Cleaner Production Letters 3 (2022) 100019

Contents lists available at ScienceDirect

Cleaner Production Letters

journal homepage: www.journals.elsevier.com/cleaner-production-letters

Ecological network analysis of a metabolic urban system based on input–output tables: Model development and case study for the city of Vienna

O. Galychyn [a,*], B.D. Fath [b,c], E. Buonocore [a], P.P. Franzese [a]

[a] International PhD Programme / UNESCO Chair "Environment, Resources and Sustainable Development", Department of Science and Technology, Parthenope University of Naples, Naples, Italy
[b] Department of Biological Sciences at Towson University, Maryland, USA
[c] Advancing Systems Analysis, International Institute for Applied Systems Analysis, Laxenburg, Austria

ARTICLE INFO

Keywords:
Urban metabolic systems
Emergy
Ecological network analysis
Indirect effects
Vienna

ABSTRACT

The rapid economic growth accompanied by health concerns and other global environmental problems in cities and regions has boosted the popularity of the 'urban metabolism' topic among academics and policymakers. Currently, 56.2% of the world's population lives in cities, accounting for 80% of the global GDP. It is projected that the current trend for world economic growth complemented by population growth and migration will continue affecting the resource production and consumption in cities and the impact this has on other urban areas. Here, we developed a new model approach that combines emergy input-output tables with ecological network analysis to investigate urban metabolism generally, and applied it to Vienna, Austria. This novel approach allows researchers to study the hierarchy of sectors and functional relationships along all possible metabolic paths of ecological and socio-economic flows exchanging in an urban economy and between the urban economy and its environment. Then, using system-level analyses (flow and contribution analyses) we determined the status of the system components. Finally, the critical components responsible for the status (distribution structure of each industry) and emergy consumption of the other sectors were identified using pairwise control and utility analyses. The results showed that the "agriculture, forestry and fishing" and "mining and quarrying" sectors had the lowest ability to receive financial inputs from the other sectors, reflecting a shortage of agricultural and mining products to meet consumers' demand. Moreover, "agriculture, forestry and fishing" had the highest energy dependence on the other sectors, indicating the lack of self-sufficiency in energy use and the inability of this sector to deliver energy effectively to consuming sectors. This also implies the importance of this sector in achieving the energy efficiency improvement and economic development goals for consumer cities. This work contributes to the existing literature on ecological network analysis via an introduction of the two-step approach that combines the diagnosis of low activity components in the system taken from traditional ecological network analysis with the novel identification of components behind the low activity of the other components. In addition, direct and indirect control, and indirect utility analysis were introduced for the analysis of the impact of the direct energy and indirect pairwise economic control and relational interactions of sectors in cities. Finally, this work explored the inner workings of the service part of the urban economy to reveal the role each tertiary sector plays in the development of primary and secondary sectors of an urban economy. The model developed in this study will provide support for city managers and policymakers to guide resource consumption towards an efficient and sustainable urban metabolic system worldwide.

1. Introduction

Along with a rising urban population and economic growth in face of the global environmental problems such as climate change and health concerns, research employing an 'urban metabolism' approach is becoming more popular among academics and policy makers. Globally, the planet's 7.9 billion people generate 84.537-billion-dollar GDP, and by 2026 these figures are expected to grow by 6% and 31%, respectively

* Corresponding author.
E-mail address: oleksandr.galychyn001@studenti.uniparthenope.it (O. Galychyn).

https://doi.org/10.1016/j.clpl.2022.100019
Received 6 August 2021; Received in revised form 17 August 2022; Accepted 2 September 2022
Available online 14 September 2022

("World population projections," 2020; "Global GDP, 2014–2024," 2021). The population and GDP of Vienna have grown by 11% and 31%, respectively ("World population projections," 2020; "Global GDP, 2014–2024," 2021). Although urban areas occupy only 3% of the land surface (United Nations Environment Programme, 2019), they contribute the most to the world economy by generating more than 80% of the global GDP, about 6.2 billion dollars (United Nations Department of Economic and Social Affairs, 2019). Moreover, it is projected that the current pace of economic growth spurred by population growth will continue during the next decade, necessitating an increase of natural resources to support urban economies. Here, we track natural resources using an accounting framework based on embodied solar energy, referred to as *emergy* (Odum, 1996; Herendeen, 2004). This rise of emergy investment will affect distribution structure of trophic levels (consumer and producer), and utilities exchanged among sectors in cities, ultimately affecting emergy received and absorbed by the external environment. In this context, identification of critical sectors in production and consumption patterns in cities plays a key role in modifying the consumption of natural resources and in promoting efficient and sustainable development of other urban areas.

Input-output analysis, introduced by Leontief in 1966 for economic studies, has been extended to be applied to environmental elements, such as water (Hite and Laurent, 1971), energy (Casler and Wilbur, 1984; Zhang et al., 2016a), primary resources (Niza et al., 2009; Merciai and Schmidt, 2017), and wastes (Dias et al., 2014; Liang et al., 2017). This method covers final consumption activities and excludes the utilization of elements by producers. This problem has been resolved by integrating systems ecology perspective and economic input-output analysis (Chen, 2013; Chen et al., 2019). However, this method previously was limited to single elements, such as energy (Bullard and Herendeen, 1975; Li et al., 2020), water (Zhang et al., 2016b; Wang et al., 2020), greenhouse gases (Xia et al., 2019; Zhu et al., 2020). Although Xu et al. (2021) calculated embodied intensity of three elements (energy, water, and carbon), they failed to compare these elements due to the different units of measurement. This method also underestimates consumption of extractive industries (agriculture and mining) (Wieland et al., 2019).

Recently Guevara and Domingos (2017) improved the energy model used in this method to account more precisely for consumption of extractive sectors. However, their model was not tested at the regional scale (Bagheri et al., 2018) and only accounted for a single element (energy).

Input-output analysis did not estimate completely the environmental elements implied in utilization of intermediate products (indirect element consumption among sectors). To solve this problem, input-output analysis was combined with ecological network analysis to analyse the system's structure and functions (Zhang et al., 2014c, 2014d). Ecological network analysis can account for the embodied consumption involved in producing intermediate products (Zhang et al., 2014c).

Hannon (1973) developed this method based on the Leontief approach and synecology perspective (Odum, 1959), which was later expanded by Patten (1978). Most of studies applied ecological network analysis to study natural ecosystems (Liu et al., 2019; Muhtar et al., 2021). In recent years, however, studies that examine urban ecosystems appeared more frequently (Chen et al., 2020; Zheng et al., 2021). Regrettably, only a single attempt has been made to account for an indirect and total emergy consumption of industrial sectors and environment using ecological network analysis (Zhang et al., 2009). However, due to the use of highly aggregated input-output data, the study failed to identify problematic sectors.

Consequently, this study could pave a pathway for improved analysis of structural distribution and functional relationships within urban socio-ecological systems by building an urban emergy metabolic network model. Therefore, the main research question is stated as follows: How to explore the functioning, organization, and complexity of city systems by integrating biophysical, systems, and network methods? To answer this question, we introduced a model that combines an emergy input-output model with ecological network analysis. The objective is to improve the accuracy in accounting for indirect and total emergy consumption of components in urban socio-ecological systems. Emergy was chosen in this study for two reasons: 1) using this approach, monetary and energy flows can be converted into common units (solar emergy joules) and compared (Zhang et al., 2009; Pulselli et al., 2015). 2) Emergy allows to count for the primary solar energy embodied in production by the ecological sub-system (Brownet al., 2012; Asamoah et al., 2017), allowing to analyse the total environmental and socio-economic support provided to each product or sector of urban economy (Viglia et al., 2018; Pan et al., 2021). For example, transformities incorporate plant biomass production through photosynthesis in addition to sugar fermentation processes to produce bioethanol. Thus, we can assess the status (total contribution exchange) and consumption of each industrial sector more accurately. For this reason, a high importance should be placed on accounting for both the environmental and socio-economic intersectoral flows.

The sectors in previous studies on ecological network analysis were assumed to be responsible for their status, not attempting to identify the source sectors (Yang et al., 2016; Tang et al., 2021). Our approach, however, introduces a two-step analysis (Morris et al., 2020). First, one identifies the system components' status (traditional step in ENA), followed by a second step to identify the components (industrial sectors) behind the low status and emergy (total energy and monetary) consumption of the other sectors by using pairwise control and utility analyses.

In this study, we also introduced pairwise direct and indirect controls and indirect utilities to analyse how direct energy and indirect monetary transfer affect other system components, and the sectors affecting other sectors through the detrimental investment relationship (mutualism, competition or exploitation). In this way, the sectors responsible for the status and emergy consumption of other sectors could be identified more effectively and more relevant corrective measures can be proposed.

The rest of the article is organized as follows: Section 2 introduces briefly network properties (i.e., network mutualism) assessed in this study. Section 3 explains the methods and data used in this study. Section 4 discusses the results of this work. Finally, the article concludes in Section 5, and explores important implications for policy, limitations, and possible future recommendations based on findings.

2. Overview of network properties

2.1. Structural analysis

In this study, structural and functional properties of an urban network were assessed. Functional properties that were used in this study are flow and utility properties. Structural analysis was used to analyse pattern and connectivity of network models (Fath and Borrett, 2006).

Path analysis is one type of structural analysis that is used to identify all possible pathways between each pair of components in the network (Fath and Borrett, 2006; Fath, 2012). For this purpose, a structural connectance matrix (A^m) is used. A^m refers to the number of paths between compartments with different "m" pathway lengths. Assuming the network has a certain level of connectivity, as "m" increases, so does the number of indirect pathways (Fath and Borrett, 2006; Zhang et al., 2014c). It is an important feature since identifying pathways with significant metabolic length "m" reflects the highest indirect flows and cycling in the network (Fath and Borrett, 2006; Zhang et al., 2009). In addition, long path length is associated with the considerable economic cost and benefits of cycling (Zhang et al., 2009).

This analysis estimates structural connectance matrix, number of nodes, network connectance, link density and rate at which paths increase (called path proliferation) using the *Matlab* software (Fath and

Borrett, 2006; Fath, 2012).

2.2. Functional analysis

Functional analysis consists of Flow, Storage, Utility, and Control Analyses. In this study, however, we did not use Storage Analysis because of the low quality of initial data available. It is important to note the system should be in a steady state in order to perform each type of the functional analysis (Allesina and Bondavalli, 2003; Fath et al., 2007; Matamba et al., 2009).

2.2.1. Throughflow analysis

This type of analysis is compatible with the Input-Output Analysis (Matamba et al., 2009). This means that flow input data from the input-output table can be directly used in this analysis (Fath and Borrett, 2006). Throughflow serves as a measure of the energy, matter, or trade volume flows in each model node, and it can be an indicator of the relative importance of each node (Borrett, 2013; Borrett and Scharler, 2019). Two types of flows are determined by throughflow analysis: direct flows between nodes and indirect flows (flows passing along two or more paths before reaching a target node) (Zhang et al., 2014c). Ultimately, Flow Analysis is used to determine direct, indirect, and integral (direct plus indirect) flow intensity matrices. The integral matrix (N) represents the amount of direct and indirect input flows (total input flows) required to produce 1 unit of input flow from the external environment (boundary flow). This matrix can be used to determine total flow into the system, if the inputs from the environment are known (Fath et al., 2001).

2.2.2. Control analysis vs Contribution Analysis

Control Analysis measures total dependence and control between each pair of components (Fath and Borrett, 2006; Lu et al., 2012; Yang et al., 2016; Yang et al., 2017). Correspondingly to Throughflow Analysis, flows can also be portioned into direct, indirect, and integral flows (Lu et al., 2012; Yang et al., 2017).

This approach, however, does not estimate the control or dependence of each component in a holistic way (Fath and Borrett, 2006; Li et al., 2018; Yang et al., 2016). Zhang et al. (2014a), however, introduced a method that allowed to estimate the dependence and the influence of each component on all other components within the context of analysing the development pattern of Beijing (China). In their work, the Throughflow Analysis was complemented with Contribution Analysis to estimate the contribution weights of each component in the system based on backward linkages (control of the system) and forward linkages (dependence on the system) (Zhang et al., 2014d). Contribution Analysis can assist the policy makers in developing corrective measures to deal with supply and use imbalances along the 'full supply chain' (Zhang et al., 2014d). However, the Contribution Analysis cannot reveal the dependence and control relationships between each pair of components (Zhai et al., 2019; Xia and Chen, 2020). This is also a serious limitation since the proportion of integral (total) control or dependence between each pair of sectors cannot be estimated. In other words, we cannot determine which sector in the network is more responsible for high (low) levels of total consumption by the target sector. Zhai et al. (2019) applied both Contribution Analysis and Control Analysis to estimate direct and integral influences and dependences of components on regional energy metabolic systems. However, in their study the indirect and direct control relationship between each pair of components was not addressed. Therefore, in this paper, both analyses were applied to identify the hierarchy of each component in the system based on its influence on pairwise and systemic level (Fath et al., 2001) and the reasons behind their status in urban metabolic system based on indirect and total dependence in pairwise (dependence on specific component) and systemic levels (dependence on all other components) between system and target sector (Fath et al., 2001) to improve the functioning development of Vienna's metabolic system.

2.2.3. Utility analysis

The distribution of benefits and costs between each pair of components in the system can be determined by Utility Analysis (Fath and Patten, 1998; Fath, 2012). This analysis is used to assess both direct and integral (direct and indirect) benefits and costs between any two components (Fath, 2012; Zhang et al., 2014b). This analysis reveals a nature of relationship between any two components: mutualism (+,+), competition (−,−), control (−, +), exploitation (+, −), and neutral relationships (0,0) (Zhang et al., 2009). Integral relationships are divided into mutualism, exploitation, and competition (Fang and Chen, 2015). The analysis can be stopped on assessing integral utility of relationships between pairwise sectors (Lu et al., 2012) or it can assess an overall mutualism and synergism of the system: the ratio of positive to negative utility in the network system and total importance of mutualistic and competitive relationships, respectively (Lu et al., 2012; Guan et al., 2019). The two indicators above allow us to assess the state of the system in terms of fitness and symbiosis (Guan et al., 2019). This is especially relevant to the urban metabolic system since higher overall symbiosis and mutualism among industries contribute to the better ecological element utilization efficiency (Boons et al., 2016; Zhang et al., 2014b).

3. Methods and data

This section introduces the overall methodology used to develop and analyse a network model of Vienna's metabolic system used in this study.

3.1. Development of the urban metabolic network model

The emergy input-output model consists of 16 production components (industrial sectors) and consumption components (final demand). Names and abbreviations of the components and sub-sectors names are

Table 1
Names and abbreviations of sectors and sub-sectors.

Sector	Sector names	Sub-sector names
AGR	Agriculture, forestry, and fishing	
MIN	Mining and quarrying	
MAN	Manufacturing	
EC	Electricity, gas, water supply, sewerage, waste, and remediation services	Electricity, gas, steam and air conditioning supply Water supply; sewerage, waste management and remediation activities
CON	Construction	
WR	Wholesale and retail trade, repair of motor vehicles	
TS	Transportation and storage	
AC	Accommodation and food service activities	
INF	Information and communication	
FIN	Financial and insurance activities	
RA	Real estate activities	
OBS	Professional, scientific, technical, administrative, and support service activities	Professional, scientific and technical activities Administrative and support service activities
ADS	Public administration and defence, social security	
ED	Education	
HS	Human health and social work activities	
ER	Arts, entertainment, and recreation, repair of household goods and other services	Arts, entertainment and recreation Other service activities Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

presented in Table 1. The components represent Vienna's socio-economic sub-system (Vienna's metabolic system) (Zhang et al., 2014c). In addition, inputs from environment and to environment represent the ecological subsystem of Vienna socio-ecological system. Previous studies already emphasized the importance of environmental support to the socio-economic subsystem (Zhang et al., 2014c, 2014d; Wang et al., 2019).

In this study, the 'environment' includes the internal environment within Vienna's regional boundary: open green spaces within the city (i.e., Vienna's Danube area) and countryside (i.e., the border area of the Vienna Woods, Viennese part of the Marchfeld region), and the environment outside of the investigated system (i.e., renewable energy imported from outside of Vienna Region Thus, the studied system is limited to the natural environment within the administrative boundary of Vienna city, and the natural environment is outside this region. The consumption sector (domestic sector) was not included in the model since domestic sectors do not produce products (Zhang et al., 2014d). Therefore, inclusion of this sector compromises the steady state of the system (Fath et al., 2007). The emergy input-output model used in this study is shown in Table 2. To construct this model, the following research methods were utilized. The supply-side commodity-by-industry input-output (Liu and Vilain, 2004) and location quotient (LQ) approaches based on value added and final energy consumption were used to obtain the regional shares of monetary and energy production, respectively. Then, these shares were applied to disaggregate Vienna's monetary and energy balance data. Consequently, the regional energy use data were integrated with regional energy supply data through the Leontief's "commodity by industry model". The matrix inversion method was integrated with the reflexive method to estimate transformities of industrial sectors (Patterson, 2014). Regional monetary and energy input-output tables were multiplied by their respective transformity values and summed to build the emergy input output table.

A network model of Vienna metabolic system based on balanced emergy input-output table is shown in Fig. 1. Each pair of components is denoted by letters 'i' and 'j', and the flow from component i to the component j is denoted as 'f_{ji}'. In this way, this model allows the capture of the whole socio-ecological system of Vienna, and its exchanges with the natural environment (Zi and Yi) (Wang et al., 2019).

The next step is to classify all components of the network model using the trophic pyramid as analogy. Unlike the previous studies, we did not combine the components in accordance with the trophic level but only grouped them. The reason for this decision was because an aggregation of compartments can limit the quality of the results obtained, particularly the higher indirect effects and mutualism in the network (Baird et al., 2009). In other words, internal factors responsible for unsustainable or inefficient structural distribution of industries and detrimental functional relationships within the system cannot be identified when complex systems are analysed as simple networks (Zhang et al., 2014b; Yang et al., 2016; Zhu et al., 2019). This allowed us to disaggregate the tertiary sector into 11 sectors showed in the lower right corner of Table 1 and to use them as separate compartments to uncover the extent of status in terms contribution exchange with other sectors (status) and consumption, and to what extent they affect other sectors statuses and consumption of energy and monetary resources. Uncovering metabolism of the tertiary part of urban economy is very important because they are drivers of industrial development, and by them the sectors restricting or contributing to the industrial base in cities could be identified. More generally, the largest proportion of indirect flows allocated mainly to consumers (other sectors of service economy) can lead to the rapid economic development affecting surrounding ecosystems through land use and cover change and associated carbon emissions (Xia and Chen, 2020). Overdevelopment of the industrial sector (primary and secondary sectors) affects consumers using services provided by the tertiary industries (Zhai et al., 2019; Guan et al., 2019).

The primary producers in the urban metabolic system are sectors that can directly utilize natural resources (i.e., solar energy, water, minerals). 'Agriculture, forestry and fishing' and "mining and quarrying" sectors are included in this category. Primary consumers, on the other hand, utilize primary products to produce secondary products (i.e., crude oil, hard coal, natural gas).

The Table 1 contains names and abbreviations of 16 production components (industrial sectors) and sub-sectors (industrial sub-processes) of Vienna's emergy input-output model.

All values in Table 2 are expressed in 10^{15} seJ. Each value in the table represents a sum of ecological and socio-economic flows (emergy flows implied in direct paths) exchanged among industrial sectors in Vienna's metabolic system expressed as solar emergy joules (abbreviated sej). Solar equivalent joule (sej) is a unit used to measure the quality of available solar energy consumed both directly and indirectly in transformations to make a product or service.

These sectors include "manufacturing", "electricity, gas, water supply, sewerage, waste, and remediation services". It is not clear in which category 'construction' sector should be placed. Zhang et al. (2014a) placed the "construction" sector into 'consumer category based on trophic level analogy. Zhai et al. (2019) applied Zhang's analogy to the energy metabolism to refine the classification of compartments in the urban metabolic system in accordance with the embodied energy production and consumption patterns. Since this study focuses on emergy embodied in energy and monetary flows among the sectors, placing this sector in tertiary consumer category will help to understand the role of this sector in the emergy metabolic system. Tertiary consumers include sectors that utilize both primary and secondary products to provide their

Table 2
Sectoral emergy consumption driven by final demand in Vienna's metabolic system (10^{15} seJ).

In Out	AGR	MIN	MAN	EC	CON	WR	TS	AC	INF	FIN	RA	OBS	ADS	ED	HS	ER
AGR	0.51	0.0003	0.17	0.071	2.1	7.2	2.6	2	0.51	1.3	0.23	3.6	1.5	0.46	0.59	0.75
MIN	0.0001	0.021	0.15	0.44	7.1	8.2	26	5.3	1.3	1.6	1.4	4.5	4.7	3.8	2.3	1.1
MAN	74	1.3	9.9	43	51	200	300	130	40	24	14	47	74	27	26	15
EC	170	1.3	8.6	18	110	160	520	210	39	44	16	57	130	83	38	18
CON	36	1.8	780	100	1700	320	310	230	24	39	46	150	240	39	23	23
WR	37	1.3	280	280	160	1100	1500	840	220	140	200	270	340	130	140	180
TS	43	28	2800	1000	310	1000	5300	700	96	92	96	350	520	150	140	60
AC	330	4.2	840	1200	320	830	390	1300	73	100	230	190	260	38	220	400
INF	6.5	0.62	180	290	9.7	72	47	35	200	8.3	8.9	22	86	17	50	27
FIN	0.65	0.022	110	85	14	41	120	130	47	170	10	43	100	36	23	14
RA	0.002	0.017	11	71	430	54	73	98	17	120	120	91	86	8.7	32	16
OBS	3.5	0.24	110	50	31	150	260	480	150	35	27	180	180	110	73	29
ADS	250	21	700	3900	220	350	760	640	180	130	230	250	9300	170	260	96
ED	0.0018	0.08	110	230	89	95	130	200	39	24	43	50	70	290	69	26
HS	59	7.1	430	2900	190	530	420	620	120	77	140	170	240	250	4800	280
ER	18	0.56	47	110	62	120	230	170	44	26	37	55	97	27	37	160

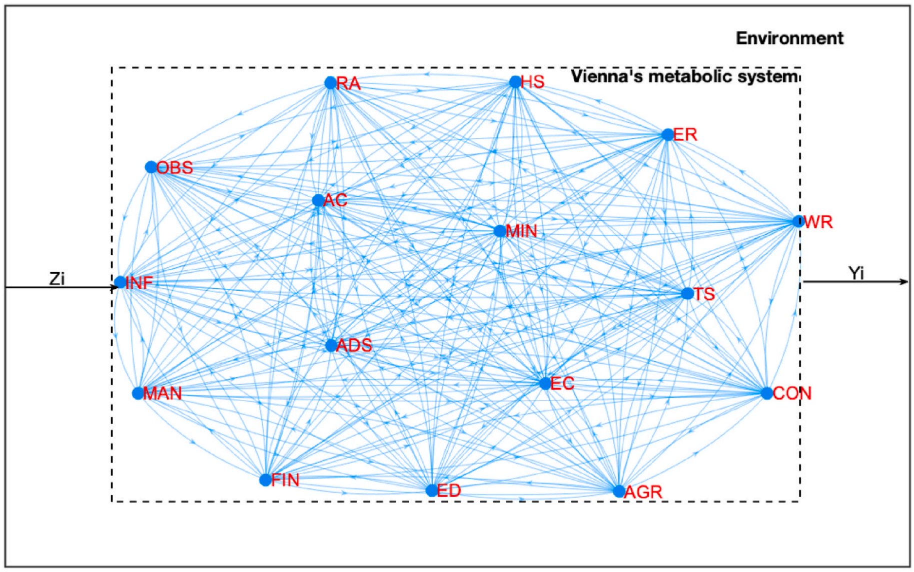

Fig. 1. Network model of Vienna's metabolic system. Zi and Yi represent inputs from and to the external environment of the urban metabolic system, respectively.

goods and services. This group includes tertiary industries and domestic sector. Tertiary industries also fall under that category since those sectors consume products produced by primary producers, primary and secondary consumers. Domestic sector is located at the top of food chain. This sector mainly consumed finished products (i.e., electricity, heat) provided by the other sectors.

3.2. Ecological network analysis of urban metabolic system

The model should meet steady-state requirements in order to perform ecological network analysis (Fath et al., 2001; Fath and Borrett, 2006). This means that the model should conform to the first law of thermodynamics and mass conservation (Fath et al., 2001; Zhang et al., 2014b; Li et al., 2018). Unless this condition holds, other analysis methods are needed. The steady-state requirement is given by Equation (1) (Fath and Borrett, 2006):

$$T_i = T_j \tag{1}$$

where T_i and T_j represent sum of flows into each sector i and out of each sector j, respectively.

This formula further could be written as in Equation (2):

$$f_{ij} + Z_i = f_{ji} + Y_i \tag{2}$$

where Z_i and Y_i are emergy embodied in natural energy inputs and outputs, respectively.

Therefore, the system is at steady state if the sum of total flows from each compartment i and from the environment Z_i is equal to the sum of total flows out of each compartment i and out of environment Y_i.

The next step involves estimation of indirect and integral flows between each pair of components. For this purpose, non-dimensional input-oriented transfer efficiencies along all pathways in the system must be known (Fath et al., 2001; Zhang et al., 2009, 2014c). The elements of non-dimensional output-oriented transfer efficiency matrix (G) are estimated using Equation (3):

$$g_{ij} = \frac{f_{ij}}{T_i} \tag{3}$$

where g_{ij} is the amount of emergy embodied in total (direct and indirect) input flows to each sector i (T_i) required to produce 1 sej of emergy flow from each sector j to each sector i (f_{ij}). Thus, the matrix (G) is called an input-oriented non-dimensional ecological element exchange efficiency matrix (Zhang et al., 2014c). It is based on forward linkages in the system of interest (Fath et al., 2001; Fath and Borrett, 2006). This matrix shows how much of original input emergy is actually used in exchange between each pair of sectors. This efficiency decreases along with the increase in path length between i and j due to dissipation (Fath et al., 2001).

The sum of the initial, direct, and indirect transfer efficiencies represents the output-oriented integral (total) transfer efficiency between each a pair of sectors in the system, Equation (4):

$$N = G^0 + G^1 + G^2 + G^3 \ldots + G^m + \ldots = (I - G)^{-1} \tag{4}$$

where G^0 is 'cyclic feedback matrix' that involves flows within each sector. The values of this matrix are equivalent to the identity matrix (I) (Fath, 2012). G^1 is an intensity of emergy exchange between each pair of sectors along the direct path. G^2, G^3 *and* G^m are indirect intensities of emergy exchange between each along various lengths of m $(m \geq 2)$.

Then, we can obtain the integrated emergy flow transfer matrix (Y) where each element (y_i) reflects the total contribution to each sector i from all other sectors (Zhang et al., 2014c; Zheng et al., 2016; Zhai et al., 2019). This matrix is given by Equation (5):

$$Y = diag(T_i) \times N \tag{5}$$

where T_i *and* N as above.

Knowing this allows us to compute "integral pulling force weight (W_i)" and "integral driving force weight (W_j)":

$$W_i = \sum\nolimits_{j=1}^{n} y_{ij} \Big/ \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{n} y_{ij} \tag{6}$$

$$W_j = \sum\nolimits_{i=1}^{n} y_{ij} \Big/ \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{n} y_{ij} \tag{7}$$

where $\sum_{j=1}^{n} y_{ij}$ is the total emergy contributed by the system to sector i and $\sum_{i=1}^{n} y_{ij}$ is the total emergy contributed by sector i to the system. The driving force weight indicates the ability of the sector i to provide emergy support to other sectors through backward linkages (supply linkages). It can reveal the degree of control of sector i to the other sectors in the system (Grimm et al., 2008; Zhai et al., 2019). The pulling force weight reflects the ability of the sector i to receive emergy inflows from other sectors through forward linkages (demand linkages). This factor reflects the degree of dependence of sector i on other sectors in the system (Zhai et al., 2019; Zhang et al., 2021). These two factors can provide insight on the development stage and role of each sector in the system (Zhang et al., 2014a; Zhai et al., 2019).

However, the indirect contributions, which have been explored by Zhai and et al. (2019), affect total contribution weights (integral pulling and driving force weights) considerably. Therefore, it is crucial to determine and compare indirect and direct pulling and driving force weights (Zhai et al., 2019), Equations (8) and (9).

$$F_i = \sum_{j=1}^{n} e_{ij} \Big/ \sum_{j=1}^{n} \sum_{i=1}^{n} e_{ij} \tag{8}$$

$$F_j = \sum_{i=1}^{n} e_{ij} \Big/ \sum_{j=1}^{n} \sum_{i=1}^{n} e_{ij} \tag{9}$$

where F_i *and* F_j are direct pulling and driving force weights, respectively, and $\sum_{j=1}^{n} e_{ij}$ is the direct contribution by the system to sector i (in emergy units) and $\sum_{i=1}^{n} e_{ij}$ is the direct contribution by sector i to the system (in emergy units).

Knowing both integral and direct pulling and driving force weights, the indirect pulling and driving force weights can be determined by Equations (10) and (11):

$$E_i = W_i - F_i \tag{10}$$

$$E_j = W_j - F_j \tag{11}$$

where E_i *and* E_j are indirect pulling and driving force weights, respectively. In this way, direct and indirect flow contributions in output and input directions can be compared (Zhai et al., 2019).

Secondly, Utility Analysis should be performed to reveal the nature of relationship between each pair of sectors (Fath and Borrett, 2006; Zhang et al., 2014b; Zhai et al., 2019). This involves computing integral utility intensity matrix (U) based on the elements of direct utility intensity matrix (D). Direct utility intensity matrix (D) is given by Equation (12):

$$D = \frac{(f_{ij} - f_{ji})}{T_i} \tag{12}$$

Matrix (D) is used to determine the relations between any pair of sectors in the urban metabolic system based on direct intensity of ecological elements exchanged between them (Fath, 2012). Initially, the matrix is computed using the Equation (12). Then, the positive and negative signs are taken from exchanges (nondimensional intensities of net flows) between sector i and sector j. Finally, the signs are combined to determine relationships between each pair of sectors: mutualism (+,+), competition (−), control (−, +), exploitation (+, −), and neutral relationships (0,0) (Zhang et al., 2009; Li et al., 2018).

If matrix D reveals only the nature of direct relationship, integral utility intensity matrix (U), on the other hand, reveals the total benefits or total costs of any relation between each pair of components (Lu et al., 2012; Xia and Chen, 2020). As with flows, indirect benefits and costs are more responsible in change of system's state from stable to unstable, and vice versa (Lu et al., 2012). The integral utility intensity matrix (U) is given by Equation (13).

$$U = D^0 + D^1 + D^2 + D^3 \ldots + D^m + \ldots = (I - D)^{-1} \tag{13}$$

where D^0 utility of flows (benefits) generated in the sectors themselves (Zhang et al., 2014d), D^1 utilities (benefits or costs) between each pair of sectors along the direct path, D^2, D^3 *and* D^m are indirect utilities (indirect benefits or costs) of emergy exchange between each pair sectors along various lengths of m ($m \geq 2$). D^0 is also equal to identity matrix (I). Then, matrix U should be dimensionalized to obtain values of total benefits and costs from the relations between each pair of sectors in the system (Zhang et al., 2016b). The dimensionalized integral utility matrix (Y) is obtained from Equation (14):

$$Y = diag(T_i) \times U \tag{14}$$

From this matrix mutualism index (M) and synergism index (S) can be estimated, Equations (13) and (14):

$$MI = \frac{Sign\ U(+)}{Sign\ U(-)} \tag{15}$$

$$SI = \sum Y(+) + \sum Y(-) \tag{16}$$

where $\sum U(+)$ and $+\sum U(-)$ are sum of flows with positive and negative utilities, respectively. Mutualism index (MI) is the ratio of the number of positive signs of U to the number of negative signs of U. If MI is greater than 1, it means that the total benefits of interactions outweigh costs in the system and hence the system can be considered mutualistic and healthy (Tan et al., 2018). The synergism index is a ratio of integral flows with positive utilities to the integral flows with negative utilities (Tan et al., 2018). When S > 0, synergism is said to occur, i.e., systems have positive net benefits (greater benefits than costs) resulting from relations between each pair of sectors (Zhang et al., 2016b).

The last step involves the network control analysis. It follows the similar logic to the Flows and Utility Analysis in that transfers efficiencies are divided into initial, direct, and indirect to determine integral (total) transfer efficiency between each pair of sectors in the system (Lu et al., 2012). However, integral transfer efficiencies are determined in terms of both backward and forward linkages in the system of interest. The elements of non-dimensional input-oriented transfer efficiency matrix is estimated from Equation (17):

$$g_{ji} = \frac{f_{ji}}{T_j} \tag{17}$$

Then, following the Flow Analysis procedure, the input-oriented integral (total) transfer efficiency between each pair of sectors in the system (N^i) was estimated, Equation (14) (Tan et al., 2018; Zhai et al., 2018), Equation (18):

$$N^i = (G^i)^0 (G^i)^1 + G^i)^2 + (G^i)^3 \ldots + (G^i)^m + \ldots = (I - G^i)^{-1} \tag{18}$$

where $(G^i)^0$ is input-oriented 'cyclic feedback matrix' that involves flows within each sector (Zhai et al., 2019). $(G^i)^1$ is an input-oriented intensity of flow between each pair of sectors along the direct path. $(G^i)^2, (G^i)^3$ *and* $(G^i)^m$ are input-oriented indirect intensities of emergy flows between each pair of sectors along various lengths of m ($m \geq 2$).

The pairwise integral control relationships between sectors can be expressed by matrix (CN) (Fath and Borrett, 2006; Zhai et al., 2018, 2019), as per Equation (19):

$$CN = \frac{N}{N^i} \tag{19}$$

where N and N^i as above.

Each element of CN matrix represents the proportion of the integral flow from sector i to sector j to the integral flow from sector j to sector i (Li et al., 2018). This matrix was subsequently modified, so that when $n_{ji}/n'_{ij} < 1$, $cn_{ji} = 1 - n_{ji}/n'_{ij}$, otherwise, $cn_{ji} = 0$ (Yang et al., 2012; Zhai et al., 2018, 2019).

The values of the modified matrix were limited to range between 0 and 1 (Yang et al., 2012). The component i depends on j if i provides to j less output than it receives from j ($cn_{ij} = n_{ji}/n'_{ij} < 1$). On the contrary, if the sector i provides more output to j than it receives from j, then the sector i controls sector j (Li et al., 2018; Zhai et al., 2018, 2019).

As the total pairwise control or dependence is equal the sum of direct and indirect controls or dependencies. Thus, based on the CN matrix, the pairwise indirect control relationships can be determined (IN) (Equation (20)).

$$IN = \frac{N - G^0 - G^1}{N^i - (G^i)^0 - (G^i)^1} \tag{20}$$

The following modification was introduced to avoid negatives and values of indirect control been larger than integral values: when $0 < in_{ij} < cn_{ij}$, $in_{ji} = in_{ij}$, otherwise, $in_{ji} = 0$. Thus, total dependence of each sector was updated by adding emergy implied in indirect flows. Thus, data applied to contribution, control and utility analysis allowed us to reveal the status and functions of each sector within the system and systems' state (mutualism and synergism). Finally, the dependence in pairwise and systemic levels, then, allowed us to detect the sectors responsible for the condition of each target sector. By this methodology, any issues in organisation and functioning in any system characterized by complex interactions such as urban metabolic systems can be identified and assessed.

3.3. Data collection and sources

In this study, we used Vienna's emergy input-output table referred to the year 2015. Since the original model was not in the steady state required to perform ecological network analysis, the model was updated. By using the Generalized RAS (GRAS) balancing approach (Temurshoev et al., 2013), we estimated a new matrix with the same column and row totals as the original one (Temurshoev, 2021). The resulting model conformed to the steady state rule and included the intersectoral, boundary input and output flows.

The compartmental storage data were not available. The capital formation reflects a steady-state storage value of each sector of Vienna's metabolic system (Zhang et al., 2014a). A prior knowledge of steady-state storage values of the donating sectors is an essential requirement to perform the Storage Analysis (Fath et al., 2001; Fath and Borrett, 2006). Since this analysis is out of scope of our work, the total value of final demand of the urban economy was assigned to storage vectors. This category was chosen because the storage values at the donating and the receiving sectors are equal at steady state (Fath et al., 2001). Since the capital formation is an integral part of 'final demand', the storage values used in our study were overestimated. Nevertheless, the assembled system was sufficient to perform ecological network analysis.

4. Results and discussion

This section will discuss the results of ecological network analysis applied to the emergy input-output table of Vienna region.

4.1. Flow analysis

In this study we obtained an integrated emergy flow transfer matrix (Y). The elements of this matrix revealed the total emergy consumed by each sector in the urban metabolic system. Results are shown in Fig. 2.

The Fig. 2 shows the total emergy consumption for each sector in the urban metabolic system. We noticed that the hierarchy of all sectors in terms of the total emergy consumption remains the same. The division of sectors based on their consumption is presented in Appendix A.

The results of ecological network analysis indicate that the 'public administration' plays a key role in the urban metabolic system. Along with the economic growth more financial investments and labour force required to drive an increased demand on general activities of public administration such as provision of transport infrastructure. The high indirect consumption of TS, HS and EC sectors could be related to the promotion of development of these sectors by local administration. On the hand, the AC, MAN, WR, CON, ED, OBS, ER and INF sectors are underrepresented in the Vienna region. The moderate consumption of 'manufacturing', 'wholesale and retail' and 'construction' conforms to their respective positions in supply chain, indicating that their demand are in line with their general consumption characteristics (e.g., tertiary industries indirectly consume ecological elements). The indirect consumption of information and communication' sector is lower than expected, indicating that the more efforts should be put to develop this sector. The proportion of the direct emergy consumption was higher than indirect consumption. The low indirect consumption of 'real estate activities' and 'financial and insurance activities' was also unexpected. These sectors do not contribute to the consumer part of economy, which supports development of industrial base through investments. It should be obvious that these sectors use few pathways to transfer most of their emergy. Thus, it is necessary to improve energy transfer and utilization efficiency to decrease direct consumption of those sectors and to increase demand of producing sectors on their products. The structure of emergy consumption for each sector in the system is presented in Appendix B.

4.2. Contribution Analysis

We used this analysis to assess the total influence and dependence of each sector on the urban metabolic system (Zhai et al., 2018, 2019). This approach not only assesses the influence in a more holistic way than

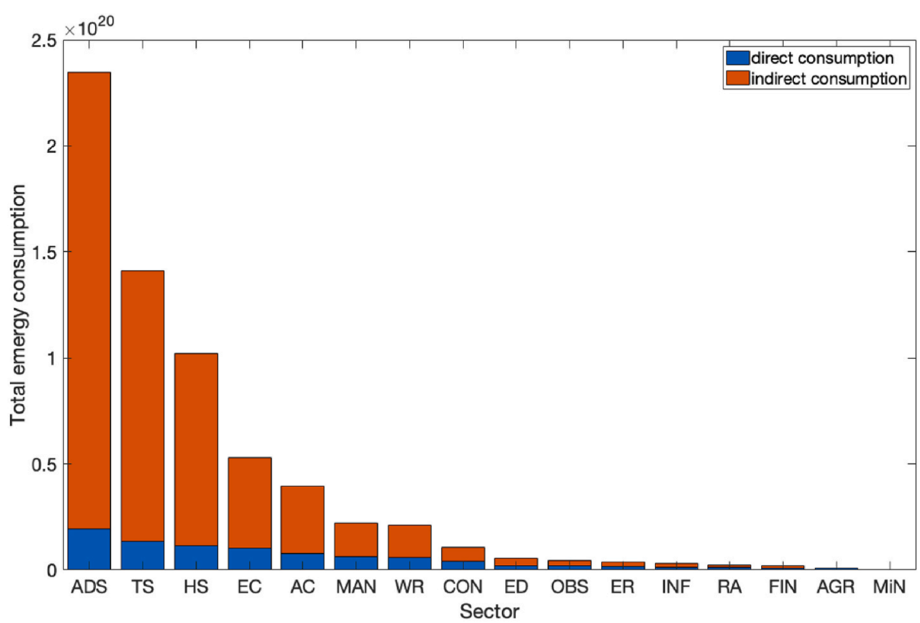

Fig. 2. Total emergy consumption for each sector of Vienna's metabolic system.

control analysis but also considers both the forward and backward linkages in the system of interest (Zhai et al., 2018). Fig. 3 shows that the pulling force hierarchy represents an irregular inverted pyramid structure. This result reveals an existence of sectors that obstruct functioning of the system because upper consumers do not have enough support to pull development in lower producers (Zhai et al., 2019).

This structure is caused by insufficient pulling weight of AGR and MIN sectors and too strong pulling weights of ADS, TS and HS sectors. Those results conform to the dominating nature of tertiary industries, and supplementary nature of production industries in Vienna's economy. This all means that Vienna's economy is not dominated by production industries. The indirect pulling force of the EC and MAN sector was lower than direct, suggesting investment to these sectors from the rest of the economy lags far behind their production. Therefore, these sectors should not be targets of economic development of the Vienna region. ADS and TS sectors also receive more emergy in direct ways than in indirect, but their integral pull weight is the highest. This highlights their key role in promoting development of the Vienna region. The rest of the sectors can be characterized by decreases in their indirect pulling weights.

The highest decrease in indirect pulling weight was detected in CON and WR sectors: −0.04 and −0.03, respectively. This compromises their integral contribution to the upstream industries (AGR and MIN). The structure of those sectors should be regulated to increase their indirect consumption of emergy implied in payments provided by tertiary industries for their products. The high decrease of indirect pulling weight are also observed in AC, ED and ER sectors. Therefore, their demand for services of other tertiary industries should be increased to receive more payments from the downstream sectors in exchange of purchased services and to develop enough to also promote economic development of other two sectors (CON and WR). Also, this suggests that investments into these three sectors fall behind the demand for their services.

This reflects Vienna's position as financial capital with most of the investment in education, research, and tourist attractions generated within the region as of 2015 (The Municipal Department 23 - Economic Affairs, Labour and Statistics, 2016), leading to the high pulling ability.

Fig. 4 shows ecological hierarchy of driving weight. This structure partially resembles an irregular inverted pyramid. Overall, this structure represents a satisfactory state of development because some sectors with internal problems can still be identified. It indicates that producers do not support some consumers. AGR and MIN sectors had high total driving weights that suggested that their ability to deliver emergy is far too strong. From one point of view, they provide the basic support for Vienna's economy. However, Fig. 4 indicates that their indirect driving force weight is much higher than direct. This indicates that demand for investments by downstream sectors is ahead of their demand for agricultural and mining products. Therefore, those sectors are forced to use services from tertiary industries to upgrade their production base, and in this process tertiary industries benefit from labour and payments received from the AGR and MIN sectors. However, the long distance of transferring emergy to downstream sectors for these type of sectors (Zhai et al., 2018) also means that not all flows reach their destination due to dissipation (i.e., ER, HS, ED in Fig. 3). Thus, it is advised to increase pulling force weight of AGR and MIN sectors, and to decrease indirect delivery ability of those sectors by increasing efficiency of emergy transfer along shorter paths. AGR and MIN sectors, unlike other industries, do not only produce and transfer their products to intermediate sectors but also deliver energy to intermediate sectors due to their producer function. Thus, the decentralised generation of electricity for tertiary industries for these two producers such as standalone agro-photovoltaic system might be a solution to reduce energy losses stemming from the long central distribution channels and to avoid intermediate consumers, if such system is positioned to have a direct connection with its consumers (Ha & Kumar, 2021; Weselek et al., 2019).

If all the energy supply reaches their destination, then tertiary (service) industries will save the funds for their development, thereby decreasing their dependency on payments to producers (AGR and MIN) for their services. The increased efficiency of monetary transfers along shorter paths lies in a transition from indirect to direct distribution channels characterized by a minimum number of intermediate industries possible to reach consumers (tertiary industries and households) (i.e., direct farm sale to consumers, on-farm retail market where farmer sells their directly their produce to retailers such as food processors) (Brown and Miller, 2008).

The direct distribution channel facilitates the delivery of agricultural and mining products of the tertiary consumers, but also minimises the losses associated with the payment from tertiary industries reaching AGR and MIN sectors in full, leading to the increase of its indirect and total pulling force weights. These two measures should improve the efficiency of emergy (energy and monetary) transfer along the shortest paths to decrease indirect delivery ability of AGR and MIN sectors, and

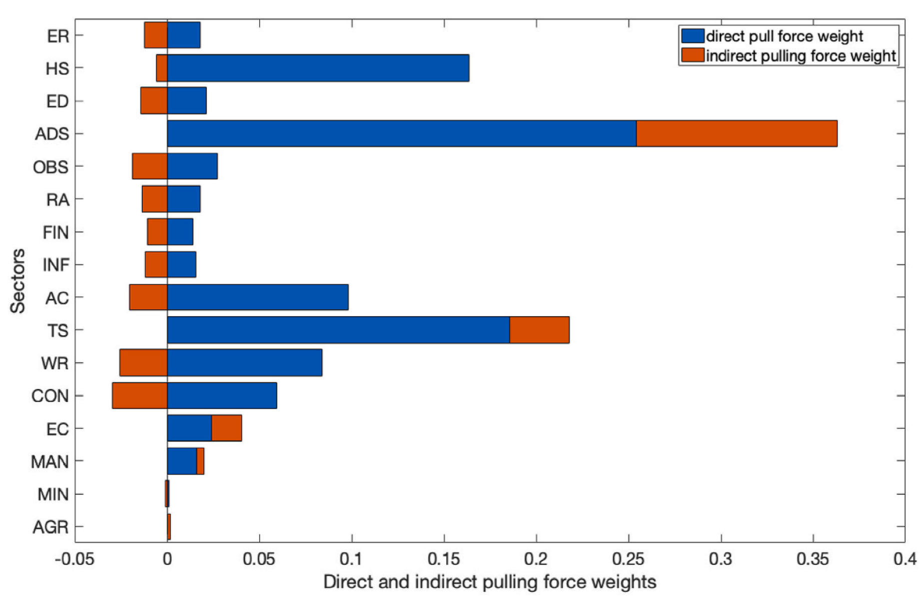

Fig. 3. Input-oriented direct and indirect weights of each sector in 2015. The figure shows direct energy and indirect monetary contribution of all industrial sectors in the Vienna's urban metabolic system to each industrial sector separately.

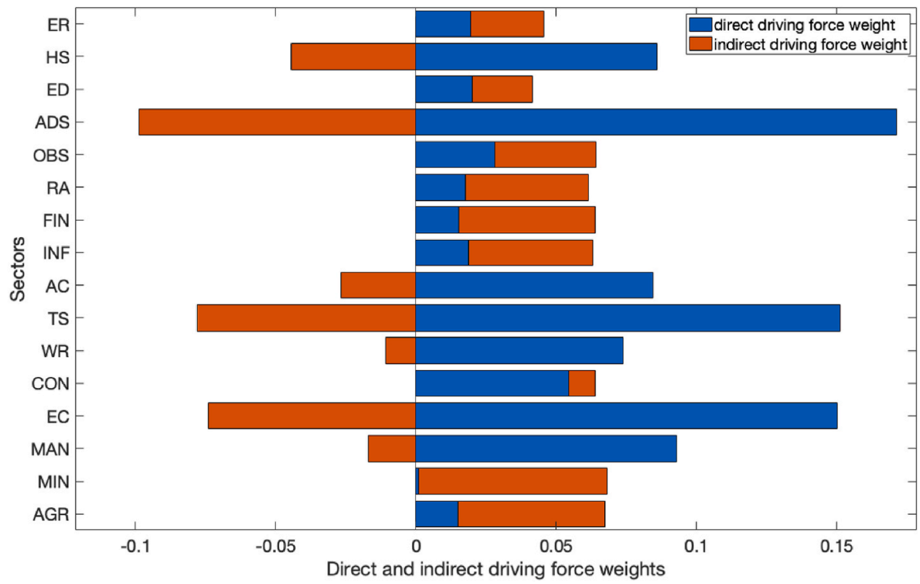

Fig. 4. Output-oriented direct and indirect weights of each sector in 2015. The figure shows direct energy and indirect monetary contribution of each industrial sector to all the sectors in the Vienna's urban metabolic system.

to increase their pulling force weights.

Contrary to the producers, WR and CON have a poor delivery ability to downstream sectors. And their direct driving force is five times higher than indirect. This implies that these sectors mainly use indirect pathways to deliver emergy to downstream sectors and that the efficiency of emergy transfer is low. Their low indirect and total consumption is going against Vienna's development strategy aimed to further promote development of commercial and service industries. The normal functioning of those sectors could be achieved through policy intervention to increase their indirect delivery abilities in the process of emergy utilization. The significant drop in indirect driving weights is noticeable in ADS, TS and EC sectors: −0.1, −0.08 and −0.07, respectively, implying that the investments into production of these sectors fall behind demand for their investments by the other sectors. For TS and EC sectors this reflects most products used by these sectors (i.e., natural gas, diesel) are imported from outside of the Vienna region. In the case of the ADS sector, it shows that this sector does not contribute much to the economy despite being a key sector responsible for provision of social services. The reorganisation of this sector is recommended to provide its services to the growing population. Overall, their productivity should be improved to efficiently transfer emergy along indirect pathways to AGR and MIN sectors since the structure of pulling weight depends on those industries. MAN and AC sectors were in proper shape in terms of the total driving weights and drop in indirect weights were insignificant: −0.02 and −0.01, respectively. Industrial development is also one of priorities of Vienna's government. Therefore, this is in line with their policy. Since among all downstream sectors only 'construction' uses manufacturing products directly to produce finishing products (i.e., buildings), higher indirect contribution from 'manufacturing' to the downstream sectors is required for healthy development of urban metabolic systems. Lastly, shapes of FIN, RA, INF and OBS sectors deviate from norm due to the small indirect and integral driving weights: 0.05, 0.04, 0.0.4 and 0.03, respectively. Generally, the role of those sectors is to indirectly drive the technological advancements in upstream sectors (Zhai et al., 2018). Due to their social function these sectors connect other sectors through indirect paths (Zhai et al., 2018). Thus, it is necessary to develop those industries to upgrade the ability of AGR and MIN sectors to receive emergy.

4.3. Control analysis

The pairwise indirect control relationships in 2015 are shown in Fig. 5. The values of the IN matrix range from 0 to 1, with the latter being a maximum indirect influence of one component on another component. Dark blue colour represents the absence of control of one component on another component or the absence of dependence of the latter. Conversely, the dark red colour stands for a complete influence of one component on another component or a complete dependence of the latter. For example, $in_{12} = 0.98$ means the dependence of AGR on MIN was 98% in 2015 or the control of MIN over AGR was 98% (Li et al., 2018; Piezer et al., 2019; Zhai et al., 2018). The elements of control matrix range from 0 to 0.29, indicating that indirect control is much lower than direct and, therefore, do not contribute significantly to the integral pairwise relationships between components. However, four pairwise relationships deviate from this pattern, exhibiting some degree of control and dependence. The OBS had the highest control in the network, while the AC sector had the highest dependence. This means that AC is a self-sufficient sector and moderately stable in terms of indirect flows (dependence <50%).

The high dependence of the AC sector on the OBS sector points to the low production capacity of the AC sector. This inhibits the AC sectors ability to meet demands of other sectors on its service (i.e., short term accommodation to hold conference). Therefore, the AC sector relies on imports (i.e., monetary) from OBS sector to purchase event accommodation to have a capacity to provide more services to satisfy demand of OBS sector conference venue. Thus, the higher the dependence the more the sector relies on imported products from other sectors to replenish its production to meet demand of consuming sectors (i.e., electricity for TS sector to provide purely battery-electric buses to transport labour force to respective tertiary sector such as OBS) (Ajanovic et al., 2021). The 98% (out of 100%) control of OBS sector over AC sector means that AC sector's dependence on OBS is 98%. Generally, in this way, control and dependency of a sector indicate the extent of self-sufficiency of the sector in emergy (monetary and/or energy) use.

Also, the second and third by magnitude control were effectuated by ER and ADS sectors over TS, respectively. This simply shows that AC receives the most emergy implied in direct energy transfer through the OBS sector. The same applies to TS in relation to ER and ADS sectors. Generally, these degrees of control fall within stability thresholds. In addition, in a healthy system majority of flows between tertiary sectors

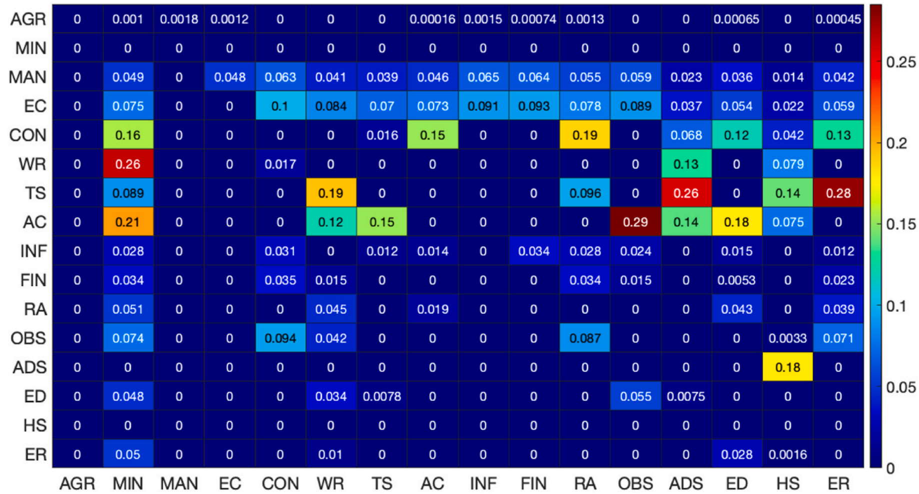

Fig. 5. Pairwise control relationship between components along indirect paths in 2015. Warm colours represent total control and cold colours represent total dependence received or transferred between each pair of sectors. Note: The columns and rows describe degree of control and dependence, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

are received in an indirect way considering their social function (Zhai et al., 2018). TS and AC meet this stability condition (direct dependence lower than indirect). Finally, the WR sector is slightly dependent on the MIN sector, not even 0.27. However, the ability of the WR sector to deliver emergy to MIN is worthier than its ability to receive emergy from MIN. This demonstrates that the WR sector does not effectively support the MIN sector. Therefore, the production structure WR sector should be regulated to effectively transfer emergy to MIN sector.

The number of sectors that rely on the MIN sector is 14, while there are 2, 1 and 0 sectors depending on EC, MAN and AGR. Conversely, EC, MAN and AGR are dependent on 13, 14 and 9 sectors, respectively. From the demand-side perspective, EC, MAN and AGR are sectors that require direct support from other sectors to deliver flows to them (Zhang et al., 2014a; Li et al., 2018). Therefore, input of other sectors would affect direct energy consumption of those three sectors. The production structure of the three sectors must be adjusted to reduce their direct energy consumption. This would necessitate a further study to break these industries into sub-processes and then to employ ecological network analysis to see how much direct and indirect pulling and driving weight each sub-process has in the system. Then, we can identify the most affected sub-processes by other sub-processes to propose the corrective measures targeted at the specific sub-processes. For example, the manufacture of chemicals and chemical products could have the highest energy dependence in the Manufacturing sector. This additional detailed step is out of the scope of this study.

In general, energy intensive sub-processes in these sectors could also be substituted with labour intensive ones. In addition, it is important to substitute energy intensive process such as manufacturing cement with manufacturing of timber or other low energy consumption sub-processes. It is important to use unprocessed materials such as corn, timber, or natural gas in manufacturing process directly. For example, substituting traditional manufacturing with the low carbon manufacturing (LCM) will decrease direct energy consumption (Tridech and Cheng, 2011). Lastly, introducing more energy dependent sub-processes within each sector will lead to the energy consumption deficit among sub-processes and associated mutual energy consumption reduction. Conversely, if the sub-processes directly control each other, namely deliver excessive amount of energy to each other, decreasing the energy delivery from one sub-processes will result in decrease of the energy delivery from a second one (Li et al., 2018).

Integral pairwise relationships between sectors are shown in Fig. 6. The MIN sector completely dominates the system by heavily controlling

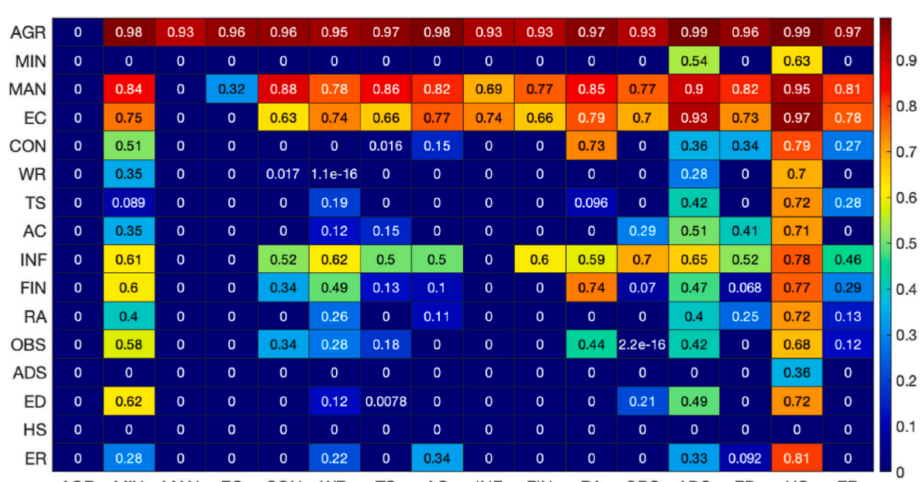

Fig. 6. Pairwise control relationship between components along integral paths in 2015. Warm colours represent total control and cold colours represent total dependence received or transferred between each pair of sectors. Note: The columns and rows describe degree of control and dependence, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

all other compartments. This sector also shows moderate direct dependence only on 2 sectors: HS and ADS, which suggests that this industry has not been developed in the Vienna region. The AGR sector is ranked as the highest emergy receiver in the system based on colour. Extremely high total control over this sector is demonstrated by 2 upstream sectors (MIN and EC) and 5 downstream sectors (CON, AC, RA, ADS and HS). Conversely, the MIN sector has control over 13 sectors, while only the ADS and HS sector have a control over it. AGR and MIN sectors need to deliver a large amount of flows to downstream industries in order to receive the feedback required for their development. This means that these sectors should effectively supply and receive emergy flows. Thus, both sectors are inadequate in terms of control and dependence. Also, the dependence of the AGR sector on 7 sectors is predominantly direct, suggesting that AGR has low capacity to receive emergy indirectly from the other sectors. The indirect dependence of the AGR on MIN and EC sectors is much lower than direct, suggesting the AGR sector poorly receives indirect inputs (payments) from EC and MIN, which hinder its production capacity. Moreover, the production of the AGR sector depends on energy inputs from MIN and EC to meet demands of downstream industries, leading to low direct deliver ability of this sector. CON, AC, RA, ADS and HS are sectors that normally are not in direct contact with upstream sectors (Zhai et al., 2018). There are no sectors depending on AGR, suggesting that AGR sector lacks self-sufficiency in emergy use and, therefore, is the most vulnerable sector to shortages of energy flows in Vienna Region. Therefore, adjustment in production structure is necessary to reduce direct energy consumption of the AGR sector and to improve its ability to receive emergy indirectly. The other important measure is to increase the demand for mining products in Vienna region followed by an increase of payments provided to the MIN sector. Finally, stimulating the demand for agricultural products by tertiary sectors at the middle of supply chain (i.e., demand for agro-waste such as sugar beet waste named carbonation lime residue as partial replacement of cement in "construction" sector) should improve indirect receiving capacity of AGR while avoiding too long circulation paths that limit the acceptance of investments by AGR sector. These policy measures would contribute to the healthy development of Vienna's metabolic system.

4.4. Utility analysis

Based on the results of direct utilities in Vienna's metabolic system along direct paths, Fig. 7 reveals the mutual emergy metabolic relationships between each pair of sectors. There were a few large gaps in emergy metabolic relationships among sectors, but most relationships were homogeneous.

In Fig. 7 the beneficial relationships are represented by warm colours, while disadvantageous relationships are represented by cold colours. Judging by the colour of different grids, the neutral pairwise relationships between sectors dominated along diagonal during the study year. This means that there was not any direct benefit of sector's flows to itself (Zhai et al., 2019). From Fig. 4 the EC sector is exploited by three tertiary industries: ADS, HS and INF. Also, the CON sector is exploited by the RA sector. This simply shows that the EC sector is in constant pressure of expansion to meet energy demand of the growing pillar tertiary sectors. This also means that energy production lags behind the economic growth (Zhang et al., 2014d). Moreover, the energy requirements of the CON sector grow to keep up with the growing demand for non-residential properties such as hospital buildings (Zhang et al., 2014d). A similar problem is associated with the exploitation relationship between TS and MAN. Although the development of the MAN sector is in line with the urban development plan till 2025 (Anthopoulos, 2019; Vienna City Administration, 2014, 2019), the energy requirements of MAN sector are also far behind demand of TS sector for its manufacturing products (i.e., rolling stock). Therefore, EC, CON and MAN should indirectly exploit the other industries to improve their competitiveness, or their productivity should be increased until the development of the ADS, HS, INF, RA and TS sectors will stabilize. The same solution can be applied to the direct exploitation of ER by AC.

The strong exploitative relationships were identified between AC and AGR, ADS and AGR, ADS and MIN and week exploitation between AGR and MIN. The fact that AGR and MIN are exploited by ADS and AC suggests that these sectors (AGR and MIN) have a low ability to satisfy the energy demand of all downstream industries, resulting from their dependence on imports. All tertiary sectors need to improve their competitiveness to exploit or to be in mutualism with AGR and MIN sectors. The competitiveness of downstream sectors could be improved by exploiting other industries (EC and MAN) for energy or be in mutualistic relations with them (Zhai et al., 2018). Fig. 7 shows that CON, TS, INF, ADS and HS pursue this strategy. Furthermore, improving the competitiveness of MIN sector and managing development of AGR and MIN sectors in an integrative manner will contribute to the mutual relationships between these sectors.

Fig. 8 presents a pairwise integral relationship between components. Based on colour of different grids, values on diagonals outweigh the non-diagonal values due to indirect flow that occur within each sector always provides positive self-feedback (benefits) to itself (Zhai et al., 2019). Judging by the colour of different grids competition relations occupy almost all cells in the Fig. 8, which suggest that indirect utilities have a little positive effect on the system. However, Yang and et al. (2016) found that any relationships that fall in range from −0.5 to 0.5 can be

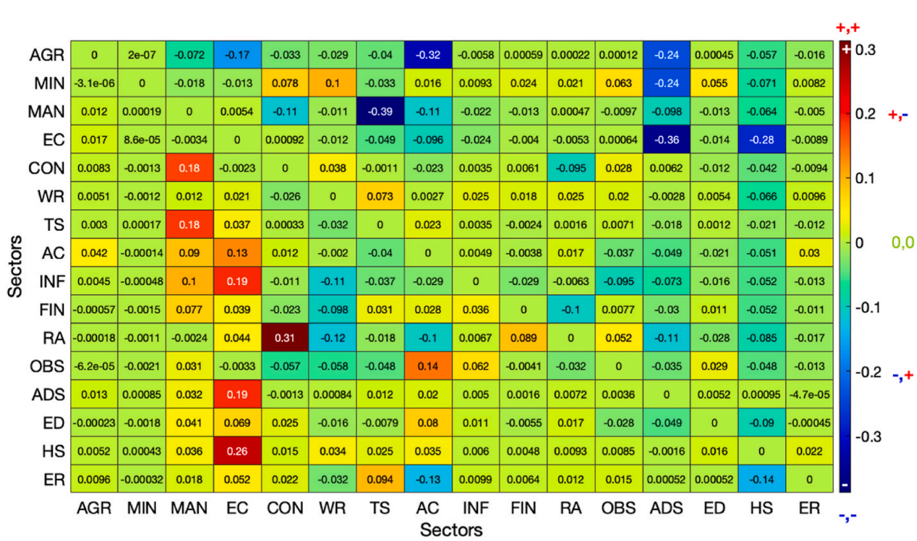

Fig. 7. Pairwise utility relationship between components along direct paths in 2015. The warm colours reflect the direct benefits (+), and the cold colours reflect the direct costs (−) received or transferred between each pair of sectors. The values in matrix ranges from −1 to 1. The four combinations of signs result in four pairwise relationships between sectors: mutualism (+,+), competition (-,-) exploitation (+,-), exploited (-,+) and neutral (0,0). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

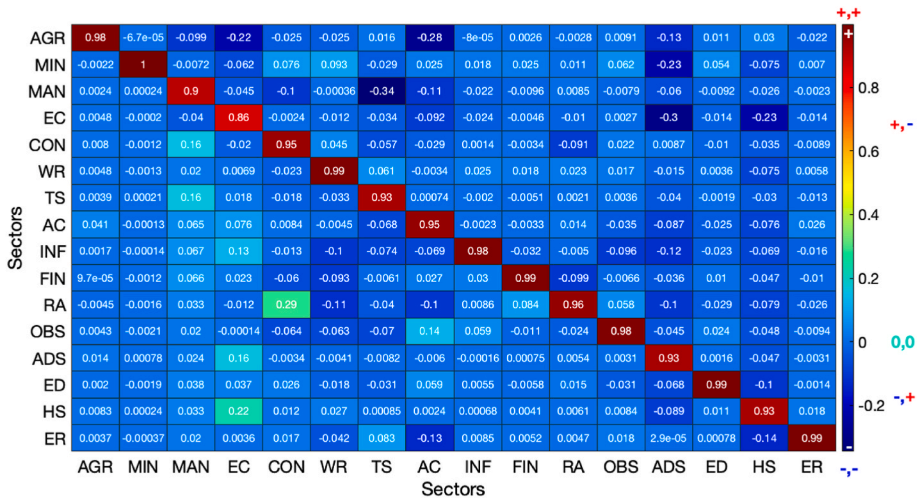

Fig. 8. Pairwise utility relationship between components along integral paths in 2015. The warm colours reflect the total benefits, and the cold colours reflect the total costs received or transferred between each pair of sectors. The values in matrix ranges from −1 to 1. The four combinations of signs result in four pairwise relationships between sectors: mutualism (+,+), competition (−,−) exploitation (+,−) and exploited (−,+). Indirect effects changed neutral (0,0) into mutualistic relations (+,+). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

defined as weak linkages. In our case all relationships, except values on diagonals, fall in that range as shown in Figs. 8 and 9. The only strong exploitation relationship based on Fig. 9 is between RA and CON, where indirect contribution is too small (>0.1). The CON is exploited by the RA sector through emergy inputs to satisfy requirements of RA sectors, which contributes to expansion of the housing market. However, Fig. 9 shows the RA is exploited by the CON sector through investments to satisfy requirements of CON sector. Thus, RA sector should be supported indirectly by the other sectors to improve its competitiveness. However, this indirect support is originated from weak mutualistic relationships between RA and MAN, RA and WR, RA and AC, which are sufficient to offset weak negative utilities resulted from indirect exploitation relationship between CON and RA.

Also, this shows that CON sector is not good in receiving inputs indirectly (investments) due to large indirect consumption implied in the products or services of this sector (Zhai et al., 2018). Thus, reducing the number of indirect paths will improve its indirect receiving ability and push this sector to shift to the harmonious relationship. It is also evident that the producers (AGR, MIN) are in competition with consumers, with EC being the highest competitor to AGR in terms of integral and indirect utilities. Those sectors also compete in an indirect way with all other sectors in the system, meaning that the AGR sector has low ability to drive other industries, but this ability is wasted due to competition for investments allocated to other sectors. Therefore, the eventual mutualism between these two components (AGR and EC) could be attained by decreasing energy consumption of EC to the level of AGR to shift to the competitive relationship, conductive to the mutual energy consumption reduction (Lu et al., 2012; Li et al., 2018), and through indirect support of AGR and EC sectors by other sectors. Conversely, the shift from competition relationship between AGR and all other sectors (except MIN), to a normal state where AGR sector indirectly exploit all consumers will contribute to the system-level mutualism (Zhang et al., 2014b; Zhai et al., 2019).

The mutualism index (MI) and synergism index (SI) resulting from the ecological network analysis are 0.93 and 12.53, respectively. This implies that negative relationships outweigh beneficial relationships in the system and, therefore, with MI < 1, the system is not as healthy and mutualistic as many of the observed ecosystems. Conversely, the value of SI implies that much more benefits are obtained from the relationships compared to costs (SI > 0), and that the level of cooperation between sectors in the management of Vienna's metabolic system is extremely high (Fan and Fang, 2019). However, for system mutualism to occur MI should be more than 1 and SI should be more than 0 (Lu et al., 2012). Although SI seems to be high, the high value resulted mainly by indirect benefits generated by sector themselves, rather than intersectoral relationships (Tan et al., 2018). Therefore, overall symbiosis (excluding diagonal elements) is much lower than calculated SI (−2.79). The system provides less benefits at higher costs (Tan et al., 2018). These results stem from competitive indirect relationships between each pair of components. Aside from recommendations discussed above,

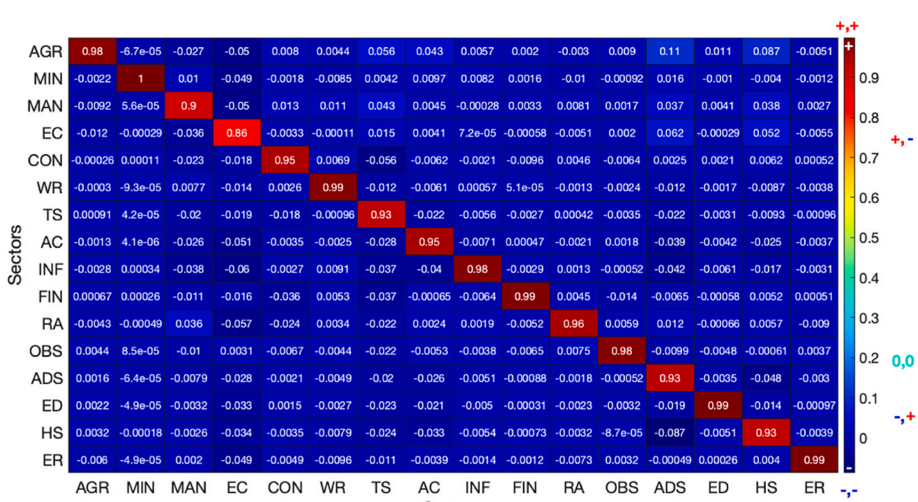

Fig. 9. Pairwise utility relationship between components along indirect paths in 2015. The warm colours reflect the indirect benefits (+) and the cold colours reflect the indirect costs (−) received or transferred between each pair of sectors. The values in matrix ranges from −1 to 1. The four combinations of signs result in four pairwise relationships between sectors: mutualism (+,+), competition (−,−) exploitation (+,−) and exploited (−,+). Indirect neutral relationships (0,0) did not exist in a such matrix. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

eco-industrial parks can contribute to emergy utilization efficiency and overall mutualism by sharing output residuals among industries (Zhang et al., 2014b) and by developing selective high-value linkages through collaborative learning (Boons et al., 2016), such as transactions of agrivoltaic systems between MAN and AGR to improve productivities of land and assembly lines.

4.5. Research implications, limitations, and future scope

An Emergy network model of urban metabolic system allows to assess the magnitude of 'economic services' among all sectors in urban economy. There are many hidden pathways that are not captured by traditional input-output analysis leading to an underestimation of indirect flows in the urban metabolic system (Zhang et al., 2014c). The major disadvantage of this approach is the impossibility of accommodating multiple currencies in the network model. To allow multiple currencies (i.e. water and energy) multiple models need to be constructed. Moreover, those models cannot be easily unified and compared (Fath et al., 2007). The emergy network analysis overcomes this problem, allowing to study both the ecological and socio-economic intersectoral flows in urban economy and between urban economy and environment. As a result, this model provides a more comprehensive description of emergy flows in the urban metabolic system. The final difference between our study and previous research is that we not only covered integral and direct flows but also examined pairwise indirect control and utilities, as well as indirect driving force and pulling force weights. These properties assess the contribution of indirect effects of system internal processes to the status and role of each sector in urban metabolic system, which reveals hidden problems in internal structure and functions caused by indirect interactions not evident in previous studies.

This approach can be used to prioritize the consumption and footprints of sectors in urban economy to inform supply-side and demand-side climate mitigation policies (Wieland et al., 2019). This model can also assist decision makers with development of industrial structure towards efficient and sustainable emergy consumption (i.e., stability of components and synergy among them).

In this study, we also discovered some limitations that should be addressed. The first limitation is related to the application of ecological network analysis. To run this analysis the system should be in steady state. This requirement prevents analysing urban metabolic systems represented by non-square matrices (underdetermined or overdetermined) unless it is converted to the determined system of equations by removing final demand categories (consumption of households, capital formation, government, and exports) and balancing the table. The other problem was that the values of pairwise direct (DN) and indirect control relationships (IN) ranged from −1 to 1, which was unacceptable since rescaled integral control matrix (CN matrix) was populated with values on the interval [0,1] (Yang et al., 2012; Zhai et al., 2018). Therefore, we were required to apply amendments to the IN matrix to avoid negatives and values of indirect control being larger than integral values: if $0 < in_{ij} < cn_{ij}$, $in_{ji} = in_{ij}$, otherwise, $in_{ji} = 0$.

Future studies can incorporate information indices (ascendency, overhead and robustness index) to analyse the impact of each sector resulting from indirect control weights to the overall system's efficiency and stability. This could provide insights on key sectors that limit system efficiency and the most vulnerable sectors in the system. Then, analysis of indirect pairwise controls and utilities between compartments can help to identify the sectors responsible for inefficiency or vulnerability of each target sector in the system. Consequently, future directions can follow a path of analysis of changes in system's efficiency and stability over time to monitor Vienna's metabolic system performance in terms of emergy utilization and system's performance. These directions would promote more sustainable and efficient development of Vienna's metabolic system.

5. Conclusion

The analysis of system-level hierarchy of sectors revealed that producers ("agriculture, forestry and fishing" and "mining and quarrying") are unsupported by downstream industries in an indirect way and, therefore, cannot satisfy demand of downstream sectors for their production. Moreover, there are many problems within tertiary industries preventing them from supporting producers. Some consumers pull most of development in the system ("public administration and defence, social security" and "human health and social work activities"), while other sectors rely on imported products ("electricity, gas, water supply, sewerage, waste, and remediation services" and "transportation and storage"), leading to the low indirect driving abilities of these sectors. In addition, few sectors have no importance in the system ("wholesale and retail trade, repair of motor vehicles" and "construction").

The pairwise control and utility analyses identified sectors responsible for disorders in the target sector. The results showed that the lack of monetary control of "wholesale and retail trade, repair of motor vehicles" over "mining and quarrying" sector contributed to the low energy consumption of the "mining and quarrying" sector. In addition, low monetary and strong energy dependence of "agriculture, forestry and fishing" sector on "mining and quarrying" and "electricity, gas, water supply, sewerage, waste, and remediation services" sectors hindered production capacity of "agriculture, forestry and fishing" sector. Finally, we found that the competition between "agriculture, forestry and fishing" and "electricity, gas, water supply, sewerage, waste, and remediation services" sectors contributed the most to the unstable state of "agriculture, forestry and fishing". The low values of system-level indicators (mutualism and synergism) reflected the dominance of pairwise competitive indirect relationships in the system. The establishment of numerous eco-industrial parks can improve the overall level of mutualism and synergism in Vienna's metabolic system in long-term perspective.

Future studies could identify the key sectors limiting the system's efficiency by applying information indices to the network analysis. Another possible direction would be to add the time data for monitoring the system stability and efficiency in terms of emergy utilization. These directions would contribute to the healthier state of Vienna's metabolic system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to express their gratitude to Dr. Dominik Wiedenhofer (BOKU) for his advice on Vienna's economic data collection.

Appendix A. Consumption-based sectoral classification

The position of sectors in the industrial supply chain affects the total emergy consumption. Zhang et al. (2014c) divided sectors into five categories based on the magnitude of gap between the direct and indirect consumption intensity. This classification was applied in this study for flows. Firstly, the flows were divided into three groups based on the consumption: “highest” total consumption ($\geq 1.5E + 20$ *sej*), high total consumption (between $0.5E + 20$ *sej* and $1.5E + 20$ *sej*), and low total consumption $\leq 0.5E + 20$ *sej*). Then, the first two groups were subdivided based on relative proportions of direct and indirect emergy flows. The first group (higher total consumption; indirect is higher than direct consumption) includes only “ADS”. The second group with both high total consumption and higher indirect consumption (between $0.5E + 20$ *sej* and $1.5E + 20$ *sej*) includes ‘TS’, ‘HS’ and ‘EC’. The third group is characterized by moderate total consumption, indirect is higher than direct consumption. This group includes ‘AC’, MAN′, ‘WR’, ‘CON’, ‘ED, ‘OBS’, ‘ER’ and ‘INF’. The fourth group incorporates sectors with low total consumption with indirect consumption being lower than direct consumption. ‘RA’, ‘FIN’, ‘AGR’ and ‘MIN’ fall in this category.

Appendix B. Structure of emergy consumption

The total emergy consumption for each sector should be correlated with the structure of emergy consumption for each sector in the system to determine where policy interventions should be most likely applied to decrease emergy consumption.

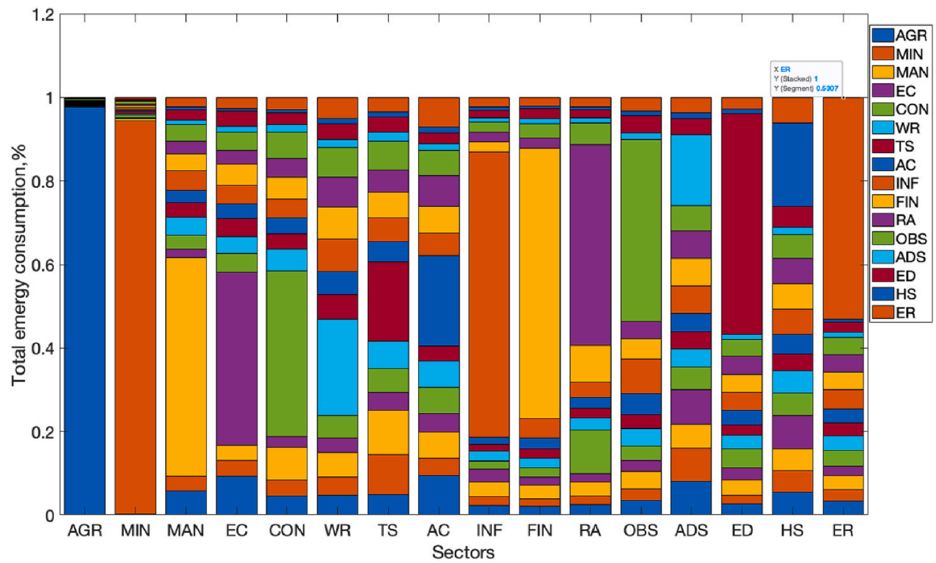

Fig. B.1. Emergy metabolic structure for each sector of Vienna’s metabolic system.

Figure B.1 reveals that the largest proportion of total emergy consumption in the ADS and HS sectors is attributed to the inputs from other sectors: 92% and 80%, respectively. Surprisingly, it shows that these sectors are receiving compartments and, therefore, should play a more active role in donating emergy to other sectors. This reflects the lack of self-sufficiency in emergy use and vulnerability to the external risks, such as sudden price change. Therefore, the productivity of public administration activities, hospital activities and other sub-processes in these sectors should be improved.

‘AGR’ and ‘MIN’ are self-sufficient sectors because they mostly consume directly their own primary products 98% and 95%, respectively. However, their total consumption is far too low to satisfy demand of other sectors (except for EC, MAN and TS sectors). Therefore, it is important to decrease the huge direct emergy consumption, improve emergy utilization efficiency of all processes in these sectors and to increase their indirect emergy consumption (to increase demand of consumers on their products).

The highest use of INF and FIN is attributable to their own consumption: 68% and 65%, respectively. They have capacity to deliver more emergy to other industries than they receive from them. Thus, it is necessary to promote development of those industries by increasing the share of emergy supplied from other industries, especially, underrepresented agricultural and mining products in the use of those sectors. The own production of ER, ED and EC is also higher than the emergy imported from other industries. Thus, these sectors should be modified to increase their own production and to promote development of ‘AGR’ and ‘MIN’ sectors. In addition, the CON sector has the capacity to contribute 40% out of the total emergy use to the other sectors and its products are consumed mostly by downstream industries (i.e., TS, HS). This result suggests that it is necessary to adjust this component to satisfy demand of tertiary industries. All other sectors from the third and fourth category only utilize the emergy supplied from other sectors and do not contribute to the system. Therefore, the structure of those sectors should be adjusted to promote their capacity to deliver flows to other industries.

References

Ajanovic, A., Siebenhofer, M., Haas, R., 2021. Electric mobility in cities: the case of Vienna. Energies 14 (1), 217. https://doi.org/10.3390/en14010217.

Allesina, S., Bondavalli, C., 2003. Steady state of ecosystem flow networks: a comparison between balancing procedures. Ecol. Model. 165 (2–3), 221–229. https://doi.org/10.1016/s0304-3800(03)00075-9.

Anthopoulos, L., 2019. Chapter 7: the smart city of Vienna. In: Smart City Emergence: Cases from Around the World, first ed. Elsevier, pp. 105–126. https://doi.org/10.1016/B978-0-12-816169-2.00005-5.

Asamoah, E.F., Zhang, L., Liang, S., Pang, M., Tan, S., 2017. Emergy perspectives on the environmental performance and sustainability of small-scale gold production systems in Ghana. Sustainability 9 (1), 2034. https://doi.org/10.3390/su9112034.

Bagheri, M., Guevara, Z., Alikarami, M., Kennedy, C.A., Doluweera, G., 2018. Green growth planning: a multi-factor energy input-output analysis of the Canadian economy. Energy Econ. 74, 708–720. https://doi.org/10.1016/j.eneco.2018.07.015.

Baird, D., Fath, B.D., Ulanowicz, R.E., Asmus, H., Asmus, R., 2009. On the consequences of aggregation and balancing of networks on system properties derived from ecological network analysis. Ecol. Model. 220 (23), 3465–3471. https://doi.org/10.1016/j.ecolmodel.2009.09.008.

Boons, F., Chertow, M., Park, J., Spekkink, W., Shi, H., 2016. Industrial symbiosis dynamics and the problem of equivalence: proposal for a comparative framework. J. Ind. Ecol. 21 (4), 938–952. https://doi.org/10.1111/jiec.12468.

Borrett, S.R., Scharler, U.M., 2019. Walk partitions of flow in Ecological Network Analysis: Review and synthesis of methods and indicators. Ecol. Indicat. 106 (1), 105451 https://doi.org/10.1016/j.ecolind.2019.105451.

Brown, C., Miller, S., 2008. The impacts of local markets: a review of research on farmers markets and community supported agriculture (CSA). Am. J. Agric. Econ. 90 (5), 1298–1302. https://doi.org/10.1111/j.1467-8276.2008.01220.x.
Brown, M.T., Raugei, M., Ulgiati, S., 2012. On boundaries and 'investments' in Emergy synthesis and LCA: a case study on thermal vs. photovoltaic electricity. Ecol. Indicat. 15 (1), 227–235. https://doi.org/10.1016/j.ecolind.2011.09.021.
Bullard, C.W., Herendeen, R.A., 1975. The energy cost of goods and services. Energy Pol. 3 (4), 268–278. https://doi.org/10.1016/0301-4215(75)90035-x.
Casler, S., Wilbur, S., 1984. Energy input-output analysis. Resour. Energy 6 (2), 187–201. https://doi.org/10.1016/0165-0572(84)90016-1.
Chen, Z.M., 2013. Embodied carbon dioxide emission by the globalized economy: a systems ecological input-output simulation. J. Environ. Informat. 21 (1), 35–44. https://doi.org/10.3808/jei.201300230.
Chen, S., Liu, Z., Chen, B., Zhu, F., Fath, B.D., Liang, S., Su, M., Yang, J., 2019. Dynamic carbon emission linkages across boundaries. Earth's Future 7 (2), 197–209. https://doi.org/10.1029/2018ef000811.
Chen, S., Chen, B., Feng, K., Liu, Z., Fromer, N., Tan, X., Alsaedi, A., Hayat, T., Weisz, H., Schellnhuber, H.J., Hubacek, K., 2020. Physical and virtual carbon metabolism of global cities. Nat. Commun. 11 (1) https://doi.org/10.1038/s41467-019-13757-3.
Dias, A.C., Lemos, D., Gabarrell, X., Arroja, L., 2014. Environmentally extended input–output analysis on a city scale – application to Aveiro (Portugal). J. Clean. Prod. 75, 118–129. https://doi.org/10.1016/j.jclepro.2014.04.012.
Fan, Y., Fang, C., 2019. Research on the synergy of urban system operation—based on the perspective of urban metabolism. Sci. Total Environ. 662, 446–454. https://doi.org/10.1016/j.scitotenv.2019.01.252.
Fang, D., Chen, B., 2015. Ecological network analysis for a virtual water network. Environ. Sci. Technol. 49 (11), 6722–6730. https://doi.org/10.1021/es505388n.
Fath, B.D., 2012. Analyzing ecological systems using network analysis. Ecol. Quest. 16 (1), 20–27. https://doi.org/10.2478/v10090-012-0008-0.
Fath, B.D., Borrett, S.R., 2006. A MATLAB® function for network environ analysis. Environ. Model. Software 21 (3), 375–405. https://doi.org/10.1016/j.envsoft.2004.11.007.
Fath, B.D., Patten, B.C., 1998. Network synergism: emergence of positive relations in ecological systems. Ecol. Model. 107 (2–3), 127–143. https://doi.org/10.1016/s0304-3800(97)00213-5.
Fath, B.D., Patten, B.C., Choi, J.S., 2001. Complementarity of ecological goal functions. J. Theor. Biol. 208 (4), 493–506. https://doi.org/10.1006/jtbi.2000.2234.
Fath, B.D., Scharler, U.M., Ulanowicz, R.E., Hannon, B., 2007. Ecological network analysis: network construction. Ecol. Model. 208 (1), 49–55. https://doi.org/10.1016/j.ecolmodel.2007.04.029.
Global GDP 2014-2024, 2021. Statista. April 12. https://www.statista.com/statistics/268750/global-gross-domestic-product-gdp/.
Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008. Global change and the ecology of cities. Science 319 (5864), 756–760. https://doi.org/10.1126/science.1150195.
Guan, Y., Huang, G., Liu, L., Huang, C.Z., Zhai, M., 2019. Ecological network analysis for an industrial solid waste metabolism system. Environ. Pollut. 244, 279–287. https://doi.org/10.1016/j.envpol.2018.10.052.
Guevara, Z., Domingos, T., 2017. The multi-factor energy input–output model. Energy Econ. 61, 261–269. https://doi.org/10.1016/j.eneco.2016.11.020.
Ha, Y., Kumar, S.S., 2021. Investigating decentralized renewable energy systems under different governance approaches in Nepal and Indonesia: how does governance fail? Energy Res. Social Sci. 80 (102214) https://doi.org/10.1016/j.erss.2021.102214.
Hannon, B., 2021. The structure of ecosystems. J. Theor. Biol. 41 (3), 535–546. https://doi.org/10.1016/0022e5193(73)90060-X.
Herendeen, R.A., 2004. Energy analysis and EMERGY analysis—a comparison. Ecol. Model. 178 (1–2), 227–237. https://doi.org/10.1016/j.ecolmodel.2003.12.017.
Hite, J.C., Laurent, E.A., 1971. Empirical study of economic-ecologic linkages in a coastal area. Water Resour. Res. 7 (5), 1070–1078. https://doi.org/10.1029/wr007i005p01070.
Leontief, W., 1966. Essays in Economics. Theories and Theorizing. Oxford University Press.
Li, J., Huang, G., Liu, L., 2018. Ecological network analysis for urban metabolism and carbon emissions based on input-output tables: a case study of Guangdong province. Ecol. Model. 383, 118–126. https://doi.org/10.1016/j.ecolmodel.2018.05.009.
Li, Y., Chen, B., Chen, G., Meng, J., Hayat, T., 2020. An embodied energy perspective of urban economy: a three-scale analysis for Beijing 2002–2012 with headquarter effect. Sci. Total Environ. 732, 139097 https://doi.org/10.1016/j.scitotenv.2020.139097.
Liang, S., Wang, Y., Zhang, T., Yang, Z., 2017. Structural analysis of material flows in China based on physical and monetary input-output models. J. Clean. Prod. 158, 209–217. https://doi.org/10.1016/j.jclepro.2017.04.171.
Liu, L.N., Vilain, P.B., 2004. Estimating commodity inflows to a substate region using input-output data: commodity flow survey accuracy tests. J. Transport. Stat. 7 (1), 23–39.
Liu, L., Zhang, H., Gao, Y., Zhu, W., Liu, X., Xu, Q., 2019. Hotspot identification and interaction analyses of the provisioning of multiple ecosystem services: case study of Shaanxi province, China. Ecol. Indicat. 107, 105566 https://doi.org/10.1016/j.ecolind.2019.105566.
Lu, Y., Su, M., Liu, G., Chen, B., Zhou, S., Jiang, M., 2012. Ecological network analysis for a low-carbon and high-tech industrial Park. Sci. World J. 1–9. https://doi.org/10.1100/2012/305474, 2012.
Matamba, L., Kazanci, C., Schramski, J., Blessing, M., Alexander, P., Patten, B., 2009. Throughflow analysis: a stochastic approach. Ecol. Model. 220 (22), 3174–3181. https://doi.org/10.1016/j.ecolmodel.2009.07.001.
Merciai, S., Schmidt, J., 2017. Methodology for the construction of global multi-regional hybrid supply and use tables for the EXIOBASE v3 database. J. Ind. Ecol. 22 (3), 516–531. https://doi.org/10.1111/jiec.12713.
Morris, Z.B., Weissburg, M., Bras, B., 2020. Ecological network analysis of urban–industrial ecosystems. J. Ind. Ecol. 25 (1), 193–204. https://doi.org/10.1111/jiec.13043.
Muhtar, P., Xia, J., Muyibul, Z., Zihriya, B., Abliz, A., Zhang, M., 2021. Evaluating the evolution of oasis water metabolism using ecological network analysis: a synthesis of structural and functional properties. J. Clean. Prod. 280, 124422 https://doi.org/10.1016/j.jclepro.2020.124422.
Niza, S., Rosado, L., Ferrão, P., 2009. Urban metabolism. J. Ind. Ecol. 13 (3), 384–405. https://doi.org/10.1111/j.1530-9290.2009.00130.x.
Odum, E.P., 1959. A descriptive population ecology of land animals. Ecology 40 (1). https://doi.org/10.2307/1929948, 166–166.
Odum, H.T., 1996. John Wiley & Sons. Environmental Accounting.
Pan, Y., Zhang, B., Wu, Y., Tian, Y., 2021. Sustainability assessment of urban ecological-economic systems based on emergy analysis: a case study in Simao, China. Ecol. Indicat. 121, 107157 https://doi.org/10.1016/j.ecolind.2020.107157.
Patten, B.C., 1978. Systems approach to the concept of environment. Ohio J. Sci. 78 (4), 206–222. https://kb.osu.edu/handle/1811/22549.
Patterson, M., 2014. Evaluation of matrix algebra methods for calculating transformities from ecological and economic network data. Ecol. Model. 271, 72–82. https://doi.org/10.1016/j.ecolmodel.2013.03.011.
Piezer, K., Petit-Boix, A., Sanjuan-Delmás, D., Briese, E., Celik, I., Rieradevall, J., Gabarrell, X., Josa, A., Apul, D., 2019. Ecological network analysis of growing tomatoes in an urban rooftop greenhouse. Sci. Total Environ. 651, 1495–1504. https://doi.org/10.1016/j.scitotenv.2018.09.293.
Pulselli, F.M., Coscieme, L., Neri, L., Regoli, A., Sutton, P.C., Lemmi, A., Bastianoni, S., 2015. The world economy in a cube: a more rational structural representation of sustainability. Global Environ. Change 35 (1), 45–51. https://www.eusteps.eu/wp-content/uploads/2020/10/Unit-3_Pulselli-et-al.-2015.pdf.
Tan, L.M., Arbabi, H., Li, Q., Sheng, Y., Densley Tingley, D., Mayfield, M., Coca, D., 2018. Ecological network analysis on intra-city metabolism of functional urban areas in England and Wales. Resour. Conserv. Recycl. 138, 172–182. https://doi.org/10.1016/j.resconrec.2018.06.010.
Tang, M., Hong, J., Guo, S., Liu, G., Shen, G.Q., 2021. A bibliometric review of urban energy metabolism: evolutionary trends and the application of network analytical methods. J. Clean. Prod. 279, 123403 https://doi.org/10.1016/j.jclepro.2020.123403.
MATLAB Central File Exchange Temurshoev, U., 2021. Generalized RAS, matrix balancing/updating, biproportional method, Retrieved February 1, 2021. https://www.mathworks.com/matlabcentral/fileexchange/43231-generalized-ras-matrix-balancing-updating-biproportional-method.
Temurshoev, U., Miller, R.E., Bouwmeester, M.C., 2013. A note on the GRAS method. Econ. Syst. Res. 25 (3), 361–367. https://doi.org/10.1080/09535314.2012.746645.
The Municipal Department 23-Economic Affairs, Labour and Statistics, 2016. Vienna in figures 2016. https://www.wien.gv.at/statistik/pdf/viennainfigures-2016.pdf.
Tridech, S., Cheng, K., 2011. Low carbon manufacturing: characterisation, theoretical models and implementation. Int. J. Manuf. Res. 6 (2), 110. https://doi.org/10.1504/ijmr.2011.040006.
United Nations Department of Economic and Social Affairs, 2019. World urbanization prospects: the 2018 revision. United Nations, New York. https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf.
United Nations Environment Programme, 2019. Emissions Gap Report 2019. UNEP, Nairobi. https://wedocs.unep.org/bitstream/handle/20.500.11822/30797/EGR2019.pdf?sequence=1&isAllowed=y.
Vienna City Administration, 2014. Smart city wien framework strategy. https://www.wien.gv.at/stadtentwicklung/studien/pdf/b008384a.pdf.
Vienna City Administration, 2019. STEP 2025 – urban development plan Vienna. https://www.wien.gv.at/stadtentwicklung/studien/pdf/b008379b.pdf.
Viglia, S., Civitillo, D.F., Cacciapuoti, G., Ulgiati, S., 2018. Indicators of environmental loading and sustainability of urban systems. An emergy-based environmental footprint. Ecol. Indicat. 94, 82–99. https://doi.org/10.1016/j.ecolind.2017.03.060.
Wang, X., Zhang, Y., Yu, X., 2019. Characteristics of Tianjin's material metabolism from the perspective of ecological network analysis. J. Clean. Prod. 239 (118115) https://doi.org/10.1016/j.jclepro.2019.118115.
Wang, L., Fan, Y.V., Varbanov, P.S., Alwi, S.R., Klemeš, J.J., 2020. Water footprints and virtual water flows embodied in the power supply chain. Water 12 (11), 3006. https://doi.org/10.3390/w12113006.
Weselek, A., Ehmann, A., Zikeli, S., Lewandowski, I., Schindele, S., Högy, P., 2019. Agrophotovoltaic systems: applications, challenges, and opportunities. A review. Agron. Sustain. Dev. 39 (4) https://doi.org/10.1007/s13593-019-0581-3.
Wieland, H., Giljum, S., Eisenmenger, N., Wiedenhofer, D., Bruckner, M., Schaffartzik, A., Owen, A., 2019. Supply versus use designs of environmental extensions in input–output analysis: conceptual and empirical implications for the case of energy. J. Ind. Ecol. 24 (3), 548–563. https://doi.org/10.1111/jiec.12975.
World population projections, 2020. Worldometer - real time world statistics. https://www.worldometers.info/world-population/world-population-projections/.
Xia, C., Chen, B., 2020. Urban land-carbon nexus based on ecological network analysis. Appl. Energy 276 (115465). https://doi.org/10.1016/j.apenergy.2020.115465.
Xia, L., Zhang, Y., Yu, X., Li, Y., Zhang, X., 2019. Hierarchical structure analysis of urban carbon metabolism: a case study of Beijing, China. Ecol. Indicat. 107, 105602 https://doi.org/10.1016/j.ecolind.2019.105602.
Xu, W., Xie, Y., Cai, Y., Ji, L., Wang, B., Yang, Z., 2021. Environmentally-extended input-output and ecological network analysis for Energy-Water-CO2 metabolic system in

China. Sci. Total Environ. 758, 143931 https://doi.org/10.1016/j.scitotenv.2020.143931.

Yang, Z., Mao, X., Zhao, X., Chen, B., 2012. Ecological network analysis on global virtual water trade. Environ. Sci. Technol. 46 (3), 1796–1803. https://doi.org/10.1021/es203657t.

Yang, S., Fath, B., Chen, B., 2016. Ecological network analysis of embodied particulate matter 2.5 – a case study of Beijing. Appl. Energy 184, 882–888. https://doi.org/10.1016/j.apenergy.2016.04.087.

Yang, W., Wang, S., Chen, B., 2017. Embodied carbon emission analysis of eco−industrial park based on input−output analysis and ecological network analysis. Energy Proc. 142, 3102–3107. https://doi.org/10.1016/j.egypro.2017.12.451.

Zhai, M., Huang, G., Liu, L., Su, S., 2018. Dynamic input-output analysis for energy metabolism system in the Province of Guangdong, China. J. Clean. Prod. 196, 747–762. https://doi.org/10.1016/j.jclepro.2018.06.084.

Zhai, M., Huang, G., Liu, L., Zhang, X., 2019. Ecological network analysis of an energy metabolism system based on input-output tables: model development and case study for Guangdong. J. Clean. Prod. 227, 434–446. https://doi.org/10.1016/j.jclepro.2019.04.039.

Zhang, Y., Yang, Z., Yu, X., 2009. Ecological network and emergy analysis of urban metabolic systems: model development, and a case study of four Chinese cities. Ecol. Model. 220 (11), 1431–1442. https://doi.org/10.1016/j.ecolmodel.2009.02.001.

Zhang, Y., Yang, Z., Yu, X., 2009. Ecological network and emergy analysis of urban metabolic systems: model development, and a case study of four Chinese cities. Ecol. Model. 220 (11), 1431–1442. https://doi.org/10.1016/j.ecolmodel.2009.02.001.

Zhang, L., Hu, Q., Zhang, F., 2014a. Input-output modeling for urban energy consumption in Beijing: dynamics and comparison. PLoS One 9 (3), e89850. https://doi.org/10.1371/journal.pone.0089850.

Zhang, Y., Liu, H., Fath, B.D., 2014b. Synergism analysis of an urban metabolic system: model development and a case study for Beijing, China. Ecol. Model. 272, 188–197. https://doi.org/10.1016/j.ecolmodel.2013.10.003.

Zhang, Y., Zheng, H., Fath, B.D., 2014c. Analysis of the energy metabolism of urban socioeconomic sectors and the associated carbon footprints: model development and a case study for Beijing. Energy Pol. 73, 540–551. https://doi.org/10.1016/j.enpol.2014.04.029.

Zhang, Y., Zheng, H., Fath, B.D., Liu, H., Yang, Z., Liu, G., Su, M., 2014d. Ecological network analysis of an urban metabolic system based on input–output tables: model development and case study for Beijing. Sci. Total Environ. 468/469, 642–653. https://doi.org/10.1016/j.scitotenv.2013.08.047.

Zhang, B., Qiao, H., Chen, Z.M., Chen, B., 2016a. Growth in embodied energy transfers via China's domestic trade: evidence from multi-regional input–output analysis. Appl. Energy 184, 1093–1105. https://doi.org/10.1016/j.apenergy.2015.09.076.

Zhang, J.C., Zhong, R., Zhao, P., Zhang, H.W., Wang, Y., Mao, G.Z., 2016b. International energy trade impacts on water resource crises: an embodied water flows perspective. Environ. Res. Lett. 11 (7), 74023. https://doi.org/10.1088/1748-9326/11/7/074023.

Zhang, J., Huang, G., Liu, L., Zhai, M., Xie, Y., Xin, X., Meng, H., 2021. Economic sensitivity analysis of dual perspectives induced by energy scarcity for energy-dependent region. Sci. Total Environ. 768 (144876) https://doi.org/10.1016/j.scitotenv.2020.144876.

Zheng, H., Fath, B.D., Zhang, Y., 2016. An urban metabolism and carbon footprint analysis of the Jing-Jin-Ji regional agglomeration. J. Ind. Ecol. 21 (1), 166–179. https://doi.org/10.1111/jiec.12432.

Zheng, H., Li, A., Meng, F., Liu, G., Hu, Y., Zhang, Y., Casazza, M., 2021. Ecological network analysis of carbon emissions from four Chinese metropoles in multiscale economies. J. Clean. Prod. 279, 123226 https://doi.org/10.1016/j.jclepro.2020.123226.

Zhu, X., Mu, X., Hu, G., 2019. Ecological network analysis of urban energy metabolic system—a case study of Beijing. Ecol. Model. 404, 36–45. https://doi.org/10.1016/j.ecolmodel.2019.04.016.

Zhu, B., Su, B., Li, Y., Ng, T.S., 2020. Embodied energy and intensity in China's (normal and processing) exports and their driving forces, 2005–2015. Energy Econ. 91, 104911 https://doi.org/10.1016/j.eneco.2020.104911.