Ecological Indicators 83 (2017) 201–217

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Research paper

Measuring ecological characteristics of environmental building performance: Suggestion of an information-network model and indices to quantify complexity, power, and sustainability of energetic organization

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ARTICLE INFO

Keywords:
Average mutual information
Building energy network
Building performance
Complexity
Maximum power

ABSTRACT

The authors present preliminary study in pursuance of developing a flow network-based methodology of building performance evaluation, as current efficiency-centered methods do not fully account for the complex building performance in which nature, economy, and humans are inseparably involved. Based on the principle of entropy, this study defines building as a thermodynamic system that networks useful resources—energy, material and information—through close interconnection with the global environment. Measures of information content in energy-flow networking and ecological performance indicators from Shannon's information theory, Ulanowicz's ascendency principle, and Odum's maximum empower principle are discussed and integratively applied to developing a generic building performance evaluation model. For the holistic indication of building sustainability, this work attempts to reconcile Ulanowicz's and Odum's statements about ecosystem development and also integrates *e*mergy (spelled with an "*m*") and information metrics. Environmental behaviour of the building model was tested with simulation to validate consistency with system-level principles. Results reveal that network complexity corresponds to system power and resilience (*L*) and fitness (*F*) tend to peak at an intermediate level of efficiency. This finding demonstrates applicability of Odum's maximum power principle to building study, suggesting that increasing complexity (and power) of emergy-flow networking be a fundamental characteristic of sustainable building performance.

1. Introduction

Contemporary buildings are complex environmental systems. They increasingly embrace various scales of dynamic energetic phenomena in which economy, nature, and human dwelling are inseparably involved in direct or indirect ways. Despite their multidimensionality in energy and resource use, performance in current building codes and rating systems is simply described in term of the fixed quantities of energy (Joules, Watts, or Btu) and efficiency (%). Although energy-saving construction and operation are important to achieve building sustainability, quantity-based performance indication conceals intricate interaction among different types of energy use and complex material processes through a building, overlooking its broader environmental impact to global sustainability. Improving efficiency of high-tech air-conditioning systems, for example, blinds enormously complicated production processes exploiting expensive materials. We also usually discount that renewable equipment (*e.g.*, solar panels) requires a great deal of nonrenewable energy and human inputs to concentrate dilute natural power (Yi et al., 2017). So-called high-efficient buildings, moreover, often end up inefficient, like Jevons paradox, because their high standard of living promotes extra consumption of high-quality energy (McDonald, 2017).

The reason behind the dominance of efficiency-oriented description on building sustainability, in spite of mixed signals, is that we regard a building as a machine or a static object mechanically assembled. Buildings are machines; we build them purposefully, and they create artificial environments by design. Once a building sits on a site, however, it is "open" to the biosphere as well as ambient settings. All the physical phenomena during its life time, *e.g.*, keeping the indoor comfortable (by either occupants or some equipment) or the weathering of building structures and materials, draw energy in, whether big or small, from the external worlds, and disperse it to the outside. Thermodynamically, indeed, a building is not a stand-alone machine, but a very communicative one.

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http://dx.doi.org/10.1016/j.ecolind.2017.07.056
Received 25 March 2017; Received in revised form 5 July 2017; Accepted 28 July 2017

We can find an identical energetic feature in living organisms. They obtain energy from the environment and use it to live, adapting themselves through metabolic processes. As Schrödinger (1945) states, if we admit that this is the most fundamental characteristic of life, buildings (including occupants and surroundings) can be understood as the living in such a way that living and non-living things undergo the same physical process − energy dispersion (Sampson, 2007; Hosey, 2012). In this context, buildings can be likened to living systems, although, technically, buildings are neither alive nor purely organic.

The analogy between building and life, in effect, is not new. Buildings are compared quite often to living organisms. One employs it as a metaphor of formal representation, or some others highlight functional resemblance (Steadman, 2008). In the study of building performance, however, the thermodynamic analogy has been elucidated by few (Salingaros, 1997; Fernández-Galiano, 2000; Braham, 2015), and not developed to a concrete methodology based on physical science. Though some recently attempted to model a building with biological accounts (Gamage and Hyde, 2012), misunderstanding of the analogy is widespread in the green building industry. Even in the most rigorous sustainable building standard – The Living Building Challenge (LBC), it says, “ideal built environment should function as cleanly and efficiently as a flower (International Living Future Institute).” The photosynthesis efficiency of a flower is, in fact, less than 6%, while the efficiency of a photovoltaic panel ranges from 10 to 20%. This metaphoric agenda hides the fact that upper-class organisms in a trophic chain have greater transfer efficiency.

To integrate different approaches into a larger whole, accordingly, building performance should be evaluated based on a systematic approach that builds on a holistic thermodynamic understanding of nature and artificial systems. Everything-as-a-thermodynamic-process dwells on the flow-specific aspect of energy, *i.e.*, transfer and conversion between different energy forms, and, thus, thermodynamic interpretation of environmental phenomena enables to integrate the living and non-living in energy streams, thereby characterizing a building as an energy-channeling component within a whole environmental life cycle.

Therefore, it is important to find a methodology to describe, analyze, and measure building performance by incorporating dynamic networking of all kinds of energies and resources exchanged, both internally and externally, all the way through global ecosystems. To this end, this study introduces a new measure to building study, *information* (or *information entropy*), and seeks to incorporate it into performance indices. A modern concept of information was suggested by Wiener (1948) to suggest study of system feedback and responsive machine control in cybernetics. Shannon (1948) provided a mathematical definition of information through logarithmic uncertainty in a communication channel so that it quantifies signal transport attributes in a non-deterministic way.

Information has gained wide popularity in various areas—statistics, mechanics, social science, and biology. Meadow and Wright (2008) states that any system incessantly processes information by self-organizing matter and energy, and information content has an enormous effect on how systems operate. Furthermore, Kelly (2011) argues that the performance of contemporary goods and technologies should be evaluated by their information capacity, rather than materialistic values of their carriers. Thus, information is a measure of the ‘quality’ of energetic performance. In biology, Koestler (1967) asserts that energy particles (called ‘*holons*’) tend to develop a hierarchical organization in biotic systems and information of this hierarchy is the inherent hallmark of all living systems.

This approach does not negate the importance of energy efficiency, but calls for a comprehensive paradigm of building energy study, because pursuing greater efficiency (or vice versa) is not aimless, yet owes to system dynamics of a larger whole. To develop a specific method, whether or not thermodynamic accounts are immediately applicable needs to be validated first, and also, it is necessary to identify that an individual building develops a specific internal configuration of energy transfer pathways and how to network energies between the global environment and local building components. Then, building performance can be diagnosed by monitoring the topologies of network patterns. To find answers of these queries from R.E. Ulanowicz and H.T. Odum, this research intends to (i) prove the consistency of eco-systemic characteristics and building performance and (ii) establish a model for generic building sustainability analysis. Furthermore, this work attempts to illustrate, with thermodynamic accounts, how building performance incorporates informational aspects of ecosystems.

Section 2, following, explores system-level principles that are applicable to ecological indications of building sustainability. It shows that thermodynamic principles justify the physical-biological system analogy. Sections 2.1 and 2.2 discuss the relevance and discrepancy between the law of entropy and maximum power principle that characterize ecosystem developmental behaviour. Section 2.2 introduces mathematical measures of information content and definitions of informational ecosystem indices suggested by Shannon (1948) and Ulanowicz (1986). In Section 3, principles and system measures from Section 2 are validated for their applications to buildings. This step is critical to defining the scope of modelling as well as demonstrating the consistency of the maximum empower principle and information-based indications of system development. Section 4 presents a schematic building network model and pilot simulation with informational indices, confirming the applicability of ecosystem principles. Findings from this test provide a rationale for the use of information as a new building sustainability indicator.

2. System-level principles of energy transport and measures of performance

2.1. Thermodynamic principles of living system analysis

The second law of thermodynamics (SLT; i.e., the law of entropy) is a universal principle applicable to the entire physical/non-physical energy processes. According to the SLT, if energy in a system is depleted and becomes wasteful (low quality energy; e.g., heat), the system will perish, and, conversely, if it gains useful energy (high-quality energy), it survives. Since work indispensably involves an entropy increase as it discounts the potential energy of a source, it is reasonable to postulate that production of entropy is a dominant indicator of all biological metabolisms.

On the largest system scale—the universe, the SLT is axiomatic, for the universe is assumed to be a closed system. Nevertheless, it does not immediately clarify an internal logic of open (living) systems driving them to keep persisting against the death (e.g., why a highly-ordered system is naturally selected, survives in competition, and eventually well-fitted to the environment.), as the systems continuously moving towards a non-equilibrium state are not always subject to the overall increase in entropy of the universe. This contradiction was noticed by Lotka (1922) and Schrödinger (1945). They state that the ‘course of events in a physical system’ did not strictly follow the SLT, and mentioned ‘freedom of choice’ in the course of system processing of energy transformation is the main method of maintaining an ordered equilibrium (Lotka, 1922). Thus, a more immediate principle is needed.

2.1.1. Theorems of entropy production

As any form of nutritional substance on the earth is present in a form of energy (Odum and Odum, 1976), the vitality of all physical, non-physical systems needs energy that always produces entropy. The theorem of minimum entropy production (MinEP) suggested by Prigogine (1945) states that a stationary or near-equilibrium system tends to maintain the lowest entropy production rate. The MinEP’s general mathematical derivation proves that an orderly stable state must produce lower entropy, which is consistent with the SLT. Nevertheless, the MinEP explains local system states with strict linear conditions and a state of very slow, purely diffusive transfer (Nicolis and Prigogine, 1977;

Martyushev, 2013); it does not justify the transient increase of entropy of non-equilibrium, nonlinear systems, which are seen far more generally in animate systems. For the extension of SLT to living systems, Jaynes (1957) and Ziegler (1963) advocated maximum entropy production (MaxEP), and Schneider and Kay (1994) adopted it afterwards for the formulation of ecosystem models and functions. If an open system has a sufficient degree of freedom for system organization (*e.g.*, molecular structure), it evolves towards a steady state with a 'complex' configuration that produces maximum entropy. MaxEP generally explains that the development of a complex energy transport structure is evident in living systems, and that entropy and structural complexity are key indicators of the organizing behaviour of both biotic and abiotic systems (Schneider and Kay, 1994; Toussaint and Schneider, 1998; Meysman and Bruers, 2010). Importantly, both of the theorems of entropy production (MaxEP and MinEP) are concerned with a dynamic dimension, the '*rate*' of entropy increase (or the *magnitude of duration* of energy discounting) in system energy transport, whereas the SLT does not explicitly employ a temporal dimension to describing energy dissipation (Odum and Pinkerton, 1955; Ulanowicz and Hannon, 1987).

2.1.2. Maximum power and optimal efficiency

Prior to the development of entropy production principles in mechanics, Lotka (1922) predicted that living organisms tend to maximize the rate of resource utilization for their growth and biotic systems with a higher temporal intensity of available energy are more likely to succeed in the struggle for existence. Inspired by the Lotka's theorem, Odum suggested maximum power principle (MPP) by extending Lotka's statements to all types of systems, arguing that 'living and man-made processes do not operate at the highest efficiencies that might be expected of them' (Odum and Pinkerton, 1955). To explain the rule of system operation, MPP correlates system power with efficiency: all the systems sacrifice efficiency of energy transport to obtain the greatest useful energy and vice versa (reciprocity of power and efficiency) (Odum and Pinkerton, 1955). It is important to note that the effect of efficiency optimization in a system does not necessarily appear over individual components but it is a system-level attribute; system efficiency cannot be maximized under normal external conditions, even if a single compartment attains 100% efficiency.

Odum refined MPP to a system-level principle, e*m*ergy (spelled with an "*m*"), that explains accumulated impacts of all upstream direct/indirect energy budgets finally proposing the *maximum empower principle* (MePP) (Odum, 1996). MePP is an extension of MPP that sets temporal intake of 'all available energy' as a cardinal index of biological development (Cai et al., 2004; Ulgiati et al., 2007). Conflation of the energy quality (transformity) and quantity (emergy) in MePP elucidates the system's hierarchical transformation of energy from the most primitive inputs (sunlight, mineral, rainwater, etc.) (Hall, 2004). Maximum power explains trade-offs between the entropy change rate and system efficiency. In this sense, MaxEP, MPP, and MePP are compatible with one another; they all deal in common with quantitative changes in total useful energy of a system.

Maximum power at a system level may sound controversial to the sustainability of the global environment, as the struggle for the maximized harnessing of available energy can be seen as a greedy act; however, those principles explain a logic of system response—system's reactive spontaneity to a modification of the external environment; narcissistic behaviour of an organism is not always self-centered but can be self-reinforcing to benefit ecosystems on a global scale, if it finds sustainability of the geo-biosphere more profitable. Therefore, MaxEP, MPP and MePP suggest that sustainability at a system level is subject to maximum power with intermediate efficiency and the power is the cause of the complex configuration of systems energy circulation.

2.1.3. Energy transport mechanism

Optimal system operation of living systems seeks an alignment of resource distribution to their components as well as system redundancy against extraneous perturbations (Ulanowicz, 1997). Schneider and Kay (1994) find that external stress on a system eventually affects the entropy production rate (system behaviour), and triggers to rearrange the internal motions of energy and mass. By the same token, living system mechanisms to obtain external resources are revealed through the configuration of internal energy transport structure. Transfer mechanisms maximizing power tend to drain wasted energy as quickly as possible, as a form of heat; i.e., the system develops a form of effective energy transport structure to degrade useful energy fast. In other words, entropy production entails a structure of energy dissipation. An elaborated structure of energy circulation must emerge in the growth and development of systems. Increased available energy intake towards development does not only affect quantity of the energy flow but also leads to notable characteristics of system properties and configuration of pathways through self-organization such as: (i) higher diversity, (ii) development of feedback loop (iii) pulsing between producers and consumers, (iv) relatively higher efficiency after growth (a state of minimum entropy production) (v) hierarchical structure of energy transaction based on energy 'quality' (Jørgensen, 1992; Toussaint and Schneider, 1998; Cai et al., 2004). For network analysis, the most critical aspects of self-organizing complexity are (i) autocatalytic organization through augmented cycling activities and (ii) generation of diverse pathways for increasing connections. Diversity of system components, pulsing, and the appearance of hierarchical trophic levels are the results of the construction of a complex structure (Fig. 1).

2.2. Rule of energy flow networking: maximum complexity and optimal autocatalysis

According to the theories of systems ecologists (though which are

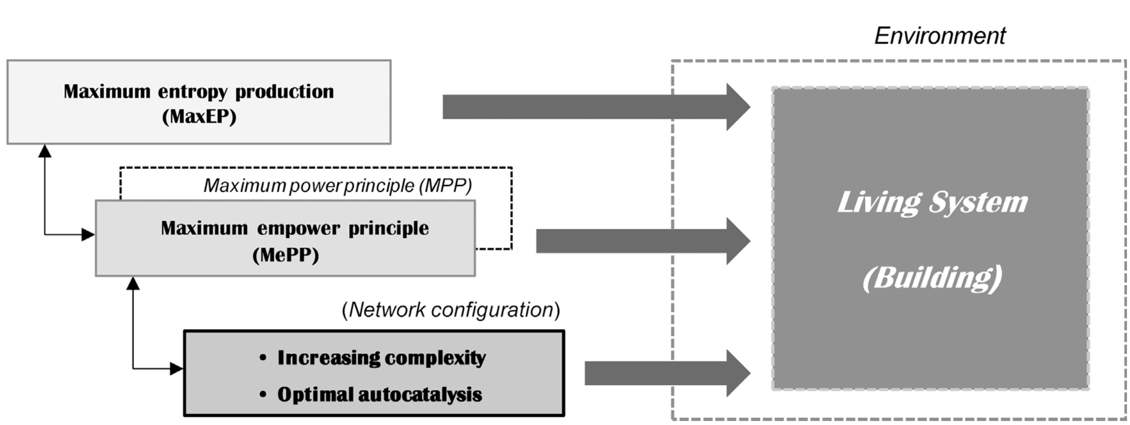


Fig. 1. Compatibility of system-level principles: The MaxEP, MPP, and MePP are extended statements of the SLT, and complexity and autocatalysis are network-based surrogates of principle indicators.

partly phenomenological), maximum power results in indirect (non-adjacent) connections of energy transport between system compartments to maximize the complexity of energy flow networking (Odum; Jørgensen, 1992). In this mechanism, relations of sources, producers, energy storage, and consumers in ecosystems are progressively reconstructed with increasing compartmental connectivity and energy storage. Connections are, however, not always conducible to sustainability, as disoriented complications in energy flux may lead to a loss of potential energy that can makes systems fragile in the end (Ulanowicz, 1997). Thus, living systems are self-structuralized to develop a circuit of 'energy augmentation'— an *autocatalytic* network (Ulanowicz, 1997).

Autocatalysis is defined as the construction of an energy circulation loop that proliferates and amplifies power through recycling and feedback; an outcome of energetic reactions becomes a catalyst for first reactants (inputs) so that a single energy source continuously spreads over the whole system with the least number of pathways. Autocatalytic mechanisms are compatible with maximum power in that the greater number of circulations, the more complex the system organization, which leads to an increased amount of potential energy. Not only that, an increased amount of internal material flowing through autocatalysis corresponds to longer cycling lengths and a decrease of turnover time of the cycling (Patten, 1992; Schneider and Jay, 1994). However, even though autocatalysis is a fundamental activity that enhances network quality toward mutual cyclic development, fully autocatalytic connections do not always ensure maximum power, because the single-path structure is too inflexible to introduce new energy sources (Fig. 2). Ulanowicz (1997, 2009) finds that autocatalytic energy flow networking increases system efficiency and it tends to be 'balanced' to seek system reliability for the development of living systems.

2.3. Information and measurement of energy networking and performance

Although *Information* is a new concept in assessing building performance, a building can be conceived as a form of information (Yi, 2016). For example, in a building, adding a new material to a building envelope changes internal heat distribution due to information encoded in the material. It is important to note that information works as a constraint to make living systems perform properly under the principles. Living systems maximize energy to maintain a non-equilibrium (active) state, but this is only accomplished by continuous application of information (Gatenby and Frieden, 2007), as it maps energy and matter over specific patterns by controlling nodes and links of transfer pathways (Janssen et al., 2006). Semantically, information has a dual meaning: (i) It is a system attribute, as all living systems consist of matter, energy, and 'information' (Jørgensen, 1992); (ii) It is a technical measure of flow networks and a key indicator of the environmental performance of living systems, as it is transmitted through and stored in a *topology* of resource distribution. Accordingly, information determines (i) a level of connectivity between system components, (ii) network centrality, and (iii) the strength of power storage. This informs that building environmental performance can be measured with information content that characterizes energy-flow networking patterns.

2.3.1. Quantification of information

While Wiener (1948) suggested that system information can be measured by stochastic distribution of quanta, quantitative definitions and mathematical formulations were introduced by Shannon (1948) in his information theory. Information to measure uncertainty of a signal distribution is given by,

$$H = k\left(p_1 log\frac{1}{p_1} + p_2 log\frac{1}{p_2} + ... + p_n log\frac{1}{p_n}\right) = -k\sum_{i=1}^{n} p_i \log(p_i) \quad (1)$$

where k is a positive constant that amounts to unit selection (it is usually set to 1), n is number of total channels, and p denotes a probability of a specific signal (or a quantum in a communication channel) so that p_i is an occurring frequency of a specific signal on the i-th of n channels. Information (H) of a system is represented such that $p^H = p_1p_2 \ldots p_n$.

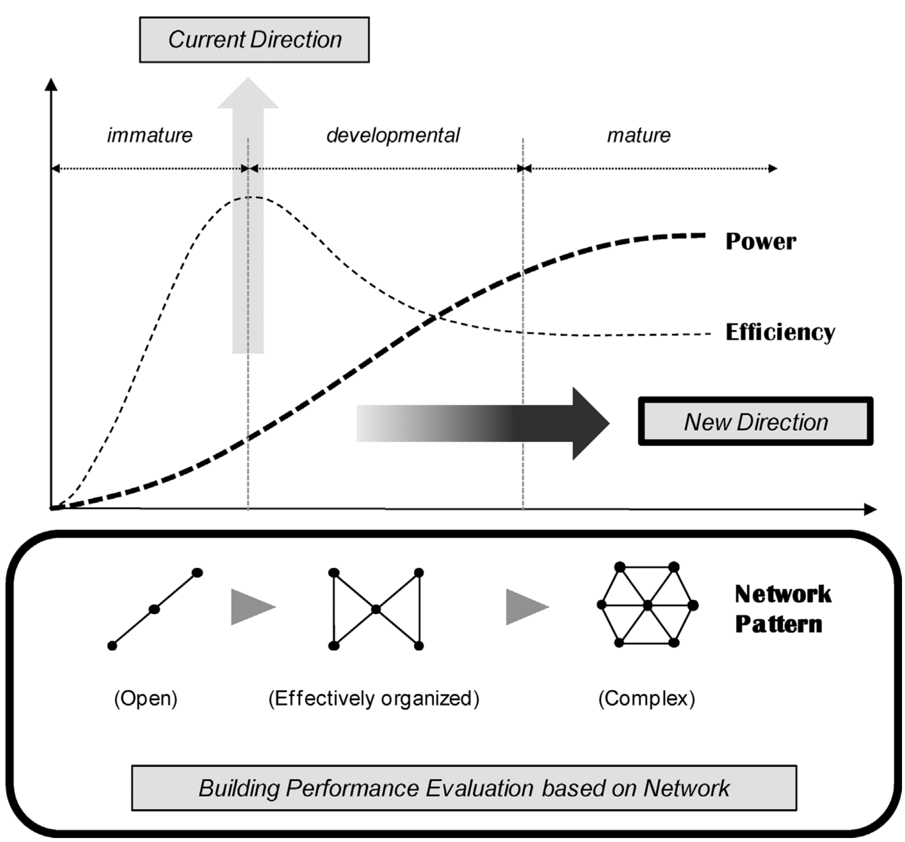


Fig. 2. Direction of sustainability and suggestion of a network-based performance evaluation.

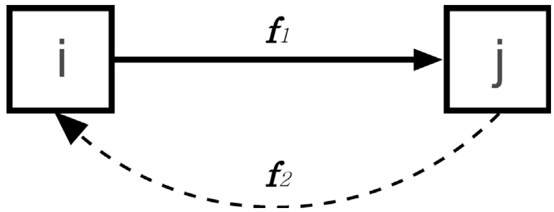


Fig. 3. Representation of the AMI concept.

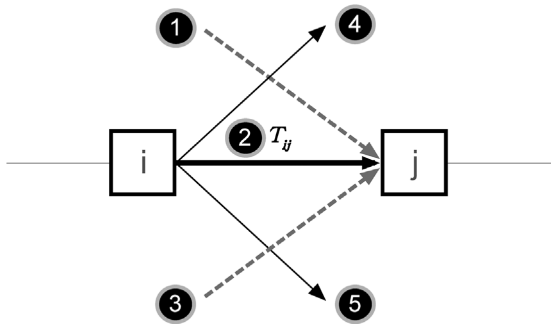


Fig. 4. Formulation of AMI: (1) external import to j, (2) internal transfer from i to j (T_{ij}), (3) internal transfer to j, (4) flows out of i to other comportments, (5) export and dissipation.

H is termed Shannon index, (information) entropy or a degree of uncertainty in signal distribution. The negative sign in Eq. (1) means that information is inversely proportional to the probability of a target signal. Introducing the quantity of a medium on a flow path, H can be interpreted as "diversity" in media distribution (Rutledge et al., 1976) or "complexity" of a network pattern. However, H does not account for dependency or communication between network channels and average mutual information (AMI) is suggested to measure a degree of interconnection.

Mathematically, mutual information is defined as a subtraction of uncertainty due to "unknown (unobserved)" events given probabilistic events of flow distributions (Shannon, 1948; Latham and Scully, 2002). Then, AMI is a weighted sum of the uncertainty of an individual flow. In a communication network, information is the stochastic index of a network structure that is indeterminate but apparently away from an arbitrary configuration. Suppose that a simple binary network is composed of two elements namely i and j (Fig. 3). The inflow to j (f_1) from i yields a constraint of the flow capacity. However, as j develops a positive feedback path (f_2), the flow out of j may influence f_1 conversely. Thus, both i and j become a *source* and a *reservoir* simultaneously. AMI quantifies a degree of association between the two nodes. For this pair of nodes, "mutual" means "directly/indirectly relational" resulted from feedback or an unspecific source connection. Therefore, AMI is a suitable measure to identify a constraint of implicit interactions in thermodynamic transport.

AMI is calculated by the logarithm of the probabilistic ratio of a posteriori to a priori event (Shannon, 1948), which means subtraction of uncertainty gained from known sources (a priori) from total uncertainty (a posteriori). Fig. 4 displays all possible flows between the pair. Let uncertainty of a unit pair be U_{ij}, by information theory (Shannon, 1948), U_{ij} is obtained by,

$$U_{ij} = -k \log \frac{T_j}{T} - \left(-k \log \frac{T_{ij}}{T_i}\right) = k \log \frac{T_{ij} T}{T_i T_j} \tag{2}$$

where T is total system throughput, T_i is the total flows leaving from i (② + ④ + ⑤), T_j is total inflow to j (① + ② + ③), and T_{ij} is transfer from i to j. Setting the coefficient k of the scalar constant to 1, the weighted sum of unit uncertainty becomes AMI as follows,

$$\text{AMI} = \sum_{i=1}^{m} \sum_{j=1}^{n} U_{ij} = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{T_{ij}}{T} \log \frac{T_{ij} T}{T_i T_j} \tag{3}$$

where m is total number of outflow paths of i, and n is total number of inflow paths of j.

2.3.2. Scaled- and non-scaled informational indicators: metabolic interpretations

Rutledge et al. (1976) applied Shannon index to characterize diversity of biological succession. Based on the hypothesis that the ecosystem organizations mature towards autocatalytic networking, Hirata and Ulaniwocz (1984) proposed an AMI-based index in order to assess the developmental pattern of an ecosystem structure. In an operational process, efficiency is maximized if and only if an ecosystem medium (energy or mass) is circulated via an autocatalytic loop. The information of autocatalysis results in an effective self-enhancing mutualism that prunes untoward (less efficient) links. In this regard, AMI is well-

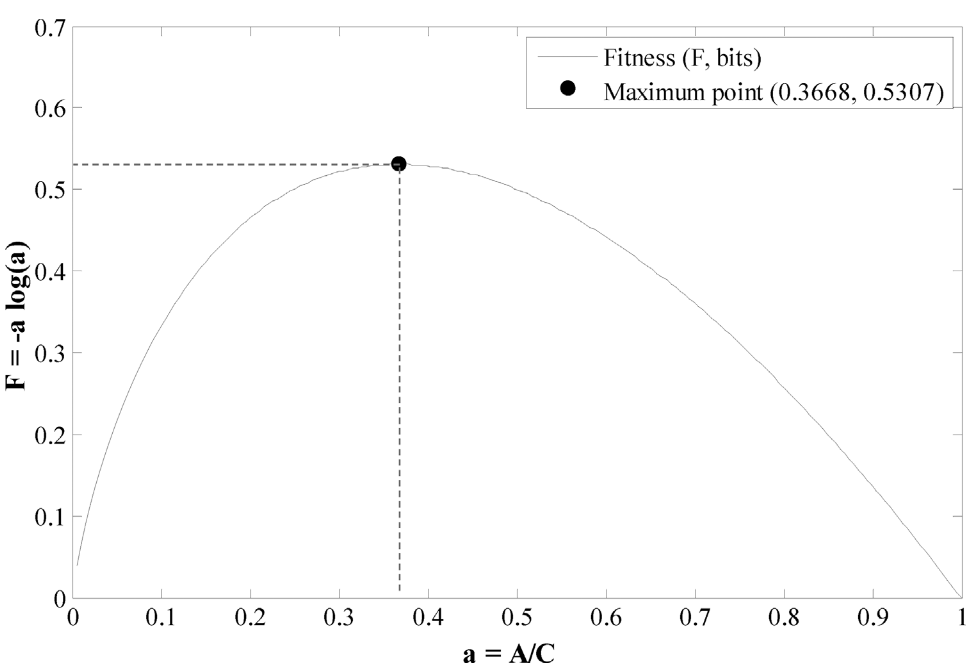
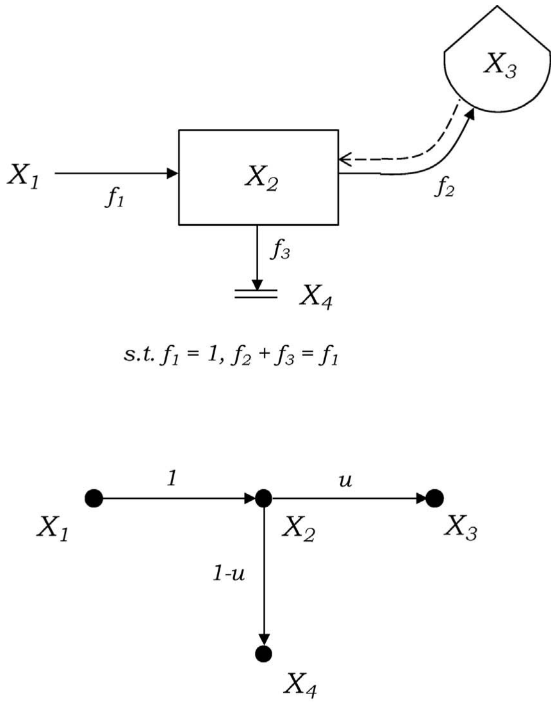


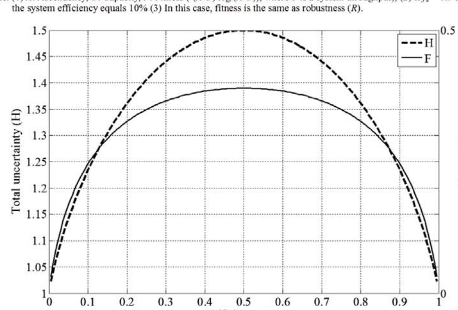
Fig. 5. Fitness curve (redrawn from Ulanowicz, 2009): This graph shows that the adjustment of system networking becomes a critical player to maximizing fitness.



(a) System representation: system diagram (upper) and digraph (below)

Efficiency, u (%)	AMI	A	C (H)	L	F
0	1	2	2 (1)	0	0
10	1	2	2.47(1.24)	0.24	0.25
20	1	2	2.72(1.36)	0.36	0.33
30	1	2	2.88(1.44)	0.44	0.37
50	*1*	*2*	*3.00(1.50)*	*0.50*	*0.39*
70	1	2	2.88(1.44)	0.44	0.37
80	1	2	2.72(1.36)	0.36	0.33
90	1	2	2.47(1.24)	0.24	0.25
100	1	2	2(1)	0	0

Note: (1) A: Ascendency, C: Capacity, F: Fitness ($-(A/C)\log(A/C)$), where T is a system throughput), (2) If $f_2 = 0.9$ and $f_3 = 0.1$, then the system efficiency equals 10% (3) In this case, fitness is the same as robustness (R).



(b) Test result of system attributes (resilience and total uncertainty)

Fig. 6. Test of the measure of resilience (and robustness): This result shows that complexity (H) or resilience (L) is consistent with MePP in a steady system state. (a) System representation: system diagram (upper) and digraph (below); (b) Test result of system attributes (resilience and total uncertainty).

suited to indicate efficient patterning, because it is also maximized if the quantities are evenly distributed over a fully-circulating alignment. From this finding, Ulanowicz defines "*ascendency* (A)" as a measure of system development by scaling up AMI (Eq. (3)) with total system throughput (T) such as:

$$A = T{\cdot}\mathrm{AMI} = T\sum_{i=0}^{m+2}\sum_{j=0}^{n+2}\frac{T_{ij}}{T}\log\frac{T_{ij}T}{T_iT_j} = \sum_{i=0}^{m+2}\sum_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}T}{T_iT_j} \tag{4}$$

(0: external input (import), $m + 1$ and $n + 1$: system output to external environment (export), $m + 2$ and $n + 2$: depreciation)

Ascendency is interpreted as an indicator of "structure-enhancing configurations (Ulanowicz, 2009)", and the capability of system repair for self-development. However, full autocatalysis is a result of mechanical construction and highly improbable in reality, because it easily fails (brittle) in the case of unpredictable events (noise), which occurs quite frequently in the real world in which local systems are immersed. Accordingly, to maintain system integrity (order), local ecosystems prepare for the emergencies by embracing internal disorder, which Ulanowicz (1980) calls "*overhead* (ϕ)." The concept of overhead is critical to the quantitative definition of resilience in that it stands for system's flexibility and potential of future evolution (Ulanowicz et al., 2009). Overhead is calculated by subtracting ascendency from total system *capacity* (C). The capacity is calculated by multiplying system throughput (T) and overall uncertainty of particle distribution (Shannon index, H). During the system's development, it is hypothesized that capacity gradually increases. Capacity is given by:

$$C = T{\cdot}H = -T\sum_{i=0}^{m+2}\sum_{j=0}^{n+2}\frac{T_{ij}}{T}\log\frac{T_{ij}}{T} = -\sum_{i=0}^{m+2}\sum_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}}{T} \tag{5}$$

And, then, overhead is computed as:

$$\begin{aligned}\phi = C - A &= -\sum_{i=0}^{m+2}\sum_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}}{T} - \sum_{i=0}^{m+2}\sum_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}T}{T_iT_j}\\ &= -\sum_{i=0}^{m+2}\sum_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}^2}{T_iT_j}\end{aligned} \tag{6}$$

where C ≥ ϕ ≥ 0 and C ≥ A ≥ 0.

System resilience (L) is defined,

$$L = \frac{\phi}{T} = H - AMI \tag{7}$$

The scaled indicators (A, ϕ, and C), were integrated by Ulanowicz (1997) to suggest new indices of ecosystem resilience, namely, "*fitness* (F)" and "*robustness* (R)." Fitness is the ratio of ascendency to capacity multiplied by the logarithm of the ratio, and robustness is a sum of the fitness of each particle such that:

$$F = -\frac{A}{C}\log\frac{A}{C} = \frac{\Sigma_{i=0}^{m+2}\Sigma_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}T}{T_iT_j}}{\Sigma_{i=0}^{m+2}\Sigma_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}}{T}}\log\frac{\Sigma_{i=0}^{m+2}\Sigma_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}T}{T_iT_j}}{\Sigma_{i=0}^{m+2}\Sigma_{j=0}^{n+2}T_{ij}\log\frac{T_{ij}}{T}} \tag{8}$$

$$R = T{\cdot}F \tag{9}$$

F implies the average uncertainty of an energy quantum towards ecosystem's *order*— *i.e.*, a normalized factor of effective accumulation of useful energy (indicated by A). Ulanowicz (2009) interprets that the greater A/C (> 0.37), the more brittle a system becomes because the

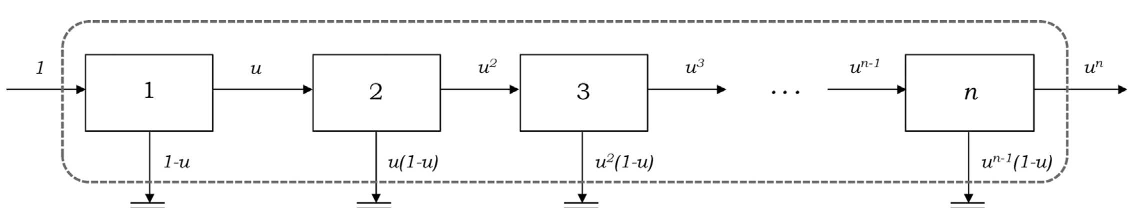
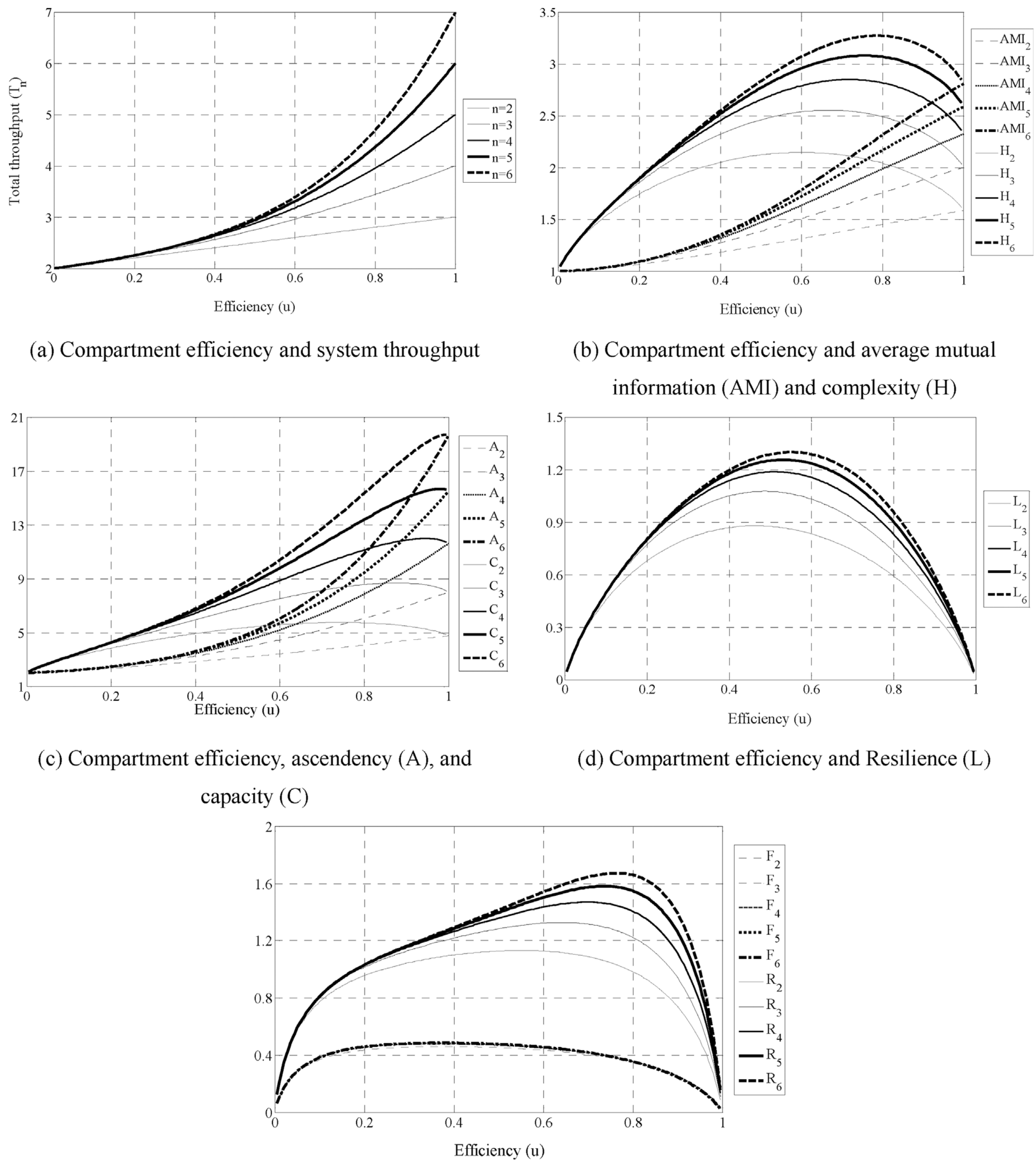


Fig. 7. General structure of a one-way flow system with n compartments.



(a) Compartment efficiency and system throughput

(b) Compartment efficiency and average mutual information (AMI) and complexity (H)

(c) Compartment efficiency, ascendency (A), and capacity (C)

(d) Compartment efficiency and Resilience (L)

(e) Compartment efficiency, fitness (F), and robustness (R)

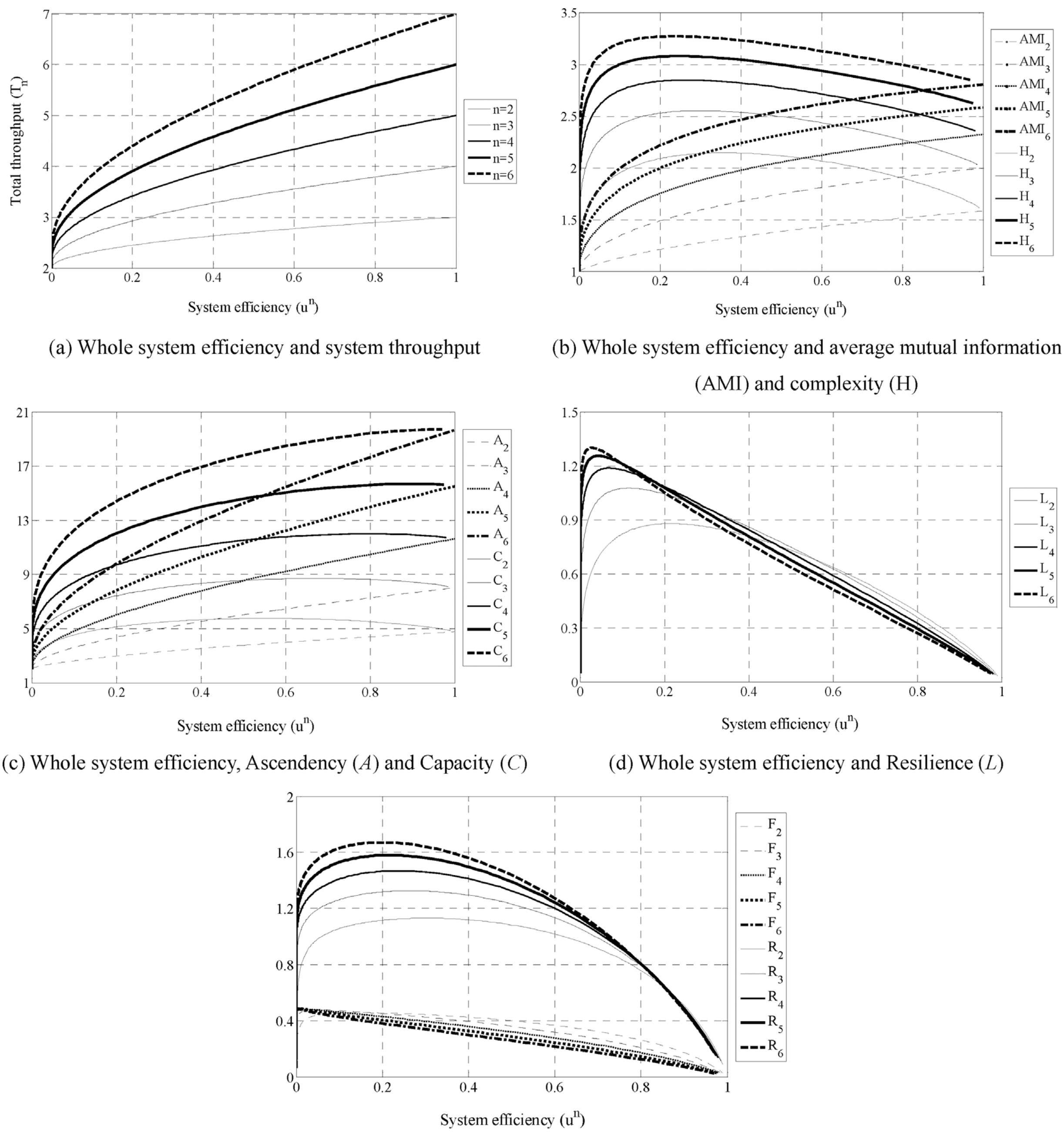
Fig. 8. Compartment efficiency (u) and information indices.

system is too organized (greater AMI). Therefore, F is maximized at a balance point (0.3368, 0.5307) as in Fig. 5. Robustness (R) is a scaled fitness augmented by the magnitude of TST. Although R is more suitable to evaluating different kinds of systems (as it involves total resource quantity), fitness would make greater sense if one seeks to identify an inherent resilient attribute of system activities or a fraction of redundant flux in throughput. Also, fitness can be thought of an index of sustainability in a sense (Ulanowicz, 2009; Kharrazi et al., 2013), because it indicates a balance of versatility and rigidity prepared for future occurrence. Environmental systems with a fixed value of fitness may improve overall resilience by increasing energy flow quantity, thereby enhancing robustness.

3. Reconciled system principles and network-based performance analysis

3.1. Information indices reconciled with maximum power

System-level indices and principles shall be synthetically applicable to building performance evaluation. MPP (Lotka, 1922; Odum, 1963) and exergy-storage hypothesis outlined by Jørgensen (1992) state that increased system throughput develops various routes of resource distribution with feedback and they accelerates diffusivity in a network organization. However, despite consistency between maximum power and complexity of network topology, it is not clear if an informational



(a) Whole system efficiency and system throughput

(b) Whole system efficiency and average mutual information (AMI) and complexity (H)

(c) Whole system efficiency, Ascendency (A) and Capacity (C)

(d) Whole system efficiency and Resilience (L)

(e) Whole system efficiency and fitness (F) and robustness (R)

Fig. 9. System efficiency, AMI, fitness, and robustness (bits).

measure of complexity can be a firm index to system power and sustainability, because MPP and MePP basically focus on resource "stock", while information measures "flow". To identify interchangeability at an indicator level, it is needed to reconcile maximum power and Ulanowicz's ecological lemmas with information indices.

Although information indices do not make a direct correlation to maximum power, Ulanowicz's statements about ascendency and AMI are similar to Odum's statement, maximum power at 50% efficiency.[1] Also, the MePP's finding about a sustainable ecosystem construction, "self-rewarding loop (Odum 1971)", recalls the autocatalysis in system energy networking. This agreement can be demonstrated by a hypothetical experiment (Fig. 6). Suppose a thermodynamic system is in a steady state development. Then, the system's energy transformation processes are aggregated into a single compartment (X_2) so that it simplifies this test. This system has only three energy pathways: inflow (f_1), outflow (f_2), and degradation (f_3). Let X_1, X_3, and X_4 denote a source, a storage (or a consumer), and a sink respectively. The system operation can be depicted as a digraph (Fig. 6(a)), and the system efficiency is computed by f_2/f_1, denoted as u. Since the system is steadily working, f_1 shall equal $f_2 + f_3$.

To parameterize each flow with efficiency, let the input be a unit flux. Then, f_2 and f_3 are denoted as u and $1–u$ and total throughput becomes 2. Now, we can calculate the informational indicators (AMI, H, A, C, ϕ, and F) in various magnitude of efficiency by altering the values of f_2 and f_3:

[1] Ulanowicz disagrees with H.T. Odum's maximum power at 50% efficiency (Ulanowicz, 1980), and rather emphasizes that ascendency synthesizes E.P. Odum's 24 attributes of ecosystem development (Odum, 1969)."

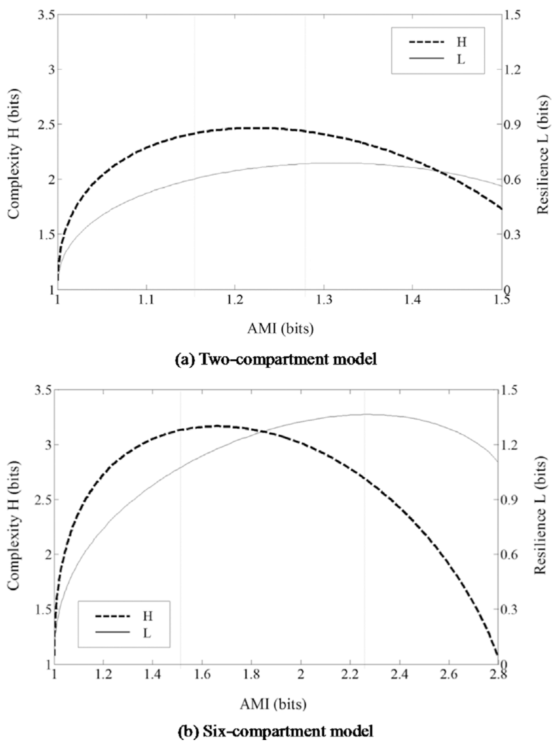


Fig. 10. Variation of complexity (H, total system uncertainty) and fitness. (a) Two-compartment model; (b) Six-compartment model.

$$\mathrm{AMI} = \frac{1}{2}\log_2 2 + \frac{u}{2}\log_2 2 + \frac{1-u}{2}\log_2 2 = 1 \tag{10}$$

$$\begin{aligned} \mathrm{H} &= -\left(\frac{1}{2}\log_2\frac{1}{2} + \frac{u}{2}\log_2\frac{u}{2} + \frac{1-u}{2}\log_2\frac{1-u}{2}\right) \\ &= 1 - \frac{u}{2}\log_2 u - \frac{1-u}{2}\log_2(1-u) \end{aligned} \tag{11}$$

where $0 \leq u \leq 1$.

The results are presented in Fig. 6(b). AMI and A are constant, as the direction of pathways and total throughput are fixed ($f_1 + f_2 + f_3 = 2$). Fixed values of AMI and A are due to the constant throughput and the constraint that the number of autocatalytic links is constant. It finds that, if efficiency reaches 50%, system complexity (H) and capacity (C) are maximized as well as resilience (L) and fitness (F). In this condition, the only way of system development is to increase flow diversity (uncertainty of information content). The diversity of quantum flows is ensured with an assumption of growth in steady state without any external perturbation, which is a fundamental premise of the maximum power principle.

Even if the system size is limited, an increase of capacity means a gain of uncertainty in the identification of the system's energy flow configuration. That is, energy networking becomes highly sensitive to the position and intensity of a single particle on flow pathways. If the "*utility*" and "*quality*" highlighted in MePP is interpreted as an equivalent to *significance* of a single energy particle's contribution to the overall energy transaction, then this case suggests that the concept of network complexity and maximum power based on an input-output analysis are, inevitably, two sides of the same coin.

3.2. Efficiency and information indices

To convert efficiency-centered indication of system performance to information, it is necessary to characterize information indices in association with efficiency change. On this purpose, a multi-compartment system with a one-way energy flow chain is considered so that it generally represents an open-loop living (or building) system (Fig. 7).

This model consists of n system compartments. No export, import, and backward flows are considered to represent a simple scheme. Efficiency of each unit compartment is set to equal, and denote it as u so an output of a single compartment is the multiplication of u. Limiting our discussion to the steady-state flux, *i.e.*, gain and loss at each node are the same, if 1 is an initial input to the system, the total flow transaction eventually gives a useful medium of u^n from the n-th compartment. Hence, efficiency of the entire system is measured u^n. Total system throughput (TST, T_n) is the sum of all individual values on the pathways such that:

$$T_n = 2 + u + u^2 + \ldots + u^{n-1} \tag{12}$$

And system complexity, AMI, and resilience are computed by:

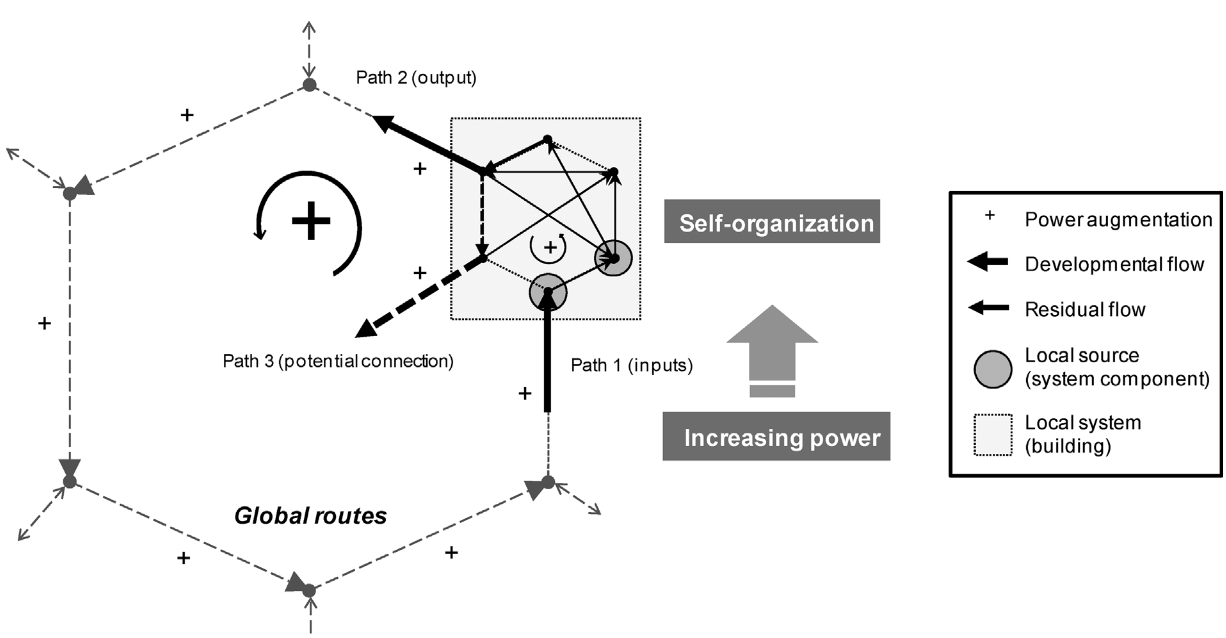


Fig. 11. Network-based scheme of building sustainability.

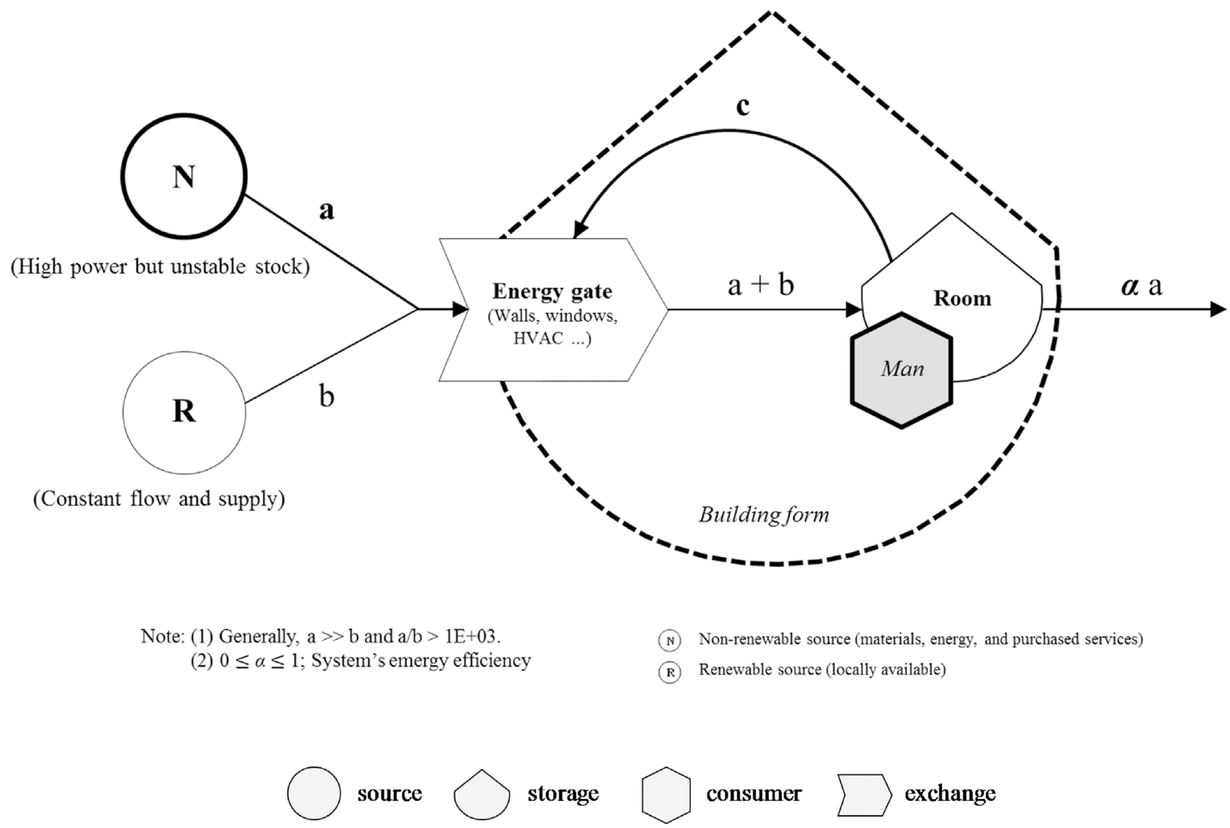


Fig. 12. Generic building model of thermodynamic metabolism.

$$\mathrm{H}_n = log(\mathrm{T}_n) - ((u^2)' + (u^3)' + ... + (u^n)' + u^n)\frac{1}{\mathrm{T}_n}log(u) - (1 - u^n)\frac{1}{\mathrm{T}_n}log(1 - u) \tag{13}$$

$$\mathrm{AMI}_n = log(\mathrm{T}_n) - (1 - u^n)\frac{1}{\mathrm{T}_n}log(\mathrm{T}_n - 1) - (u^2 + 2u^3 + 3u^4 + ... + (n-1)u^n)\frac{1}{\mathrm{T}_n}log(u) \tag{14}$$

$$L_n = \frac{(1 - u^n)}{\mathrm{T}_n}log\frac{T_n - 1}{1 - u} - \frac{2\log(u)}{T_n}\left(u + u^2 + u^3 + ... + u^{n-1} + \frac{2 - n}{2}u^n\right) \tag{15}$$

System ascendency and capacity are calculated as,

$$A_n = T_n log(T_n) - (1 - u^n)log(T_n - 1) - (u^2 + 2u^3 + 3u^4 + ... + (n-1)u^n)log(u) \tag{16}$$

$$C_n = T_n log(T_n) - ((u^2)' + (u^3)' + ... + (u^n)' + u^n)log(u) - (1 - u^n)log(1 - u) \tag{17}$$

Fig. 8 exhibits variations of the system-level attributes and information indices according to variations in the number of compartments and efficiency of each compartment within the test flow chain. In Fig. 8(a) ~ (c), we observe that T, AMI, A, and C increase, while complexity (H) peaks at an intermediate efficiency level and decreases. It is noticeable that TST exponentially increases after a certain level of efficiency, and this trend becomes intensified as the system adds compartments. Also, ascendency variation shows a similar trajectory. This result reveals that as a system grows with increasing compartmental efficiencies, the augmentation of the flow scale strongly affects ascendency.

The profile of H in Fig. 8(b) is similar to the result of the single compartment model (Fig. 6). H is maximized at about 50 ~ 80% efficiency, a little higher than 50%. It is important to note that AMI increases in parallel with efficiency, which substantiates that AMI is closely related to network efficiency. By definition, AMI refers to a system's retaining ability of quantum (flow medium) within pathways (Shannon, 1948; Ulanowicz, 1986). As greater compartmental efficiency ensures that more initial inputs stay all the way through the flow structure, a resource flow through a longer energy chain with high efficiency augments AMI. These phenomenon appears consistent with a mechanistic understanding that increasing efficiency followed by energy conservation assures system growth (greater *TST*) and development (greater AMI). Although it seems that system sustainability gain advantage solely from thermodynamic minima (reduction of energy loss and maximum efficiency), the curves of L, F, and R in Fig. 8(d) and (e), show that the system is likely to be unstable if efficiency (u) increases excessively.

In Fig. 8, resilience (L) profiles look similar to H, but the values peak within a narrow range of efficiency. F is maximized relatively earlier, at around 20 ~ 30% efficiency. It shows that environmental systems are more flexible (adaptable) before flow networking is fully organized (increased AMI). It is interesting to observe that scaled fitness (robustness) increases along with an increase of capacity, and sharply drops after a peak efficiency.

These results reveal that augmentation of compartmental efficiency does not always work positively with system attributes such as power, potential of reorganization, adaptability, and resistance to external stress.

On the other hand, indices are examined with the whole system efficiency (u^n), to characterize index behaviour from an external observation (Fig. 9). Interestingly, *TST* and AMI increases at high efficiency become abated, and system complexity (H) increases as compartments are added (system growth). By the way, compared with Fig. 8, H peaks at a far lower level of efficiency (about 10 ~ 30%), and efficiency at the maximum H is reduced as the system grows (this result complies with the fact that ecosystems trophic efficiency is around 10%

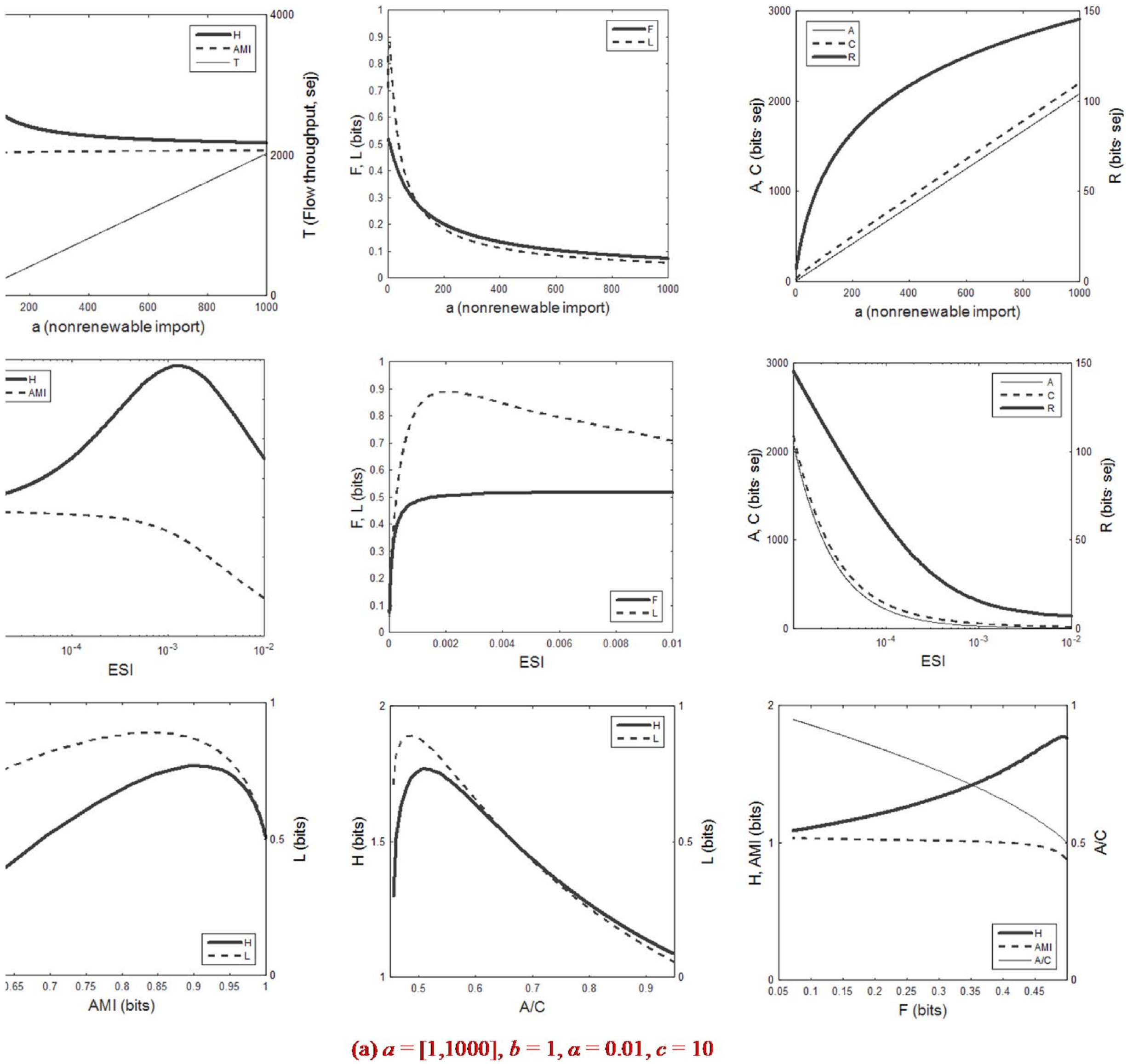


Fig. 13. Simulation results of information indices with the generic building model. (a) a = [1,1000], b = 1, α = 0.01, c = 10; (b) a = 1000, b = [0,10], α = 0.01, c = 10; (c) a = 1000, b = 1, α = [0,1], c = 10; (d) a = 1000, b = 1, α = 0.01, c = [1,100].

or less). Similar to this, L, F, and R are also maximized at lower efficiency and this trend is intensified as the system flow network is more complicated (Fig. 9(d) and (e)), but the increment of AMI and capacity is mitigated, while the system gets bigger. It shows that increasing efficiency sets a certain limit on the system development.

Figs. 8 and 9 show that system description can be very different according to the resolution of analysis, because whole system properties are not always identical to compartmental properties. Nevertheless, all results suggest that H, F, or L indicates a maximized system attribute at the expense of efficiency, and AMI is closely related to efficiency (maximum efficiency leads to maximum AMI). However, it should be noted that AMI is different from the efficiency of a unitary process. Whereas overall system efficiency (u^n) diminishes by adding a new compartment, AMI increases.

In Fig. 10, it is clear why sacrificing efficiency is preferred in developing living systems; even though the six-compartment model is obviously less efficient, it maximized other positive system attributes (H, L, and F). In other words, this result implies that *system development goes through a trade-off between efficiency and complexity or resilience*; greater H or L with compromised efficiency. However, though H, L, and F are all positive indices of system development, it is the most important to notice that these graphs show that H is maximized at network efficiency of about 50% (A/C or AMI/H). H of the two compartment model presents a maximum value of 2.46 at 1.21 AMI (A/C = 49.2%), and that of the six compartment model is 3.15 at 1.68 AMI (A/C = 53.3%). Compared this result with Fig. 6 and MePP, this strongly suggests that H stands for system *power* that is maximized at around 50% efficiency, and demonstrates an agreement between maximum network complexity (information) and power. It also recalls the Ulanowicz (1986, 1997)'s statement that maximum AMI (or A, ascendancy) is not always desirable for self-organizing ecological communities, and, an ecosystem in a steady state would seek compromise on AMI to increase adaptability and power (Ulanowicz, 2009).

H and L do not necessarily peak at the same efficiency or AMI (Fig. 10). More complex systems network tends to have greater power and resilience, but they are maximized at different developmental levels. Therefore, we may suppose that environmental systems pursue to maximize resilience, according to external conditions, if maximum power is not available or desirable. We expect, accordingly, that living systems change system states back and forth between maximum power and maximum resilience, by switching priority depending on external thermodynamic constraints.

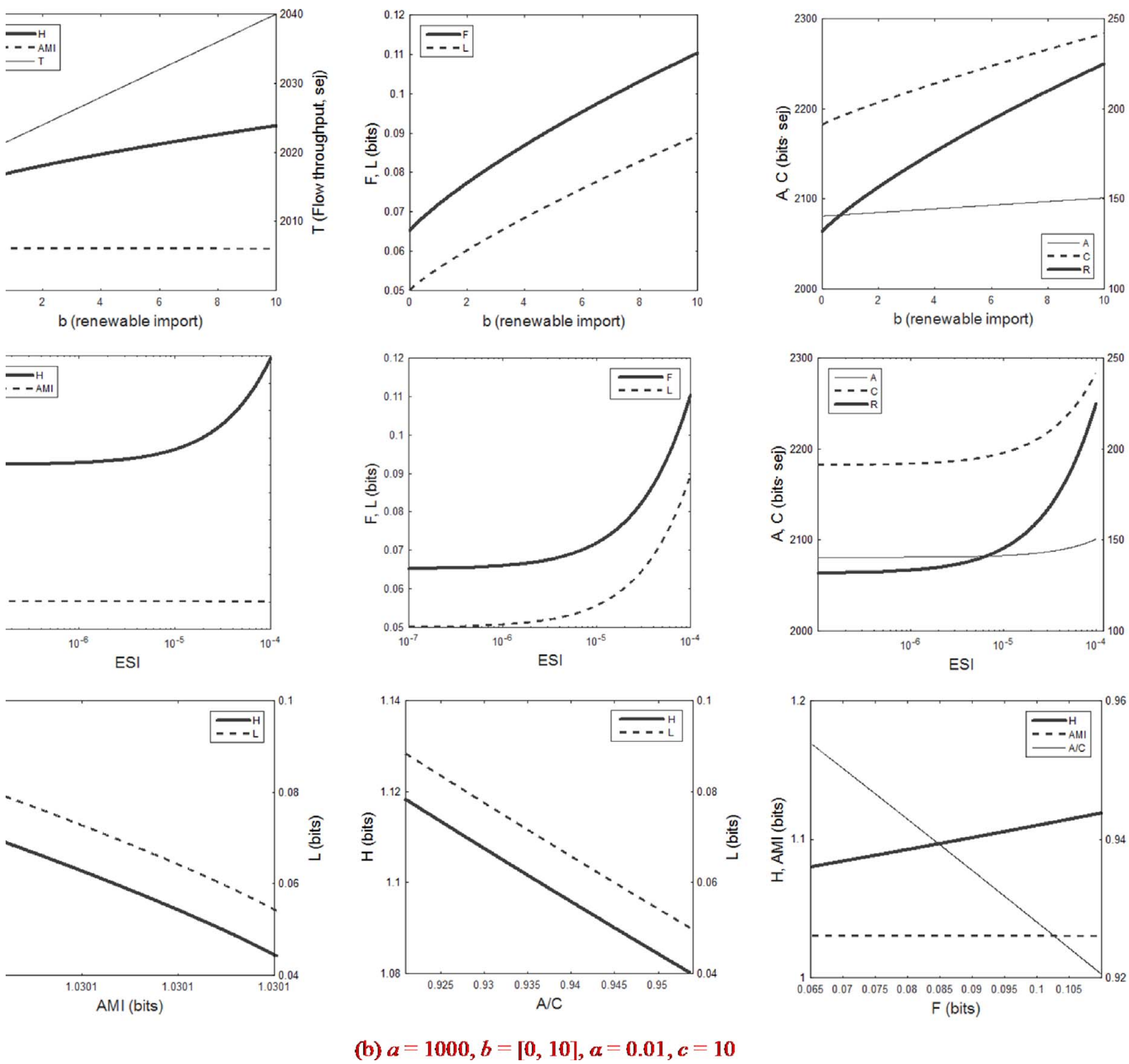


Fig. 13. (*continued*)

3.3. Energy-networking based definition of building performance and sustainability

The living system-based understanding of system performance needs to redefine building sustainability based on flow networking of environmental sources. While current quantity-focused building sustainability (energy use reduction) does not clearly indicate the "dependence" of building performance to external systems, environmental principles based on autocatalytic mechanisms and the degree of useful power suggests that it is far more important to notice flowing patterns of energy carriers and relationship between building system components than energy stock. In this regard, building performance and sustainability can be characterized with energy networking between a local and global environment at a system level (Fig. 11). In Fig. 11, energy flowing within a building organizes complex subsystem loops to maximize power and, simultaneously, they branch out to feed the entire environmental network; hypothetical output path 1 and 2 help the global loop augment potential power through autocatalysis, and the remote global sources indirectly strengthen building energy sources. The building system performs according to the external loop and sustainability depends on resilience and fitness that assures the local system's spontaneous interplay of the indirect and direct effect, thereby the ability of existence under an unpredictable global condition. In this understanding, building sustainability refers to *potential* of environmental adaptation through dynamic energy networking that draws its spontaneous move contributing to a continuous global increase of the system power in accordance with the global system as well as other local systems.

4. Modeling of generic building energy networking and informational performance simulation

4.1. Measurement: integration of emergy and information

Measurement of building information incorporates an emergy unit into Eqs. (1) ~ (9). Emergy is a metric of solar embodied energy that records all direct/indirect upstream consumption of useful global environmental resources of a product or system (Odum, 1996). Emergy also unifies different metrics of energy/material by *solar emjoule* (sej). Although Ulanowicz (1986) states that "optimal ascendency translates into maximal work, when the medium of interest is energy," use of emergy allows for building performance (local system operation) to be characterized at a global environmental level. Emergy is though a donor-side measurement, and does not consider downstream impact in general. Thus, emergy integrated with the symmetrical feature of information-based calibration allows us to measure both upstream and

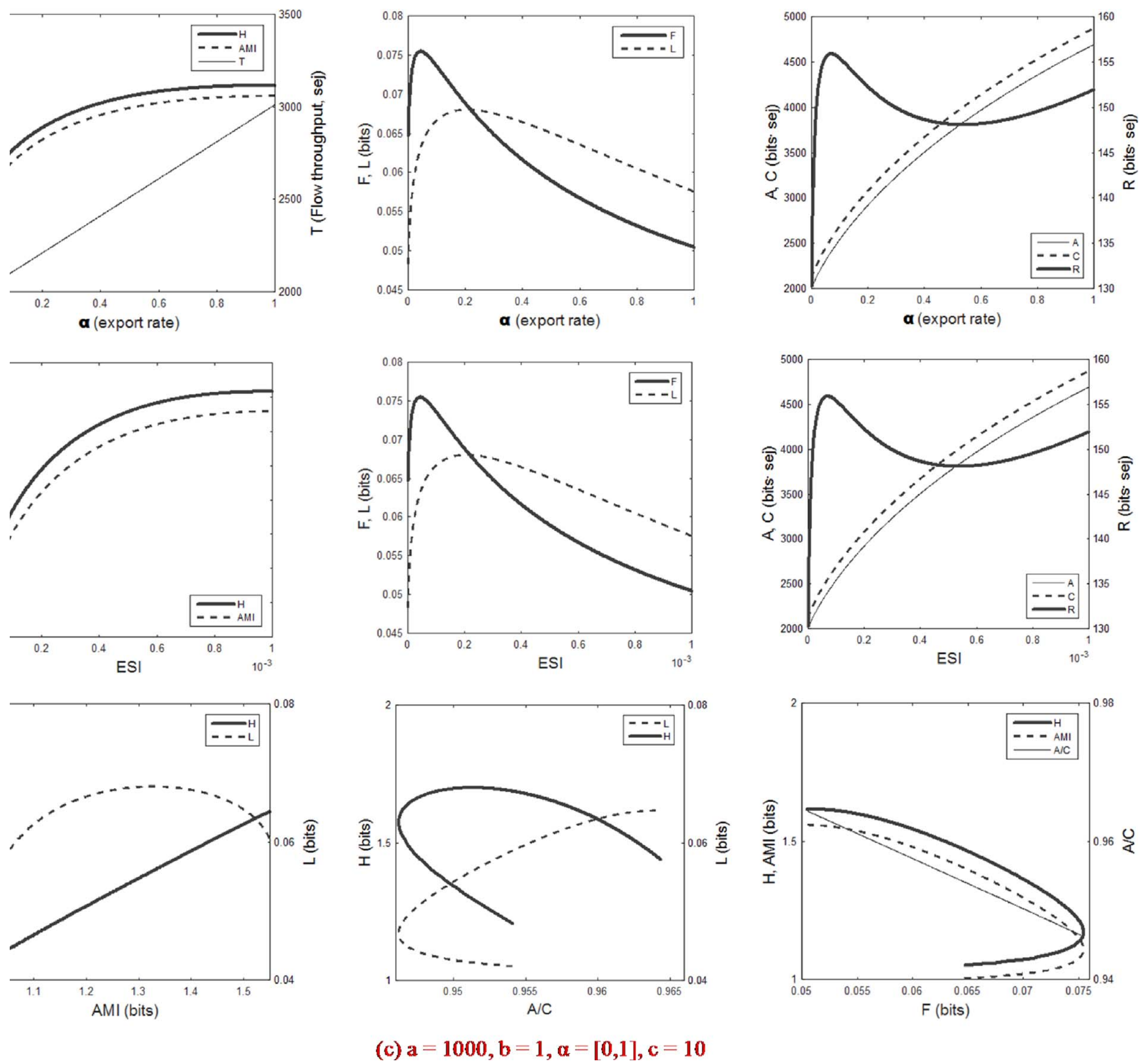


Fig. 13. (*continued*)

downstream impact comprehensively.

Emergy-based information is practically desirable as well; for high-trophic level systems (such as buildings) that use small high-quality energy, information measured with energy units becomes less sensitive to network change (Christensen, 1994). Information-emergy integration also enable to compare informational indices with emergy sustainability index (*ESI*), which is obtained by,

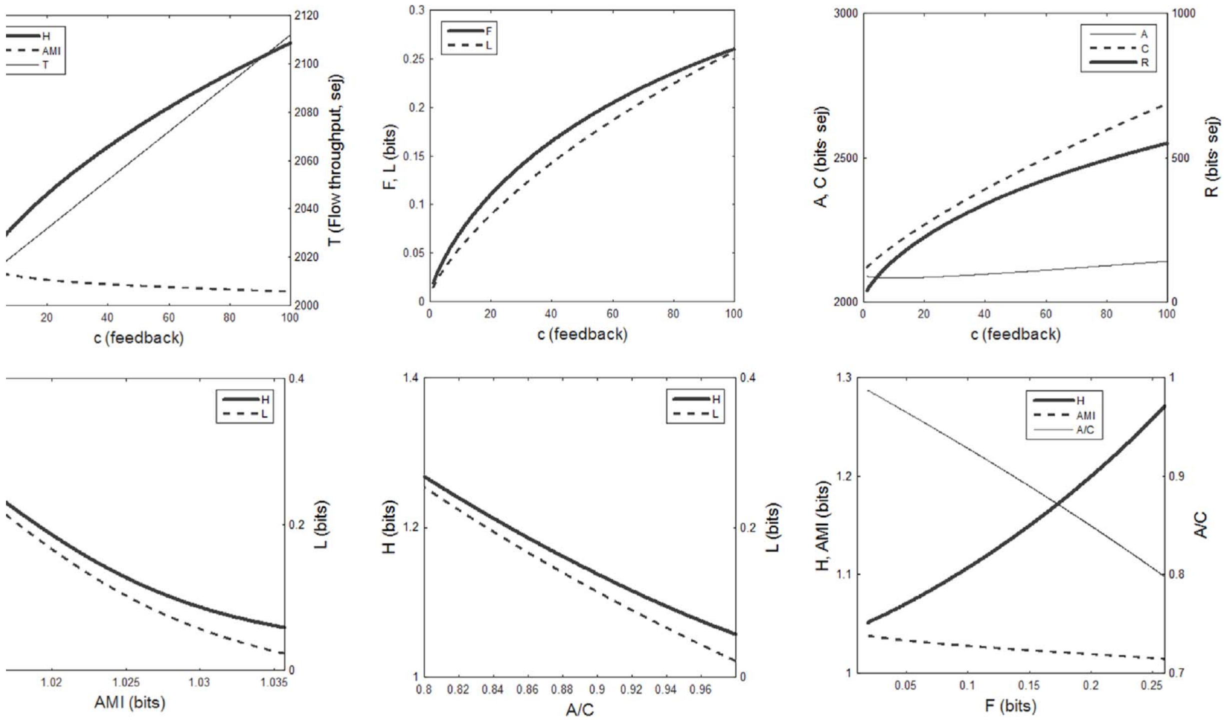
$$ESI = Y{\cdot}RN/P{\cdot}(N + P) \quad (18)$$

where Y refers to emergy yield of a system, RN is local renewable emergy inputs, and P and N are purchased, nonrenewable inputs respectively. Comparison of *ESI* with information indices will clarify which index is a proxy of system power.

4.2. System design and parameters

The following generic building system was designed to emulate the metabolism of a living system as simply as possible (Fig. 12). This network model was designed to have primary building components only, and was drawn with the energy diagram symbols of emergy theory. Flow quantity over each path indicates an emergy value of each flow. Most physical elements that are in charge of building energy transactions (*e.g.*, building façade, mechanical equipment, windows, and doors) were lumped into a single component named energy gate. A building form organizes material and energy, and operation and maintenance are related to the *energy gate*, a *throttle valve* of energies and materials to the form (*e.g.*, window opening, thermostat control).

It was assumed that the building has three categories of environmental sources: renewable (**R**) and nonrenewable (**N**) that include both energy and matter and information. However, despite its importance, building information is accumulated from a storage whose capacity and location are unknown. So, this model monitors pattern changes of the emergy flow networking to detect its effects. This is because (i) information content is only measured by observing change in system organization; (ii) the two external sources (**R** and **N**) have distinctively different characteristics (stock-constrained and flow-constrained); and (iii) this test aims in part to demonstrate that information-based performance indication includes the common notion of building sustainability (*e.g.*, reduction of nonrenewable energy use). Emergy gained from the resource reservoir through an energy gate is transmitted to interior space (room and man), and computed as $a + b$ according to an emergy accounting rule. Behavioral reactions (opening windows, lighting control, etc.) that control the energy gate and feedback from interior space to other building components are represented as a



(d) $a = 1000, b = 1, \alpha = 0.01, c = [1, 100]$

Fig. 13. (*continued*)

backward flow (c). Buildings yield useful outputs to external environment (water, extra electricity, etc.), but the quantity is varying depending on the (emergy) efficiency of the system. In this model, total system throughput (TST, T) is a function of four parameters and computed by adding up all flow quantities such that:

$$T(a, b, c, \alpha) = (2 + \alpha)a + 2b + c \tag{19}$$

And according to Eqs. (1)~(9), H, AMI, and L are calculated respectively as follows:

$$\mathrm{H}(a, b, c, \alpha, T) = log_2 T - \frac{1}{T}\{alog_2 a + blog_2 b + clog_2 c + (a + b)log_2(a + b) + \alpha alog_2(\alpha a)\} \tag{20}$$

$$\mathrm{AMI}(a, b, c, \alpha, T) = log_2 T - \frac{1}{T}\{(a + b + c)\log_2(a + b + c) + (c + \alpha a)\log_2(c + \alpha a) + (a + b)\log_2(a + b) - clogc\} \tag{21}$$

$$L(a, b, c, \alpha, T) = \frac{1}{T}\{(a + b + c)\log_2(a + b + c) + (c + \alpha a)\log_2(c + \alpha a) - alog_2 a - blog_2 b - 2clog_2 c - \alpha alog_2(\alpha a)\} \tag{22}$$

On the other hand, from Eq. (18),

$$\boldsymbol{ESI} = \frac{\alpha a/a}{(0 + a)/b} = \frac{\alpha b}{a} \tag{23}$$

System ascendency and capacity are calculated by multiplying AMI and H by a system scale (T). Additionally, according to emergy theory and general building conditions, parameters are subject to following constraints.

$$\begin{cases} \frac{a}{b} > 1E + 03 \\ a + b \geq c \\ a + b \geq \alpha a \\ 0 \leq \alpha \leq 1 \\ a, b, c \geq 1 \end{cases} \tag{24}$$

4.3. Simulation results

In order to identify performance of each parameter and their contribution to building sustainability, simulation was conducted by changing parameter values (Figs. 13 and 14). First, to confirm consistency of information-based examination and the general notion of building sustainability, information profiles were observed by changing each parameter (a, b, c, α) (Fig. 13). Results show that reducing nonrenewable source use (a) and increasing renewable import (b) cause H, F, and L to increase, while adjusting AMI and efficiency (A/C) to decrease (Fig. 13(a), (b)). It is very important to note that H and L are maximized around A/C of 0.5, which demonstrates maximizing power at medium efficiency. Also, notice that the positive indicators of ecosystem development (H, F, and L) sharply increase as the system self-organizes to reduce a as well as to increase b. It clearly proves that indication of metabolic development based on this system design incorporates a reductive notion of building sustainability. The results of Fig. 13(a) and (b) are also exactly consistent with the Odum's ecosystem-based statement about sustainability that "*a self-organizing mechanism that eliminates any one pathway from being more limiting than others is contributable to the maximum processing of the available energy* (Odum, 1995)," because, by definition, greater H refers to releasing a constraint (greater uncertainty) in resource selection and distribution.

A similar trend is found with system export. In Fig. 13(c), H increases as an export rate (α) increases. However, increasing α activates autocatalytic connections and makes the flow organization more deterministic and vulnerable to external perturbation. As a result, AMI increases while F and L are reduced. This suggests that system export rate (efficiency of transport) also be adjusted to an intermediate level (10 ~ 30% in this model) to maintain adaptability and the potential of self-organization.

Fig. 13(d) explains that augmented feedback (c) limits AMI and A/C, causing H, L, and F to increase. This indicates that development of feedback loops in system networking (*e.g.*, occupant activities for building energy control) contributes to building sustainability. It

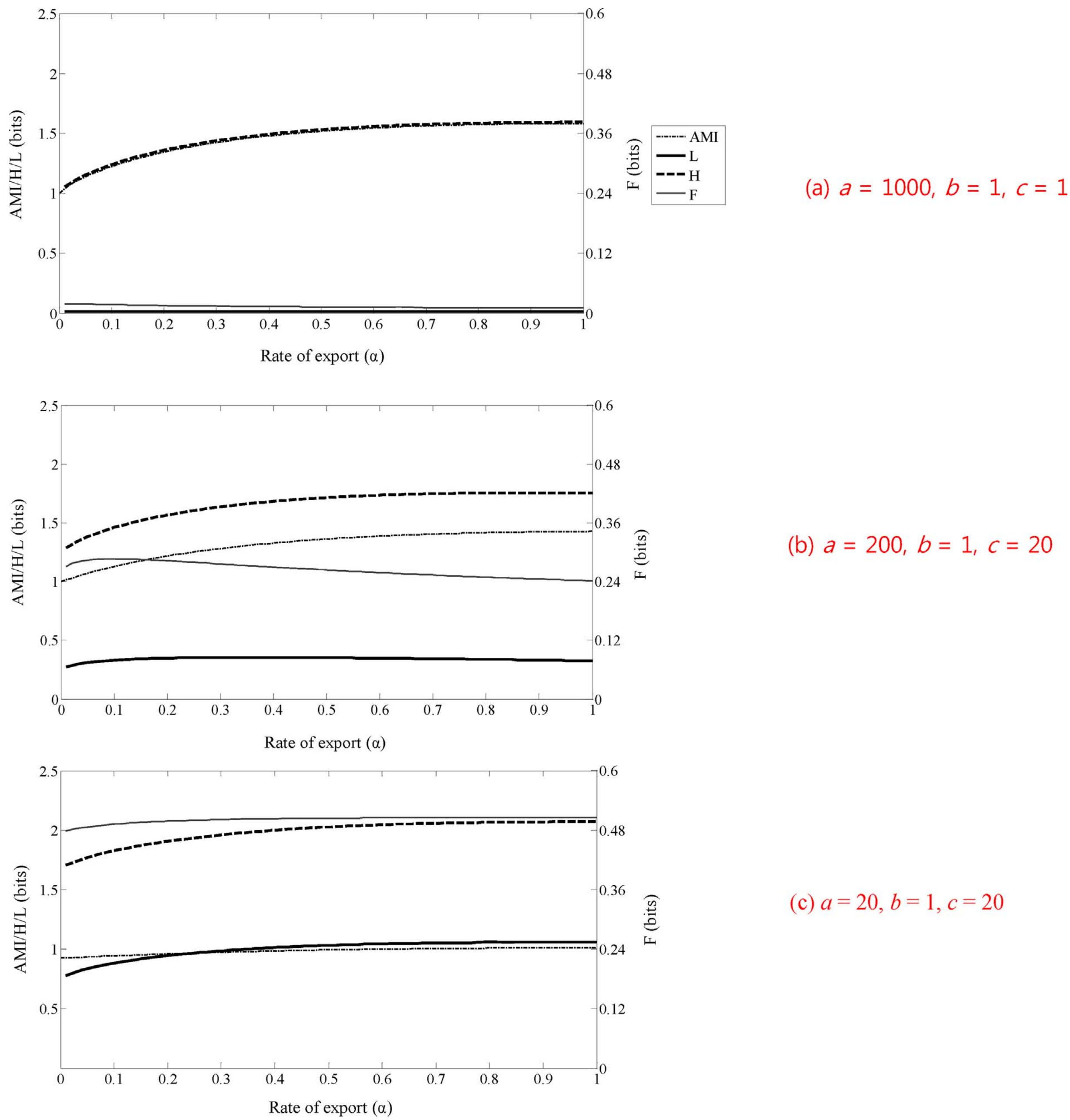


Fig. 14. Results of simulation: Export rate and information change. (a) $a = 1000$, $b = 1$, $c = 1$; (b) $a = 200$, $b = 1$, $c = 20$; (c) $a = 20$, $b = 1$, $c = 20$.

suggests that appropriate partitioning of export and feedback from a and b be significant to sustainability, since α and c are limited by the inputs.

Meanwhile, since H, L, and F are all positive signs of sustainability in general, it is confusing to tell which is the most critical for sustainability. However, comparison them with *ESI* presents that H is the only factor constantly in parallel with *ESI*. Considering that greater *ESI* is induced by increasing empower, the result confirms that complexity (H) is a proxy of system *power*, and consistency between increasing power and increasing network complexity. Fig. 13(c) also demonstrates that F and L are in reverse proportion with power (H) in an occasional system setting.

Scaled indices (A, C, and R) appear strongly influenced by extensive quantities (*TST*). However, this result paradoxically highlights that a small change of information (rearrangement of a transport structure) induces such a large quantity change, and also demonstrates significance of H as a surrogate of potential power. Finally, Fig. 14 clarifies information change according to simultaneous variations of parameters (a, α, and c). Supposing that the renewable source flow (b) is constant as a unit quantity (b actually takes a very little share of building inputs), feedback (c) increased from 1 to 20, while in declining nonrenewable flows (a; from 1000 to 20). Results present that resilience (L) and power (H) increase at the expense of AMI, and which demonstrates that resilience (L) is concerned with creating a redundant pathway (feedback), thereby making the system more complex (H) and accumulate information. Therefore, it follows that increasing resilience is more desirable to increasing power rather than creating autocatalytic connections.

5. Conclusions

Although well-functioning buildings have features such as a strong climatic adaptability and the maintenance of a high level of thermal comfort, creating an internal pattern of resource transfer that is conducive to sustainability, its evaluation has been overlooked in building-performance studies. In an effort to complement reductive methods, this work proposes a network-based approach to building-performance evaluation. Ecological principles and indices are discussed and employed to describe environmental building systems and sustainability. The system-level principles were hypothesized to work at the building level for the alignment of resource distribution, material selection, and energy flux patterns. Therefore, it was demonstrated theoretically that the system-level principles (maximum power, increasing fitness and resilience, and optimal efficiency) are applicable to characterize building performance and sustainability. Simulation tests with a generic building network model showed that informational indices incorporate M(e)PP in parallel with the general notion of building sustainability and reduction of non-renewable source use with increasing renewability and recycling benefits, gaining power and optimizing efficiency.

Suggestions of this approach is transformative in two regards: (i) to shift our attention from a deterministic judgment about building performance of a static state into a *probabilistic* description of the building's dynamic behavioural *tendency* heading to evolutionary design, (ii) the quantity of energy and mass is still influential, but the main target of performance evaluation should be their flowing direction and distribution throughout the building ecosystem's metabolic network. Furthermore, increasing power (H) with AMI and A/C adjusted also suggests that building's efficiency should be balanced according to overall system power; efficiencies on some parts of a building need be maximized or minimized depending on its power stock.

However, the utility of this approach to building study obtains generality with a clear awareness of a few queries and confusions unsolved. First, although in Eqs. (4)–(5) coupling an external measure (T) and internal factors (H, AMI) shows that an integration of extensive and intensive dimensions is possible, whether building size and sustainable performance are associated or not remains vague. Second, case study experiments with different types of buildings need be performed to identify a clearer energetic parallelism between buildings and living systems, as living systems theories from a thermodynamic understanding have been validated with empirical evidence in nature.

Paul Stoy (2010) criticizes ecosystem theories, stating that they are (i) overly abstract, (ii) oversimplified, (iii) not universally applicable, and (iv) difficult to test. In effect, MePP does not render a full insight on the system development in harsh environments (e.g., scarcity of resources, presence of external disturbance) (Odum and Pinkerton, 1955; Stoy, 2010; Ulanowicz, 1980). Ulanowicz's principle also draws a limit to inference due to (i) lesser number of rigorous empirical tests (in data approximation and system modelling) and (ii) selection of flow metrics (Odum, 1996). Admittedly, both theories rely on a network construction, which suffers from much uncertainty arising mainly from (i) difficulty in estimating unknown medium values (parameter uncertainty) and (ii) modelling (there may exist some network pathways unknown to an observer.) (Ulanowicz, 1986; Stoy, 2010). Nevertheless, it cannot be negated as a 'phenomenological statement cannot be completely verified, neither can it be entirely falsified' (Ulanowicz, 1980). Even though the emergy and ascendency theorems are primarily developed for ecosystems, such principles can be applied to building study, since growth and development are general phenomena in all environmental disciplines, regardless of temporal intervals or physical scales (Odum and Pinkerton, 1955; Ulanowicz, 1986). A flow-network based approach to building study will offer a great deal of advantages in the holistic description of causality of building performance. Then, consequently, we will be able to state that environmentally sustainable buildings shall be the more *informative* ones.

Appendix A. Interpretation of AMI

Figs. A1–A3 show AMI calculated for three sample networks. Fig. A1 demonstrates that AMI is a measure of system organization. In Fig. A1 (a), T_i equals to T, and T_{ij} also equals to T_j, thus AMI becomes zero which means no flow from unknown sources (all flows to B, C, and D come from A). In the perfect autocatalytic loop (Figs. A1(c) and A3(a)), AMI reaches the maximum.

Fig. A2 demonstrates AMI is not only the measure of the profile of network construction. A target of AMI measurement is the unit of flows, *i.e.*, a quantum of the flows, because average mutual uncertainty is dependent on the relative flow quantity to which a quantum belongs to. That is, AMI is a *quantum-based* description of a network configuration.

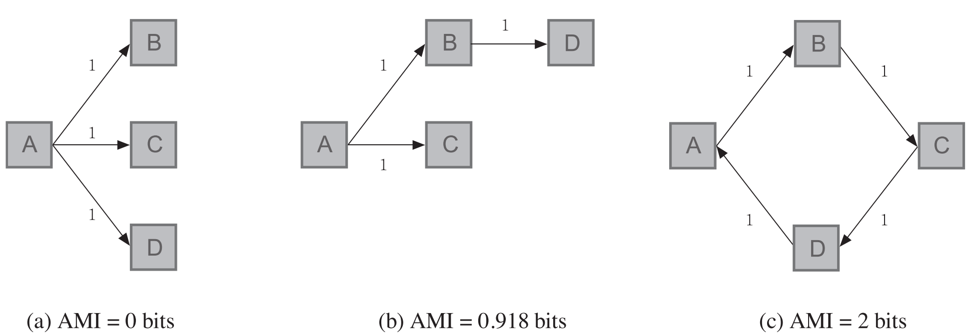


Fig. A1. AMI is the measure of a network.

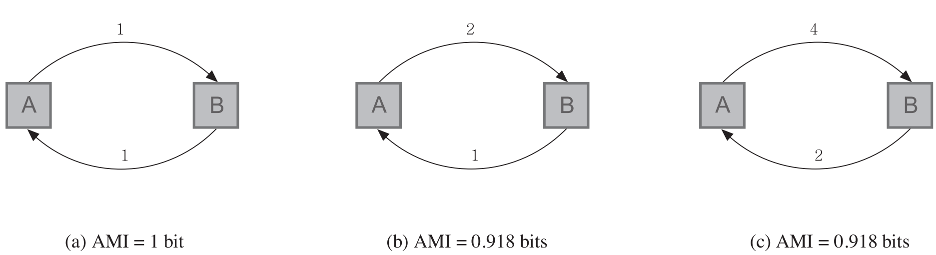
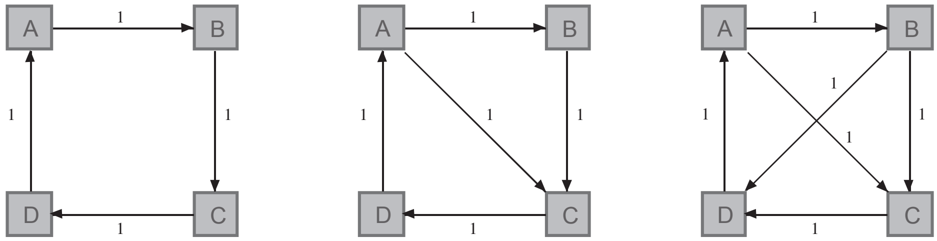


Fig. A2. AMI measures a probabilistic distribution of individuals.



(a) AMI = 2 bits (b) AMI = 1.522 bits (c) AMI = 1.252 bits

Fig. A3. AMI is not the measure of the intricacy of a configuration. Pruning of redundant paths increases AMI.

As depicted in Fig. A3, AMI is maximized if a quantity of medium is evenly distributed on each path branching into a perfectly cyclic direction. However, the maximum level of AMI, which becomes the same as the total information of the system network, can never be achieved for local systems because systems always encompass open ends such as sources and sinks. AMI is, therefore, reduced by presence of external connections. The level of complication at which AMI is compromised depends on network characteristics.

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Glossary

H (bits): Shannon index; a degree of uncertainty in the distribution of resources (Shannon, 1948); diversity of resource flux per individual; complexity of network flow pattern; a proxy of the potential power of energy network organization
AMI (bits): Average mutual information per individual (Shannon, 1948); a portion of efficient resource transfer; a degree of order in the network organization
L (bits): A degree of redundancy (or disorder) per individual (Shannon, 1948); a degree of freedom in the selection of flow pathways; system resilience ($L = H - AMI$) (Ulanowicz, 1997); a proxy of system's self-organizing potential (Meadows and Wright, 2008)
C: System capacity (Ulanowicz, 1986); C = H·T (system size)
A: System ascendency (Ulanowicz, 1986); A = AMI·T
ϕ: System overhead (Ulanowicz, 1986); $\phi = C - A$
F: Fitness (Ulanowicz, 1986); a degree of adaptability; the logarithm of the ratio of AMI (A) to H (C)
R: Robustness (Ulanowicz, 1986); $R = F{\cdot}T$