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Article

Quantitative Analysis of Dynamic Behaviours of Rural Areas at Provincial Level Using Public Data of Gross Domestic Product

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Abstract: A spatial approach that incorporates three economic components and one environmental factor has been developed to evaluate the dynamic behaviours of the rural areas at a provincial level. An artificial fish swarm algorithm with variable population size (AFSAVP) is proposed for the spatial problem. A functional region affecting index (Θ) is employed as a fitness function for the AFSAVP driven optimisation, in which a gross domestic product (GDP) based method is utilised to estimate the CO_2 emission of all provinces. A simulation for the administrative provinces of China has been implemented, and the results have shown that the modelling method based on GDP data can assess the spatial dynamic behaviours and can be taken as an operational tool for the policy planners.

Keywords: spatial analysis; functional region; dynamic behaviours; social behaviours; carbon dioxide emission; public data; gross domestic product; swarm algorithm; artificial fish

1. Introduction

During the past two decades, China's rapid economic growth has been making China become one of the largest contributors to the global economy and natural environment issues [1]. Combining with China's large population, rapid urbanisation, increasing household wealth demands and local economic redisbtribution, unbalanced pressure has deployed on regional development and caused low efficient environmental recycle. Issues of the local impact of various air pollutants on the regional economic development, such as carbon monoxide (CO), nitrogen oxides (NO_x), sulphur dioxide (SO_2), have been extensively discussed.

The global warming is one of the most serious environmental issues that human currently confronts. The mechanism of global warming has not yet been fully understood. However, it has been considered closely related to the emission of the anthropogenic greenhouse gases, such as carbon dioxide (CO_2) and methane (CH_4). These issues has attracted researchers' extensive interest, and in reality various countermeasures, such as technological development, abatement policies based on economic mechanisms and international negotiations, have been discussed and partially applied into practices [2,3].

As it has been widely accepted, CO_2 emission is connected with the human activities mainly through the consumption of fossil fuel type energy, for example the operation of a fossil fuel power station. To evaluate the dynamic behaviours of the regional areas coupled with energy consumption and CO_2 emissions, a few interdisciplinary studies have been conducted. Berling-wolff and Wu outlined the historical development of urban growth models, which indicated the different disciplines and diverse theories could be brought together to hybrid the newly developed models including fuzzy logic theory and neural network theory [4]. Nejadkoorki *et al.* proposed a model for the road traffic CO_2 emissions of an urban area with three components [5]. Weiss *et al.* presented a bottom-up model for the non-energy use of fossil fuels and its CO_2 emissions [6]. Bala discussed rural energy supply projections and assessed the contributions to global warming. Dynamic system models have provided an overall energy balance analysis [7]. Generally speaking, these study integrated interdisciplinary factors and in particular used the interaction between economic activities and surrounding environmental factors.

In recent years, computational intelligence methods, such as genetic algorithms (GA), swarm algorithms, fuzzy logic methods and artificial neural network (ANN), have been widely used in empirical applications [8–22].

The artificial fish swarm algorithm (AFSA) [23] is one of the swarm algorithms, which is inspired by the social behaviours of the fish school in searching, swarming and following. A schooling fish can response quickly to the changes in the direction and speed of their neighbours, and the information of their behaviours can be passed to others and help them move from one configuration to another almost as one unit. By borrowing this intelligence of the social behaviours, the AFSA is parallel and independent to the initial values, and able to achieve a global optimum. In this paper, an AFSA method with the variable of population size (AFSAVP) is proposed, which is applied to the intelligent approach for a spatial analysis that incorporates three economic components and one environmental factor of carbon dioxide emission.

2. Variable Population Size Fish Swarm Algorithm

Inspired by the swarm intelligence of the fish schooling behaviours, the AFSA is an artificial intelligent algorithm that firstly simulates the behaviour of an individual artificial fish (AF) and then constructs an AF schooling. Each AF searches its own local optimal solution and passes information to its self-organized system, and finally achieves the global optimal solution.

The AFSAVP provides a one-variable AF population P. As stated in Equation (1), the AF school population P is made up of two sub-schools: the replaceable school P_R and the non-replaceable school P_N. Equation (2) gives P_R at generation t, which is calculated by its own size plus the off-size ΔP_R at generation $t-1$. As stated in Equation (3), the off-size replaceable population is proportional to the size of P_R, where λ is a reproduction rate set by users.

$$P(t) = P_R(t) + P_N(t) \tag{1}$$

$$P_R(t) = P_R(t-1) + \Delta P_R(t-1) \tag{2}$$

$$\Delta P_R(t) = \lambda P(t) \tag{3}$$

The AFSAVP work-flow is given in Figure 2, which is similar to the basic AFSA [23,24]. The AFSAVP includes five steps of operations: (1) behaviour selection; (2) searching behaviour; (3) swarming behaviour; (4) following behaviour and (5) bulletin. A "max-generation" is the trial number of an AF school searching for food under a given initial condition, which is one of the widely used criteria for the AFSAVP simulation termination.

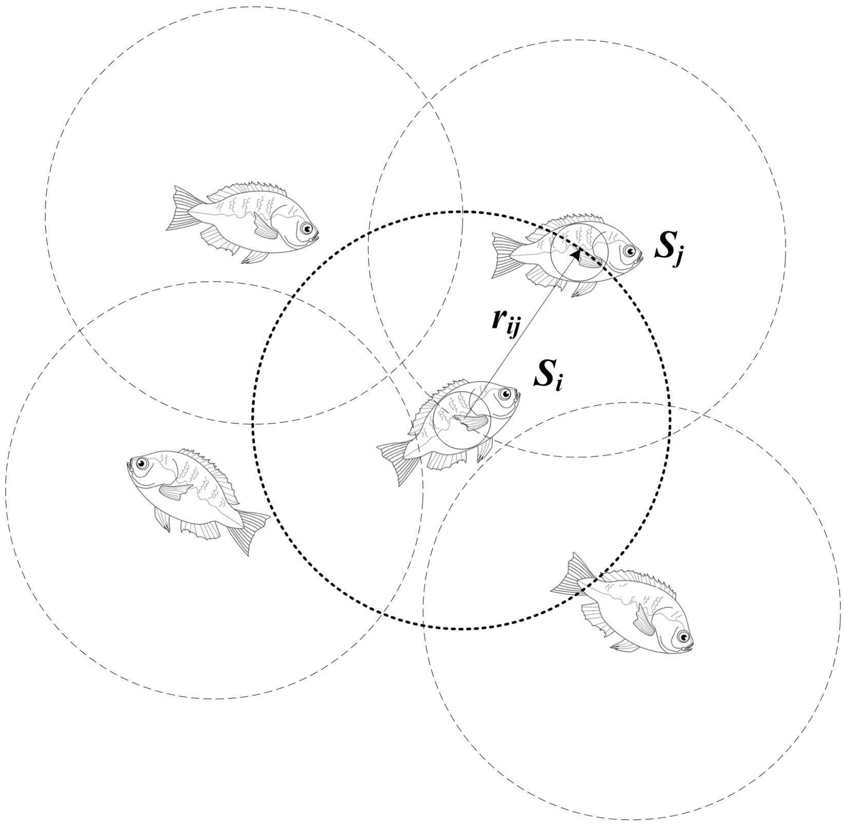
Behaviour Selection: in the AFSAVP, the behaviour selection step takes searching behaviour as the default or initial behaviour for each AF. According to the food density, the number of companion and the visual conditions, the AF school select their behaviours, which includes searching behaviour, following behaviour and swarming behaviour.

Searching Behaviour: for a certain AF individual k, $S_k = \{s_1, \ldots, s_M\}$ is its finite state set, there is M states that an AF can perform in. Within the AF's visual field, if the current state of this AF is S_i and the next state is S_j, the AF moves from S_i to S_j randomly and check the state updating conditions as stated in Equations (4) and (5). As demonstrated in Figure 1, $r_{ij} = \|S_j - S_i\|$ is the distance between the i^{th} and j^{th} individual AF. $\digamma = f(S)$ is the food density for this AF, where $\digamma$ is the fitness function. δ is the iterate step, υ is the AF visual constant.

$$S_{i+1} = \begin{cases} S_i + RAND \cdot \delta \cdot \dfrac{S_j - S_i}{\|S_j - S_i\|} & \text{if } \digamma_j > \digamma_i \\ \\ S_i + RAND \cdot \delta & \text{otherwise} \end{cases} \tag{4}$$

$$S_j = S_i + RAND \cdot \upsilon \tag{5}$$

Figure 1. The state distance between the i^{th} and j^{th} individual.



Swarming Behaviour: suppose the number of this AF's neighbours is α, the central state is S_c, the food density is $F_c = f(S_c)$ and η is the crowd factor. Within its visual field ($r_{ij} < \upsilon$), if the $F_c/\alpha > \eta F_i$ and $\eta \geq 1$, the AF implements the central state driven step; otherwise, when the $F_c/\alpha \leq \eta F_i$ or $\eta = 1$, the AF will go on with the searching behaviour, as expressed in Equation (6).

$$S_{i+1} = \begin{cases} S_i + RAND \cdot \delta \cdot \dfrac{S_c - S_i}{\|S_c - S_i\|} & \text{if } \dfrac{F_c}{\alpha} > \eta F_i \quad and \quad \eta \geq 1 \\ \\ equation(4) & \dfrac{F_c}{\alpha} \leq \eta F_i \quad or \quad \eta = 0 \end{cases} \tag{6}$$

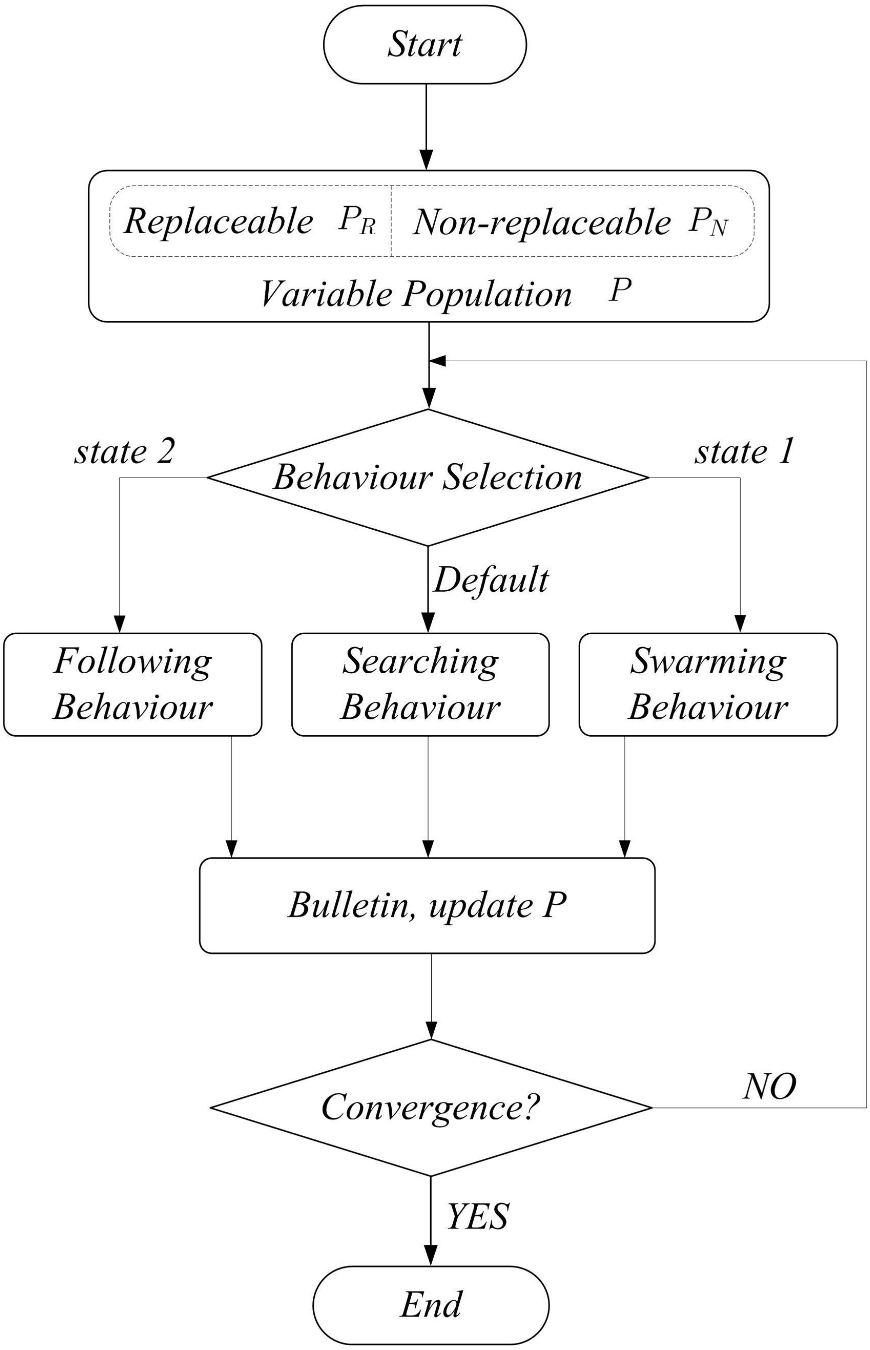
Following Behaviour: when the AF's companions reach "max" state S_{max} with the number α within the neighbourhood, the food density reaches F_{max} at the mean time. As stated in Equation (7), with the same conditions as Equation (6), the AF updates its state in highest food density area; otherwise, the AF will go on with the searching behaviour, as expressed in Equation (6).

$$S_{i+1} = \begin{cases} S_i + RAND \cdot \delta \cdot \dfrac{S_{max} - S_i}{\|S_{max} - S_i\|} & \text{if } \dfrac{F_{max}}{\alpha} > \eta F_i \quad and \quad \eta \geq 1 \\ \\ equation(4) & \dfrac{F_{max}}{\alpha} \leq \eta F_i \quad or \quad \eta = 0 \end{cases} \tag{7}$$

Bulletin: the bulletin operation is a step to compare each AF's current state S_i with the historical state data, the bulletin data will be replaced and updated only when the current state is better than the last one, as described by Equation (8).

$$S_{j+1} = \begin{cases} S_j & \text{if } F_j > F_i \\ S_i & \text{otherwise} \end{cases} \tag{8}$$

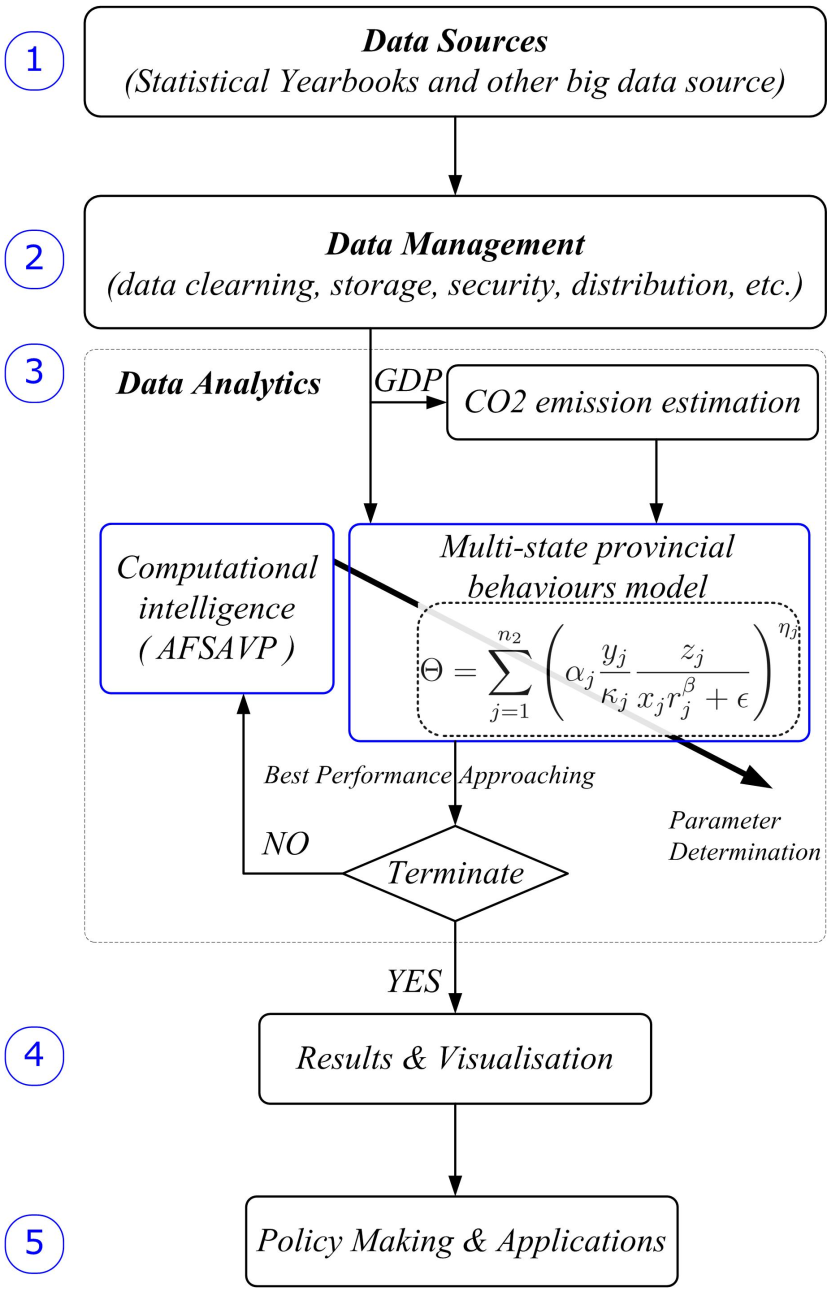
Figure 2. The variable population size fish swarm algorithm workflow.



3. Quantitative Analysis Framework

A framework of this quantitative analysis of dynamic behaviours is given in Figure 3, which summarises five steps for the overall process. Step 1 is to introduce the data source, which includes statistical yearbooks, independent reports and other big data sources. Step 2 is data management, which is to capture, clean, store, manage, and process the data within an applicable time scale. Step 3 is the data analytics, in which the gross domestic product (GDP) is used to estimate CO_2 emission and the AFSAVP method is utilised to optimise the parameters of the multi-state dynamic behaviours model. Step 4 is to visualise the outputs and present the results. In step 5, the result is employed for advising policy makers and data enabled applications.

Figure 3. Framework of quantitative analysis of dynamic behaviours.



According to "Revised 1996 IPCC Guidelines: Reference Manual, Volume 3" [25], the estimation of the CO_2 emissions, which is related to the productive activity for the rural area of each province, requires three major data for each of fuel type: the heat conversion factors (HCF), the carbon emission factor (CEF) and the fraction of carbon oxidised (FOC) in each sector. As listed in Table 1, the three types of data are provided by different data sources [26,27] for the rural areas with local impacts, which includes three aspects: liquid (row A), solid (row B) and gaseous (row C).

Table 1. Heat conversion factor, carbon emission factor, fraction of carbon oxidised of various fossil fuels [25–27].

i	Fuel	Conversion Factor $\alpha_i(TJ/10^3\ t)$	Emission Factor $\beta_i(t\ C/TJ)$	Fraction of Carbon Oxidised γ_i
0	**TCE**	**29.27**	**24.74**	**0.90**
	(A) Liquid			
	Primary Fuel:			
1	Crude Oil	42.62	20.00	0.98
	Secondary Fuel:			
2	Gasoline	44.80	18.90	0.98
3	Kerosene	44.67	19.55	0.98
4	Diesel Oil	43.33	20.20	0.98
5	Residual Fuel Oil	40.19	21.10	0.98
6	LPG	47.31	17.20	0.98
7	Naphtha	45.01	20.00	0.80
8	Bitumen	40.19	22.00	1.00
9	Lubricants	40.19	20.00	0.50
10	Other oil	40.19	20.00	0.98
	(B) Solid			
	Primary Fuel:			
11	Raw Coal	20.52	24.74	0.90
	Secondary Fuel:			
12	Clean Coal	20.52	24.74	0.90
13	Washed Coal	20.52	24.74	0.90
14	House Coal	20.52	24.74	0.90
15	Coking Coal	28.20	29.50	0.97
16	Coal Tar	28.00	22.00	0.75
	(C) Gaseous			
17	CNG	48.00	15.30	0.99

To set the local specific values of the FOC, Qu [27] suggests that the sector specific values of FOC for coal vary between 80%–95%, which are smaller than the IPCC default value of 98%. Equation (9) is the CO_2 emission estimation (E) approach provided by IPCC [25], which includes main fuel combustion as listed in Table 1. China typically converts all its energy statistics into the metric tons of standard coal equivalent (TCE), a unit that bears little relation to the heating value of coals actually being used in China [28], whose HCF, CEF and FOC are given in the row i = 0 in Table 1.

$$E = \sum_{i=1}^{n_1} \tau\gamma_i \left(\alpha_i\beta_i A_i \times 10^{-3} - S_i\right) \tag{9}$$

where,

- ∘ E is the CO_2 emission, 10^3t;
- ∘ τ = 44/12 is the molecular weight ratio of CO_2 to C (Conversion between C and CO_2 can be calculated using the relative atomic weights of the carbon and oxygen atoms C = 12, O = 16. The atomic weight of carbon is 12 and that of CO_2 is 12 + 16 + 16 = 44, *i.e.*, one carbon and two oxygen atoms. To convert from C to CO_2 thus requires multiplication by 44/12, or 3.67 [25].);
- ∘ γ_i is the fraction of carbon oxidised (i = 1,2,..., n_1), n_1 = 17;
- ∘ α_i is the heat conversion factor, $TJ/10^3t$;
- ∘ β_i is the carbon emission factor, which is considered as the carbon content per unit of energy for its close link between the carbon content and energy value of the fuel, tC/TJ;
- ∘ S_i is the non-energy use, 10^3t;
- ∘ A_i is the apparent consumption, t;

$$A_i = O_i + I_i - X_i - B_i - R_i \tag{10}$$

- ∘ O_i is the energy production, t;
- ∘ I_i is the import energy, t;
- ∘ X_i is the export energy, t;
- ∘ B_i is the international bunkers, t;
- ∘ R_i is the stock change, t;

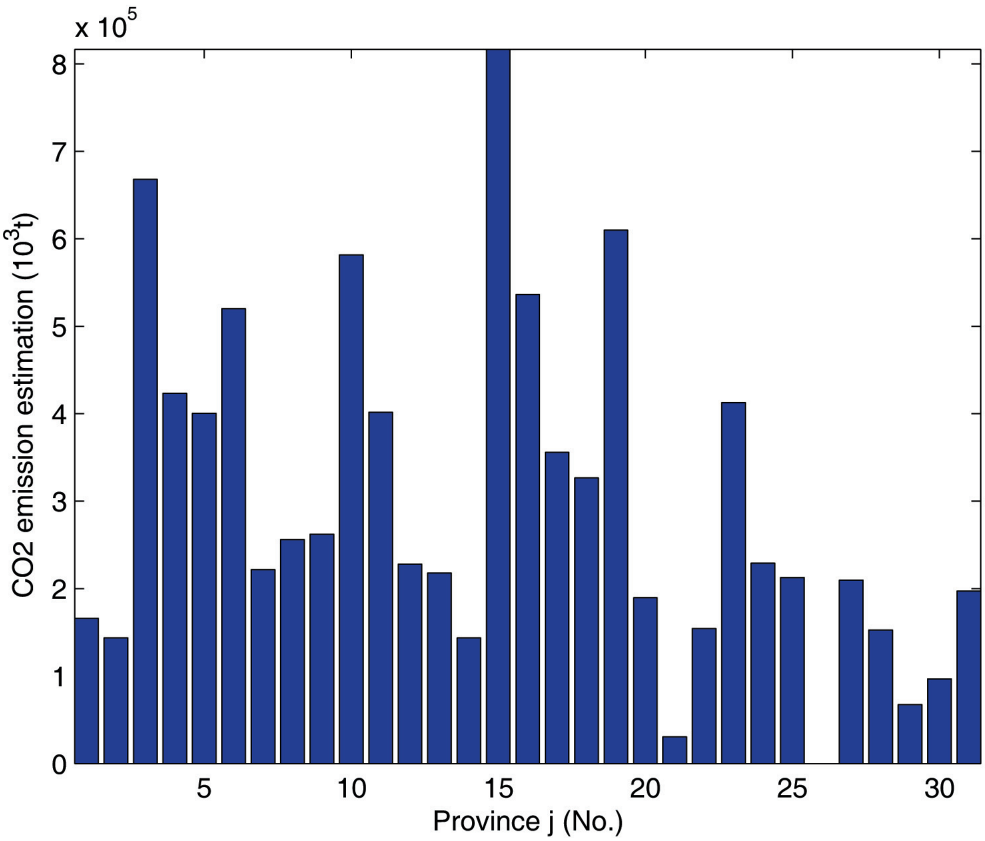
Subject to the requirements outlined above, to ensure the comparability of country inventories, the IPCC approach to the calculation of emission encourages the use of fuel statistics collected by an officially recognised national body. However, practically, the IPCC approach can hardly be utilised for the CO_2 emission estimation with two main reasons. Firstly, recent satellite data has shown that the drop in coal consumption is probably unrealistic and the coal consumption data should not be used [2,3]. Secondly, the CO_2 emissions data by fuel combustion and each local province are not directly available.

To handle this problem, Chen *et al.* have proposed a *GDP* approach [12], which employs the GDP data to estimate the CO_2 emission. Empirical studies indicate that the *GDP* approach provides a reasonable CO_2 emission result that is consistent with other researchers' works [29,30]. As given in Equation (11), the TCE/GDP energy statistics of provincial data are listed in Table 2. κ_j is the CO_2 emission estimation of each province j, as expressed in Equation (12), j = 1,2,...n_2, n_2 = 31, which is also shown in Figure 4.

Table 2. China energy statistical data [31].

j	**Province**	e_j	g_j	f_j	$\hat{A}_j$	$\hat{B}_j$	κ_j
1	Beijing	0.662	104880300	719.61	69430758.6	476.38182	165,916.0
2	Tianjing	0.947	63543800	910.42	60175978.6	862.16774	143,800.2
3	Hebei	1.727	161886100	1492.81	279577294.7	2578.08287	668,095.1
4	Shanxi	2.554	69387300	2288.87	177215164.2	5845.77398	423,484.4
5	Neimenggu	2.159	77618000	1887.32	167577262	4074.72388	400,453.0
6	Liaoning	1.617	134615700	1223.81	217673586.9	1978.90077	520,166.2
7	Jiling	1.444	64240600	885.93	92763426.4	1279.28292	221,673.2
8	Heilongjiang	1.290	83100000	865.90	107199000	1117.011	256,169.3
9	Shanghai	0.801	136981500	884.13	109722181.5	708.18813	262,198.9
10	Jiangshu	0.803	303126100	1149.44	243410258.3	923.00032	581,668.1
11	Zhejiang	0.782	214869200	1202.08	168027714.4	940.02656	401,529.4
12	Anhui	1.075	88741700	1106.81	95397327.5	1189.82075	227,967.3
13	Fujian	0.843	108231100	1098.56	91238817.3	926.08608	218,029.9
14	Jiangxi	0.928	64803300	942.16	60137462.4	874.32448	143,708.2
15	Shandong	1.100	310720600	1001.08	341792660	1101.188	816,768.7
16	Henan	1.219	184077800	1266.23	224390838.2	1543.53437	536,218.2
17	Hubei	1.314	113303800	1103.90	148881193.2	1450.5246	355,775.7
18	Hunan	1.225	111566400	975.49	136668840	1194.97525	326,592.3
19	Guangdong	0.715	356964600	1085.49	255229689	776.12535	609,912.5
20	Guangxi	1.106	71715800	1254.15	79317674.8	1387.0899	189,542.4
21	Hainan	0.875	14592300	979.24	12768262.5	856.835	30,511.8
22	Chongqing	1.267	50966600	1090.19	64574682.2	1381.27073	154,311.7
23	Sichuan	1.381	125062500	1156.37	172711312.5	1596.94697	412,721.6
24	Guizhou	2.875	33334000	2452.21	95835250	7050.10375	229,014.0
25	Yunnan	1.562	57001000	1654.94	89035562	2585.01628	212,764.9
26	Xizang	0	3959100	0	0	0	0
27	Shaanxi	1.281	68513200	1256.02	87765409.2	1608.96162	209,729.7
28	Gansu	2.013	31761100	2539.00	63935094.3	5111.007	152,783.4
29	Qinhai	2.935	9615300	4061.64	28220905.5	11920.9134	67,438.7
30	Ningxia	3.686	10985100	5084.09	40491078.6	18739.95574	96,760.5
31	Xingjiang	1.963	42034100	1331.24	82512938.3	2613.22412	197,178.1
	$\hat{E}$						9,232,883.4

Figure 4. CO_2 emission estimation of province j.



The energy consumption data constructed from the GDP g_j and its related energy consumption e_j and electricity consumption f_j of the province j can be collected and are officially provided by the "Chinese Energy Statistical Yearbook" [31]. $\hat{A}_j$ is the CO_2 estimation of the equivalent *energy* consumption of province j, $\hat{B}_j$ is the CO_2 estimation of the equivalent *electricity* consumption, as given in Equations (13) and (14).

$$\hat{E} = \sum_{j=1}^{n_2} \kappa_j \tag{11}$$

$$\kappa_j = \tau\gamma_0\alpha_0\beta_0 \left(\hat{A}_j + \nu_0\hat{B}_j\right) \times 10^{-3} \tag{12}$$

$$\hat{A}_j = e_j g_j \tag{13}$$

$$\hat{B}_j = f_j g_j \tag{14}$$

where,

- ∘ $\hat{E}$ is the total TCE CO_2 emission estimation of the provincial rural areas, $10^3 t$;
- ∘ κ_j is the CO_2 emission estimation of province j by GDP, as listed in Table 2, $10^3 t$;
- ∘ g_j is the gross domestic product (GDP) of province j, $10^4 CNY$;

∘ e_j is the TCE energy consumption per GDP unit of province j, TCE/$10^4 CNY$;

∘ f_j is the electricity consumption per GDP unit of province j, kWh/$10^4 CNY$;

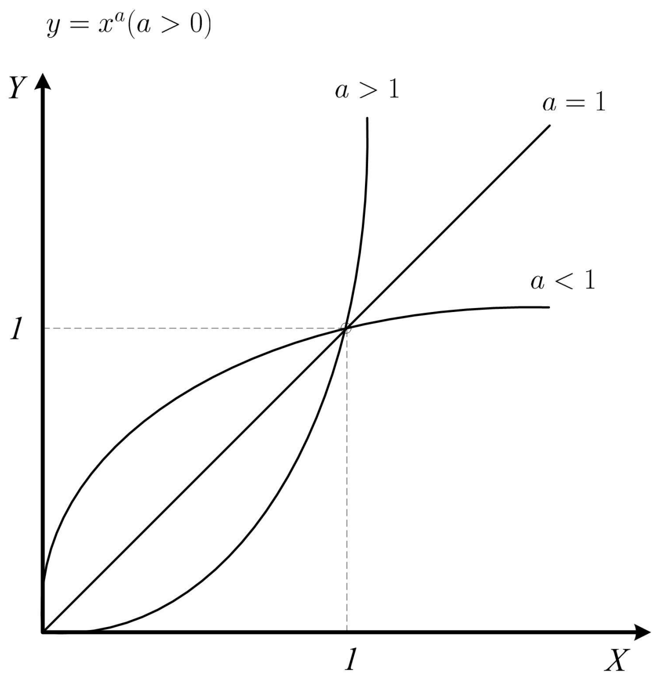
∘ ν_0 is the ratio of electricity to TCE, which is 0.01182 in this case (Electricity is converted to TCE by the equation 104 kWh = 1.229 TCE, that is, ν_0 = 1.229/104 = 0.01182 [31]);

∘ τ, γ_0, α_0 and β_0 are the molecular weight ratio of CO_2 to C, the TCE fraction of carbon oxidised, the TCE heat conversion factor and the TCE carbon emission factor, as given in Table 1, j = 1,...,n_2.

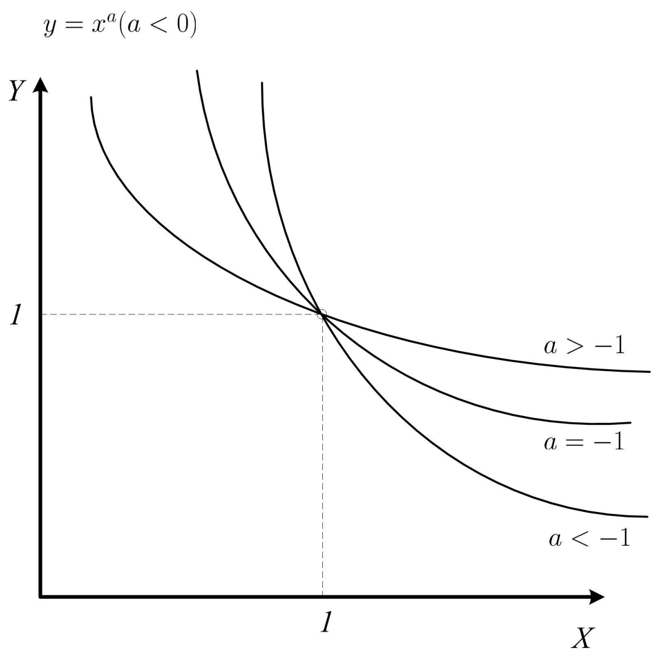
4. Multi-State Dynamic Behaviours Modelling

As demonstrated in Figure 5, the multi-state system (MSS) is expressed by a power function ($y = x^a$), in which a is the multi-state factor (MSF) that can provide different multi-state combinations by different a's values. Figure 5(a) and Figure 5(b) represent an increase ($a > 0$) and a decrease ($a < 0$) in economic activities, respectively. The power function MSS representation can provide a qualitative tool to perform a functional distance related interactive analysis and can be utilised as a fitness function for the AFSAVP optimisation process.

Figure 5. Multi-state representation via power functions.



(a) $(a > 0)$



(b) $(a < 0)$

In this paper, the statistics data of 31 provinces are adopted from China Statistical Yearbook 2009 [32]. In order to estimate the rural-urban(R-U) spatial interactions, a functional region affecting index (Θ) with a "law-of-gravity" interpretation [12] can be characterised as Equation (15) by using the basic form of a Cobb–Douglas (C-D) production function [33], which can provide a qualitative tool to perform a distance-related interactive analysis and can be utilised as the fitness function for AFSAVP optimisation.

A case in Figure 6 shows the *Sichuan* province location and its functional distance measurement. Taking *Sichuang* province (province j = 23) as an example, O is the capital of China (Beijing), r_1 and r_2 are the shortest and longest radii (the distances r_1 and r_2 are provided by the GIS system *China Map*, http://www.51ditu.com/) from O to *Sichuan*, A and B are the closest and farthest locating points of *Sichuan* to *Beijing*.

$$\Theta = \sum_{j=1}^{n_2} \left(\alpha_j \frac{y_j}{\kappa_j} \frac{z_j}{x_j r_j^{\beta} + \epsilon} \right)^{\eta_j} \tag{15}$$

where,

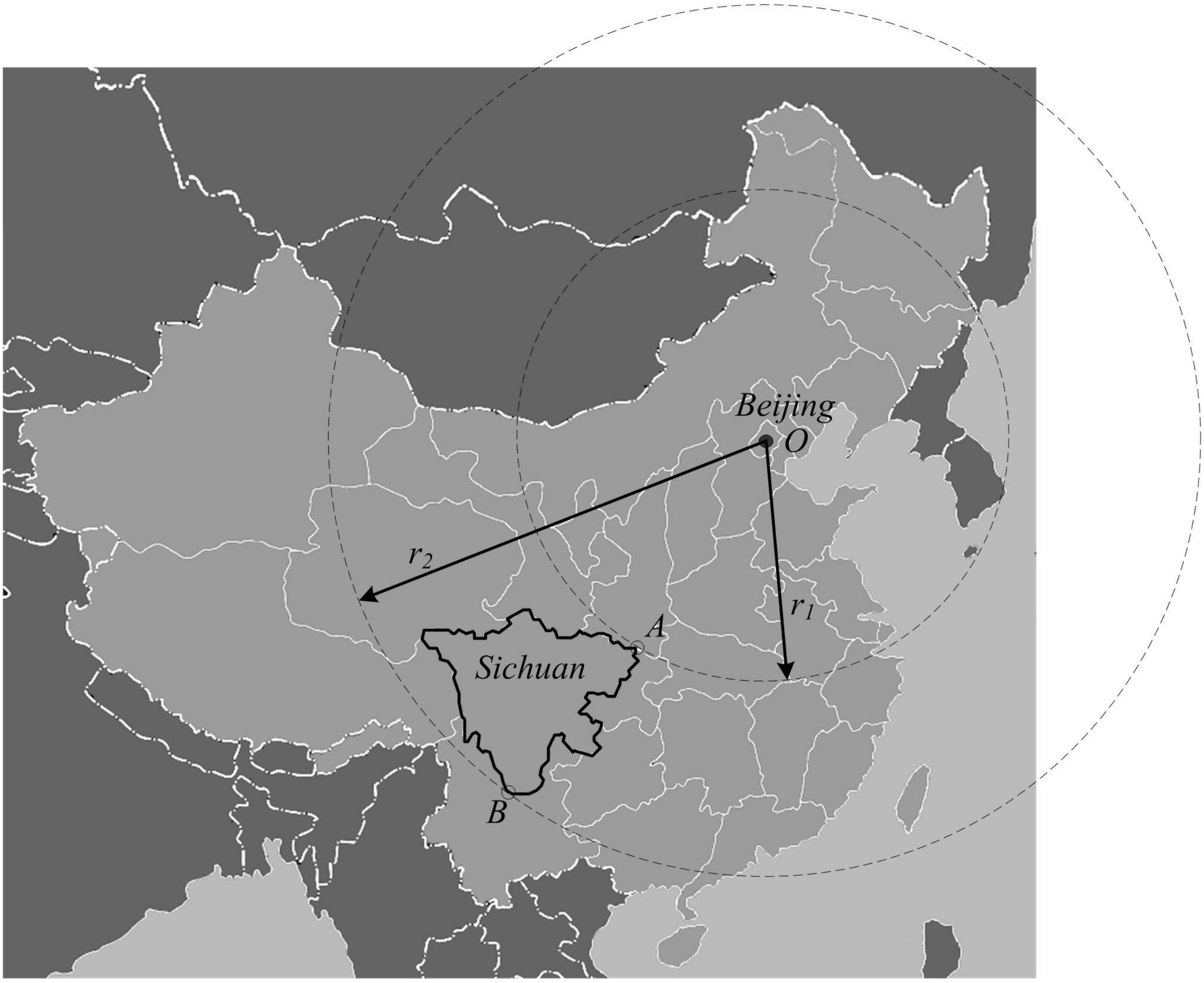
- ∘ Θ is the functional region affecting index;
- ∘ x_j is the number of enterprises in the province j, n_2 is the number of the provinces;
- ∘ y_j is the total profits of province j, $10^4 CNY$;
- ∘ z_j is the non-agricultural employment of province j, 10^4persons;
- ∘ α_j = α_{1j}/α_{0j} is the population effect coefficient of province j, α_{1j} is the local non-agricultural population, α_{0j} is the population of province j, 10^4persons;
- ∘ κ_j is the CO_2 emission of province j, as listed in Table 2;
- ∘ η_j is the multi-state factor of province j, $\eta_j \in$ [-1,1], as defined in Equation (16), which is the normalised g_j, g_{min} and g_{max} are the min and max values of g_j. According to the historical data and statistics, η_j is utilised to describe the MSS weighted behaviour of the uncertainty analysis;

$$\eta_j = 2 \left(\frac{g_j - g_{min}}{g_{max} - g_{min}} \right) - 1 \tag{16}$$

- ∘ β is the factor of the functional distance r_j, $\beta \in$ [0.5,3];
- ∘ ϵ is the floating point relative accuracy, which prevents the singularity in case of the r_j^{β} is approaching to 0 and Θ is approaching to ∞, numerically;
- ∘ r_j is the mean value of point-to-point distance from the point O to each province j, as defined in Equation (17), kilometre (km).

$$r_j = \frac{r_{j1} + r_{j2}}{2} \tag{17}$$

Figure 6. Functional distance measurement of Sichuan province.



5. Fitness Function Definition

In order to evaluate the dynamic behaviour related to the functional distance, the CO_2 emission and population in the provincial economic production, the Θ feature is utilised as the fitness function defined in Equation (18) by the form of Equation (15), which is a cumulative measurement for the functional region and CO_2 emission spatial determination of the agreement between the statistical data and the AFSAVP driven data pool. All the statistical data for the parameters of Equation (18) are listed in Table 3, and the data source is the "China Statistical Yearbook 2009" [32].

$$F(X,Y,Z) = \sum_{j=1}^{n_2} \left(\alpha_j \frac{y_j}{\kappa_j} \frac{z_j}{x_j r_j^{\beta} + \epsilon} \right)^{\eta_j} \tag{18}$$

Table 3. Statistical data for each province [32].

No. j	**Province**	r_{j1}	r_{j2}	α_{0j}	α_{1j}	μ_{x_j}	μ_{y_j}	μ_{z_j}
1	Beijing	0.00	129.00	1695	1439	7205	5570000	123.38
2	Tianjing	49.45	168.99	1176	908	7950	7527900	133.12
3	Hebei	30.96	442.47	6989	2928	12447	13698400	316.85
4	Shanxi	162.97	781.31	3411	1539	4415	6342500	214.93
5	Neimenggu	206.83	1617.23	2414	1248	3993	7714400	104.57
6	Liaoning	228.33	789.91	4315	2591	21876	7815800	366.23
7	Jiling	689.29	1280.97	2734	1455	5257	3962300	126.99
8	Heilongjiang	884.94	1752.25	3825	2119	4392	15816900	155.99
9	Shanghai	976.53	1091.77	1888	1673	18792	9672400	304.01
10	Jiangshu	542.23	1059.09	7677	4169	65495	39729300	1104.06
11	Zhejiang	995.88	1434.05	5120	2949	58816	16342000	814.55
12	Anhui	571.47	1153.69	6135	2485	11392	6067300	210.8
13	Fujian	1276.24	1783.64	3604	1798	17212	8961100	380.06
14	Jiangxi	1069.41	1689.04	4400	1820	7367	5079600	178.56
15	Shandong	216.72	625.65	9417	4483	42629	39235600	912.7
16	Henan	420.97	932.24	9429	3397	18700	22877800	417.36
17	Hubei	851.83	1336.87	5711	2581	12067	9090300	235.9
18	Hunan	1127.46	1718.28	6380	2689	12391	6635600	225.55
19	Guangdong	1584.55	2230.41	9544	6048	52574	32726000	1493.38
20	Guangxi	1548.86	2166.34	4816	1838	5427	2311400	114.6
21	Hainan	2223.53	3046.98	854	410	548	807400	12.61
22	Chongqing	1071.13	1511.45	2839	1419	6119	3086800	132.13
23	Sichuan	1097.36	2011.97	8138	3044	13725	8445600	297.54
24	Guizhou	1382.45	1984.45	3793	1104	2676	1818300	73.53
25	Yunnan	1646.04	2522.81	4543	1499	3320	3101400	84.34
26	Xizang	1812.45	3418.07	287	65	88	45000	1.79
27	Shaanxi	443.33	1193.68	3762	1584	4025	10089900	131.83
28	Gansu	764.54	2032.18	2628	845	1940	1094600	69.13
29	Qinhai	1221.63	2406.28	554	227	515	1771700	17.42
30	Ningxia	774.43	1068.55	618	278	901	391300	25.89
31	Xingjiang	1677.43	3590.93	2131	845	1859	7795200	57.84

with the following assumptions of uncertainties,

- $\circ$ X = $[x_1, x_2, ..., x_j, ..., x_{n_2}]$ is the vector of the enterprise number, $X \sim N(\mu_X, \sigma_X^2)$. Let μ_X = $[\mu_{x_1}, \mu_{x_2}, ..., \mu_{x_j}, ..., \mu_{x_{n_2}}]$ and σ_X = $[\sigma_{x_1}, \sigma_{x_2}, ..., \sigma_{x_j}, ..., \sigma_{x_{n_2}}]$ be the mean and the standard deviation vectors of X, respectively, that is, $x_j \sim N(\mu_{x_j}, \sigma_{x_j}^2)$, μ_{x_j} and σ_{x_j} are the mean and the standard deviation of x_j;

○ Y = $[y_1, y_2, ..., y_j, ..., y_{n_2}]$ is the vector of the total profits, $Y \sim N(\mu_Y, \sigma_Y^2)$. Let μ_Y = $[\mu_{y_1}, \mu_{y_2}, ..., \mu_{y_j}, ..., \mu_{y_{n_2}}]$ and σ_Y = $[\sigma_{y_1}, \sigma_{y_2}, ..., \sigma_{y_j}, ..., \sigma_{y_{n_2}}]$ be the mean and the standard deviation vectors of Y, respectively, such that $y_j \sim N(\mu_{y_j}, \sigma_{y_j}^2)$, μ_{y_j} and σ_{y_j} are the mean and the standard deviation of y_j;

○ Z = $[z_1, z_2, ..., z_j, ..., z_{n_2}]$ is the vector of the non-agricultural employment, $Z \sim N(\mu_Z, \sigma_Z^2)$. Let μ_Z = $[\mu_{z_1}, \mu_{z_2}, ..., \mu_{z_j}, ..., \mu_{z_{n_2}}]$ and σ_Z = $[\sigma_{z_1}, \sigma_{z_2}, ..., \sigma_{z_j}, ..., \sigma_{z_{n_2}}]$ be the mean and the standard deviation vectors of Z, respectively, such that $z_j \sim N(\mu_{z_j}, \sigma_{z_j}^2)$, μ_{z_j} and σ_{z_j} are the mean and the standard deviation of z_j;

○ δ_{x_j}, δ_{y_j} and δ_{z_j} are the coefficients of variation (CV) of x_j, y_j and z_j respectively, with the definition in Equation (19) [34]. The rest parameters α_j, β, r_j, κ_j, ϵ and η_j are as discussed in Section 4;

$$\delta_j = \frac{\sigma_{x_j}}{\mu_{x_j}} \tag{19}$$

6. Empirical Results and Discussions

The empirical data analysis for the AFSAVP driven hybrid modelling of the dynamic behaviours are implemented by the $SwarmFish$ [35] toolbox and the parameters of the AFSAVP calculation are stated in Table 4, in which the termination condition is 100,000 max generations, the coefficients of variation δ_j for all x_j, y_j and z_j are set to 15%, the experiment number is 100, the non-replaceable P_N and replaceable population P_R are 50 and 10, iterate step δ is 0.5, visual υ is 10, crowd η is 0.618, try number is 5 for each AF.

Table 4. Parameters for the AFSAVP simulations.

	max generations	100,000
	experiment number	100
	population	60
P_N	non-replaceable population	50
P_R	replaceable population	10
	CV (δ_j)	15%
δ	iterate step	0.5
υ	visual	2.5
η	crowd	0.618
	try number	5

Figures 7–10 are the fitness plots for 100, 1000, 10,000 and 100,000 generations, whose "x-axis" is the evolution generations and "y-axis" is the fitness values. These figures demonstrate the short term (generation = 100), short-middle term (generation = 1000), middle term (generation = 10,000) and long term (generation = 100,000) dynamic behaviours, in which the solid line, dotted line and dash-dot line

are the “max”, “min” and “mean” values of fitness evolution process. Different from the fitness shape for engineering applications, the fluctuations of the non-monotonic fitness curves indicate the dynamic behaviours of the provincial areas.

Figure 7. Θ fitness plot, 100 generations.

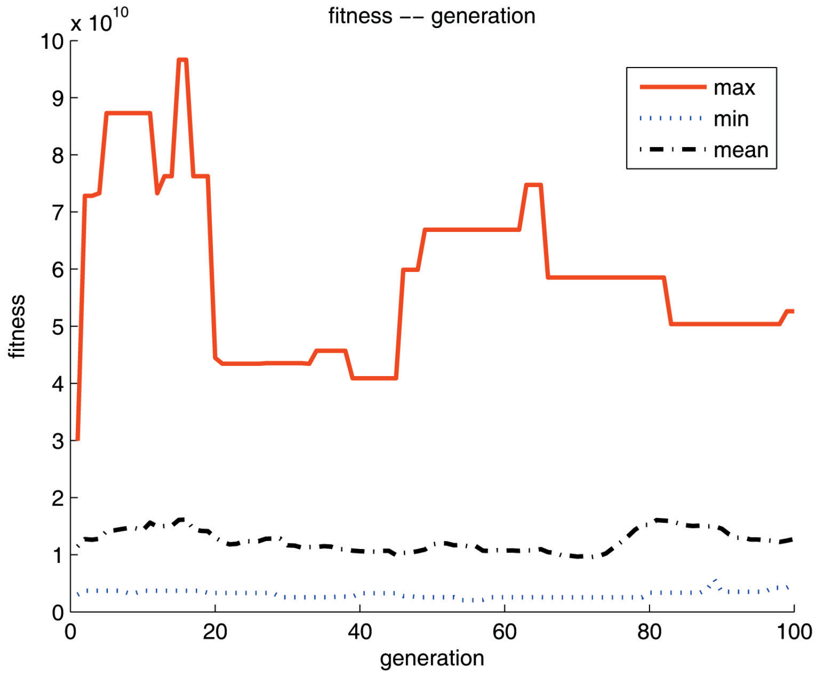


Figure 8. Θ fitness plot, 1000 generations.

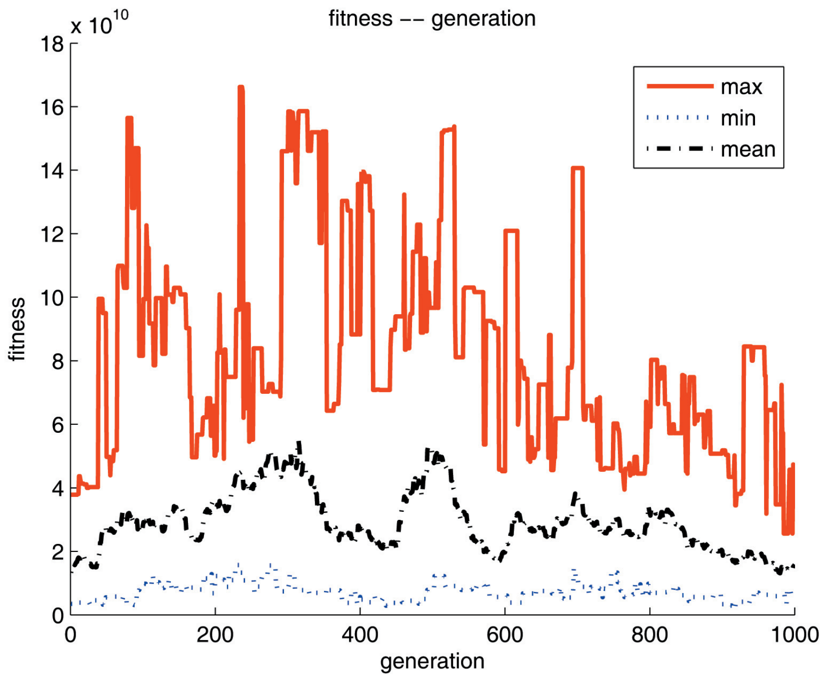


Figure 9. Θ fitness plot, 10,000 generations.

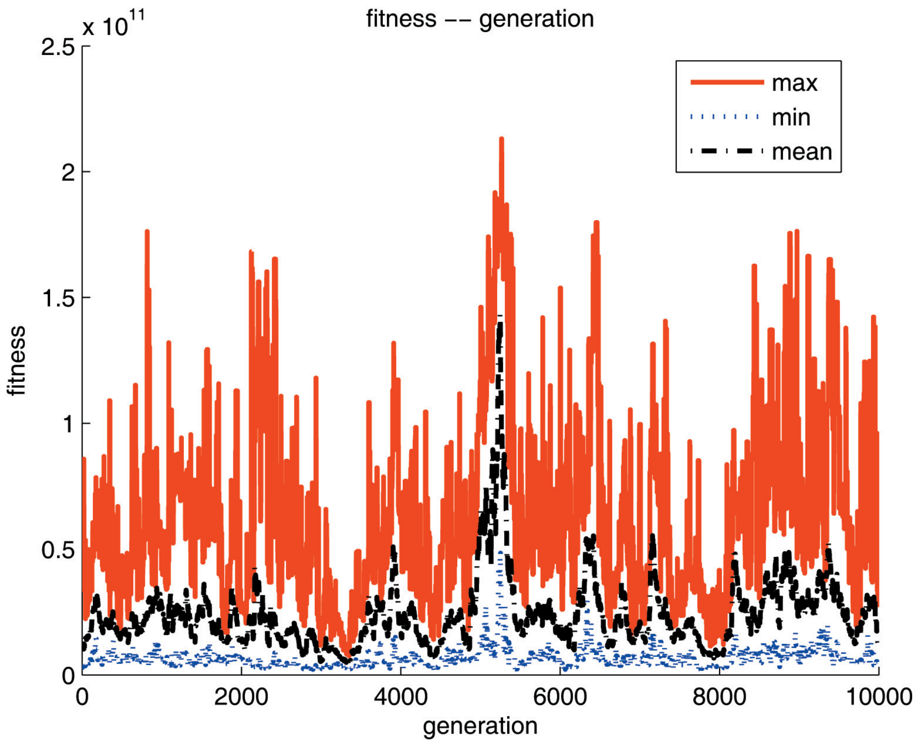


Figure 10. Θ fitness plot, 100,000 generations.

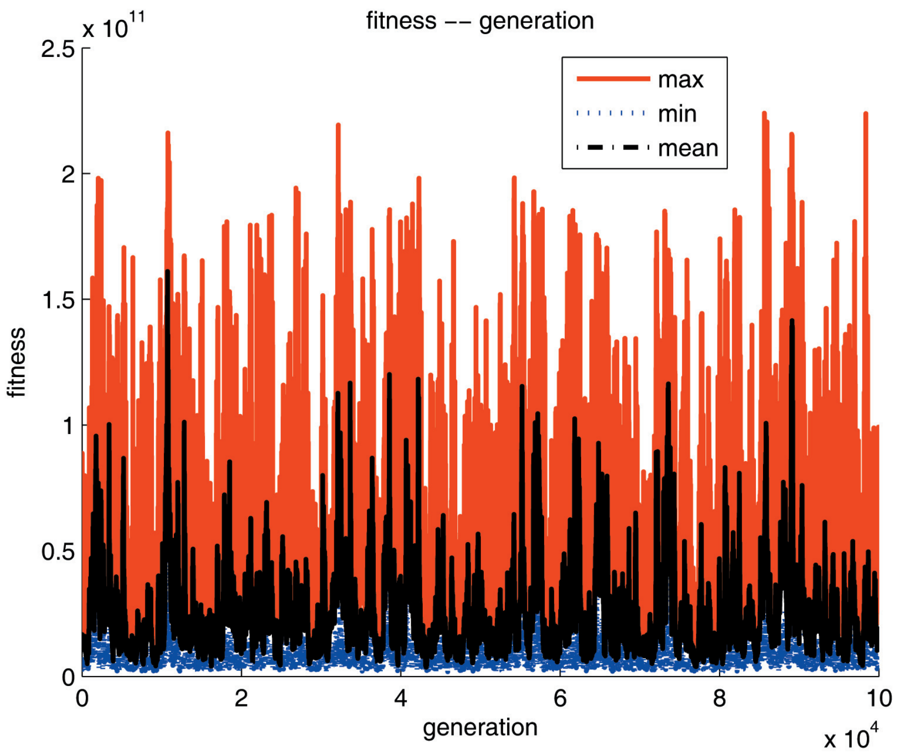


Figure 11 is the phase portrait of the "max" fitness at 100,000 generations, which demonstrate an isolated closed "limit cycle" phenomenon. This closed and isolated cycle indicates that the limiting nature of motions of the provincial dynamic system is in an overall stable state with limit active trajectories, depending on the motion patterns and evolutionary uncertainties.

Figure 11. Fitness phase portrait of the dynamic behaviours, 100,000 generations.

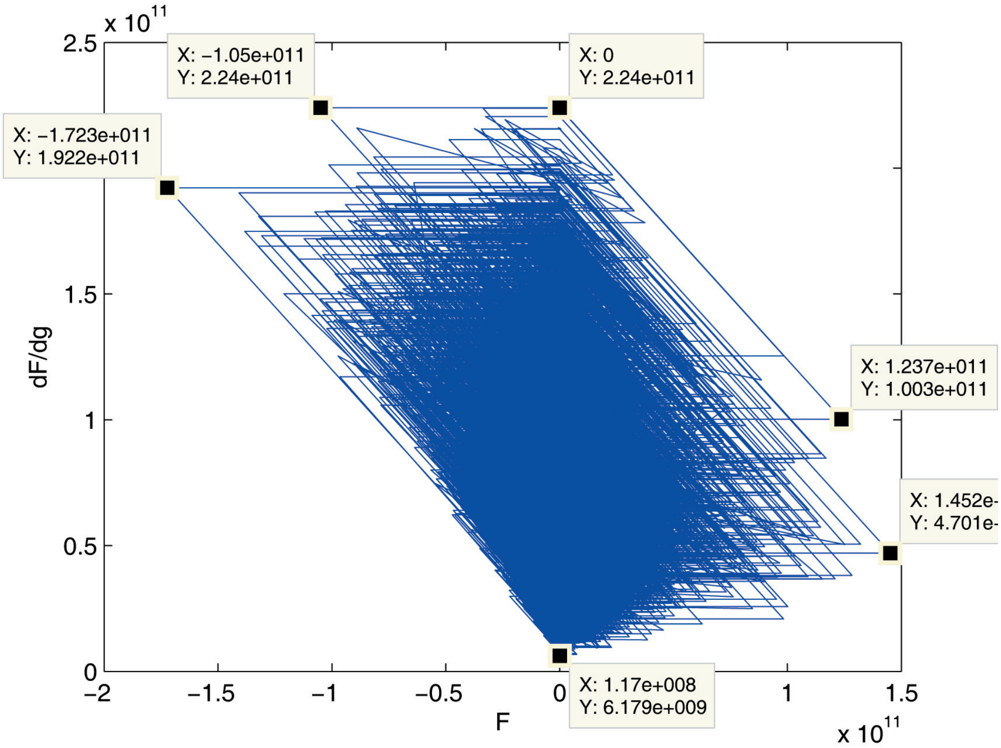


Table 5 states one of the set of estimation $\hat{X} = [\hat{x}_1, \hat{x}_2, ..., \hat{x}_j, ..., \hat{x}_{n_2}]$, $\hat{Y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_j, ..., \hat{y}_{n_2}]$ and $\hat{Z} = [\hat{z}_1, \hat{z}_2, ..., \hat{z}_j, ..., \hat{z}_{n_2}]$ for each province. Compared with the year book data μ_{x_j}, μ_{y_j} and μ_{z_j} in Table 3, the negative percentage errors of $\Delta x_j(\%)$, $\Delta y_j(\%)$ and $\Delta z_j(\%)$ indicate that the scale of the non-agricultural activities in the rural areas are in a decreasing trend, which matches the practical situation, that is, the rural areas of provinces are designed as the agriculture oriented functional regions administratively [32].

Table 5. An estimation $\hat{X}$, $\hat{Y}$ and $\hat{Z}$ optimised by the AFSAVP.

No. j	**Province**	$\hat{\boldsymbol{x}}_j$	$\boldsymbol{\Delta x_j}(\%)$	$\hat{\boldsymbol{y}}_j$	$\boldsymbol{\Delta y_j}(\%)$	$\hat{\boldsymbol{z}}_j$	$\boldsymbol{\Delta z_j}(\%)$
1	Beijing	2103.37	-70.81	5259913.76	-5.57	121.52	-1.50
2	Tianjing	7162.66	-9.90	3875238.80	-48.52	55.39	-58.39
3	Hebei	5471.55	-56.04	3607953.26	-73.66	94.19	-70.27
4	Shanxi	2828.75	-35.93	1177466.56	-81.44	64.13	-70.16
5	Neimenggu	671.11	-83.19	4232075.41	-45.14	31.17	-70.19
6	Liaoning	5099.33	-76.69	5457102.47	-30.18	102.12	-72.12
7	Jiling	3598.66	-31.55	1516642.78	-61.72	19.86	-84.36
8	Heilongjiang	2098.07	-52.23	15558105.89	-1.64	97.39	-37.56

Table 5. *Cont.*

No. j	**Province**	$\hat{x}_j$	$\Delta x_j(\%)$	$\hat{y}_j$	$\Delta y_j(\%)$	$\hat{z}_j$	$\Delta z_j(\%)$
9	Shanghai	13194.87	-29.78	2140995.88	-77.86	177.82	-41.51
10	Jiangshu	56854.80	-13.19	23504968.27	-40.84	603.88	-45.30
11	Zejiang	20379.23	-65.35	7582321.11	-53.60	492.79	-39.50
12	Anhui	9517.09	-16.46	1358894.06	-77.60	90.46	-57.09
13	Fujian	16657.98	-3.22	7250945.22	-19.08	210.31	-44.66
14	Jiangxi	5670.41	-23.03	835757.42	-83.55	119.53	-33.06
15	Shandong	28488.65	-33.17	30320955.80	-22.72	519.93	-43.03
16	Henan	14565.92	-22.11	18769763.12	-17.96	353.91	-15.20
17	Hubei	2328.84	-80.70	4579725.46	-49.62	154.24	-34.62
18	Hunan	5928.32	-52.16	2768458.57	-58.28	75.74	-66.42
19	Guangdong	15277.99	-70.94	17910952.88	-45.27	1449.28	-2.95
20	Guangxi	3994.28	-26.39	1908639.57	-17.42	105.45	-7.98
21	Hainan	208.35	-61.98	609757.68	-24.48	6.32	-49.91
22	Chongqing	4728.64	-22.72	1044767.55	-66.15	29.81	-77.44
23	Sichuan	3303.15	-75.93	4154033.67	-50.81	201.85	-32.16
24	Guizhou	1815.92	-32.14	1590913.14	-12.51	36.29	-50.64
25	Yunnan	2506.39	-24.51	841518.18	-72.87	52.04	-38.29
26	Xizang	17.85	-79.72	10045.12	-77.68	0.98	-45.02
27	Shaanxi	972.27	-75.84	2669041.76	-73.55	62.65	-52.47
28	Gansu	380.545	-80.38	1003010.38	-8.36	13.59	-80.34
29	Qinhai	119.59	-76.78	546449.00	-69.16	8.28	-52.45
30	Ningxia	638.53	-29.13	302537.17	-22.68	9.70	-62.52
31	Xingjiang	1448.19	-22.09	1602668.49	-79.44	16.49	-71.49

7. Conclusions and Future Work

In recent years, the quantitative analysis is widely utilised to assist the functional region planning decisions, which tries to take good advantage of the available statistical data. This paper provides an evolutionary alternative of dynamic behaviour modelling for functional region with distance factor and CO_2 emission factor. In this paper, the AFSAVP is firstly introduced, then the GDP-based TCE approach for the CO_2 emission estimation is discussed. For the hybrid modelling of provincial regions, the Θ factor is proposed to describe the interaction of the production inputs and outputs with the source data uncertainties, which indicates a sort of distance-based relationship between a Θ combination of the X, Y and Z inputs and the possible maximum output under current productive capability, in which the experience of a policy-maker can be incorporated in a natural or artificial way. It is clear that the CO_2 emission is related to the complicated dynamic behaviours of the functional region. The GDP/TCE approach to the CO_2 emission estimation is a practical way to deal with the lack of direct fossil fuel data source.

This paper's results are consistent with the actual behaviours of the functional regions, which suggests some interesting issues for further investigation on the real-time public sector policy making, in which the consumer price index (CPI) will be one of the dynamic decision criteria for the further reliability analysis of a multi-state Θ modelling or the analysis of the regional system maintenance and sustainability.

Notations

AFSAVP	artificial fish swarm algorithm with variable population size
CO	carbon monoxide
CO_2	carbon dioxide
CH_4	methane
CNY	Chinese yuan (renminbi)
F	fitness function
GDP	gross domestic product
GA	genetic algorithms
kWh	kilowatt hour
NO_x	nitrogen oxides
SO_2	silicon dioxide
Θ	functional region affecting index
TCE	metric tons of standard coal equivalent

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