The forecasting model research of rural energy transformation in Henan Province based on STIRPAT model

Lei Wen

North China Electric Power University - Beijing Campus: North China Electric Power University

Qianqian Song (✉ songqianqianada@126.com)

North China Electric Power University <https://orcid.org/0000-0002-9615-2994>

Research Article

Keywords: Rural power consumption, Rural power consumption, Rural energy transformation, Henan Province, STIRPAT model

Posted Date: January 28th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1203734/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Abstract

In order to find the model of rural energy transformation in Henan Province. This paper examines the effects of population, per capita income, total value of agricultural output, per capita housing area, electric motor power, total power of rural durable goods on rural power consumption (PC) and effective irrigation area, per capita housing area, total power of agricultural machinery, total value of agricultural output, rural population, and energy intensity on rural total energy consumption (TEC) employing Tapio decoupling model. In addition, PSO-BOP is used to predict the values of each influencing factor in 2020-2025. Last, the STIRPAT model is used to forecast TEC and PC from 2020-2025 based on the data of rural energy consumption in Henan Province from 2009-2019. The results show that other factors besides population promote TEC and PC to different degrees. Moreover, the influencing factors, TEC and PC form a virtuous cycle of mutual promotion. Then, TEC and PC consumption show an increasing trend year by year in 2020-2025. It is worth noting that after 2022, the variation of PC is greater than that of TEC. To sum up, improving rural electrification level is a necessary way to realize its low-carbon energy transition.

1. Introduction

Energy is an important material foundation for the survival and development of human society. It is vital to the national economy and people's livelihood and the strategic competitiveness of a country. In today's world, the massive use of fossil energy brings about a series of problems in the fields of environment, ecology and global climate change. Countries around the world have taken the initiative to solve the dilemma and accelerate energy transformation and development. Yet now, around 2.8 billion people worldwide still rely on traditional biomass for cooking, heating and so on, 95% of which are concentrated in rural areas in Asia and Africa (Ma et al. 2021b; Han et al. 2021).

China is a big agricultural country with vast rural area and the rural population. About half of China's population lives in the countryside. Since the reform and opening up, the traditional rural energy consumption structure has also undergone significant changes (Jin et al. 2019). Nonetheless, China's combined agricultural and rural greenhouse gas emissions account for about 15 percent of national emissions (Han et al. 2021). Promoting rural energy revolution and realizing rural energy transformation and upgrading are crucial measures to implement the spirit of the 19th CPC National Congress and General Secretary Xi Jinping's strategic thought on energy revolution. Therefore, it is an effective way to realize the green development of rural areas to explore the path of low-carbon energy transition in China.

Henan is the largest agricultural province in central China, with a population of 96.4 million. Residents of Henan Province are heavily concentrated in the countryside. As an important province with a large population and large grain and agricultural production, Henan is the main battlefield of the rural revitalization strategy (Wu et al. 2015; Zi et al. 2021).

In January 2017, the People's Government of Henan Province issued the 13th Five-Year Energy Development Plan of Henan Province, which put forward eight key tasks, including accelerating the

development of non-fossil energy, strengthening rural energy construction and building a smart energy system. The supply-side structural reform in the energy sector has achieved remarkable results. The average annual concentration of PM_{2.5} and PM₁₀ has dropped by more than 30%, and all environmental indicators have reached the best level in the past five years. The 14th Five-Year Plan points out that it is necessary to build a low-carbon and efficient rural energy support system in Henan Province, continue to promote the energy revolution, and actively develop new and renewable energy.

In addition, the strategic Plan for Rural Revitalization of Henan Province (2018-2022) specifies the key tasks of "promoting the rural energy revolution". It is mainly reflected in optimizing the rural energy supply structure and constructing a clean, low-carbon, safe and efficient modern rural energy system.

Therefore, exploring the driving factors of rural energy consumption in Henan Province and predicting the trend of total energy consumption (TEC) and power consumption (PC) in Henan Province are crucial steps to explore the mode of rural energy transformation and upgrading in Henan Province.

For these reasons, the main tasks of this paper are to analyze the current situation of rural energy consumption in Henan Province, explore the driving factors affecting TEC and PC in rural areas of Henan Province, and forecast TEC and PC to analyze their changing trend. So as to explore the low-carbon energy transformation model of Henan Province. In addition, the technical roadmap for this article is shown in Fig. 1.

The contributions and originalities of this paper can be summarized as follows:

- (1) In this paper, the decoupling states between rural PC and TEC and its influencing factors in Henan Province are analyzed by using decoupling principle creatively.
- (2) Since there is multicollinearity among the 6 influencing factors of TEC, and the same problem exists among the 6 influencing factors of PC. Therefore, based on STIRPAT model, this paper uses ridge regression method to fit the linear equations of TEC and PC originally, and the validity of the fitted equations are verified. Rather than simply summing up the primary energy consumption of rural Henan Province.
- (3) In addition, this paper optimizes the BP neural network by PSO, and innovatively predicts the values of influencing factors of PC and TEC.
- (4) Finally, the consumption of TEC and PC in 2020-2025 are obtained by STIRPAT using ridge regression. Also, the forecast results of TEC and PC are analyzed to find the mode of rural energy transformation in Henan Province.

The rest of the article is structured as follows: Section 2 provides a relevant literature review for rural energy consumption, rural power consumption and the application of STIRPAT model. Variable selection for total energy consumption and power consumption of Henan Province are introduced based on Tapio decoupling model in Section 3. Theoretical model construction and data in Section 4. Section 5 analyzes

and discusses the results of regression equations. Section 6 provides the conclusions and policy recommendations.

2. Literature Review

2.1. Research on rural energy consumption

In China's rural areas, energy consumption is mainly used for villagers' life, such as heating, cooking, lighting, transportation and agricultural production activities, such as irrigation, planting, harvesting and fertilization (Ma et al. 2021a). Due to China's rapid urbanization process, energy consumption in rural areas is increasing. Moreover, a large amount of CO₂ gas is emitted, which poses a threat to the health of villagers (Amagai et al. 2014).

Technological advances in energy efficiency and replacing conventional energy with renewable energy are generally regarded as effective measures to solve the problem of harmful gas emissions (Wu 2020; Du et al. 2021; Su et al. 2022). However, the consumption of fossil fuels supports the total consumption of rural energy, and the use of clean energy is less.

Consequently, many scholars have explored the transformation mode of rural energy. Han et al. (Han et al. 2021) used the space-time model to study the space-time characteristics of energy ladder in agriculture and rural life of developing countries, taking China as an example, by analyzing rural life and production activities. From the perspective of information reliability and standard non-compensation, Peng et al. (Peng et al. 2021) constructed a decision support framework for managing the choice of new energy in rural areas. This is of great significance to the realization of the national low-carbon sustainable goal. He et al. (He et al. 2014) proposed to reduce the total energy consumption in rural areas by improving the energy efficiency of rural buildings. Jia et al. (Jia et al. 2022) analyzed the impact of the energy consumption revolution on the health of the elderly in rural areas and its mechanism. And put forward, should improve the rural medical security level. So as to improve the physical and mental health of the elderly to ensure the successful realization of the rural energy revolution. Yahyaoui et al. (Yahyaoui et al. 2016) explored the installation scheme of renewable clean energy power generation devices in remote rural areas. It provides important policy suggestions for the green and sustainable development of rural areas. Ma et al. (Ma et al. 2021a) analyzed the current situation of energy consumption in rural China, obtained the main factors affecting rural energy consumption, identified the key factors to improve energy efficiency, and provided a meaningful reference for rural low-carbon energy transformation. Lemence and Tamayao (Lemence and Tamayao 2021) identified hybrid solar systems as a powerful solution for sustainable energy in rural Philippines, and developed a grid connection solution with the lowest cost for solar photovoltaic. Zou and Luo (Zou and Luo 2019) used Tobit model to estimate the determinants of energy consumption of rural households in China, based on the data of 1,472 rural households in a comprehensive survey. The results show that households with higher economic and educational levels have higher levels of electrification of energy consumption (Zou and Luo 2019; Li et al. 2021). Imran et al. (Imran et al. 2019) collected primary data from 196 households in four districts of

Pakistan's Punjab province to explore the impact of biomass energy on human health in rural areas. Zi et al. (Zi et al. 2021) analyzed the cooking energy mode in rural areas of Henan Province and learned that the low-carbon transformation of cooking energy is of great help to the transformation of rural energy.

Thus, only by analyzing the current situation of rural energy consumption can we find a way out of rural energy transformation. However, most of the above literature is cross-regional analysis of the path of national rural energy transformation. Hence, this paper focuses on the analysis of the current situation of rural energy in Henan Province.

2.2. Research on rural power consumption

Studies on power consumption in rural areas have found that, with the improvement of rural living standards, energy consumption increases and electricity consumption also shows a rising trend (Tesfamichael et al. 2020; Agrawal et al. 2020). The increase of per capita income makes the transformation of rural energy use to commercialization (Asmare et al. 2021). That is, the villagers will gradually shift their dependence on non-commercial energy sources such as straw, firewood and bulk coal to electricity (Riva and Colombo 2020). The improvement of rural electrification can not only improve the efficiency of people's work and study, but also diversify people's ways of entertainment and study, thus improving people's physical and mental health (Han et al. 2020). Electrification has also increased the use of household appliances in rural areas and improved the quality of life of the people (Mahajan et al. 2020), thereby changing lifestyles, improving the per capita income, and accelerating the pace of urbanization in rural areas towards a relatively well-off society (Sedai et al. 2021).

Yet 1.2 billion people still do not use electricity, and most of them live in rural areas (Robert and Gopalan 2018; Vinicius et al. 2021). Therefore, the driving factors for improving rural electrification level should be explored while improving grid coverage.

Ma et al. proposed that the purchase rate of energy-saving household appliances is greatly affected by the education level of rural households, per capita income and government subsidies (Ma et al. 2018), as well as the influence of place and custom (Zou and Mishra 2020). (Rahman et al. 2013) analyzed that the success of rural electrification program in Bangladesh is significantly related to the driving factors of system investment, community participation, anti-corruption characteristics, standardized practices and performance incentives. It provides a meaningful reference for rural electrification in other countries. Minaei et al. (Minaei et al. 2021) proposed to improve rural electrification by improving the quality of life in rural and remote areas through clean electricity.

Nonetheless, these studies only focus on the influencing factors of rural electrification from a single perspective. Correspondingly, the task of this paper is to explore the driving factors affecting rural electricity consumption from various aspects.

2.3. Research on STIRPAT

STIRPAT model has been successfully applied to study the environmental pollution caused by various factors. Based on STIRPAT model, the scenario of peak household carbon dioxide emissions at provincial level in China was simulated by Zhao et al.(Zhao et al. 2021). Wu et al., Ghazali and Ali (Ghazali and Ali 2019; Wu et al. 2021, p. 2) used the extended STIRPAT model to analyze the drivers of the downward trend of CO₂ emissions in developed countries. Using the extended STIRPAT model, Lin et al.(Lin et al. 2017) explores the impact of urbanization and real economy development on co₂ emissions in developing countries.

Also, some literatures also use STIRPAT model to explore the driving factors of energy consumption. Gani (Gani 2021) researched the impact of fossil fuel power generation on environmental quality, based on a STIRPAT model that incorporated economic, social and institutional factors. Using STIRPAT model, Shahbaz et al. (Shahbaz et al. 2017) re- investigated the relationship between urbanization and energy consumption in Pakistan during 1972Q1-2011Q4. And it confirmed that urbanization increases energy consumption. Employing the extended STIRPAT model, Wang et al. (Wang et al. 2013) inspected the effects of population, economic level, technological level, urbanization level, industrialization level, service level, energy consumption structure and foreign trade level on energy consumption in Guangdong from 1980 to 2010. The empirical results show that population, urbanization level, per capita GDP, industrialization level and service level can lead to the increase of total energy consumption, and then increase CO₂ emissions.

Whereas, there is no literature to assess the main drivers of rural energy in China applying STIRPAT model. Therefore, the primary purpose of this paper is to investigate the driving factors affecting rural energy consumption in Henan Province based on STIRPAT model.

3. Analysis Of The Current Situation Of Rural Energy In Henan Province

This section introduces the decoupling principle to analyze the influencing factors of rural energy consumption and electricity consumption in Henan Province.

3.1. Variable selection

3.1.1. The decoupling theory

The word "decoupling" originated in physics. Decoupling means that environmental pressure and economic growth are no longer interdependent, and changes in environmental pressure indicators such as carbon emissions are no longer synchronized with changes in economic development, and do not affect each other (Gong et al. 2021). The Tapio decoupling model analyzes the decoupling relationship between variables through the concept of elasticity. Tapio decoupling model is not only not affected by the change of statistical dimension, but also can decompose the causal chain of the decoupling index by using the identity, so as to realize the in-depth analysis and research on the influencing factors behind the decoupling state (Duan et al. 2021). This paper studies the decoupling relationship between rural TEC

and its influencing factors in Henan Province and the decoupling relationship between rural PC and its influencing factors.

The expression is as follows:

$$D = \frac{\Delta Q / Q}{\Delta Y_i / Y_i}$$

1

where, D is decoupling elasticity index; Q is rural TEC or EC; Y is the influencing factor.

Consequently, the equation of energy influencing factors based on decoupling theory can be written as:

$$D = \frac{\Delta E / E}{\Delta W_i / W_i}$$

2

where, W_i represents the ownership of various factors affecting rural TEC in Henan Province; ΔW_i represents its increment; E and ΔE represent the rural TEC and its increment in Henan Province in the current year.

Consequently, the equation of electricity influencing factors based on decoupling theory can be written as:

$$D = \frac{\Delta C / C}{\Delta N_i / N_i}$$

3

where, N_i represents the ownership of various factors affecting rural PC in Henan Province; ΔN_i represents its increment; C and ΔC represent the rural PC and its increment in Henan Province in the current year.

Tapio decoupling indicators take the positive and negative values of ΔQ and ΔY , as well as the elastic values of 0.8 and 1.2 as critical values, respectively, to judge the state and degree of decoupling. Eight decoupling states are defined according to the value of decoupling elasticity (Wenbo and Yan 2018), as shown in Table 1.

Table 1
Classification of Tapio decoupling states.

Decoupling state	Decoupling type	ΔQ	ΔYi	Elastic coefficient D
Negative decoupling	Negative decoupling of growth (NDG)	>0	>0	$D > 1.2$
	Strong negative decoupling (SND)	>0	>0	$D < 0$
	Weak negative decoupling (WND)	>0	>0	$0 < D < 0.8$
Concatenate	Growing concatenate (GC)	>0	>0	$0.8 < D < 1.2$
	Recession concatenate (RC)	>0	>0	$0.8 < D < 1.2$
Decoupling	Weak decoupling (WD)	>0	>0	$0 < D < 0.8$
	Strong decoupling (SD)	>0	>0	$D < 0$
	Recession decoupling (RD)	>0	>0	$D > 1.2$

3.1.2. The variable selection

In this paper, EIA, PS, PAM, V, POP and EE are taken as the influencing factors of TEC in Henan Province. Based on the data of TEC and influencing factors in rural areas of Henan Province from 2009 to 2019, the decoupling analysis is conducted based on equation (2). The results are shown in Table 2 and Fig. 2.

Table 2
Decoupling states between TEC and influencing factors.

Time	EIA	PS	PAM	V	POP	EE
2009-2010	NDG	NDG	GC	WD	SND	SND
2009-2011	NDG	NDG	NDG	WD	SND	SND
2009-2012	NDG	NDG	NDG	WD	SND	SND
2009-2013	NDG	NDG	GC	WD	SND	SND
2009-2014	NDG	NDG	GC	WD	SND	SND
2009-2015	NDG	NDG	NDG	WD	SND	SND
2009-2016	NDG	GC	NDG	WD	SND	SND
2009-2017	NDG	GC	NDG	WD	SND	SND
2009-2018	NDG	NDG	NDG	WD	SND	SND
2009-2019	NDG	NDG	NDG	WD	SND	SND

According to the Table 2, there is a negative decoupling of growth between EIA and total energy consumption TEC. The association between PAM and TEC is negative decoupling of growth and growing concatenate. Also, the relationship between PAM and TEC is negative decoupling of growth and growing concatenate. The relationship between V and TEC shows weak decoupling. POP and EE show strong negative decoupling relationship with TEC.

As shown in Fig. 2, EIA, PS, PAM, and V all show positive decoupling effects on TEC. Among them, the most influential factor is the EIA, which shows a trend of wave rise. In addition, the decoupling index of PS, PAM and V have approximately the same trend. However, POP and EE have a negative decoupling effect on TEC, and the decoupling elasticity index of POP is large.

In terms of PC, V, EEP, POP, PI, PS, and TP are taken as the influencing factors of PC in Henan Province. Based on the data of PC and influencing factors in rural areas of Henan Province from 2009 to 2019, the decoupling analysis is conducted based on equation (3). The results are shown in Table 3, and Fig. 3.

Table 3
Decoupling states between PC and influencing factors.

Time	V	PI	PS	EEP	POP	TP
2009-2010	WD	WD	NDG	NDG	SND	WD
2009-2011	WD	WD	NDG	NDG	SND	WD
2009-2012	WD	WD	NDG	NDG	SND	WD
2009-2013	WD	WD	NDG	NDG	SND	WD
2009-2014	WD	WD	NDG	NDG	SND	WD
2009-2015	WD	WD	NDG	NDG	SND	WD
2009-2016	WD	WD	NDG	NDG	SND	WD
2009-2017	WD	WD	NDG	NDG	SND	WD
2009-2018	WD	WD	NDG	NDG	SND	WD
2009-2019	WD	WD	NDG	NDG	SND	WD

The Table 3 shows that the variables V, PI and TP show weak decoupling with rural electricity consumption PC in Henan Province. In addition, the states of PS and EEP are negative decoupling with PC. However, there is a strong negative decoupling between POP and PC.

As shown in Fig. 3, the analysis of V, PI, PS, EEP and TP from 2009 to 2019 show a positive decoupling effect on PC. Among them, EEP has the most significant impact on PC, the second is the PS, and V, PI and TP have the same influence on PC.

4. Theoretical Model Construction And Data

In this study, to fully investigate the characteristics of rural energy usage of Henan Province in total energy consumption (TEC) and power consumption (PC). Firstly, STIRPAT method is used to fit and forecast the total amount of rural energy consumption and electricity consumption in Henan Province, and the model is verified. The next, PSO- BP is involved to predict the change of the influencing factors of TEC and PC in Henan Province.

4.1. Theoretical model construction

4.1.1. The STIRPAT theory

The STIRPAT model originated from IPAT(Impact by Population Affluence and Technology), first proposed by Ehrlich and Holdren (1971) (Yang et al. 2018; Gani 2021; Zhao et al. 2021).The IPAT identity ($I = PAT$) is often used as a basis for investigating the effects of various factors on environmental

pollution. Hence, STIRPAT model has become an important tool for analyzing energy consumption and other types of pollution (Huo et al. 2020; Lin and Li 2020).

$I = PAT$ (4)

where, I is the impact, which is usually measured by the emission level of pollutants; P is the size of the population; A is the wealth of a country; T is the technical index.

In order to fully study the factors affecting environmental change, IPAT model is too simple and has its limitations. Therefore, using this model as the basis, Dietz and Rosa proposed the STIRPAT model as follows (Huo et al. 2020; Lin and Li 2020):

$$I_t = aP_t^b A_t^c T_t^d \epsilon_t$$

5

where, a is the intercept term; P , A , and T are the same as in Equation (4); B , C and D represent the elasticity of environmental impact on P , A and T respectively. ϵ_t is a random disturbance, and the subscript t indicates the year.

STIRPAT model has been widely used to analyze the factors affecting environmental pollution (Li et al., 2011; Wang et al., 2013). To eliminate possible heteroscedasticity, all variables are in logarithmic form. Thus, the equation can be rewritten as:

$$\ln I_t = \ln a + b(\ln P_t) + c(\ln A_t) + d(\ln T_t) + \epsilon_t \quad (6)$$

where, P represents population size (10E4 persons); A is per capita GDP (yuan); T is a technical indicator, measured by energy efficiency (energy consumption in ISI/its actual output – ENE).

To further investigate the driving forces of TEC in rural areas of Henan Province. Based on the specific situation of Henan Province, total rural machinery power, effective irrigation area, energy intensity, rural population, total agricultural output value and per capita housing area of farmers are incorporated into STIRPAT model for improvement and expansion. The rewritten expression is:

$$\ln TEC_t = \ln a + \beta_1 \ln PAM_t + \beta_2 \ln EIA_t + \beta_3 \ln EE_t + \beta_4 \ln POP_t + \beta_5 \ln V_t + \beta_6 \ln PS_t + \xi_t$$

7

where, TEC_t represents the rural energy consumption of Henan Province in t years (10E4■ tons); PAM represents the total power of agricultural machinery; EIA stands for effective irrigation area; EE stands for energy intensity; POP stands for rural population; V represents the total value of agricultural output; PS represents per capita residential area; t is the year.

In addition, total agricultural output value, electric motor power, rural population, per capita income, per capita housing area of farmers and total power of rural durable goods are incorporated into STIRPAT

model for improvement and expansion. The econometric model and equation of rural PC in Henan Province is established:

$$\text{LnPC}_t = \text{Lna} + \beta_1 \text{LnV}_t + \beta_2 \text{LnEEP}_t + \beta_3 \text{LnPOP}_t + \beta_4 \text{LnPI}_t + \beta_5 \text{LnPS}_t + \beta_6 \text{LnTP}_t + \xi_t$$

8

where, P represents the rural PC of Henan Province (100 million kw■h); V represents the total agricultural output value; EEP stands for electric motor power; POP stands for rural population; PI stands for per capita income; PS represents per capita housing area; TP represents the total power of rural durable goods.

The relevant variables in Equations (7) and (8) are defined in Table Nomenclature.

4.1.2. The BP theory

BP network (Back Propagation) was proposed by a group of scientists headed by Rumelhart and McClland in 1986 (Wen and Yuan 2020a; Kim et al. 2020). BP is a kind of multilayer feed-forward network trained by error backpropagation algorithm, which is one of the most widely used neural network models. The learning process of BP includes the forward propagation of information and the back propagation of error. After repeated training, the network weight and deviation changes are calculated continuously in the direction of relative error function gradient descent, gradually approaching the target. A typical three-layer BP neural network structure is shown in Fig. 4 (Keshtkarbanaeemoghadam et al. 2018). In the figure, $\sum$ represents weighted sum; f is the activation function.

4.1.3. The particle swarm optimization (PSO) theory

Particle Swarm Optimization (PSO) was proposed by Dr. Eberhart and Dr. Kennedy in 1995 inspired by artificial life. It simulates the random foraging behavior of a flock of birds in space (Suman et al. 2021; Malik et al. 2021).

Assuming that none of the birds know exactly where the food is, but they do know roughly how far it is, the simplest and most effective method is to search the area around the bird that is currently closest to the food. Hence PSO treats each bird as a particle with position and velocity. Then, the particle uses the closest location it has found to the food and the closest location the group has found so far to change its direction of flight. Finally, the whole population is directed to the same place, and that place is the area closest to the food.

In the process of optimization, the velocity and position of each particle are updated according to the following formulas:

$$V_{i,d}^{T+1} = wV_{i,d}^T + c_1r_1(P_{ibest} - x_{i,d}^T) + c_2r_2(g_{best,d} - x_{i,d}^T)$$

9

$$x_{i,d}^{T+1} = x_{i,d}^T + v_{i,d}^{T+1}$$

10

where, $d=1, \dots, n$; x_i^T and v_i^T represent the position and velocity of the i th particle in the T iteration respectively. $c1$ represents self-cognition coefficient; $c2$ represents social cognition coefficient; $r1$ and $r2$ are random numbers between $[0,1]$; P_{ibest} represents the individual optimal position found by the i th particle until the T iteration; g_{best} represents the global optimal position of the whole population until iteration T ; $x_{i,d}^{T+1}$ and $v_{i,d}^{T+1}$ represent the position and velocity of the i th particle obtained after the $T+1$ iteration of the particle d , respectively.

4.1.4. The PSO-BP model

Based on the introduction of BP and PSO above, this paper uses PSO to improve BP to predict the changes of various influencing factors (Wen and Yuan 2020b; He et al. 2020; Wu 2021). The specific steps are as follows:

Step 1: The fitness function of PSO is set as shown in formula (11).

$$F(z) = e$$

11

where e is the error function in formula (12):

$$e = \lambda MAE + \mu RMSE + \eta MAPE \quad (12)$$

where λ and μ are non-negative weights. Also, the expressions of MAE and RMSE are shown below:

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - \hat{a}_i| \quad (13)$$

$$RMSE = \frac{1}{n} \sum_{i=1}^n \frac{|a_i - \hat{a}_i|}{a_i} \quad (14)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|a_i - \hat{a}_i|}{a_i} \quad (15)$$

where, a_i and $\hat{a}_i$ are the actual value and predicted value respectively, and n is the number of samples.

Step 2: Initialize the position and velocity of each particle, initialize parameters $c1, c2$, maximum velocity V_{max} , and minimum velocity V_{min} , population size N , and maximum iteration T_{max} .

Step3: The fitness function of each particle in the population is calculated, and the initial individual optimum and the total optimum are obtained.

Step4: Update the velocity and position of each particle according to equations (9) and (10). Also, update individual and global optimality.

Step5: If the iteration number is equal to Tmax, the algorithm ends. And output the optimal value and the optimal particle.

Step 7: Otherwise, iter = iter+1, returning step 4.

Step 8: The value of the optimal particle is taken as the weights and thresholds of BP.

Step 9: Finally gets a trained network of BP.

The flow chart of PSO-BP is shown in Fig. 5. In the figure, E is the error of backpropagation, and ε is the number that is infinitely close to 0.

$$\begin{aligned}
 E &= \frac{1}{2} (\mathbf{d} - \mathbf{O})^2 = \frac{1}{2} \sum_{k=1}^L (\mathbf{d}_k - \mathbf{O}_k)^2 = \frac{1}{2} \sum_{k=1}^L \left[\mathbf{d}_k - f \left(\sum_{j=0}^m \mathbf{w}_{jk} \mathbf{y}_j \right) \right]^2 \\
 &= \frac{1}{2} \sum_{k=1}^L \left\{ \mathbf{d}_k - f \left[\sum_{j=0}^m \omega_{jk} f \left(\sum_{i=0}^n \mathbf{v}_{ij} \mathbf{x}_i \right) \right] \right\}^2 \quad (16)
 \end{aligned}$$

where, O is the output vector of the output layer; d is the expected output vector; x is the expected input vector; l is the dimension of the output vector of the output layer; w is the connection weight between the output layer and the hidden layer; v is the connection weight between the input layer and the hidden layer; m is the dimension of the hidden layer output vector.

4.2. Data

Data were mainly drawn from government statistical yearbooks. The energy consumption and power consumption of Henan Province are from China Energy Statistical Yearbook (National Bureau of Statistics, 2020). The data of influencing factors total power of agricultural machinery, effective irrigation area, energy intensity, rural population, per capita housing area, total value of agricultural output, electric motor power, per capita income, and total power of rural durable goods are from the Statistical Yearbook of Henan Province (Henan Bureau of Statistics, 2020).

5. Results And Discussion

5.1. Recognition results of regression equation

5.1.1. Multicollinearity analysis

The multicollinearity test is performed based on the data of each influencing factor and rural TEC and rural PC from 2009 to 2019. The multicollinearity test results of various influencing factors of rural TEC are shown in Table 4 and Table 5. The multicollinearity test results of various influencing factors of rural PC are shown in Table 6 and Table 7.

Table 4
Correlation test results of factors of TEC.

	InPAM	InEIA	InEE	InPOP	InV	InPS
InPAM	1					
InEIA	0.904**	1				
InEE	0.932**	0.769**	1			
InPOP	0.973**	0.921**	0.856**	1		
InV	0.992**	0.898**	0.927**	0.980**	1	
InPS	0.941**	0.897**	0.776**	0.981**	0.944**	1

Table 5
OLS regression results of factors of TEC.

OLS result	Unstandardized coefficient	t-Statistic Sig.	VIF
Constant	-13.214	0.105	-
InPAM	-1.790	0.023	133.725
InEIA	3.104	0.014	9.217
InEE	0.582	0.009	34.595
InPOP	0.122	0.610	125.312
InV	0.218	0.486	132.827
InPS	1.087	0.121	75.874
Adjusted R ²	0.973	-	-
F-statistic Sig.	0.000	-	-

According to the results shown in Table 4, it is clear that more than half of the variables are correlated, among which the relationship values of total agricultural machinery power, energy efficiency, population, gross output value and housing area per capita are all high.

In addition, VIF is the most common collinearity evaluation standard. The VIF values of agricultural machinery power, population, total agricultural output value and housing area per capita, energy

efficiency are all well above 10 in Table 5. That is, there is a serious multicollinearity between these variables.

Table 6
Correlation test results of factors of PC.

	InV	InEEP	InPOP	InPI	InPS	InTP
InV	1	-	-	-	-	-
InEEP	0.991**	1	-	-	-	-
InPOP	-0.969**	-0.976**	1	-	-	-
InPI	0.981**	0.986**	-0.985**	1	-	-
InPS	0.962**	0.973**	-0.978**	0.985**	1	-
InTP	0.993**	0.995**	-0.979**	0.988**	0.971**	1

Table 7
OLS regression results of factors of PC.

OLS result	Unstandardized coefficient	t-Statistic Sig.	VIF
Constant	-53.941	-2.737	-
InV	-0.171	-0.395	80.080
InEEP	-8.295	4.454	115.347
InPOP	1.147	0.646	38.552
InPI	-0.166	-0.441	92.217
InPS	-0.852	-1.236	39.439
InTP	-0.248	-0.707	165.934
Adjusted R ²	0.961	-	-
F-statistic Sig.	0.000	-	-

According to the results shown in Table 6, it is obvious that more than half of the variables are correlated, and the VIF values of all the influencing factors of rural electricity consumption are much higher than 10 in Table 7. That is, there is a serious multicollinearity between these variables.

5.1.2. Construction of regression equations based on STIRPAT

In this paper, ridge regression is used to estimate the coefficients in STIRPAT model for TEC and PC.

In the aspect of TEC, according to the ridge regression equation, Fig. 6 and Fig. 7 respectively show the relationship between ridge trace and $\{R\}^2$ and k. Each independent variable first changes rapidly with the increase of k value, and then becomes rapidly stable after $k = 0.67$. Fig. 6 shows that $\{R\}^2$ of ridge regression changes at a high rate of change before $K = 0.67$, and the change rate becomes much lower when the value of k is 0.67. Thus, the minimum value of k ($k = 0.67$) can be performed with a high adjustment $\{R\}^2$ of 0.941. Therefore, it is reasonable to choose k as 0.67 in this paper.

F test can be passed and the result of F-Sig is $0.000\ 0049 < 0.05$. This implies that there is a linear relationship between the independent variable TEC and the dependent variables. At the same time, the t-sig of constant term and regression coefficient is less than 0.1, in Table 8. This indicates that all independent variables should be introduced into the regression equation. Finally, the fitting ridge regression equation of LnTEC is as follows:

$$\{\ln\}TEC = -3.985 + 0.226\{\ln\}PAM + 1.362\{\ln\}EIA - 0.103\{\ln\}EE - 0.500\{\ln\}POP + 0.115\{\ln\}V + 0.260\{\ln\}PS \quad (17)$$

Table 8
Test results of each independent variable and constant for TEC.

Variable	constant	lnPAM	lnEIA	lnPHI	lnPOP	lnV	lnPS
Coefficient's t Sig	-3.985*	0.226*	1.362**	-0.103**	0.500***	0.115***	0.260**
Note: *** significant at 1%, ** significant at 5%, * significant at 10%.							

In the aspect of PC, ridge regression is used to estimate the coefficients in the STIRPAT model (Fig. 8 and Fig. 9), and $k = 0.66$.

F test can be passed and the result of F-Sig is $0.0001732 < 0.05$. This implies that there is a linear relationship between the independent variable TEC and the dependent variables. At the same time, the t-sig of constant term and regression coefficient is less than 0.1, in Table 9. This indicates that all independent variables should be introduced into the regression equation. Finally, the fitting ridge regression equation of LnPC is as follows:

$$\{\ln\}PE = 2.545 + 0.151\{\ln\}V + 0.554\{\ln\}EEP - 0.572\{\ln\}POP + 0.105\{\ln\}PI + 0.213\{\ln\}PS + 0.081\{\ln\}TP$$

18

Table 9
Test results of each independent variable and constant for PC.

Variable	constant	lnV	lnEEP	lnPOP	lnPI	lnPS	lnTP
Coefficient's t Sig	2.545*	0.151***	0.554***	-0.572**	0.105***	0.213*	0.081***
Note: *** significant at 1%; ** significant at 5%; * significant at 10%.							

5.2. Discussion of regression results

5.2.1. Prediction results of influencing factors

In this paper, PSO-BP model is used to predict the factors affecting rural TEC and PC in Henan Province. In addition, the rolling method of the prediction of the first three years and the next year is adopted to obtain the predicted values of influencing factors affecting TEC and PC in Henan Province during 2020-2025, as shown in Table 10 and Table 11.

Table 10
The estimated values of each influence factor of TEC.

Year	PAM (M■kw)	EIA (M■ha.)	EE	POP (M)	V (B■RMB)	PS (sq.m.)
2020	12 4.51	5.4367	0.25	49.08	815.4	52.15
2021	12 5.15	5.4369	0.26	47.77	849.7	52.71
2022	12 5.32	5.4383	0.25	46.83	856.5	52.76
2023	12 5.56	5.4376	0.24	46.34	822.2	52.93
2024	12 5.68	5.4380	0.24	46.11	821.1	52.93
2025	12 5.74	5.4379	0.25	46.03	869.4	52.98

From Table 10, it can be seen that PAM, V, and PS increase to varying degrees over time from 2020 to 2025, POP shows a decreasing trend, also EIA and EE have changed very little. This means that with the gradual increase of V and PS, the use of coal, oil, natural gas and other primary energy will inevitably increase in rural areas of Henan Province.

Figure 10 shows the trends of the influencing factors of TEC from 2009 to 2025. Among them, EE and POP show a decreasing trend, while other influencing factors increased year by year.

Table 11
The estimated values of each influence factor of PC.

Year	V (B■RMB)	EEP (M■kw)	POP (M)	PI (RMB)	PS (sq.m.)	TP (W/ 100 households)
2020	815.4	12.473	49.08	16436	52.15	400790
2021	849.7	12.476	47.77	18242	52.71	418510
2022	856.5	12.477	46.83	19665	52.76	428810
2023	822.2	12.478	46.34	21453	52.93	423440
2024	821.1	12.478	46.11	22996	52.93	428140
2025	869.4	12.478	46.03	25332	52.98	431930

From Table 11, it can be seen that of the six factors affecting rural PC in Henan Province from 2020 to 2025, only the number of POP is constantly decreasing, while V, EEP, PI, PS and TP are increasing to

varying degrees in Henan Province over time.

This means that the increase of EEP, PS and TP will directly lead to the increase of rural electricity consumption. The increase of V and PI improves the living standard of villagers and indirectly leads to the increase of PC.

Figure 11 shows the trends of the influencing factors of PC from 2009 to 2025. Among them, only POP shows a decreasing trend, while other influencing factors increased year by year.

5.2.2. Prediction results of TEC and PC

In order to predict rural TEC and PC in Henan Province, the predicted values of influencing factors in 2020-2025 are put into Equation (17) and Equation (18) respectively.

Thus, the predicted TEC and PC in rural areas of Henan Province from 2020 to 2025 can be calculated, as shown in Table 12 and Table 13.

Table 12
Predicted values of TEC in rural areas of Henan Province from 2020 to 2025.

Year	TEC (B=tons)	Year	TEC (B=tons)
2020	248.448	2023	258.550
2021	253.012	2024	259.237
2022	257.044	2025	260.165

As shown in Table 12, from 2020 to 2025, the TEC in Henan Province keeps a steady growth, and the predicted values of TEC in 2020 and 2025 are 24.84 million tons and 26.02 million tons, respectively. The TEC in rural areas of Henan Province in 2025 is 4.72% higher than that in 2020.

Table 13
Predicted values of PC in rural areas of Henan Province from 2020 to 2025.

Year	PC (B=kw=h)	Year	PC (B=kw=h)
2020	39.078	2023	41.752
2021	40.498	2024	42.240
2022	41.435	2025	43.034

As shown in Table 13, the total rural PC in Henan Province keeps a steady growth from 2020 to 2025, and the predicted values of PC in 2020 and 2025 are 39.078 billion kwh and 43.034 billion kwh, respectively. In 2025, rural PC in Henan Province will increase by 10.12% compared with 2020.

As can be seen from Fig. 12, both PC and TEC in Henan Province are increasing year by year. However, the growth range of TEC will decrease significantly from 2022, while that of PC will increase significantly,

which means that the implementation of Henan Province's rural revitalization strategic plan has achieved significant results in the key task of "promoting rural energy revolution".

Nonetheless, after converting the annual PC in rural areas of Henan Province into standard coal, it accounts for less than 30% of TEC. This shows that rural electrification in Henan Province is at a low level and relies more on fossil energy such as coal, oil and natural gas. According to the forecast values of TEC and PC in Henan Province from 2020 to 2025, in the future, rural TEC in Henan Province will still rely more on fossil energy without transformation. This will undermine the goal of carbon peaking by 2030.

Consequently, the realization of Henan Province's rural energy transformation needs the substitution of low-carbon energy and the improvement of electrification level.

6. Conclusions And Policy Implications

Rural areas account for 12% of global carbon emissions. China, as a major agricultural country, is exploring a low-carbon transformation model of rural energy as a necessary path to achieve carbon neutrality by 2060. This paper takes rural areas of Henan Province as an example to explore the path suitable for the low-carbon transformation of rural energy in Henan Province. The research results of this paper can be summarized into the following aspects.

(1) In this paper, the decoupling states between rural PC and TEC and its influencing factors in Henan Province are analyzed by using decoupling principle. The results show that there are different degrees of decoupling between TEC and PC.

(2) Since there is multicollinearity among the 6 influencing factors of TEC, and the same problem exists among the 6 influencing factors of PC. Therefore, based on STIRPAT model, this paper uses ridge regression method to fit the linear equations of TEC and PC, and the validity of the fitted equations are verified. Rather than simply summing up the primary energy consumption of rural Henan Province.

(3) In addition, this paper optimizes the BP neural network by PSO, and innovatively predicts the values of influencing factors of PC and TEC. The results show that the influencing factors gradually increase year by year. Among them, EIA and EE are basically unchanged, while POP gradually decreases. It is shown that the increase of V can increase PI, thus improving people's living standard, thus improving the work and study efficiency in rural areas, and conversely improving V. Which also means that each influencing factor is complementary to each other.

(4) Finally, the consumption of TEC and PC in 2020-2025 is obtained by STIRPAT using ridge regression. According to the forecast results, the consumption of TEC and PC will continue to increase year by year in 2020-2025. However, from 2022, the growth rate of PC will be greater than that of TEC. This is a good beginning of the low-carbon energy transition in Henan Province. Nonetheless, rural TEC in Henan Province will still be more dependent on fossil fuels in 2020-2025.

These conclusions can provide the following applicable policy implications for rural energy upgrading of Henan Province and other rural areas in China.

First, rural power grid upgrading should be accelerated. (1) Unified planning. The long-term goal of the unified construction of power grid, unified power grid equipment sequence, integrated distribution of power grid services, narrowing the gap between urban and rural power supply services, and promoting the coordinated development of urban and rural power grids. (2) Classified development. First, in light of different regions, strengthen power grids in cities and industrial clusters. Second, according to different voltage levels, the development of strong simplification and orderly, speed up the construction of 110 kv and 10 kv and below power grid, according to the principle of orderly advance and backward optimization of 35 kv power grid. (3) Hierarchical progress by region. While improving the overall power supply capacity of rural power grid in the whole province, we should adhere to the principle of "raising the low and controlling the high", improve the grid load ratio in backward areas, and control the load ratio in areas exceeding the upper limit of the guidelines. (4) High-standard construction. (5) Primary and secondary coordination.

Second, promote renewable energy generation. According to the characteristics of rural regional distribution and resource endowment, different power supply should be adopted. Clean and renewable energy should be the focus of future rural development in Henan Province under the "dual carbon" target. To build a clean and low-carbon rural energy supply system, with the focus on improving the intelligence level of power grids, promote the development of small hydropower, photovoltaic, wind power, methane and other renewable energy sources in rural areas, implement the substitution of electric energy and multi-energy complementarity, improve energy efficiency, and eliminate prominent problems such as high pollution and low energy efficiency in rural development.

Third, promote electric energy substitution projects. (1) To improve the quality of agriculture and promote the electrification of agricultural production. First, centering on the goal of high-standard farmland in Henan, the government should promote comprehensive matching of farmland, water, forest, roads and electricity, and turn more "wang-tian farmland" into "high-yield farmland". Second, promoting the application of technologies such as electric flue-cured tobacco, electric tea production, electric grain drying, heat pump drying of wood, and cold storage of fruits and vegetables, so as to ensure power consumption of intelligent planting and breeding bases and enhance agricultural electrification. (2) Build beautiful villages and electrify rural residents. First, choose heating technology according to local conditions. Second, do a good job in the construction of supporting power grids in the province's 400 villages with tourism characteristics and "1000 villages demonstration" villages. Third, accelerate the layout of charging infrastructure networks, and promote clean replacement projects for different types of vehicles, including buses, taxis, municipal and official vehicles, and private passenger vehicles.

Fourth, in the establishment of national subsidy policies, should be based on the level of agricultural development in the region. The improvement of agricultural mechanization level can promote rural economy and urbanization level. Thus, the V and PI of rural areas are improved, and the living standards

of rural areas are improved, so that the work efficiency of rural areas is further improved, and a virtuous cycle is finally formed, which is the fundamental power of rural energy upgrading in Henan Province. The upgrade of rural energy can improve the utilization efficiency of rural energy, promote the great development of rural economy, improve the income of rural areas and offset the high cost of clean energy. Therefore, on the one hand, attention should be paid to the collaborative promotion of TEC and PC, while improving the use of PC in rural areas, the use quality of TEC should be improved, so as to reduce CO2 emissions in rural areas. On the other hand, agricultural mechanization can increase V and PI, thereby boosting the rural economy and thus offsetting the additional costs of renewable energy.

Abbreviations

Nomenclature	Definition	Units
TEC	Total rural energy consumption in Henan Province	10E4■tons
PAM	Total power of agricultural machinery	10E4■kw
EIA	Effective irrigation area	10E3■ha.
EE	Energy intensity	-
POP	Rural population	10E4
V	Total value of agricultural output	10E8■RMB
PS	Per capita housing area	sq.m.
PC	Rural power consumption in Henan Province	10E8 ■kw ■h
EEP	Electric motor power	10E4■kw ■h
PI	Per capita income	RMB
TP	Total power of rural durable goods	W/ 100 households

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The authors declare that data supporting the findings of this study are available within the article.

Competing interests

The authors declare no conflict of interest.

Funding

This manuscript unfunded support

Authors' contributions

All authors contributed to the study conception and design. Material preparation, Data collection and analysis were carried out by Lei Wen and Qianqian Song. The first draft of the manuscript was written by Qianqian Song and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

References

1. Agrawal S, Harish SP, Mahajan A et al (2020) Influence of improved supply on household electricity consumption - Evidence from rural India. *Energy* 211:118544. <https://doi.org/10.1016/j.energy.2020.118544>
2. Amagai K, Takarada T, Funatsu M, Nezu K (2014) Development of low-CO₂-emission vehicles and utilization of local renewable energy for the vitalization of rural areas in Japan. *IATSS Research* 37:81–88. <https://doi.org/10.1016/j.iatssr.2013.11.001>
3. Asmare F, Jaraitė J, Kažukauskas A (2021) The effect of descriptive information provision on electricity consumption: Experimental evidence from Lithuania. *Energy Econ* 104:105687. <https://doi.org/10.1016/j.eneco.2021.105687>
4. Du Q, Han X, Li Y et al (2021) The energy rebound effect of residential buildings: Evidence from urban and rural areas in China. *Energy Policy* 153:112235. <https://doi.org/10.1016/j.enpol.2021.112235>
5. Duan T, Feng J, Zhou Y et al (2021) Systematic evaluation of management measure effects on the water environment based on the DPSIR-Tapio decoupling model: A case study in the Chaohu Lake watershed, China. *Sci Total Environ* 801:149528. <https://doi.org/10.1016/j.scitotenv.2021.149528>
6. Gani A (2021) Fossil fuel energy and environmental performance in an extended STIRPAT model. *J Clean Prod* 297:126526. <https://doi.org/10.1016/j.jclepro.2021.126526>
7. Ghazali A, Ali G (2019) Investigation of key contributors of CO₂ emissions in extended STIRPAT model for newly industrialized countries: A dynamic common correlated estimator (DCCE) approach. *Energy Reports* 5:242–252. <https://doi.org/10.1016/j.egyr.2019.02.006>
8. Gong Q, Guo G, Li S, Liang X (2021) Decoupling of urban economic growth and water consumption in Chongqing and Chengdu from the “production-living-ecological” perspective. *Sustainable Cities and Society* 75:103395. <https://doi.org/10.1016/j.scs.2021.103395>

9. Han J, Zhang L, Li Y (2021) Spatiotemporal analysis of rural energy transition and upgrading in developing countries: The case of China. *Appl Energy* 118225. <https://doi.org/10.1016/j.apenergy.2021.118225>
10. Han P, Kimura F, Sandu S (2020) Household-level analysis of the impacts of electricity consumption on welfare and the environment in Cambodia: Empirical evidence and policy implications. *Econ Model* 89:476–483. <https://doi.org/10.1016/j.econmod.2019.11.025>
11. He B-J, Yang L, Ye M (2014) Building energy efficiency in China rural areas: Situation, drawbacks, challenges, corresponding measures and policies. *Sustainable Cities and Society* 11:7–15. <https://doi.org/10.1016/j.scs.2013.11.005>
12. He S, Chen W, Mu X, Cui W (2020) Constrained optimization model of the volume of initial rainwater storage tank based on ANN and PSO. *Environ Sci Pollut Res* 27:21057–21070. <https://doi.org/10.1007/s11356-020-08630-6>
13. Huo T, Li X, Cai W et al (2020) Exploring the impact of urbanization on urban building carbon emissions in China: Evidence from a provincial panel data model. *Sustainable Cities and Society* 56:102068. <https://doi.org/10.1016/j.scs.2020.102068>
14. Imran M, Ozcatalbas O, Bakhsh K (2019) Rural household preferences for cleaner energy sources in Pakistan. *Environ Sci Pollut Res* 26:22783–22793. <https://doi.org/10.1007/s11356-019-05588-y>
15. Jia P, Zhuang J, Vaca Lucero AM, Li J (2022) Does the energy consumption revolution improve the health of elderly adults in rural areas? Evidence from China. *Sci Total Environ* 807:150755. <https://doi.org/10.1016/j.scitotenv.2021.150755>
16. Jin J, He R, Kuang F et al (2019) Different sources of rural household energy consumption and influencing factors in Dazhu, China. *Environ Sci Pollut Res* 26:21312–21320. <https://doi.org/10.1007/s11356-019-05439-w>
17. Keshtkarbanaeemoghadam A, Dehghanbanadaki A, Kaboli MH (2018) Estimation and optimization of heating energy demand of a mountain shelter by soft computing techniques. *Sustainable Cities and Society* 41:728–748. <https://doi.org/10.1016/j.scs.2018.06.008>
18. Kim MK, Kim Y-S, Srebric J (2020) Impact of correlation of plug load data, occupancy rates and local weather conditions on electricity consumption in a building using four back-propagation neural network models. *Sustainable Cities and Society* 62:102321. <https://doi.org/10.1016/j.scs.2020.102321>
19. Lemence ALG, Tamayao M-AM (2021) Energy consumption profile estimation and benefits of hybrid solar energy system adoption for rural health units in the Philippines. *Renewable Energy* 178:651–668. <https://doi.org/10.1016/j.renene.2021.06.090>
20. Li H, Mu H, Zhang M, Li N (2011) Analysis on influence factors of China's CO₂ emissions based on Path–STIRPAT model. *Energy Policy* 39:6906–6911. <https://doi.org/10.1016/j.enpol.2011.08.056>
21. Li M, Jin T, Liu S, Zhou S (2021) The cost of clean energy transition in rural China: Evidence based on marginal treatment effects. *Energy Econ* 97:105167. <https://doi.org/10.1016/j.eneco.2021.105167>

22. Lin B, Li Z (2020) Spatial analysis of mainland cities' carbon emissions of and around Guangdong-Hong Kong-Macao Greater Bay area. *Sustainable Cities and Society* 61:102299. <https://doi.org/10.1016/j.scs.2020.102299>
23. Lin S, Wang S, Marinova D et al (2017) Impacts of urbanization and real economic development on CO₂ emissions in non-high income countries: Empirical research based on the extended STIRPAT model. *J Clean Prod* 166:952–966. <https://doi.org/10.1016/j.jclepro.2017.08.107>
24. Ma B, Yu Y, Urban F (2018) Green transition of energy systems in rural China: National survey evidence of households' discrete choices on water heaters. *Energy Policy* 113:559–570. <https://doi.org/10.1016/j.enpol.2017.11.046>
25. Ma S, Xu X, Li C et al (2021a) Energy consumption inequality decrease with energy consumption increase: Evidence from rural China at micro scale. *Energy Policy* 159:112638. <https://doi.org/10.1016/j.enpol.2021.112638>
26. Ma X, Wang M, Chen D, Li C (2021b) Energy choice in rural household cooking and heating: influencing factors and transformation patterns. *Environ Sci Pollut Res* 28:36727–36741. <https://doi.org/10.1007/s11356-021-13213-0>
27. Mahajan A, Harish SP, Urpelainen J (2020) The behavioral impact of basic energy access: A randomized controlled trial with solar lanterns in rural India. *Energy Sustain Dev* 57:214–225. <https://doi.org/10.1016/j.esd.2020.04.005>
28. Malik A, Tikhamarine Y, Sammen SS et al (2021) Prediction of meteorological drought by using hybrid support vector regression optimized with HHO versus PSO algorithms. *Environ Sci Pollut Res* 28:39139–39158. <https://doi.org/10.1007/s11356-021-13445-0>
29. Minaei F, Minaei M, Kougiass I et al (2021) Rural electrification in protected areas: A spatial assessment of solar photovoltaic suitability using the fuzzy best worst method. *Renewable Energy* 176:334–345. <https://doi.org/10.1016/j.renene.2021.05.087>
30. Peng H, Xiao Z, Wang J, Li J (2021) A decision support framework for new energy selection in rural areas from the perspectives of information reliability and criterion non-compensation. *Energy* 235:121435. <https://doi.org/10.1016/j.energy.2021.121435>
31. Rahman MdM, Paatero JV, Poudyal A, Lahdelma R (2013) Driving and hindering factors for rural electrification in developing countries: Lessons from Bangladesh. *Energy Policy* 61:840–851. <https://doi.org/10.1016/j.enpol.2013.06.100>
32. Riva F, Colombo E (2020) System-dynamics modelling of the electricity-development nexus in rural electrification based on a Tanzanian case study. *Energy Sustain Dev* 56:128–143. <https://doi.org/10.1016/j.esd.2020.04.001>
33. Robert FC, Gopalan S (2018) Low cost, highly reliable rural electrification through a combination of grid extension and local renewable energy generation. *Sustainable Cities and Society* 42:344–354. <https://doi.org/10.1016/j.scs.2018.02.010>
34. Sedai AK, Nepal R, Jamasb T (2021) Flickering lifelines: Electrification and household welfare in India. *Energy Econ* 94:104975. <https://doi.org/10.1016/j.eneco.2020.104975>

35. Shahbaz M, Chaudhary AR, Ozturk I (2017) Does urbanization cause increasing energy demand in Pakistan? Empirical evidence from STIRPAT model. *Energy* 122:83–93.
<https://doi.org/10.1016/j.energy.2017.01.080>
36. Su B, Goh T, Ang BW, Ng TS (2022) Energy consumption and energy efficiency trends in Singapore: The case of a meticulously planned city. *Energy Policy* 161:112732.
<https://doi.org/10.1016/j.enpol.2021.112732>
37. Suman GK, Guerrero JM, Roy OP (2021) Optimisation of solar/wind/bio-generator/diesel/battery based microgrids for rural areas: A PSO-GWO approach. *Sustainable Cities and Society* 67:102723.
<https://doi.org/10.1016/j.scs.2021.102723>
38. Tesfamichael M, Bastille C, Leach M (2020) Eager to connect, cautious to consume: An integrated view of the drivers and motivations for electricity consumption among rural households in Kenya. *Energy Research & Social Science* 63:101394. <https://doi.org/10.1016/j.erss.2019.101394>
39. Vinicius GTF, Silvia C, Aleksandar D et al (2021) Rural electrification planning based on graph theory and geospatial data: A realistic topology oriented approach. *Sustainable Energy, Grids and Networks* 28:100525. <https://doi.org/10.1016/j.segan.2021.100525>
40. Wang P, Wu W, Zhu B, Wei Y (2013) Examining the impact factors of energy-related CO₂ emissions using the STIRPAT model in Guangdong Province, China. *Appl Energy* 106:65–71.
<https://doi.org/10.1016/j.apenergy.2013.01.036>
41. Wen L, Yuan X (2020a) Forecasting the annual household electricity consumption of Chinese residents using the DPSO-BP prediction model. *Environ Sci Pollut Res* 27:22014–22032.
<https://doi.org/10.1007/s11356-020-08418-8>
42. Wen L, Yuan X, PSO (2020b) Forecasting CO₂ emissions in Chinas commercial department, through BP neural network based on random forest and. *Science of The Total Environment* 718:137194.
<https://doi.org/10.1016/j.scitotenv.2020.137194>
43. Wenbo G, Yan C (2018) Assessing the efficiency of China's environmental regulation on carbon emissions based on Tapio decoupling models and GMM models. *Energy Reports* 4:713–723.
<https://doi.org/10.1016/j.egyr.2018.10.007>
44. Wu F, Liu X, Wang W et al (2015) Characterization of particulate-bound PAHs in rural households using different types of domestic energy in Henan Province, China. *Sci Total Environ* 536:840–846.
<https://doi.org/10.1016/j.scitotenv.2015.07.101>
45. Wu Q (2021) Optimization of AI-driven communication systems for green hospitals in sustainable cities. *Sustainable Cities and Society* 72:103050. <https://doi.org/10.1016/j.scs.2021.103050>
46. Wu R, Wang J, Wang S, Feng K (2021) The drivers of declining CO₂ emissions trends in developed nations using an extended STIRPAT model: A historical and prospective analysis. *Renew Sustain Energy Rev* 149:111328. <https://doi.org/10.1016/j.rser.2021.111328>
47. Wu S (2020) The evolution of rural energy policies in China: A review. *Renew Sustain Energy Rev* 119:109584. <https://doi.org/10.1016/j.rser.2019.109584>

48. Yahyaoui I, Yahyaoui A, Chaabene M, Tadeo F (2016) Energy management for a stand-alone photovoltaic-wind system suitable for rural electrification. *Sustainable Cities and Society* 25:90–101. <https://doi.org/10.1016/j.scs.2015.12.002>
49. Yang S, Cao D, Lo K (2018) Analyzing and optimizing the impact of economic restructuring on Shanghai's carbon emissions using STIRPAT and NSGA-II. *Sustainable Cities and Society* 40:44–53. <https://doi.org/10.1016/j.scs.2018.03.030>
50. Zhao L, Zhao T, Yuan R (2021) Scenario simulations for the peak of provincial household CO₂ emissions in China based on the STIRPAT model. *Sci Total Environ* 151098. <https://doi.org/10.1016/j.scitotenv.2021.151098>
51. Zi C, Qian M, Baozhong G (2021) The consumption patterns and determining factors of rural household energy: A case study of Henan Province in China. *Renew Sustain Energy Rev* 146:111142. <https://doi.org/10.1016/j.rser.2021.111142>
52. Zou B, Luo B (2019) Rural household energy consumption characteristics and determinants in China. *Energy* 182:814–823. <https://doi.org/10.1016/j.energy.2019.06.048>
53. Zou B, Mishra AK (2020) Appliance usage and choice of energy-efficient appliances: Evidence from rural Chinese households. *Energy Policy* 146:111800. <https://doi.org/10.1016/j.enpol.2020.111800>

Figures

Figure 1

The technical roadmap.

Figure 2

Decoupling elasticity indexes between TEC and influencing factors.

Figure 3

Decoupling elasticity indexes between PC and influencing factors.

Figure 4

Schematic diagram of typical N-dimensional input neuron model.

Figure 5

The flow chart of PSO-BP.

Figure 6

Ridge regression curves.

Figure 7

Variation of K at different RSQ.

Figure 8

Ridge regression curves.

Figure 9

Variation of K at different RSQ.

Figure 10

The trend chart of six influencing factors of TEC from 2009 to 2025.

Figure 11

The trend chart of six influencing factors of TEC from 2009 to 2025.

Figure 12

Line chart of PC and TEC changes from 2020-2025.