household consumption affect residential and commercial gas use. The expansion of city-gas networks and the increase in gas-using population further improve access to natural gas. Meanwhile, technological progress, carbon constraints, energy prices, and end-use electrification may gradually weaken the dependence on natural gas in some sectors. Therefore, Sichuan’s natural gas demand is not determined by a single variable; rather, it results from the interaction of economic, demographic, technological, infrastructural, and policy related factors.

Another reason is its strong policy relevance. Under China’s carbon peaking and carbon neutrality goals, provincial governments need to clarify whether natural gas should continue to expand as a transitional fuel or gradually shift toward a more limited role in peak regulation, emergency backup, and hard-to-electrify end uses. Identifying the key drivers and causal hierarchy of natural gas demand in Sichuan can therefore provide evidence for provincial demand forecasting, infrastructure planning, and low-carbon transition policy design.

(2) Variables and data sources

The variable system is constructed according to three principles: theoretical relevance, regional applicability, and data availability. The dependent variable is Sichuan’s natural gas consumption. The explanatory variables cover economic development, industrial structure, technological progress, demographic change, urbanization, gas supply, consumption level, energy structure, infrastructure, gas access, energy price, carbon constraint, and end-use electrification.

The dataset consists of two groups of variables. The first group includes eleven variables with continuous and comparable historical data from 2008 to 2023. These variables are used in the grey relational analysis to test their statistical association with natural gas consumption. The second group includes three variables that are important for future natural gas demand but lack fully consistent long-term historical data or show limited historical variation. These variables are retained for Fuzzy-DEMATEL, ISM, and MICMAC analysis because they have strong theoretical and policy relevance.

Table 1. Presents the variables, definitions, units, and data sources used in this study.

Category	Variable	Symbol	Indicator definition	Unit	Data source
Dependent variable	Natural gas consumption	X0	Total natural gas consumption in Sichuan Province	10,000 tce	Sichuan Statistical Yearbook
Economic factor	Economic development	X1	Gross domestic product of Sichuan Province	100 million yuan	Sichuan Statistical Yearbook
Structural factor	Industrial structure	X2	Share of tertiary industry value added in GDP	%	Sichuan Statistical Yearbook
Technological factor	Technological level	X3	R&D expenditure as a share of GDP	%	Sichuan Statistical Yearbook
Demographic factor	Population size	X4	Year-end permanent resident population	10,000 persons	Sichuan Statistical Yearbook
Urbanization factor	Urbanization level	X5	Share of urban population in total population	%	Sichuan Statistical Yearbook
Supply factor	Natural gas supply	X6	Total natural gas supply in Sichuan Province	10,000 tce	Sichuan Statistical Yearbook
Consumption factor	Consumption level	X7	Per capita household consumption expenditure	10,000 yuan	Sichuan Statistical Yearbook
Energy-structure factor	Natural gas consumption share	X8	Share of natural gas in total energy consumption	%	Sichuan Statistical Yearbook
Infrastructure factor	Natural gas pipeline length	X9	Length of city natural gas supply pipelines	km	China Environmental Statistical Yearbook
Infrastructure factor	City-gas investment	X10	Investment in city-gas infrastructure	10,000 yuan	China Environmental Statistical Yearbook
Access factor	Gas-using population	X11	Population with access to natural gas	10,000 persons	China Environmental Statistical Yearbook
Price factor	Natural gas price	X12	Average industrial natural gas price in Sichuan	yuan/m^3 or equivalent price index	CEIC database
Policy factor	Carbon constraint	X13	Carbon allowance price or carbon-tax equivalent	yuan/tCO$_2$	Carbon market data and policy assumptions
Technology-transition factor	End-use electrification rate	X14	Share of electricity in final energy consumption	%	Sichuan Statistical Yearbook and energy balance tables

For the grey relational analysis, the sample period is 2008–2023. This period is selected because the main socioeconomic, energy, and infrastructure indicators are relatively continuous and comparable. All variables are checked for consistency in statistical definitions before calculation. Where monetary variables are used, they should be adjusted to constant prices if the analysis focuses on real economic effects rather than nominal expansion. Variables with different units and magnitudes are normalized before grey relational calculation to ensure comparability.

Three variables—natural gas price, carbon constraint, and end-use electrification rate—are not included in the grey relational analysis. The reasons are as follows. First, natural gas price data are affected by changes in pricing mechanisms and statistical calibres, making long-term comparison difficult. Second, carbon constraint was not a continuous and effective policy variable during the earlier part of the historical period. Third, the historical variation in electrification rate is relatively limited, whereas its future policy importance is substantial. Excluding these variables from grey relational analysis does not imply that they are unimportant; instead, they are incorporated into the expert-based causal structure analysis.

This treatment ensures consistency between data availability and methodological purpose. Grey relational analysis is used only for variables with reliable historical sequences, while Fuzzy-DEMATEL, ISM, and MICMAC are used to evaluate the broader causal structure, including policy and technology-transition variables that are difficult to capture through historical statistical data alone.

(3) Expert survey design

The Fuzzy-DEMATEL analysis requires expert evaluation of the direct influence relationships among candidate factors. To improve the reliability of the judgment matrix, this study designs an expert survey based on representativeness, professional relevance, and practical experience.

A total of 16 experts are invited to participate in the survey. The expert group includes researchers from universities and research institutes, officials or analysts from energy policy and planning institutions, and practitioners from natural gas production, pipeline, and city-gas enterprises. This composition is intended to combine academic understanding, policy knowledge, and industry experience. The experts have backgrounds in energy economics, regional energy planning, natural gas market analysis, energy system modelling, and carbon policy. Most of them have more than ten years of professional experience or hold senior professional titles or doctoral degrees.

Before the survey, each expert is provided with the definitions of the fourteen candidate factors and the scoring instructions. Experts are asked to evaluate the degree to which each factor directly influences another factor. The diagonal elements of the matrix are set to zero because a factor is not assumed to directly influence itself. The evaluation adopts a five-level linguistic scale, as shown in Table 2.

Table 2. five-level linguistic scale

Linguistic assessment	Score	Triangular fuzzy number
No influence	0	(0.0, 0.1, 0.3)
Very low influence	1	(0.1, 0.3, 0.5)
Low influence	2	(0.3, 0.5, 0.7)
High influence	3	(0.5, 0.7, 0.9)
Very high influence	4	(0.7, 0.9, 1.0)

The use of triangular fuzzy numbers allows linguistic judgments to be transformed into quantitative values while retaining the uncertainty inherent in expert evaluation. After all valid questionnaires are collected, the individual fuzzy judgment matrices are aggregated to form a group fuzzy direct-relation matrix. The CFCS defuzzification method is then applied to obtain a crisp direct-relation matrix for subsequent DEMATEL calculation.

To test the consistency of expert judgments, Kendall's coefficient of concordance is calculated. The result shows that Kendall's W is 0.73 and statistically significant at the 1% level, indicating a high degree of agreement among the experts. Therefore, the survey data are considered reliable for Fuzzy-DEMATEL analysis.

The expert survey plays a complementary role to the historical data analysis. Grey relational analysis identifies whether variables are statistically associated with natural gas consumption, while the expert survey helps determine the causal direction and influence intensity among factors. Combining these two sources of evidence strengthens the robustness of the driver identification framework and reduces the risk of relying solely on historical correlation or subjective judgment.

4. Results

(1) Statistical relevance of candidate factors

Grey relational analysis was first applied to examine the statistical relevance between historical natural gas consumption and the eleven measurable candidate factors. The results are reported in Table 3. The grey relational degrees range from 0.82 to 0.99, indicating that all selected variables show a certain degree of dynamic association with natural gas consumption in Sichuan Province. No factor falls below the commonly used relevance threshold, suggesting that the candidate factor system constructed through literature review and regional screening is generally valid.

Table 3. Grey relational degrees between natural gas consumption and candidate factors

Rank	Factor	Symbol	Grey relational degree	Relevance level
1	Gas-using population	X11	0.99	High
2	Natural gas supply	X6	0.98	High
3	Technological level	X3	0.95	High
4	Natural gas consumption share	X8	0.95	High
5	Urbanization level	X5	0.94	Medium-high
6	Natural gas pipeline length	X9	0.93	Medium-high
7	Industrial structure	X2	0.93	Medium-high
8	Population size	X4	0.92	Medium-high
9	Economic development	X1	0.91	Medium-high
10	Consumption level	X7	0.86	Moderate
11	City-gas investment	X10	0.82	Moderate

Among the eleven variables, gas-using population and natural gas supply have the highest relational degrees, reaching 0.99 and 0.98, respectively. This result indicates that their historical trajectories are highly synchronized with the growth of natural gas consumption. Technological level and natural gas consumption share also show strong associations, with relational degrees of 0.95. Urbanization level, pipeline length, industrial structure, population size, and economic development are located in the medium-high relevance range, while consumption level and city-gas investment show relatively lower but still meaningful associations.

However, the grey relational results should not be interpreted as causal rankings. A high relational degree means that the temporal pattern of a variable is similar to that of natural gas consumption, but it does not necessarily imply that the variable is a fundamental driver. For example, gas-using population and natural gas supply are highly correlated with consumption, yet they may be downstream outcomes of urbanization, infrastructure expansion, and economic development. Therefore, grey relational analysis is used here as a preliminary statistical screening step. The causal attributes and hierarchical positions of these factors are further examined through Fuzzy-DEMATEL, ISM, and MICMAC.

(2) Causal attributes of demand drivers

The Fuzzy-DEMATEL results provide a more detailed understanding of the causal relationships among the fourteen candidate factors. Table 4 reports the influence degree, influenced degree, prominence degree, and relation degree of each factor. The relation degree is used to distinguish cause factors from effect factors.

Table 4. Fuzzy-DEMATEL results for natural gas demand drivers

Factor	Symbol	Influence degree	Influenced degree	Prominence degree	Relation degree	Attribute
Economic development	X1	2.7216	2.6797	5.4014	0.0419	Cause
Industrial structure	X2	1.7638	2.2419	4.0057	−0.4781	Effect
Technological level	X3	2.6676	1.9035	4.5711	0.7641	Cause
Population size	X4	3.1677	1.1388	4.3065	2.0289	Cause
Urbanization level	X5	2.8287	2.4006	5.2293	0.4281	Cause
Natural gas supply	X6	2.1252	2.4790	4.6042	−0.3538	Effect
Consumption level	X7	1.8116	2.0036	3.8152	−0.1920	Effect
Natural gas consumption share	X8	1.9242	2.5686	4.4928	−0.6444	Effect
Natural gas pipeline length	X9	2.0367	2.4983	4.5350	−0.4616	Effect
City-gas investment	X10	2.1793	2.6627	4.8420	−0.4834	Effect
Gas-using population	X11	1.8465	2.2482	4.0947	−0.4017	Effect
Natural gas price	X12	1.8138	2.0210	3.8348	−0.2072	Effect
Carbon constraint	X13	2.3213	1.6642	3.9856	0.6571	Cause
End-use electrification rate	X14	1.7172	2.4152	4.1324	−0.6981	Effect

Five factors are identified as cause factors: economic development, technological level, population size, urbanization level, and carbon constraint. These variables have positive relation degrees, indicating that they exert stronger influence on other factors than they receive from the system. Among them, population size has the largest relation degree, reaching 2.0289. This suggests that population size is the most fundamental causal factor in the system, exerting broad influence on urbanization, economic activity, energy access, and end-use demand.

Technological level and carbon constraint also show strong positive causal attributes. Technological level affects natural gas demand through energy efficiency improvement, infrastructure modernization, and end-use substitution. Carbon constraint influences the relative competitiveness of fossil fuels and low-carbon alternatives, thereby shaping future demand pathways. Urbanization level has a moderate positive relation degree, reflecting its role in promoting city-gas access, residential energy demand, and infrastructure expansion.

Economic development has the highest prominence degree among all factors, but its relation degree is close to zero. This means that economic development is highly connected with the whole system, yet its causal role is more balanced. It is neither a purely exogenous root factor nor a passive response variable. Rather, it functions as a central transmission node that links population, technology, urbanization, industrial structure, income, and energy demand.

The remaining nine factors are classified as effect factors. These variables are mainly influenced by deeper drivers. Natural gas consumption share, city-gas investment, pipeline length, gas-using population, and natural gas supply have relatively strong negative relation degrees, indicating that they are more likely to be response or transmission variables rather than independent root causes. This finding is important because several of these variables have high grey relational degrees. The comparison between grey relational analysis and DEMATEL therefore confirms that statistical association and causal driving force are not equivalent.

(3) Hierarchical structure of drivers

Based on the total-relation matrix obtained from Fuzzy-DEMATEL, ISM was used to construct the hierarchical structure of natural gas demand drivers. The results show that the fourteen factors can be divided into five levels, as presented in Table 5.

Table 5. Hierarchical structure of natural gas demand drivers

Level	Factor	Structural role
L5 Root layer	Population size (X4)	Fundamental structural driver
L4 Deep driving layer	Technological level (X3)	Deep driver linking root factors to macro-transition variables
L3 Intermediate driving layer	Economic development (X1), urbanization level (X5), carbon constraint (X13)	Core transmission variables connecting deep drivers and near-surface factors
L2 Near-surface transmission layer	Natural gas supply (X6), city-gas investment (X10)	Transmission factors related to supply capacity and infrastructure expansion
L1 Surface response layer	Industrial structure (X2), consumption level (X7), natural gas consumption share (X8), pipeline length (X9), gas-using population (X11), natural gas price (X12), end-use electrification rate (X14)	Response indicators or sectoral adjustment variables

The ISM results reveal a clear top-down transmission mechanism. Population size is located at the root layer, indicating that demographic scale provides the most fundamental basis for long-term energy demand. Technological level is located in the deep driving layer. It acts as a key link between demographic conditions and broader socioeconomic or policy transmission variables. Economic development, urbanization, and carbon constraint form the intermediate driving layer, through which deep structural factors are translated into changes in industrial activity, residential demand, infrastructure expansion, and energy substitution.

Natural gas supply and city-gas investment are located in the near-surface transmission layer. These factors directly affect gas accessibility and system capacity, but they are themselves influenced by population, urbanization, economic development, and policy orientation. Therefore, they should not be treated as independent root drivers. The surface response layer contains variables that are more directly observable in the natural gas system, such as gas-using population, pipeline length, natural gas consumption share, and end-use electrification rate. These factors are closely related to natural gas consumption, but their position in the hierarchy shows that they mainly represent the outcomes of deeper socioeconomic and technological changes.

The hierarchical structure provides a more precise interpretation of the natural gas demand formation mechanism. It suggests that demand evolution is not driven by surface energy indicators alone. Instead, it is shaped by a chain of influence that begins with population and technology, passes through economic development, urbanization, and carbon policy, and finally manifests in gas supply, infrastructure investment, energy-use structure, and end-use substitution.

(4) Driving-dependence classification

MICMAC analysis was further conducted to validate the ISM hierarchy and classify the candidate factors according to their driving power and dependence. The results are shown in Table 6.

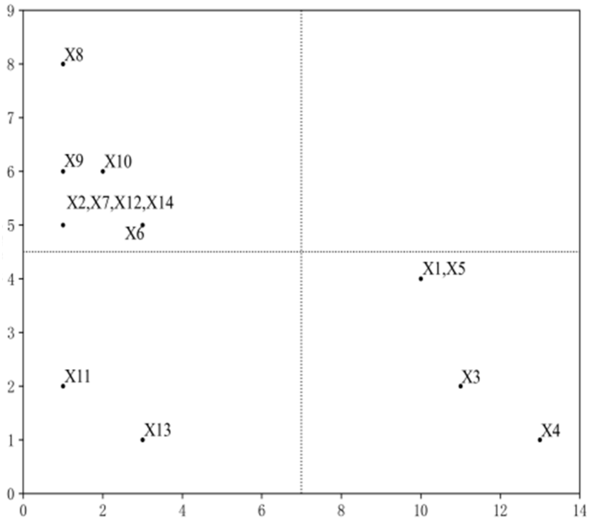
Table 6. MICMAC classification of natural gas demand drivers

Factor	Symbol	Driving power	Dependence	Classification
Economic development	X1	10	4	Independent driving factor
Industrial structure	X2	1	5	Dependent factor
Technological level	X3	11	2	Independent driving factor
Population size	X4	13	1	Independent driving factor
Urbanization level	X5	10	4	Independent driving factor
Natural gas supply	X6	3	5	Dependent factor
Consumption level	X7	1	5	Dependent factor
Natural gas consumption share	X8	1	8	Dependent factor
Natural gas pipeline length	X9	1	6	Dependent factor
City-gas investment	X10	2	6	Dependent factor
Gas-using population	X11	1	2	Autonomous factor
Natural gas price	X12	1	5	Autonomous or weakly dependent factor
Carbon constraint	X13	3	1	Autonomous policy factor
End-use electrification rate	X14	1	5	Autonomous or weakly dependent factor

Economic development, technological level, population size, and urbanization level are classified as independent driving factors. They have high driving power and relatively low dependence, indicating that they exert broad influence on other factors while being less constrained by the system. This classification is consistent with the DEMATEL and ISM results. In particular, population size has the highest driving power and the lowest dependence, confirming its role as the most fundamental structural driver.

Industrial structure, natural gas supply, consumption level, natural gas consumption share, pipeline length, and city-gas investment are classified as dependent factors. These variables have relatively low driving power but high dependence, indicating that they are mainly shaped by deeper socioeconomic and technological factors. This result further supports the interpretation that many gas-system indicators should be treated as response variables rather than root causes.

Gas-using population, natural gas price, carbon constraint, and end-use electrification rate are located in the autonomous or weakly dependent group. Their relatively low driving power and dependence suggest that their interaction with the current historical system is weaker than that of the main socioeconomic drivers. This does not mean that these variables are unimportant. Rather, it indicates that their historical effects may not have been fully reflected during the sample period. Carbon constraint and end-use electrification, in particular, are expected to become more important under future low-carbon transition scenarios. Therefore, they should be retained as policy and technology scenario variables in the forecasting framework.



Picture 1. MICMAC

As we can see in picture 1, the MICMAC results provide an independent check on the factor classification. Factors identified as deep or intermediate drivers in DEMATEL and ISM generally appear as independent driving factors in MICMAC. In contrast, factors with high statistical association but weak causal driving power are classified as dependent or autonomous factors. This cross-validation strengthens the reliability of the integrated identification framework.

5. Discussion

(1) Why high correlation does not mean causal dominance

One of the most important findings of this study is that statistical relevance and causal dominance are not equivalent in natural gas demand analysis. The grey relational analysis shows that gas-using population and natural gas supply have the highest relational degrees with natural gas consumption, indicating that their historical trajectories are highly synchronized with demand changes. However, the Fuzzy-DEMATEL, ISM, and MICMAC results reveal that these variables are not fundamental causal drivers. Instead, they are more appropriately interpreted as response or transmission variables within the natural gas demand system.

This distinction is crucial for energy demand modelling. A variable may be highly correlated with natural gas consumption because both are shaped by deeper socioeconomic processes. For instance, gas-using population increases as urbanization advances, household income improves, and city-gas infrastructure expands. Similarly, natural gas supply may grow in response to rising demand expectations, infrastructure investment, and policy support. In such cases, high correlation reflects co-movement rather than causal priority. If these variables are directly treated as exogenous drivers in forecasting models, the model may overstate their independent explanatory power and produce repeated or circular interpretations.

The integrated results of this study provide a clearer causal interpretation. Population size, technological level, economic development, urbanization level, and carbon constraint are identified as cause factors, while gas supply, gas consumption share, pipeline length, city-gas investment, gas-using population, natural gas price, and end-use electrification rate are mainly located in effect or response positions. This means that the formation of natural gas demand is not driven primarily by observable gas-system indicators, but by deeper demographic, technological, economic, urbanization, and policy forces. These deep factors influence intermediate variables, which then shape infrastructure expansion, gas accessibility, fuel structure, and end-use demand.

Therefore, the key methodological implication is that driver selection should not rely solely on correlation-based ranking. For natural gas demand forecasting, a high-correlation variable should be examined together with its causal direction, hierarchical position, and driving–dependence characteristics. The combination of grey relational analysis and Fuzzy-DEMATEL-ISM-MICMAC provides a more reliable basis for distinguishing root drivers from surface indicators.

(2) Implications for provincial natural gas demand forecasting

The results have direct implications for provincial-scale natural gas demand forecasting. Provincial energy systems often face limited historical samples, strong collinearity among socioeconomic variables, and significant policy-induced structural changes. Under these conditions, conventional variable selection based only on regression significance or correlation may be unstable and difficult to interpret. The layered driver structure identified in this study can help improve the theoretical consistency of forecasting models.

First, population size and technological level should be treated as deep structural variables. Population size determines the long-term scale of residential and service-related energy demand, while technological level affects energy intensity, equipment efficiency, and the speed of fuel substitution. These variables should be reflected in demographic assumptions, technological progress parameters, energy intensity decline rates, and end-use efficiency scenarios.

Second, economic development, urbanization, and carbon constraint should be represented as key transmission and policy variables. Economic development affects sectoral activity levels and household income; urbanization reshapes residential energy access and commercial energy demand; carbon constraint changes the relative competitiveness of natural gas, coal, electricity, and other low-carbon alternatives. These variables are especially important for scenario design because they determine whether natural gas demand follows an expansionary, plateauing, or declining pathway.

Third, variables such as gas supply, pipeline length, city-gas investment, and gas-using population should be used cautiously. They are important for model calibration and infrastructure interpretation, but they should not be automatically specified as independent exogenous drivers. In forecasting practice, these variables are better represented as endogenous outcomes, capacity constraints, access parameters, or indicators for validating demand pathways.

Fourth, natural gas price and end-use electrification deserve special treatment. Although their historical causal dominance is not as strong as that of population or technology, their future importance may increase significantly under low-carbon transition. Natural gas price can affect fuel substitution through relative cost changes, while electrification can directly reduce gas demand in transport, buildings, and some industrial end uses. Therefore, they should be incorporated as scenario variables rather than excluded because of limited historical explanatory power.

The proposed framework improves provincial natural gas forecasting by linking factor identification with model construction. It clarifies which variables should serve as exogenous drivers, which should be treated as intermediate transmission channels, and which should be used as response indicators or calibration parameters. This can reduce model misspecification and enhance the policy interpretability of forecast results.

(3) Policy implications for low-carbon transition

The findings also provide policy insights for natural gas management under low-carbon transition. Sichuan Province is both a major natural gas-producing region and a province with abundant clean electricity resources. This dual condition means that natural gas can support coal substitution and energy security in the short and medium term, but its long-term expansion must be carefully managed to avoid carbon lock-in.

First, policy design should focus on deep structural drivers rather than only on surface demand indicators. Since population, technology, economic development, urbanization, and carbon constraint play more fundamental roles, demand management should be coordinated with urban planning, industrial restructuring, technological upgrading, and carbon policy. Simply expanding gas infrastructure or increasing gas access may raise short-term consumption but does not necessarily improve the long-term sustainability of the energy system.

Second, technological progress should be placed at the centre of natural gas transition policy. The results identify technological level as a deep driving factor, suggesting that efficiency improvement and substitution technologies can reshape the long-term demand trajectory. Policies supporting industrial energy efficiency, building electrification, electric vehicles, heat pumps, and clean electricity utilization are therefore essential for preventing excessive dependence on natural gas.

Third, natural gas infrastructure planning should consider future demand uncertainty. Pipeline networks, city-gas systems, gas-fired facilities, and related end-use equipment usually have long lifetimes. If infrastructure expansion is based only on historically high correlations between gas access and consumption, future decline in demand may lead to low utilization and stranded assets. New infrastructure investment should therefore be evaluated against alternative demand scenarios, especially scenarios with stronger carbon constraints and faster electrification.

Fourth, carbon constraints should be designed to guide the transitional role of natural gas. Natural gas may help reduce coal consumption in the near term, but it remains a fossil fuel. A clear policy boundary is needed to distinguish reasonable transitional use from long-term fossil-fuel dependence. Carbon pricing, emissions monitoring, fuel-switching standards, and electrification targets should be coordinated to ensure that natural gas supports low-carbon transition rather than delaying it.

Finally, differentiated sectoral policies are needed. Industrial gas use should distinguish between feedstock demand and fuel demand. Residential gas policy should balance low-carbon transition with affordability and energy access. Transport-related gas demand should be assessed together with electric vehicle diffusion. Service-sector gas demand should be managed through building efficiency and electrification. These measures can make natural gas demand management more targeted and reduce the risk of uniform policy intervention.

(4) Robustness and limitations

The robustness of this study is supported by the consistency among multiple methods. Grey relational analysis confirms that the selected variables are statistically associated with natural gas consumption. Fuzzy-DEMATEL distinguishes cause and effect factors. ISM reveals the hierarchical transmission structure. MICMAC further validates the driving–dependence characteristics of the factors. The convergence of these results strengthens confidence in the identified driver structure.

In particular, population size, technological level, economic development, and urbanization level are consistently shown to have strong structural importance. Variables such as gas-using population, pipeline length, city-gas investment, and natural gas consumption share show high statistical relevance but weaker causal dominance. This cross-method comparison supports the central conclusion that correlation-based variable selection alone is insufficient for natural gas demand forecasting.

Nevertheless, several limitations should be acknowledged. First, the grey relational analysis is based on provincial annual data from 2008 to 2023. Although this period provides a consistent historical sample, the number of observations remains limited. Future studies could extend the dataset by using city-level panel data or higher-frequency energy statistics. Second, the Fuzzy-DEMATEL results rely on expert judgment. Although the expert group is professionally diverse and the consistency test indicates acceptable agreement, subjective evaluation cannot be fully eliminated. Future research could combine expert judgment with text mining, policy document analysis, or empirical causal inference to improve robustness.

Third, some important variables, such as carbon constraint and end-use electrification, have limited historical variation or incomplete long-term data. Their future influence may be stronger than what is reflected in the current historical system. Therefore, they should be further examined under explicit transition scenarios. Fourth, this study focuses on identifying and classifying demand drivers rather than directly producing a full demand forecast. The next step is to integrate the identified driver hierarchy into quantitative forecasting models, such as CGE-LEAP, system dynamics, or hybrid scenario models, and test whether the structured driver selection improves forecasting performance.

Despite these limitations, the integrated framework provides a useful and transferable approach for identifying natural gas demand drivers under conditions of small samples, complex interactions, and low-carbon transition uncertainty.

6. Conclusions

This study develops an integrated framework to identify and hierarchically decompose the key drivers of natural gas demand in Sichuan Province. By combining literature-based factor screening, grey relational analysis, Fuzzy-DEMATEL, ISM, and MICMAC, the study distinguishes statistical association, causal attributes, hierarchical position, and driving–dependence characteristics among candidate factors. The main conclusions are as follows.

First, the candidate factor system is statistically valid. Grey relational analysis shows that all eleven measurable variables have relational degrees above 0.82 with natural gas consumption. Gas-using population, natural gas supply, technological level, and natural gas consumption share show particularly high statistical relevance. This indicates that natural gas demand in Sichuan is closely related to socioeconomic development, gas-system expansion, infrastructure conditions, and technological change.

Second, high statistical relevance does not necessarily imply causal dominance. Fuzzy-DEMATEL results show that population size, technological level, economic development, urbanization level, and carbon constraint are cause factors, whereas several highly correlated gas-system indicators are mainly effect factors. This finding highlights the risk of mistaking surface response variables for fundamental drivers in natural gas demand forecasting.

Third, the driver system has a clear hierarchical structure. ISM results show that population size is located at the root layer, technological level at the deep driving layer, and economic development, urbanization, and carbon constraint at the intermediate driving layer. Natural gas supply and city-gas investment serve as near-surface transmission variables, while industrial structure, consumption level, natural gas consumption share, pipeline length, gas-using population, natural gas price, and end-use electrification rate mainly appear as surface response or scenario-related variables.

Fourth, MICMAC analysis further validates the classification of drivers. Population size, technological level, economic development, and urbanization level are identified as independent driving factors with high driving power and relatively low dependence. In contrast, natural gas supply, pipeline length, city-gas investment, natural gas consumption share, and consumption level are mainly dependent factors. Carbon constraint and end-use electrification show relatively weak historical interaction with the system, but they remain important future policy and technology scenario variables.

Fifth, the identified driver structure provides a more rigorous basis for natural gas demand forecasting. Deep drivers should be used to define macroeconomic, demographic, and technological assumptions. Intermediate factors should be represented through sectoral activity and household demand modules. Surface response variables should be used for calibration, infrastructure constraints, or model validation rather than being treated as independent exogenous drivers. Natural gas price, carbon constraint, and electrification rate should be incorporated as scenario variables to reflect future transition uncertainty.

The study contributes to the literature by showing that natural gas demand driver identification should move beyond simple variable ranking. A structured approach that integrates statistical association, causal direction, hierarchy, and driving–dependence classification can improve the transparency and policy relevance of provincial energy demand forecasting. The framework developed in this study can also be applied to other regions facing similar challenges of energy security, fossil-fuel transition, and carbon reduction.

Future research can extend this work in three directions. First, city-level or sector-level panel data can be used to test the spatial heterogeneity of natural gas demand drivers. Second, the identified driver hierarchy can be integrated into quantitative forecasting models to evaluate future demand peaks and emission pathways. Third, dynamic policy variables, such as carbon pricing, renewable electricity penetration, hydrogen substitution, and electrification progress, can be incorporated to better capture the evolving role of natural gas in low-carbon energy systems.

Acknowledgements

The authors gratefully acknowledge the financial support from the State Grid Corporation of China for the project "Deepening Research and Application of PV Cloud" (Grant No. SGZJ0000KXJS1800281).

References

[1] Hu, Z. K. (2022). "Dual Carbon" goals and the modernization of national governance. *Journal of Huazhong University of Science and Technology (Social Science Edition)*, 36(5), 136–140.

[2] Du, X. W. (2021). On carbon peaking and carbon neutrality. *People's Tribune (Frontiers)*, (14), 22–27, 143.

[3] Xie, K. C. (2024). Reflections and suggestions on the development of new energy systems. *Strategic Study of CAE*, 26(4), 1–8.

[4] Gao, Z. Y., Bai, H., Wang, Y. G., et al. (2023). Current status and trends of integrated development of the "natural gas + hydrogen energy" industrial chain. *Petroleum and New Energy*, (6).

[5] Luo, P. Y. (2021). Opportunities and challenges for China's natural gas industry under the "Dual Carbon" goals. *International Petroleum Economics*, (6).

[6] He, T. B., Pu, Y. S., He, Q. J., Wang, Y. D., He, R. M., Zhao, Q. P., & Yang, S. (2023). Opportunities and challenges for synergistic development of natural gas and hydrogen energy industries: A case study of the Sichuan-Chongqing region. *Natural Gas Technology and Economy*, 17(3), 67–73.

[7] Fan, J. J., Wang, J. L., Huang, H., et al. (2022). Research on the positioning and potential pathways of China's natural gas development under the "Dual Carbon" goals. *Coal Economic Research*, 42(8), 38–47.

[8] Zhou, S. H., Wang, J., & Liang, Y. (2023). The important role of natural gas in new power systems dominated by renewable energy and policy recommendations. In *Proceedings of the 33rd National Natural Gas Academic Annual Conference (2023)* (Vol. 5: New Energy and Energy Conservation and Emission Reduction).

[9] Xu, H. N., & Sun, J. (2024). Issues concerning the development of gas-fired power generation industry in Sichuan Province. *International Petroleum Economics*, (2), 65–69. Fangfang. (2011). Research on power load forecasting based on improved BP neural network [Master's thesis]. Harbin Institute of Technology.

[10] Wang, J. L., & Li, N. (2020). Influencing factors and future trends of natural gas demand in the eastern, central and western areas of China based on the grey model. *Natural Gas Industry B*, 7(5), 473–483.

[11] Li, H. B., & Zhang, J. J. (2021). Analysis of influencing factors of natural gas demand and future demand forecasting. *Operations Research and Management*, 30(9), 132–138. (in Chinese)

[12] Han, Z., & Xiong, G. P. (2018). Empirical analysis of natural gas demand in China. *China Mining Magazine*, 27(9), 47–52. (in Chinese)

[13] Liu, G. S., Guo, X. F., & Fu, H. Y. (2015). Research on influencing factors of natural gas consumption in China based on co-integration analysis and error correction model. *Journal of Gansu Sciences*, 27(2), 144–148. (in Chinese)

[14] Lu, Q. Y., Chai, J., Zhu, Q., et al. (2015). Analysis and forecasting of natural gas consumption demand. *Chinese Journal of Management Science*, 23(S1), 823–829. (in Chinese)

[15] Chai, J., Wang, Y. R., & Kin, K. L. (2019). Analysis and forecasting of China's natural gas consumption under the "New Normal". *Operations Research and Management*, 28(6), 175–183. (in Chinese)