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Relationship between Technology Input and Carbon Entropy of Industrial System: Based on a Dynamic Hamilton System

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Abstract: The carbon entropy can be effectively reduced with technological advances. To investigate the concrete relationship between carbon entropy and technology input in an industrial system, we constructed a linear model of carbon entropy in association with the technical factors, simplified as a semi-parameter model. By combining the semi-parameter model with the utility function of an carbon entropy, we formed a dynamic Hamilton system, pointing out that a quick way to realize the comprehensive emission reduction target is to increase the R&D input intensity of a traditional industry.

Keywords: Carbon entropy; The Hamilton system; Semi-parametric model

1 Introduction

The economic development is always keeping pace with technological advances. The carbon footprint has long been regarded as the price that must be paid in the process of economic development, so it is included by many a scholar in the cost of economic development and theories have been put forward to explore devices to control this cost, a very efficient of which is commonly ascribed to the technological input. The primary relationship between technological input and carbon entropy is that of a negative correlation, that is the technology can effectively reduce the carbon entropy. Since the technological advances mainly depend on the R&D input, there arises the question of whether carbon entropy will be reduced with the ever increasing R&D input.

In exploring the law of China's R&D investment, Chen [1] found that China shares the same features in R&D input intensity with many a developed country, quite similar to those of an S curve, where the R&D input intensity approximates a stable level. The logistic curve fitting was adopted by Chen in his research to analyze the R&D input intensity in China, thus predicting that the R&D input intensity will approximate a stable value, a value that is expected to best meet the demand on industrial development. Tarasyev and Watanabe [2] made an in-depth study respectively in 2001 and 2007 on the relationship between the R&D investment in and the development of Japan's automobile industry. They concluded that the R&D input intensity of an industry needs to be correlated with the level of its development, because at the initial stage the R&D input will make the automobile industry develop quickly, later the marginal benefit will decrease with more investment injected into the automobile industry, and finally the benefit will be a negative one that will affect the industrial development. There forms a dynamic equilibrium of rise and fall between the production and the R&D input. As is shown by these research results, there is a similar dynamic equilibrium between the technology input and carbon entropy of an

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industrial system, and the optimal dynamic programming theory is also applicable to a study on the relationship between technology input and carbon entropy of an industrial system.

2 Construction of the Economics Model on the Carbon Entropy of an Industrial System

The initial effort to introduce the technical factor into a neo-classical economic growth model was made by Arrow [3] in his Cobb-Douglas form:

$$Y = AK^{b_1}L^{b_2}M^{b_3}E^{b_4}T^{b_5}, \tag{1}$$

in which K is fixed investment, L is labor force, M is raw materials, E is total energy consumed, and T is technology input. According to a study made by Lu [4], the carbon entropy of an industrial system can be expressed as: $U = C/Y$, where C is undesirable output. Then by combining it with Equation (1), we obtain:

$$U = \frac{C}{AK^{b_1}L^{b_2}M^{b_3}E^{b_4}T^{b_5}}. \tag{2}$$

Equation (2) does not belong to a regular Cobb-Douglas form [5], not good for practical analysis, so we may introduce the total variable output X. A further transformation on the equation is as follows:

$$U = \frac{1}{A}\frac{C}{X}\frac{X}{T}(\frac{T}{K})^{b_1}(\frac{T}{L})^{b_2}(\frac{T}{M})^{b_3}(\frac{T}{E})^{b_4}, \tag{3}$$

in which C/X stands for undesirable output rate and is further denoted by f_1, X/T stands for the marginal income rate of technology input and is denoted by f_2, T/K stands for the substitution rate of technology for capital and is denoted by f_3, T/L stands for the substitution rate of technology for labor force and is denoted by f_4, T/M stands for the substitution rate of technology for raw materials and is denoted by f_5 and T/E stands for the substitution rate of technology for energy and is denoted by f_6.

This paper is aimed at exploring the influence of technology input on the carbon entropy of an industrial system [6], so we have a differential equation of the carbon entropy U:

$$\dot{U} = \frac{\partial U}{\partial f_1}+\frac{\partial U}{\partial f_2}\dot{X}+\frac{\partial U}{\partial f_3}\dot{K}+\frac{\partial U}{\partial f_4}\dot{L}+\frac{\partial U}{\partial f_5}\dot{M}+\frac{\partial U}{\partial f_6}\dot{E}+\frac{\partial U}{\partial f_2}\frac{\partial X}{\partial T}\dot{T}+\frac{\partial U}{\partial f_2}\frac{\partial K}{\partial T}\dot{T}+\frac{\partial U}{\partial f_2}\frac{\partial L}{\partial T}\dot{T}+\frac{\partial U}{\partial f_2}\frac{\partial M}{\partial T}\dot{T}+\frac{\partial U}{\partial f_2}\frac{\partial E}{\partial T}\dot{T}. \tag{4}$$

In Equation (4), the former half may account for the influence of production factors on undesirable output as denoted by F, the latter half may account for the influence of technology input on undesirable output as denoted by $g\dot{T}$, in which $\dot{T}$ stands for marginal technology input, or it may account for R&D input as denoted by r. $\dot{U}$ may be expressed as:

$$\dot{U} = F - gr. \tag{5}$$

3 Construction of the Utility Function of the Carbon Entropy of an Industrial System

The widely accepted model on the utility function of technology input is the utility model on R&D input constructed by Grossman [7]:

$$W_t = \int_{t_0}^{\infty} e^{-\rho(t-t_0)} \log D(t)dt.$$

Here $D(t) = \left[\int_0^n N^{\alpha}(i)di\right]^{1/\alpha}$, n stands for the number of new products, $N = Y/n$ stands for the contribution rate of a new product to desirable output. Based on this model, the utility function of R&D input in relation to the desirable output of an industrial system should be like this. In the meanwhile, $n(t) = Be^{kt}T^{b_1}R^{b_2}$. Technology investment generates technology absorption and technology spillovers, so cumulative technology input can be expressed as $T = \mu T_d + \nu R$, in which μ is the natural rate of increase in cumulative technology input, ν is absorption rate of R&D input. The utility function of the desirable output intensity of the final industrial system can be formulated as:

$$W_t = -\int_{t_0}^{\infty} e^{-\rho(t-t_0)}(\log Y(t) + a_1 \log(\mu T_d(t) + \nu R(t)) + a_2 \log R(t))dt. \tag{6}$$

4 Solution of the Dynamic System of a Carbon Entropy

The purpose of this paper is to minimize the carbon entropy, which is to let Equation (6) take the minimum value, which amounts to letting Equation (7) take the maximum value after constructing the utility function and the economics model of the carbon entropy of an industrial system.

$$W_t = \int_{t_0}^{\infty} e^{-\rho(t-t_0)}(\log Y(t) + a_1 \log(\mu T_d(t) + \nu R(t)) + a_2 \log R(t))dt. \tag{7}$$

Therefore, we get the equation set as follows:

$$W_t = \int_{t_0}^{\infty} e^{-\rho(t-t_0)}(\log Y(t) + a_1 \log(\mu T_d(t) + \nu R(t)) + a_2 \log R(t))dt,$$
$$\dot{U} = F - gr,$$
$$\dot{T} = r.$$

An optimal dynamic programming on the Hamilton system [8] is thus formed as:

$$H(t, Y, T, r, \phi_1, \phi_2) = \int_{t_0}^{\infty} e^{-\rho(t-t_0)}[\log Y(t) + a_1 \log(\mu T_d(t) + \nu R(t) + a_2 \log R(t)] + \phi_1[FY(t) - gR(t)] + \phi_2 R(t). \tag{8}$$

The control equation of the optimal dynamic programming on the Hamilton system as denoted by Equation (7) of the carbon entropy of an industrial system thus is formed:

$$\frac{\partial H}{\partial R} = e^{-\rho(t-t_0)}(\frac{a_1 \nu}{\mu T_d + \nu R} + \frac{a_2}{R}) - \phi_1 g + \phi_2 = 0.$$

In order to solve the problem of adjoint variable, we introduced the shadow cost into the desirable output rate $Y$and the cumulative technology input T_d to loosen constraints:

$$Z_1 = \phi_1^0 Y, \qquad Z_2 = \phi_2^0 T_d.$$

Then the total shadow cost is:

$$Z(t) = Z_1(t) + Z_2(t).$$

By associating with the expression of shadow cost and taking out the adjoint variable, we introduced the variable $I = Y/T_d$ to express the average output efficiency of technology input and thus the optimal R&D input intensity:

$$r^* = \frac{a_2}{gZ^0 - a_1 \lambda I}. \tag{9}$$

5 An Empirical Analysis on the Dynamic System of Carbon Entropy of China's Industry Sectors

In order to verify the correctness and feasibility of the theoretical analysis, we used the 2011-2012 data from China's industry sectors to carry out an empirical study on the dynamic system of the carbon entropy of China's industrial system.

5.1 Data sources

China has a fairly good statistical system for its industry sectors, so we carried out an empirical analysis on the carbon entropy change of China's industrial system. The primary data used in this analysis were mainly derived from China

Statistical Yearbook 2013, China Industry Statistical Yearbook (2001-2013), China Environment Statistical Yearbook (2001-2013), and China Science and Technology Statistical Yearbook (2001-2013) promulgated by the National Bureau of Statistics of the PRC.

5.2 Verification of the model on the carbon entropy of an industrial system

The model constructed in this paper on the carbon entropy of an industrial system mainly comprises a relatively complete formula and a simplified version of it, respectively expressed as Equations (3) and (5). An empirical analysis was carried out on the 2001-2012 data from China's industry sectors. We adopted typical data from "the coal mining and washing industry" to construct an economics model on the carbon entropy of an industrial system. Results of the linear regression of Equation (3) showed the goodness of fit of the model is acceptable ($R^2 = 0.9475$), the statistical magnitude of F passes the 5% significance level test as well, but only f_i among the model coefficients passes the 5% significance level test, the other coefficients are not significant. The fitting on the linear regression model of Equation (3) shows that this linear regression model explains the carbon entropy to some extent, but it is not so reasonable and needs to be adjusted further. The simplified model expressed as Equation (5) was analyzed theoretically, followed by a further analysis based on empirical data. In the results of linear regression model fitting, there exists a self-correlation between each independent variable f_i. So the functional form of each independent variable f_i in this paper may be expressed as a non-parametric expression $m(F)$. In the meanwhile, in the data from the coal mining and washing industry, there exists a certain linear relation between the carbon entropy denoted as U and R&D input intensity denoted as γ. But the direct linear fitting is not effective. With a view to the research purpose of revealing the relationship between technology input and carbon entropy, the regression results of Equation (3) may be combined with the direct fitting to divide the economics model on the carbon entropy of an industrial system into two parts. One is the influence of production factors on the carbon entropy, which forms an ambiguous relation and the non-parametric part, while the other is influence of R&D input intensity denoted as γ on the carbon entropy, which forms a fairly definite linear main. The final semi-parametric model is thus formed as follows:

$$U = m\left(F\right) + gr,$$

in which g is the coefficient of r, denoting the marginal efficiency of carbon entropy brought by technology input. The software packages of R [9] are adopted to conduct fitting on the above semi-parametric model, using f_i one by one in the process of fitting to replace F, the result showed that the semi-parametric model of f_3 has the best fitting effect among the complex relations inherent in the influence of production factors on non-desirable output intensity, where the goodness of fit of R^2 that attains 0.982 (see Table 1). Compared with the results of linear regression mentioned above, the fitting effect has been greatly improved. The semi-parametric model [10] finally constructed in this paper on China's coal mining and washing industry is expressed as:

$$U_1 = 0.1260m\left(f3\right) - 1.0599r.$$

It can be concluded that the simplified economics model denoted by Equation (5) on the carbon entropy of China's industry sectors represented by the coal mining and washing industry fits the empirical data of China's industrial sectors quite well. This conclusion provides reference for the future construction of the carbon entropy of other industry sectors in China. By adopting the same approach, we can obtain the marginal efficiency denoted by g values of the carbon entropy brought by technology input of all those industry sectors from whom complete data may be derived.

5.3 Utility function fitting of the carbon entropy of an industrial system

The carbon entropy model constructed with reference to the R&D input utility model and the desirable output rate model is expressed as Equation (6) and the solution to the optimal dynamic Hamilton system of an industrial system depends

Table 1: Fitted results of the semi parametric model on the carbon entropy in China's industry sectors

Semi-parametric model	Estimate	Std. Error	t value	Pr($>|t|$)	R-sq.(ad)	Deviance explaind
f1	0.0222	0.0160	6.944	0.0244	0.972	98.9%
r	0.0198	0.0140	4.579	0.0673		
f2	0.1242	0.0248	5.015	0.0216	0.907	97.8%
r	-0.0586	0.0190	-3.083	0.0657		
f3	0.1260	0.0112	11.197	0.0399	0.982	99.8%
r	-1.0599	0.0086	-6.946	0.0690		
f4	-0.0228	0.0399	-0.571	0.589	0.901	94.6%
r	0.0544	0.0307	1.771	0.127		
f5	0.0827	0.0078	10.592	2.21e-06	0.734	78.3%
r	-0.0215	0.0057	-4.662	0.001 2		
f6	0.0759	0.0140	5.421	0.0004	0.743	79%
r	-0.0215	0.0106	-2.025	0.073 5		

on fitting on the utility model on carbon entropy [11]. In the expression for number of new products written as $n(t) = Be^{kt}T^{b_1}R^{b_2}$, the cumulative technology input is denoted as $T_t = \mu T_{t-1} + vR$ from the perspective of R&D input absorption rate, and it is denoted from the perspective of the rate of technology expiry as

$$T_t = R_{t-m} + (1-\theta)T_{t-1}, \tag{10}$$

in which m is the average number of years for the industrialization of technology input, and θ is the rate of technology expiry.

The cumulative technology input denoted as T_t, that is technology reserve, can not be obtained through counting but only through calculation in the practical statistical work of science and technology. If the data of m and θ are available, the cumulative technology input denoted as T_t will be obtained that excludes the data for the accidental 1-phase. When $t = 1$, it can be deduced from Equation(10) that:

$$T_0 = R_{1-m}/(\delta + \theta), \tag{11}$$

in which, δ is the average growth rate of R&D input, thus by which to fit the function of new products.

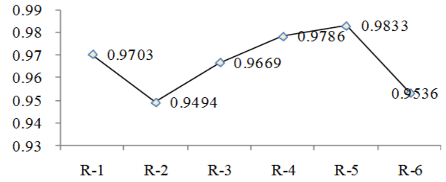
The data of R&D input were derived from the 1997-2012 data of "the coal mining and washing industry", where the average number of year of the industrialization of technology input denoted by m and the technology expiry rate denoted by θ are essentially at the same level among the traditional industry sectors whose data are complete, so the aggregate level of China's industry sectors were chosen as the value for calculation.

We argued that the statistics on the actual average year of technology use is rather difficult due to the huge number and complexity of technologies. Therefore, the elimination rate of patented inventions was chosen to calculate the technology expiry rate [12] in this paper according to the yearly technology expiry rate θ in the Patent Statistical Yearbook promulgated by the State Intellectual Property Office of the PRC, which is comparatively appropriate in contrast with the technology expiry rate of 14% $\sim$ 22% in Japan in the 1990s.

The partial correlation coefficient method adopted to compute the average number of years for the industrialization of technology input denoted by m may be referred to Li Xu [13]. The partial correlation coefficients of 1$\sim$6-phase lag that have been worked out are shown in Fig.1(a), which shows that the partial correlation coefficient of the 5^{th} year is the highest, so we may let $m = 5$. Moreover, the polynomial distribution lag model may be adopted to conduct fitting on the relationship between increased value and R&D input, thus determining the number of lag phases. Seen from the

Table 2: A summary sheet of the computation results of optimal R&D input intensities in China's industry

Industry Sector No.	g	a_1	a_2	λ	I	(%)
Coal mining and washing(X1)	1.059 9	2.135	3.529	0.2118	2.5497	3.0275
Oil and gas exploration(X2)	1.134 2	*				
Mining and dressing of ferrous metals(X3)	-					
Non-ferrous metal mining(X4)	*					
Mining and dressing of non-metallic minerals(X5)	1.0742	2.745	5.544	0.1986	5.7692	3.3979
Other mining(X6)	-					
Agricultural and sideline food processing(X7)	1.5064	-0.546	3.527	0.2391	3.9888	3.506 5
Food manufacturing(X8)	1.1765	0.791	5.644	0.2223	3.7145	3.8888
Beverage manufacturing(X9)	1.1598	1.175	6.363	0.2014	5.4431	3.8858
Tobacco products(X10)	*					
Textiles(X11)	1.7769	-0.793	4.146	0.1973	3.7599	3.2015
Manufacture of textile garments, shoes, and hats(X12)	*					
Leather, fur, feather and related Products(X13)	1.5142	*				
Timber processing and rattan products industry(X14)	*					
Furniture manufacturing(X15)	1.0629	-0.271	5.722	0.1906	3.0001	5.0002
Paper manufacturing and paper products(X16)	2.3145	*				
Printing and copying of recording media(X17)	2.1437	*				
educational and sporting goods manufacturing(X18)	1.0562	0.124	6.377	0.2466	5.1437	4.8353
Oil processing, coking and nuclear fuel processing(X19)	1.0349	0.569	5.443	0.3122	5.1411	4.5346
Chemical raw materials and chemical products(X20)	1.7692	2.124	5.776	0.3491	5.7892	2.2352
Pharmaceutical manufacturing (X21)	*					
Chemical fiber manufacturing (X22)	1.0947	2.135	3.389	0.2411	3.5388	2.8914
Rubber products (X23)	1.1802	*				
Plastic products (X24)	1.1794	0.171	5.783	0.2077	5.8838	4.2371
Non-metallic mineral products(X25)	1.1761	0.792	6.224	0.2156	5.1639	3.9835
Smelting and pressing of ferrous metals(X26)	1.0549	2.217	4.445	0.2983	3.2814	3.3537
Smelting and pressing of nonferrous metals(X27)	1.0872	2.343	3.712	0.2199	2.7834	2.9366
Fabricated metal products (X28)	1.1064	1.817	3.562	0.2273	5.7936	3.0910
General equipment manufacturing (X29)	0.9782	0.117	5.722	0.2999	5.7760	5.1039
Special equipment manufacturing (X30)	0.9645	-0.521	4.993	0.1904	2.3122	5.6615
Transportation equipment manufacturing (X31)	1.0576	-0.316	5.729	0.1966	2.1973	5.0620
Electrical machinery and equipment (X32)	1.1115	0.142	5.872	0.2011	2.7831	4.5220
Manufacture ofcomputers and other e- equipment (X33)	0.9028	-0.512	6.669	0.2032	2.147 7	6.1800
Instruments, meters and cultural and office machinery manufacturing (X34)	1.0776	-0.567	6.318	0.2221	2.0173	5.1997
Crafts and other manufacturing (X35)	-					
materials recycling and processing (X36)	-					
Electricity and heat production and supply (X37)	1.5371	1.377	4.761	0.3115	5.1827	2.6356
Gas production and supply (X38)	*					
Tap water production and supply (X39)	*					



(a) Coefficients of Partial Correlation

Lag Distribution of R	i	Coefficient	Std. Error	t-Statistic
	0	0.00021	0.00049	0.42137
	1	0.00040	0.00042	0.95950
	2	-4.3E-05	0.00037	-0.11635
	3	-7.4E-05	0.00053	-0.14006
	4	0.00136	0.00061	2.22208
Sum of Lags		0.00186	0.00020	9.06473

(b) 4-Phase Lag Fitting

Lag Distribution of R	i	Coefficient	Std. Error	t-Statistic
	0	-0.00068	0.00026	-2.63268
	1	0.00040	0.00012	3.43234
	2	0.00036	8.3E-05	4.30119
	3	3.6E-05	0.00012	0.30709
	4	0.00030	0.00014	2.14652
	5	0.00199	0.00028	7.23401
Sum of Lags		0.00241	9.5E-05	25.4325

(c) 5-Phase Lag Fitting

Lag Distribution of R	i	Coefficient	Std. Error	t-Statistic
	0	0.00021	0.00071	0.29557
	1	0.00026	0.00052	0.49768
	2	0.00023	0.00031	0.73794
	3	0.00020	0.00031	0.63971
	4	0.00024	0.00054	0.44812
	5	0.00044	0.00056	0.77450
	6	0.00086	0.00055	1.56419
Sum of Lags		0.00243	0.00032	7.56593

(d) 6-Phase Lag Fitting

Figure 1: Computation results of the average duration of the industrialization of technology input

computational results of Eviews as shown in Figs. 1 (b)-(d), the fitting effect of 5-phase lag is the best, which is consistent with the computation result of partial correlation coefficient method.

The cumulative technology input denoted as T_t may be computed via Equation(10) and Equation (11). By computing the value of each parameter, we may further conduct fitting via the above equations on the cumulative technology input. Thus fixing the approximate technology input absorption rate denoted as λ :

$$T = 1.0690T_{t-1} + 0.2664R, \qquad R^2 = 0.9764, \qquad F = 186.3.$$

(9.112) (2.958)

It can be seen here that the fitting effect of a cumulative technology input function is very good, the natural growth rate of technology reserve mounts to 6.9%, and the average absorption rate of R&D input is 26.64%. Fitting may be further conducted on the new product output value after the cumulative technology input denoted as T and the R&D input denoted as R are computed, formulated as follows:

$$N = \beta_N + b_1 T + b_2 R,$$

in which b_1 stands for correlation coefficient of T, and b_2 stands for correlation coefficient of R.

$$N = 8.7192 + 0.2155T + 0.3529R, \qquad R^2 = 0.9472, \qquad F = 80.72.$$

(14.726) (3.163) (4.051)

Thus we have $b_1 = 0.2155$, $b_2 = 0.3529$, and by referring to Grossman [7], we may have $a_1 = 2.155$, $a_2 = 3.529$.

5.4 Dynamic system solution of the carbon entropy of an industrial system

Via fitting on the carbon entropy function of an industrial system and fitting on the carbon entropy function of an industrial system, the optimal R&D input intensity denoted as r^* that can reduce the carbon entropy of an industrial system may be worked out according to Equation(7), which involves the following parameters: the marginal efficiency of carbon entropy brought by technology input $g = 1.0599$, the technology input coefficient of the number of new products $a_1 = 2.155$, $a_2 = 3.529$, the comprehensive technology absorption rate $\lambda = 0.2118$, the average output efficiency of technology input $I = 2.5497$, and the discount rate ρ.

The model based on the empirical data analysis of “the coal mining and washing industry” will be popularized to compute the optimal R&D input intensity that can reduce the carbon entropy of China’s other industry sectors, whose computation results are shown in Table 2.

6 Conclusions and Prospect

Based on the above research, we draw the following conclusions:

(1)Viewed from the results of empirical analysis, it will be easy to attain the optimal level and a better emission reduction effect by enlarging the R&D input intensity in a traditional industry, like chemistry and chemical engineering, metal melting, and mineral mining. Currently this is a relatively rapid way in which to attain the objective of comprehensive emission reduction.

(2) It can be seen from Table 2 that all values of a_2 are larger than values of a_1, showing that the R&D input makes a larger contribution to new product output value than the cumulative technology input does. Moreover, the λ values of each sector are relatively approximate to each other, showing that the comprehensive absorption rate of R&D is fairly stable.

(3) The universality of the theoretical model needs to be improved. The solution and fitting can not be done on the model due to the nonlinear features of data, so the future research will be oriented towards introducing the nonlinear function into our model to improve the model precision and universality.

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