



Individual based energy analysis: A Lagrangian model of energy memory

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ABSTRACT

Three new emergy computational methods are developed with identical outcomes to substantiate and in some cases improve the conventional emergy algebra, particularly with regard to the computations associated with system cycling. The power series, the algebraic method, and the individual-based methods are derived and presented by example. Considering energy flow and its accumulation from an individual quanta or energy particle perspective, the discrete individual-based approach that we present is constructed from a single, reasonably simple, agent-based rule of interaction. As such, emergy calculations are the result of a simulated agent-based method where discrete packets of available energy are labeled and tracked in time as they flow through system processes. To quantify energy memory, each particle has a transformity attribute derived from process inefficiencies. This agent- (or individual-) based method provides a way to compute emergy for complex multiple input, output, or even cycling systems, without assuming additional rules. We compare the outcomes from the power series, the algebraic, and the agent-based methods with the current algebra rules of conventional emergy computation. We also point out that the conventional emergy algebra, the power series, the algebraic, and the individual-based methods all need additional research and corresponding reconciliation with regard to the emergy of by-products.

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1. Introduction

Using an individual based simulation to verify our theoretical development, we propose an alternative to the theoretical algebra and associated mathematics of the concept of emergy. The word “emergy” is correctly spelled with an “m”, which may be thought of as a mnemonic for energy memory, is all the available energy of one kind (usually solar energy for environmental systems) used up both directly and indirectly in the past to make a product or service that exists in the present (Odum, 1986, 1988, 1996). Emergy units are emjoules (ej), connoting joules of energy of one particular kind used in the past (energy memory joules), which purposefully distinguishes them from energy joules (J). That is, the solar energy used in the past (sej, solar equivalent joules, or solar emjoules) to make a joule of available energy in the present is called the *transformity* (sej/J) of the product where the transformity of solar radiation is assumed equal to one by definition (1.0 sej/J). Therefore, emergy, energy, and transformity satisfy the following formula:

$$\text{Emergy (sej)} = \text{Transformity (sej/J)} \times \text{Energy (J)} \quad (1)$$

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The advantage of using emergy is that environmental, social, and economic quantities expressed in solar emjoules can be compared on the same accounting ledger subsequently serving as a common measure of often disparate system attributes. Emergy permits a quantification of the environmental work contributed to a specific social or economic activity where the accounting balance (emergy assets versus emergy liabilities) quantifies sustainability with regard to nature's value (Campbell et al., 2004; Campbell, 2005). It is important because maximizing emergy flows is hypothesized to be the criterion that determines success in evolutionary competition (Odum, 1988; Campbell, 2001, 2008). Although the emergy methodology is not completely developed and the approach is not accepted by everyone in the scientific community, its results and corresponding insights are significant and growing (Brown and Herendeen, 1996; Li, 2009). Substantial emergy studies include but are not limited to the states of West Virginia (Campbell et al., 2005), Minnesota (Campbell and Ohrt, 2009), and the San Luis Basin in southern Colorado (Campbell and Garmestani, 2012) funded by the U.S. EPA, Puerto Rico and its Luquillo National Forest (Scatena et al., 2002) funded by the USDA Forest Service, and the Mississippi delta marsh system (Martin, 2002) funded by the National Oceanic and Atmospheric Administration through the Louisiana Sea Grant Program. Emergy was used as the basis for the environmental certification ISO14001 of the Province of Siena, Italy (Ridolfi et al., 2008). The National Natural Science Foundation of China's funding of emergy analyses of

economically important sectors of the Chinese economy is growing (Li and Wang, 2009; Hu et al., 2009; Ren et al., 2010; Lei et al., 2010, 2011).

Brown and Herendeen (1996) and Odum (1996) articulate four rules of energy algebra using various models with increasing complexity to aid their demonstration:

1. All source EMERGY to a process is assigned to the processes' output.
2. Process by-products have the total EMERGY assigned to each by-product pathway.
3. When a pathway splits, the EMERGY is assigned to each 'leg' of the split based on the fraction of total energy on each leg.
4. EMERGY cannot be counted twice within a system.
 - a. EMERGY in feedbacks cannot be double counted.
 - b. Process by-products, when reunited, cannot be added to equal a sum greater than the source EMERGY from which they were derived.

Regardless of system size and complexity, energy computation for any system is expected to obey these four rules, which we subsequently refer to as the Eulerian energy rules or simply energy algebra rules for short. As such, for a given system, computing all energy values may not be a trivial task. This is especially the case if a system involves feedbacks and or multiple inputs with different transformities. For ease of introduction, Fig. 1 depicts a two-compartment system with a single feedback and two inputs with different transformities (1 for S and 10 for F) from Brown and Herendeen (1996). Energy flow from A to B is correctly computed as 460 because A receives 400 units of energy from outside and only 60% of the 100 units of energy that B receives from outside (adhering to rule 3, $3/5 = 0.6$), totaling 460 units. Also, consider that the energy output of B is 500 units because this accounts for all the energy received into B that is not double counted (adhering to rule 4a).

Although these computations are reasonable, note that the total energy input from the outside to the combined system of A and B together ($400 + 100 = 500$) does not equal the total energy from the combined system released back to the outside (200). In this paper, we provide three alternative computation methods that resolve this nontrivial issue and provide a means for the energy algebra rules to work at all hierarchical groupings. The results of our computation for this same system are shown in Fig. 7. For this relatively simple system, computations simultaneously satisfying

rules 1 and 4a are not easy. To understand the reason for this difficulty, we focus on the energy flow from process A to process B. This flow contains both new energy that entered the system from S and F and existing energy recycling between A and B. Therefore, the energy flow from A to B is not of a single homogeneous transformity. Instead, transformities of individual energy quanta will have different transformities due to their pathway history. Therefore, this suggests that the amalgamated transformity of all energy flow from A to B can also be computed as the mean of a distribution of transformities of all the energy quanta flowing from A to B.

These considerations motivate a Lagrangian or individual-based energy computation simulating individual energy quanta flowing within the system. Each individual energy quanta maintains a transformity, which depends on the processes it has experienced. In theory, such a simulation should enable a computation of the average transformity for all energy flows within the system. Accurate energy computation regardless of system size and complexity should result, which inherently satisfies all energy algebra rules.

Although the methodology is based on a simple idea, for complex systems the execution is rather involved. Therefore, we will demonstrate various aspects of the methodology on three example systems:

1. *One compartment system with single input, output, and dissipation.* We use this example to define and demonstrate the individual-based energy rule. This single Lagrangian energy rule effectively reproduces all Eulerian energy rules except rule 2. This exception is discussed later.
2. *One compartment system with two inputs each with a different transformity, output, and dissipation.* This example shows that the individual-based energy computation agrees with the conventional Eulerian methodology for systems with multiple inputs but different transformities, with the exception of rule 2.
3. *Two compartment system with single input, feedback, output, and dissipation.* We will use an individual-based method to simulate the energy flow within the system. We then compute the energy values based on the transformities of individual energy quanta. These values satisfy all energy algebra rules except rule 2 discussed later.

2. Individual-based methodology

Individual-based energy analysis works by discretizing energy into identical agents, which we refer to as quanta, or energy particles. For clarity and consistency, we use the term *particle* to refer to a discrete quantity of available energy, thus a particle, quantum, agent, or individual. The size of a particle is defined by its energy content, which is user selectable. Particle size is constant for all particles throughout the simulation, and should be small enough that any energy flow within the system can be represented by an integer number of particles. For example, if particle size is 2 J, then 100 J/day of energy flow can be represented by the movement of 50 particles over one day. Individual-based modeling software simulates the movement of particles. From Eq. (1), energy is computed by multiplying the amount of energy with the appropriate transformity. For individual-based energy analysis to be successful, we need an individual-based rule that governs how the transformity of a particle is modified by a process. Given the Eulerian energy algebra rules, energy values for a system are generally computed with knowledge of both the energy input and energy output of all processes and all associated transformities. However, a particle acquires or maintains no knowledge of the entire system. The only information a particle possesses is its own transformity. For example, it has no knowledge of the transformity

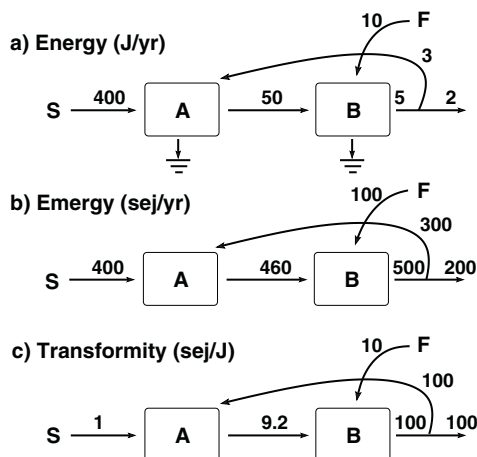


Fig. 1. Energy, energy flows, and transformities in a 2-compartment system with feedback, from Brown and Herendeen (1996).

of a particle that enters a process before or after itself. For this reason we call this an individual-based or Lagrangian energy rule.

2.1. Individual-based energy rule

When a particle leaves a process, it multiplies its transformity with the inverse efficiency of the process. The inverse efficiency of a process is defined as the multiplicative inverse of its efficiency:

$$\text{Inverse efficiency} = \frac{1}{\text{Efficiency}} = \frac{\text{Energy in}}{\text{Energy out}} \quad (2)$$

This definition is motivated by the fact that the energy particles that leave a process carry the memory of the particles that dissipate, which is characterized by the inverse efficiency. Fig. 2 depicts the individual-based rule using a single compartment energy model where 3 units of energy enter the system, 2 units dissipate, and 1 unit is output.

Therefore the efficiency of the process is 1/3. Using Eq. (2), the inverse efficiency is 3. If the transformity of the source energy is 3 as Fig. 2 depicts, then according to the individual-based energy rule, the transformity of the output energy is computed as $3 \times 3 = 9$. This computation complies with the first rule of the Eulerian energy algebra, that energy in equals energy out. While the individual-based energy rule appears to work for the simple system in Fig. 2, it quickly gets complicated when a process

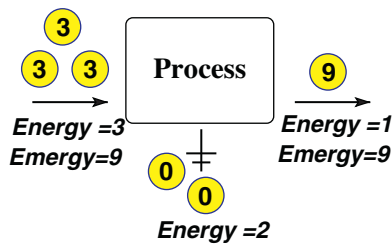


Fig. 2. One compartment system with a single input, output, and transformity. Each circle represents an energy particle. The particles are labeled with their transformity. Dissipated energy particles are assigned a zero transformity. Dimensional units are ignored for simplicity.

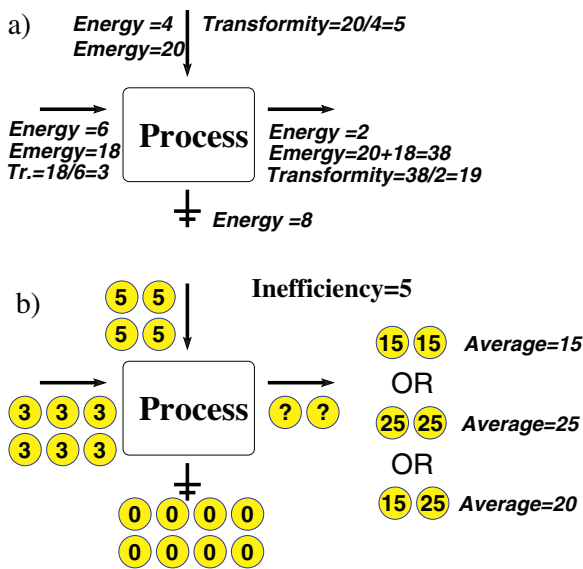


Fig. 3. One compartment system with two inputs each with different transformities (3 and 5). Each circle represents an energy particle with a single unit of energy. (a) Transformity and energy is computed using the four Eulerian rules of energy algebra. (b) Application of the individual-based Lagrangian energy rule.

receives multiple inputs with different transformities, such as the system in Fig. 3a.

Here, the transformity of the system output is computed as,

$$\frac{\text{Energy out}}{\text{Energy out}} = \frac{18 + 20}{2} = 19$$

In Fig. 3b, we apply the individual-based energy rule. The inverse efficiency of the system is

$$\text{Inverse efficiency} = \frac{\text{Energy in}}{\text{Energy out}} = \frac{4 + 6}{2} = 5.$$

Two different energy particles enter the process with transformities of 5 and 3. If an energy particle with input transformity 3 exits the system, its output transformity will be $3 \times 5 = 15$. If an energy particle with input transformity 5 leaves the system, its output transformity will be $5 \times 5 = 25$. Neither of these values are 19 as computed by the energy algebra. However, 40% and 60% of the particles entering the system have transformities of 5 and 3, respectively. Since these percentages remain the same for the process output, the average output transformity computed using the individual-based energy rule is,

$$15 \times 0.6 + 25 \times 0.4 = 19,$$

which, agrees with conventional energy algebra. Both methods (conventional and individual-based) applied to both systems satisfy the pertinent energy algebra rules. Therefore, we have not observed an advantage of the individual-based energy analysis. In fact, the method is rather cumbersome to implement. However, consider that the introduction depicted a model in Fig. 1(b), the total energy input from the outside to the combined system of A and B together ($400 + 100 = 500$) does not equal the total energy from the combined system released back to the outside (200). To explore this further, first we use the individual-based energy

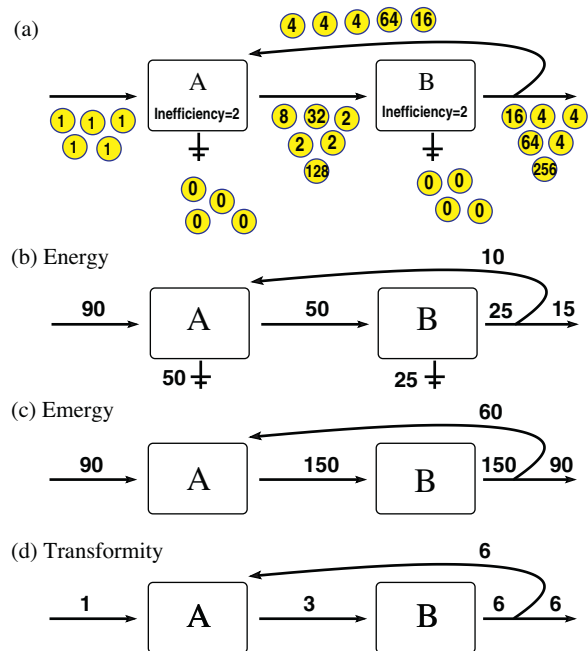


Fig. 4. Two compartment system with single input and feedback, similar to the system in Fig. 1. (a) Each circle represents an energy particle, illustrating how the transformities of individual particles change as they flow in and out of processes A and B. (b) Energy flows are shown. (c) Energy and (d) transformity values are computed using the individual-based energy methodology.

computation for this hierarchical type of model. For clarity of presentation, we use a simplified model shown in Fig. 4 for demonstration. Before we implement the individual-based energy rule to re-compute transformity and associated energy values, we need to discuss individual-based simulations in general.

An individual-based simulation, or an agent-based model, is an application specific iterative algorithm that works by applying predefined rules to individuals, or “agents”, thus changing their states according to these rules (DeAngelis, 1992; Grimm and Railsback, 2005). Individual agents are application specific entities that generally exist in high quantities in a system.

In our agent-based energy methodology, the agents are energy particles. The state of an energy particle is its transformity, which is updated as the particle passes through a process (multiplied by the inverse efficiency of the process per our individual-based energy rule). If they dissipate from a process, their transformity is set to zero. The movements of the energy particles within the system (in and out of processes) are managed by a numerical algorithm compatible with the original conserved energy flows. For example, if the energy flow from A to B is 150 J/day and the particle represents 2 J of energy, then the simulation will move 75 particles from process A to process B on average over one day. Various software are available for such simulation (e.g., Netlogo, Arena, and Swarm). We used Network Particle Tracking (NPT) (Kazanci et al., 2009; Tollner et al., 2009) to simulate the example system in Fig. 4.

In Fig. 4(a), we illustrate how an individual-based simulation works. For simplicity of presentation, all particles entering from outside the system have transformity 1. Using Eq. (2), the inverse efficiencies of process A and B both equal 2 ((90 + 10)/50 and 50/25). Therefore when a particle leaves process A toward B, its transformity is equal to, or larger than 2. Similarly, when a particle leaves process B, its transformity is at least equal to 4. Some of the output of process B is subsequently input back into process A through the feedback mechanism shown. Either these particles will dissipate or flow back to process B, in which case, their transformity will then equal 8. If we let the system progress for a period of time, we may get to observe some particles that cycle

many times between process A and B. The transformities of particles that cycle many times will be high, but the number of such particles will be relatively low as shown in Fig. 5. We then compute the individual-based energy from A to B by finding the mean transformity of the particles that flow from A to B. In Fig. 4(c) and (d), we show the energy and transformity of all flows in this system computed using the individual-based energy methodology using NPT. Note that these results satisfy all pertinent Eulerian energy algebra rules.

3. Alternative methodologies

3.1. Power series method

The perfect linear shape of the distribution in Fig. 5 is not a coincidence, as the probability that an energy particle moving from A to B will cycle back and move from A to B once again is 2/5 (on the condition that it will not dissipate at A or B). Factoring in the chance that the particle could dissipate at compartment A and B, this probability equals (2/5)(1/2)(1/2) = 1/10. This cycling behavior leads to an exponential distribution of transformities.

Instead of utilizing an individual-based simulation, we can use this observation to compute the average transformity of particles moving from A to B using a power series. All particles that enter the system and leave process A have transformity 2. Ten percent of these particles will flow from A to B again. This time, their transformity is 8. Similarly, 10% of those particles will again flow from A to B with transformity 32. Using this observation, we build a power series for the average transformity of a particle flowing from A to B as follows:

$$\frac{2 + 8(1/10) + 32(1/10)^2 + 128(1/10)^3 + 512(1/10)^4 + \dots}{1 + (1/10) + (1/10)^2 + (1/10)^3 + (1/10)^4 + \dots} = 3$$

Using a similar approach, we compute the average transformity of particles that leave compartment B to be 6. This new approach is subsequently entitled the “power series” method. Individual-based methodology involves a simulation run, followed by an analysis of the simulation output to compute the average energy values. For this model, the power series method is easier than the individual-based approach, and generates exact results. These results are consistent with those obtained by Bastianoni et al. (2011) using the properties of set theory. On the other hand, individual-based methodology provides approximate results, where the accuracy increases with longer simulation times.

The advantage of the individual-based methodology is scalability and is applicable to any system regardless of size or complexity. The simulations may require more time, but relatively accurate results are always achieved. The power series method on the other hand, is limited in this regard. Imagine a system with multiple feedback mechanisms that involve multiple common processes. The computation of the power series sum quickly becomes extremely complicated. While the power series method is preferable for small and simple systems, the individual-based methodology is the better general methodology, applicable to a wider range of systems.

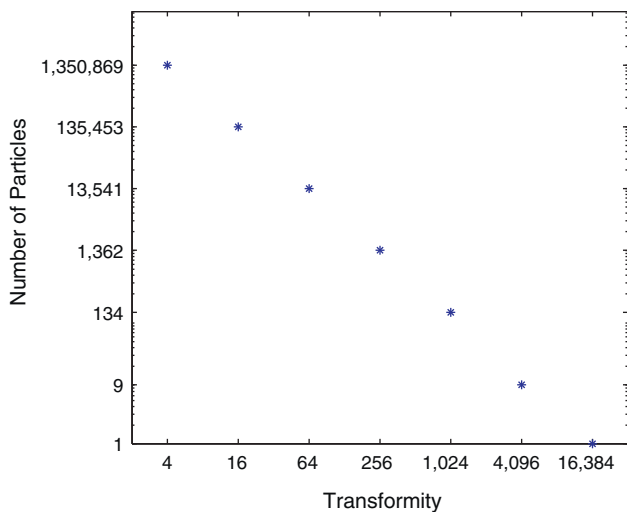


Fig. 5. Histogram of particles with different transformities for the system depicted in Fig. 4. This system was simulated using network particle tracking (NPT). The simulation ran for 10 min on a dual-core 3 GHz computer. The figure shows the transformities of energy particles leaving process B. For example, approximately 1.3 million energy particles with transformity 4 and 1 energy particle with transformity 16,384 were observed. If the simulation progresses longer, the number of particles observed for each transformity will increase. However, the shape of the histogram is expected to stay the same. The y-axis is logarithmic scale, so the histogram converges to an exponential distribution as the simulation time increases. The mean of this distribution is $5.98 \approx 6$, which is the transformity for the energy leaving process B shown in Fig. 4(d).

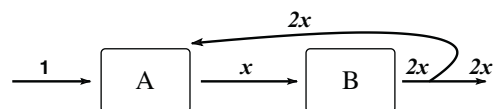


Fig. 6. Algebraic method used to compute the transformity values that are compatible with the individual-based methodology.

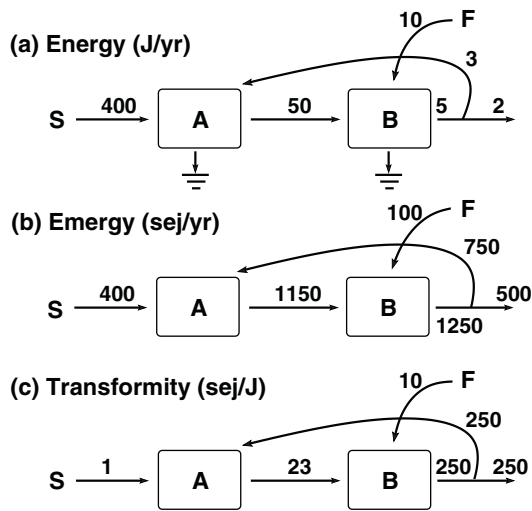


Fig. 7. Energy, emery, and transformities independently generated using the three different approaches presented in this paper for the energy system depicted in Fig. 1.

3.2. Algebraic method

Using the system shown in Fig. 6 as adapted from Fig. 4, for the algebraic method, we assign a variable x to the average transformity of the energy particles that move from A to B. Since process B has 50% efficiency, the average transformity of the particles that leave B, including the particles that cycle back to A, is $2x$. Then an algebraic equation for emery algebra rule 1 for process A can be written as:

$$1 \times 90 + (2x) \times 10 = x \times 50.$$

The solution of this equation is $x = 3$, which coincides with the power series method and the individual-based approach. Although this method is easier than the power series or individual-based methods, it shares the same issue with the power series method. It is not general and its application becomes cumbersome for larger and more complex networks.

4. Conclusions

Fig. 7(b) and (c) shows the common result of these three approaches for the same energy system originally depicted in Fig. 1(a). Most notably, the total source energy input now successfully equals the total energy output for process A ($1150 = 1150$, originally $700 \neq 460$), process B ($1250 = 1250$, originally $560 \neq 500$) and the entire system ($500 = 500$, originally $500 \neq 200$). Therefore, the first rule of emery algebra is now satisfied at all hierarchical assemblages by all three approaches presented in this paper.

We observe that the transformities in our approach are larger than the values presented by Brown and Herendeen (1996). This may be due to the inherent assumption that an energy cycle occurs once, but not repeatedly many times (for the same energy quanta). In such cases, the traditional methodology may be applicable. Otherwise, the three methods presented in this paper, in particular the individual-based methodology, are a compelling alternative for handling complex systems, particularly those with feedbacks.

5. Discussion and future work

We describe three new methodologies for computing the transformity and emery values for systems of energy flow. The most useful method was constructed from an individual-based simulation with only one rule (i.e., when a particle leaves a process,

it multiplies its transformity by the inverse efficiency of the process). Indeed, transformity is defined as the inverse of Lindeman's trophic efficiency. This method has both advantages and disadvantages. Intuitively, the premise of tracking the inefficiencies (inverse efficiencies) of individual energy quanta resonates well with the concept of energy. A one-rule system is conceptually easier to understand and the individual-based results agree with the pertinent emery algebra rules (Odum, 1996; Brown and Herendeen, 1996). This agreement actually improves the applicability of emery algebra rule 1 to different system scales. However, for large and complex systems, without a direct algebraic formulation, only the execution of a full simulation model will compute the associated emeries. This may be impractical for researchers who are not familiar with the individual-based algorithms.

Perhaps the most essential area for future work regarding individual-based emery analysis concerns emery algebra rule 2. None of the three systems used to demonstrate the individual-based methodology contains by-products. Essentially, by-products are treated differently than splits. Therefore, the individual-based method needs an additional individual-based rule that accommodates this distinction. As it stands, we believe the methodology presented in this paper provides a much needed clarification for the rules governing emery algebra for systems with feedback cycles. The ideas presented to derive these methodologies help improve our understanding of emery analysis for complex systems. However, individual-based emery by-products are an area currently open for additional research.

Various strengths and weaknesses aside, the principle contributions of this new methodology are its capability to compute the transformity and emery values accurately for an energy-flow system regardless of size and complexity and its helpful clarification of the results associated with rule 1 (emery is memorized) at different hierarchical assemblages. With the exception of the recent efforts of Le Corre and Truffet (2012) and Li et al. (2010), we have no knowledge of an alternative methodology with this capability; therefore, we hope that the methods put forward in this paper will be a helpful addition for emery analysis. Simulations may require an extended period of time for very large systems. However, this impracticality is mostly mitigated by the ever increasing availability and affordability of powerful computers. Yet, this brings out an important question for future research; can we develop a methodology that generates the same results without the need to run a simulation? The answer is currently yes for small systems, as we have shown with the power series and the algebraic methods. However, these non-simulation based approaches can quickly become intractable as we add more processes and feedbacks where the individual-based methodology will work regardless of the number of feedbacks or compartments involved.

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