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Designing Industrial Networks Using Ecological Food Web Metrics

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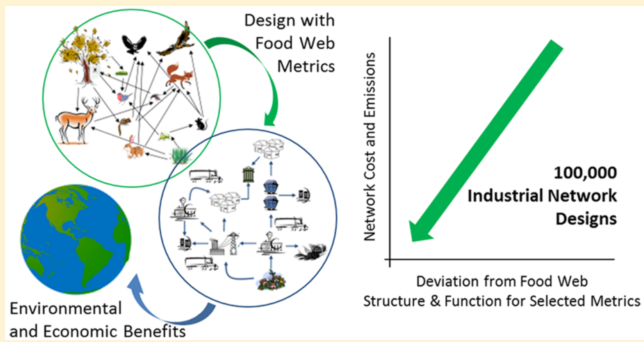
Supporting Information

ABSTRACT: Biologically Inspired Design (biomimicry) and Industrial Ecology both look to natural systems to enhance the sustainability and performance of engineered products, systems and industries. Bioinspired design (BID) traditionally has focused on a unit operation and single product level. In contrast, this paper describes how principles of network organization derived from analysis of ecosystem properties can be applied to industrial system networks. Specifically, this paper examines the applicability of particular food web matrix properties as design rules for economically and biologically sustainable industrial networks, using an optimization model developed for a carpet recycling network. Carpet recycling network designs based on traditional cost and emissions based optimization are compared to designs obtained using optimizations based solely on ecological food web metrics. The analysis suggests that networks optimized using food web metrics also were superior from a traditional cost and emissions perspective; correlations between optimization using ecological metrics and traditional optimization ranged generally from 0.70 to 0.96, with flow-based metrics being superior to structural parameters. Four structural food parameters provided correlations nearly the same as that obtained using all structural parameters, but individual structural parameters provided much less satisfactory correlations. The analysis indicates that bioinspired design principles from ecosystems can lead to both environmentally and economically sustainable industrial resource networks, and represent guidelines for designing sustainable industry networks.



INTRODUCTION

"Movement gives shape to all forms. Structure gives order to movement" - Leonardo da Vinci (paraphrased[1]).

Design inspiration for products has long been derived from nature.[2−4] Successful examples of such product level inspiration include Velcro, self-cleaning surfaces, and high-rise heating and cooling systems. Design inspiration for networks derived from natural systems has been receiving increasing attention.[5−13] The fields of Biologically Inspired Design (BID) and Industrial Ecology (IE) both look to natural systems to facilitate closed loop production in industrial systems.[14] Industrial Ecology traditionally uses natural systems as high level models.[15−18] The practice of BID in contrast uses deep analogies between human and natural systems to identify biological principles that are useful for solving human design and engineering problems.[2−4] Together these network level analogies focus primarily on parallels between industrial complexes and ecological systems.

The analogy between ecological food webs and human networks is one between two networks that both exchange materials and/or energy. Material and energy transfers between industries and/or companies create interactions and structures analogous to predator−prey species interactions in an ecological food web. Analogies between ecosystems and food webs and industrial networks, or other human systems that exchange materials and energy, is supported by previous works, for example, ref 10. The water networks (modeled in meters[3] per year of water) for three Italian cities were modified using food web analysis techniques to reduce wasted water within the city limits.[9,11,19] Carbon emissions (in kilograms per capita per year) were studied using metrics normally associated with ecological systems for flow networks representing the city of Beijing, China[20] and Vienna, Austria.[21] The city of Beijing has also been used as an economic network (following the flow of billions of yuan per year)[22] and an emissions network for transfers via economic activities (following atmospheric fine particulate matter $PM_{2.5}$)[23] and analyzed using ecological methods. Thermodynamic power cycle networks, described in terms of kilojoules per kilogram of energy flows, have been described using an ecological metric to measure cycling within the system.[24] Applying the tools ecologists used, here an Ecological Network Analysis (ENA), can inform a sustainable organization of material and energy flows among industries that was not previously in the network design space.[6,7,19,25] Expanding the number of design solutions for sustainable networks is especially important in today's world, where resources that have historically been readily available are

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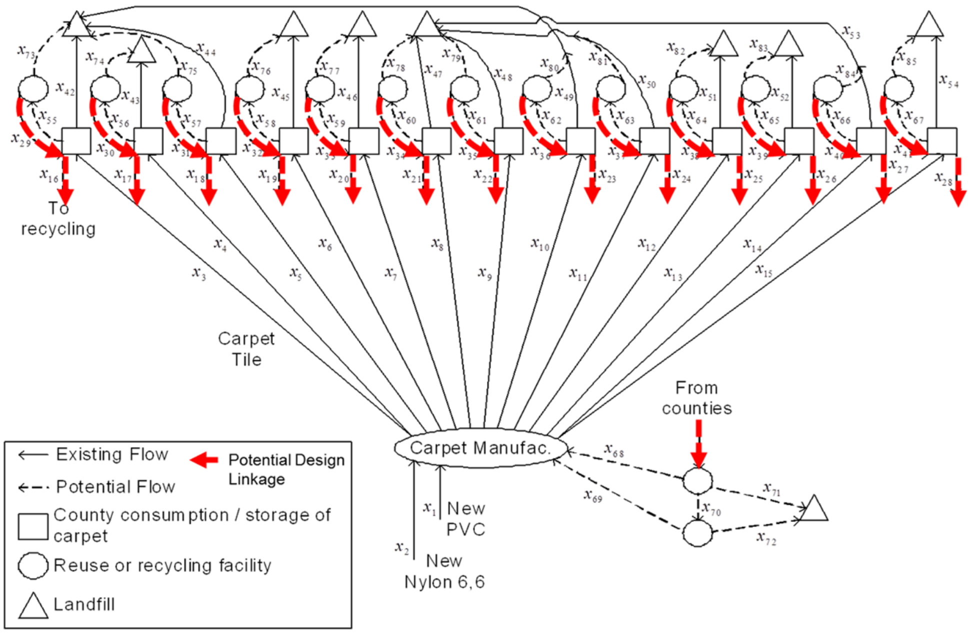

Figure 1. Carpet recycling network model showing existing and potential carpet tile and carpet tile material flows. The bolded vectors represent the linkages in the design vector.

becoming scares, and climate changes are requiring a rapid reduction in emissions.

Ecological Network Analyses (ENA) comprises a set of methods for studying ecological food webs, and as noted, has already provided insights into the structure and behavior of industrial networks.[7,12,19−22,24−29] A major theme of these works is to use ENA to provide a systems level perspective of complex collections of human industry and infrastructure, and to examine indirect relationships between system components that can be revealed by network analysis. Some of these studies have suggested that industrial networks that display ecological metric values closer to food web medians also result in networks with lower costs and emissions[25,29] or higher thermal efficiency in the case of thermodynamic networks.[24] This argues for the importance of developing methods to evaluate and implement design rules based on ecological analyses, which presently are lacking.

Previous efforts using ecosystem-inspiration in network studies have employed natural attributes to describe a human system, or used ENA to present a modification of an existing system with the goal of reducing waste or raw material input. Environmental improvements made via the use of these ecological analysis techniques have not yet been connected to traditional economic improvements, a crucial factor in all decisions relating to capitalism-based systems. Previous works also have not examined how ENA can be used to develop methods for the appropriate design of human industrial networks, evaluated how ENA may perform when compared to traditional optimization approaches, or demonstrated general features of well-performing industrial networks. This investigation focuses on these topics.

This paper examines the importance of specific food web matrix properties and metrics as quantitative guides toward the design of economically and environmentally sustainable industrial networks using a well characterized carpet recycling network as a case study. The focus of this paper is to investigate whether selected ecological metrics can (solely) be used to identify network designs that are both environmentally and economically superior. An optimization approach for designing industrial networks is developed here using select ENA metrics. As will be shown, this approach performs and correlates well with respect to resource use efficiency and waste minimization when compared to classical network optimization using traditional measures of coast and emissions reductions. Using an optimization model developed for a carpet recycling network in Atlanta, GA[25] as a typical representative close-loop industrial system, structural and flow metrics from ENA are used in different combinations to define the structure of the network and create the flows between components in the carpet recycling network model in order to meet its sustainable design goals: minimize material inputs and waste outputs.

The performance of the biologically inspired carpet network is compared to the network performance under a traditional cost optimization. This side by side comparison of the bioinspired and traditional designs quantitatively evaluates what have, in the past, been largely qualitative and metaphor-based applications of ecological ideas. Furthermore, the utility of individual ENA metrics or different subsets of metrics in arriving at sustainable system designs has not been examined. Initial analysis by Reap showed a strong positive correlation between objective function values for networks designed using a group of food web metrics and those designed following a standard cost and emissions minimization.[25] Although documenting the correlation, the initial study does not identify which ecosystem metrics were the most significant factors for this correlation, only investigated aspects of structure (i.e., the flow magnitudes were not varied), and used inaccurate values of the ecological metrics. This paper addresses these shortcomings and performs quantitative analyses to better understand which ecological metrics and properties are responsible for the correlation. The results indicate that ecological metrics can be used as design rules to improve the performance of industrial networks, and identify particularly useful metrics and sets of metrics that can accomplish this goal.

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MATERIALS AND METHODS

Carpet Recycling Network Model. The carpet network model used for the analysis here was originally developed by Reap[25,29] and based on flows of carpet tiles from steady state production to end-of-life. The data and assumptions behind the model came from a compilation of prior works by Intlekofer, Guidry, and Reap[25,30,31] based on real-world industrial data from carpet makers in the greater Atlanta Metropolitan Region. Industrial networks generally have both structural and functional features that make them analogous to ecosystems. Just like their natural counterparts, they draw energy and materials from the environment, and cycle material and energy through series of transactions among their components, with some fraction ultimately leaving the system boundaries. The advantage of using the carpet network specifically is that detailed quantitative real world data was available for a traditional optimization and performance evaluation of different instantiations of this system, which allowed explicit quantitative comparisons of traditional vs ecological optimization approaches.

The network contains one carpet manufacturing facility, 9 landfills, 15 reuse or recycling facilities, and 13 counties that consume and/or store carpet (Figure 1). This yields 38 actors with 85 possible flows of carpet materials PVC and Nylon-6,6 between them. All carpet materials are measured uniformly in kilograms (kg) of materials per year. Each of the 13 counties has two design variables, one for the amount of carpet sent to reuse and one for the amount of carpet sent to recycling. These make up the 26 design variables, hereon referred to as the "design vector" representing potential recycling and reuse flows. Detailed information for the carpet model used here can be found in the online Supporting Information.

Initial analyses by Reap varied the design vector containing the amounts of carpet sent to recycling and reuse centers (linkages x_{16}–x_{41} bolded in Figure 1). The design vector was modified such that the amount of recycled or reused of materials varied from a value of zero to a maximum established by capacity limits for reuse and recycling. A traditional objective function (Z_{trad}) and a bioinspired objective function (Z_{bio}) was then calculated and compared for each variant of the design vector. The bioinspired objective function (Z_{bio}) used a set of structural and flow based ecological metrics to organize the network, with the optimization criterion defined as reaching median values of these metrics displayed in food webs. The traditional objective function minimized the network's total financial cost and emissions. The total network cost was calculated from the sum of material, labor, and energy costs. Total network cost includes the cost of new PVC and nylon-6,6; the cost of natural gas, diesel, and electricity; landfill costs; and the cost of labor at all stages. Twelve emissions are modeled: carbon dioxide, methane, nitrous oxide, sulfur dioxide, nitrogen oxides, lead, carbon monoxide, volatiles organic carbons, mercury, hydro-carbons, particulate matter, and lead (CO_2, CH_4, N_2O, SO_2, NO_x, Pb, CO, VOCs, Hg, HC, PM, and SO_x). These emissions originate from the manufacture of virgin PVC, nylon-6,6, and a deep cleaning solution, the generation of electricity specific to Georgia (where the manufacture and recycling occurs), natural gas combustion, and from transport by trucks based on their speed, load capacity and fuel efficiency. This required the calculation of distances traveled between actors, knowledge of the types of vehicles used and their emissions based on load weight, and detailed information about manufacturing and demanufacturing processes. Detailed information for this process can be found in the original analysis[25] as well as in the Supporting Information.

Ecological Food Web Metrics and Objective Functions. A selection of 50 food webs from those outlined in[32,33] are used to update the median food web values used as biological benchmarks (Table 1). These updated values correspond to a self-imposed restriction to use only those food web studies conducted using improved ecosystem data collection techniques,[34,35] begun primarily after 1993. This data set including the specific values for each foodweb metric can be found in the online Supporting Information of a prior publication.[7] The foodwebs analyzed by ENA have from 1 to 6 *primary* producers (i.e., organisms such as plants that bring external energy into the system), and a number of consumers and detrital or decomposer (recycler) components that together make up the majority of the component species[32,33,36] and so are structurally not dissimilar to the carpet recycling network.

Table 1. Median Target Food Web Values Taken from the Post 1993 Food Web Dataset

food web metrics	median goal target values for fws collected 1993+
link density (L_D)	5.04
prey to predator ratio (P_R)	1.09
specialized predator fraction (P_S)	0.10
generalization (G)	6.18
vulnerability (V)	5.34
cyclicity (λ_{max})	4.24
Finn cycling index (FCI)	0.295
mean path length (MPL)	5.7

The food web metrics listed in Table 1 are calculated following the formulas outlined in Layton et al.,[7] eqs 1–16. The food web metrics used in this paper can be classified in two groups: six structural (L_D, P_R, P_S, G, V, and λ_{max}) and two flow metrics (FCI and MPL). For all metrics, N is the number of actors in the systems (analogous to species in a food web), and L is the number of linkages (or directed vectors) between the actors in the network. The structural metrics are all normalized measures that specify the degree to which system components are linked and the pattern of those linkages. Connectance is the only metric missing here that was used in the original model study, and is excluded here because of its strong dependence on system size, as demonstrated in previous work.[8]

It would be desirable from both a design and analysis perspective to only use structural food web metrics, as these metrics may be calculated using only very basic information about the system. Only the presence and direction of an interaction between two actors is needed (see below), which is easily obtainable information compared to information on flow magnitude. Flow based information in industry is often proprietary, making it much more difficult to obtain and present results especially from a large number of industrial sources.

Unfortunately, optimization done solely using structural metrics will give a near infinite number of solutions for a given network structure since the flow of material across every link is arbitrary, and this may not allow for accurate simulations of network performance. Thus, it is potentially possible that optimization may require some flow based models. The two

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flow based metrics used here (FCI and MPL) were selected based on their ability to measure different aspects of the cycling in the system. The Finn cycling index (FCI) is the most common parameter used to evaluate cycling in other ecological and human network studies.[21,36−40] FCI represents the amount of energy that is cycled through the system normalized to the total system flux.[41] Mean path length (MPL) represents the number of transactions a given unit of material or energy participates in before it leaves the system boundaries. Other flow based metrics exist and may be useful in future analysis to study other aspects of human network structure, for example, refs 6, 11, 20−22, and 28.

The six structural metrics are calculated using an $N \times N$ structural "food web" matrix of links between carpet network components. That is, all calculations per eqs 1−12 are based on a simple binary representation of whether a link exists between two components (actors) in the matrix. A link refers to an interaction, defined generally as a transfer of energy or material between the two components. Thus, f_{ij} represents the directional interaction from actor i to actor j, and is documented as a one in the ith row and jth column entry in the matrix. A value of zero in this entry represents no interaction from i to j (no link). Flow is columns (predators, consumers) to rows (prey, producers). The square matrix allows for the possibility of each actor simultaneously being both consumer (predator) and producer (prey).

Linkage density (L_D) is the number of links in the system normalized by the number of actors in the system.[42] The number of prey and predators (n_{prey} and $n_{predator}$) are the number of actors that provide and consume a resource, respectively.[43] The ratio of these two is the prey to predator ratio (P_R), which represents the balance of consumers to producers in the system. A very low P_R translates to a system that is highly dependent on only a few producers; consumers may have trouble finding alternate sources within the system boundaries were a producer to fail. A subset of this is the number of specialized predators ($n_{S\text{-predator}}$), which counts those consumers that interact with *only one* actor, and when normalized to $n_{predator}$ yields the specialized predator ratio (P_S); the fraction of all consumers that consume only one producer. Extreme values of P_S (i.e., close to one), may be warning signs for an "at risk" system: if a system is primarily composed of specialized interactions flexibility in the face of disturbance is limited. Generalization and vulnerability (G and V) are subsets of L and represent,respectively, the mean number of producers consumed by each actor and the mean number of consumers for which a producer may provide.[43,44] Together, these terms indicate the average number of producer−consumer interactions with whom a given producer or consumer engages. From an economic perspective these metrics may be useful for a company or industry looking to join a particular network, giving insight into the relative number of existing consumers and producers currently in a network. For example a network with a very high V (a large number of consumers on average) may be more desirable for an incoming producer than one with a very low V. Cyclicity (λ_{max}) is the maximum real eigenvalue of the inverse of the food web structural matrix. Cyclicity represents the rate at which the number of cyclic pathways grow as the number of steps in the cycle converges to infinity, and is taken to indicate the presence and complexity of internal cycling in the system:[24,33,45,46] The value of cyclicity may be zero (no cycling), one (a single cycle), or any value greater than one (strong cycling). Cyclicity is also of interest because cycling produces indirect effects between components that are connected via intermediaries— a property of food webs that is of increasing interest to those who wish to design human systems.[5,7,24,33,45] A previous application of cyclicity applied to thermodynamic power cycle networks shows that increases in the metric correspond to decreases in waste output and increases in the efficient usage of existing resources.[24] More detailed descriptions of these metrics may be found in previous works.[7,8,45,47]

$$L_D = L/N \tag{1}$$

$$f_{row}(i) = \begin{cases} 1 \text{ for } \sum_{j=1}^{n} f_{ij} > 0 \\ 0 \text{ for } \sum_{j=1}^{n} f_{ij} = 0 \end{cases} \tag{2}$$

$$n_{prey} = \sum_{i=1}^{m} f_{row}(i) \tag{3}$$

$$f_{col}(j) = \begin{cases} 1 \text{ for } \sum_{i=1}^{m} f_{ij} > 0 \\ 0 \text{ for } \sum_{i=1}^{m} f_{ij} = 0 \end{cases} \tag{4}$$

$$n_{predator} = \sum_{j=1}^{n} f_{col}(j) \tag{5}$$

$$P_R = n_{prey}/n_{predator} \tag{6}$$

$$f_{s-col}(j) = \begin{cases} 1 \text{ for } \sum_{i=1}^{m} f_{ij} = 1 \\ 0 \text{ for } \sum_{i=1}^{m} f_{ij} \neq 1 \end{cases} \tag{7}$$

$$n_{S-predator} = \sum_{j=1}^{n} f_{s-col}(j) \tag{8}$$

$$P_S = n_{S-predator}/n_{predator} \tag{9}$$

$$G = L/n_{predator} \tag{10}$$

$$V = L/n_{prey} \tag{11}$$

λ_{max} = max, real eigenvalue solution to the equation:

$$0 = \det(\mathbf{A} - \lambda \mathbf{I}) \tag{12}$$

The two flow based metrics, Finn cycling index and mean path length (FCI and MPL), are calculated using eqs 13−16. These calculations require knowledge of both structural information and flow magnitude information, that is, how much material or energy is moving across linkages as well as across system boundaries. In contrast to the calculations of the 6 structural metrics, the FCI and MPL calculations use a N+3 × N+3 food web flow matrix that includes inputs from outside the system (row zero), exports to outside the system (column N+1), and losses from the system (column N+2). A flow from

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actor i to actor j is represented as a real value by t_{ij}, which is the ith row and jth column entry in this matrix. A value of zero for t_{ij} means no material or energy flow occurs from actor i to j and, thus, no link exists. The total system throughput (TST_p) is the total amount of material or energy that moves through the system deals, both internally and that which passes in and out of the system from outside the system boundaries.[29,30] TSTp can be thought of as a measure of size or level of activity similar to gross national product GNP, which estimates the overall economic activity of a nation.[9,19] Total cycled system throughflow (TST_C) is the total amount of flow that moves through cycles in the system. The Finn cycling index (FCI) is the fraction of the total flow in the system that participates in cycles.[19,38,41] An FCI of zero represents a total dependence on external resources. For example a water network with an FCI of zero would have no water recycling in the system−all actors would only make use of fresh water. Mean path length (MPL), represents the average number of actors "visited" by a material or energy flow before exiting the system.[41,48] Flows that remain longer within the system boundaries (a larger MPL) visit more actors and thus contribute more to maintaining the functioning of the actors within the systems. A large MPL is strongly related to higher cyclicity values, since a more complex cycle will generally have a longer path. Ecosystems tend to have very complex cycling (high cyclicity values) and longer path lengths since the majority of energy in an ecosystem flows through the recyclers and back into the system.[49]

$$TST_p = \sum_{i=0}^{N+2} \sum_{j=0}^{N+2} t_{ij} \tag{13}$$

$$TST_C = \sum_{j=1}^{n} \left(\frac{t_{jj} - 1}{t_{jj}} \right) T_j \tag{14}$$

$$FCI = \frac{TST_C}{TST_p} \tag{15}$$

$$MPL = TST_p / \sum_{j=0}^{N+2} t_{0j} \tag{16}$$

The traditional objective function value (Z_{trad}) is calculated by summing equally weighted deviations between the calculated emissions and cost and a set goal target value for each. Target values for total cost and for each of the 12 emissions are taken from the best possible scenario for the model and can be found in Reap.[25] The bioinspired objective function value (Z_{bio}) is calculated by summing equally weighted deviations between the calculated metric and a median value of each food web metric derived directly from ecological network data.[7] Deviations from either the ecological or traditional objective target values are calculated using either eq 17 or 18, depending on whether metric values are larger or smaller than the target, respectively. Both models result in a nonlinear, mixed integer solution space that is very difficult to solve using traditional optimization algorithms. A stochastic search is used instead, based on examining the results of 100 000 random design vectors for each model.

$$d_{min} = 1 - \frac{\text{metric value}}{\text{metric goal target value}} \tag{17}$$

$$d_{max} = 1 - \frac{\text{metric goal target value}}{\text{metric value}} \tag{18}$$

Correlation between Ecological and Traditional Optimization. The initial analysis done by Reap[25] used one combination of nine equally weighted food web metrics in the calculation of the bioinspired objective function. As a result, the degree to which each individual metric affects the resultant correlation was unknown. The influence of each individual metric on the correlation is found here by calculating Z_{bio} from each food web metric individually, as well as from all possible combinations of all the metrics weighted equally. Important individual and metric groupings are signified by a strong positive correlation between the minimization of both Z_{trad} and Z_{bio}, as calculated by the R^2 value for linear trend lines.

The structural food web metrics alone cannot completely identify the final network design because they have no influence on flow magnitudes. For the investigation of the structural metrics the flows moving across all used linkages were set at the same constant value. The constant value chosen for this is the smallest value among the maximum flow constraints, 8268 kg year^{-1} of carpet. Each flow in the design vector has a maximum and minimum allowable magnitude of carpet flow to ensure that the model represents real conditions. Maximum constraints, for example, could be the maximum amount of carpet that a recycling center can process per year. Minimum constraints are often simpler in that flows are not allowed to be negative values, or a county must replace an X amount of kilograms of carpet per year, requiring the inflow of carpet—whether it is new carpet or from recycled sources—to *at least* be X amount of kilograms per year. Selecting a constant value of carpet flow from the model's set of maximum constraints, which are all larger than the minimum constrains, and then choosing the smallest of these maximum constraints, assures that all constraints on the system will be satisfied regardless of the design structure chosen. Equalizing the flow values assures that the relative impact of changes in the magnitude of recycling and reuse (which are components of the design vector) does not overshadow changes in the structure (i.e., a link being turned "on" or "off"—a one and zero multiplier respectively), and facilitates consistent comparisons with the ecological structural parameters (L_D, P_R, P_S, G, V, and λ_{max}). The subsequent analysis relaxes the constant flow condition and examines the correlation between traditional and bioinspired objective functions when both network structure and flow were allowed to vary.

Different network designs were generated by randomly varying the network structure. The correlations between the traditional and bioinspired objective functions are derived from on 100 000 of these network designs. For constant-flow conditions, each of the structural food web metrics in Table 1 was used as optimization criteria both individually and in all possible combinations. For consistency, the values for FCI and MPL in these scenarios were also calculated in the constant flow scenarios. The constant flow scenarios suggest that certain structural parameters are more useful predictors of traditional cost-emissions minimization, and that the food web metrics perform more poorly individually than when grouped. Therefore, when flows are allowed to vary, the analysis only examines groupings of the structural parameters, both with and without the flow-based parameters, and combinations of flow-based parameters alone. These two scenarios, with and without

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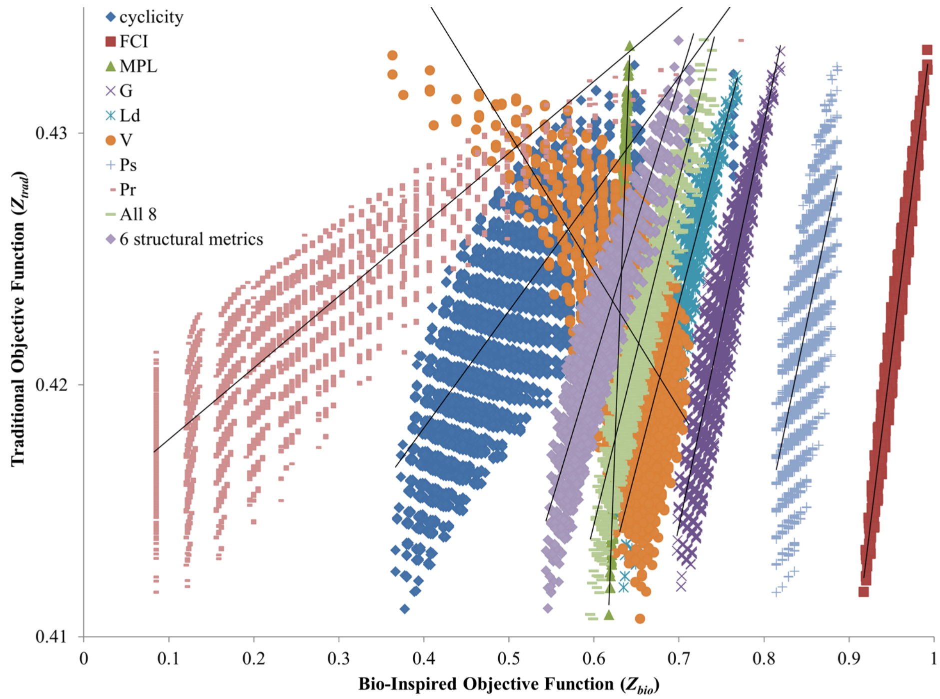

Figure 2. Relationship between the traditional and bioinspired objective function values for 100 000 random network designs when carpet flows were held constant at 8268 kg/year.

constant flow magnitude values, are presented separately in the results section below.

RESULTS

Constant Flow Correlations. *Individual Food Web Metrics.* The original correlation between Z_{trad} and Z_{bio} revealed that organizing industrial networks using ecological parameters strongly and positively affected costs and emission.[25] Optimization using each individual food web metric correlates with the emissions and cost performance that results from a traditional optimization (Figure 2) although considerable variance exists between the metrics; R^2 values range from 0.960 (FCI) to 0.316 (V). Figure 2 shows the results for each food web metric used individually alongside all 8 metrics grouped and only the six structural metrics grouped. The R^2 values for the individual metrics are listed in Table 2, and from best to worst are FCI > MPL > G > L_D > P_R > λ_{max} > P_S, > V.

The R^2 value for all six structural metrics combined is 0.876 - higher than any of the structural metrics used individually. This suggests that the structural metrics may work optimally in groups; extreme effects of individual metrics may be ameliorated by the effects of others when metrics are used in combination.

Table 2. R^2 Values Organized from Best to Worst for the Linear Relationships between Z_{bio} and Z_{trad} of Figure 2

$Z_{bio} = f()$	R^2 for Z_{bio} vs Z_{trad}
FCI	0.960
MPL	0.908
all eight metrics	0.886
six structural metrics	0.876
G	0.834
L_D	0.833
P_R	0.733
λ_{max}	0.581
P_S	0.477
V	0.316

Food Web Metric Groupings. Figure 3 shows different groupings of the six structural metrics plotted against the traditional objective function, and shows the specific combinations strongly affects the resulting correlation. The best combination is generalization, prey to predator ratio, specialized predator fraction, and cyclicity (G, P_R, P_S, and λ_{max}). When used together, these four metrics produce an R^2 value of 0.872, which is hardly different from the R^2 value of 0.876 for all six structural metrics. That this combination has a correlation so close to that of all six structural metrics is unexpected given the testing of single metrics, especially P_S and λ_{max} performed poorly alone (Table 2). These results reinforce the hypothesis that individual metrics are less useful than groups; no individual parameter in Figure 2 stands out as strongly influencing the magnitude of the correlation.

Variable Flow Correlations. The preceding section assumed a constant flow because the structural food web metrics are not able to capture differences in flow magnitudes. In this analysis, different network designs were generated by randomly varying the network structure as well as the flow amounts between the links in the network. The results for four different Z_{bio} objective functions (FCI, MPL, FCI and MPL; only the six structural metrics; all eight metrics) based on 100 000 random network designs incorporating different flow magnitudes, are plotted in Figure 4, with corresponding correlations between Z_{bio} and the traditional objective function, Z_{trad} shown in Table 3.

Mean path length (MPL) is the food web metric that is most strongly correlates with the minimization of the traditional measures total cost and emissions, with an R^2 value of 0.9916. A close third is the flow metric Finn cycling index (FCI), with the correlation of the two grouped (MPL and FCI) to traditional optimization criteria falling between the correlations displayed

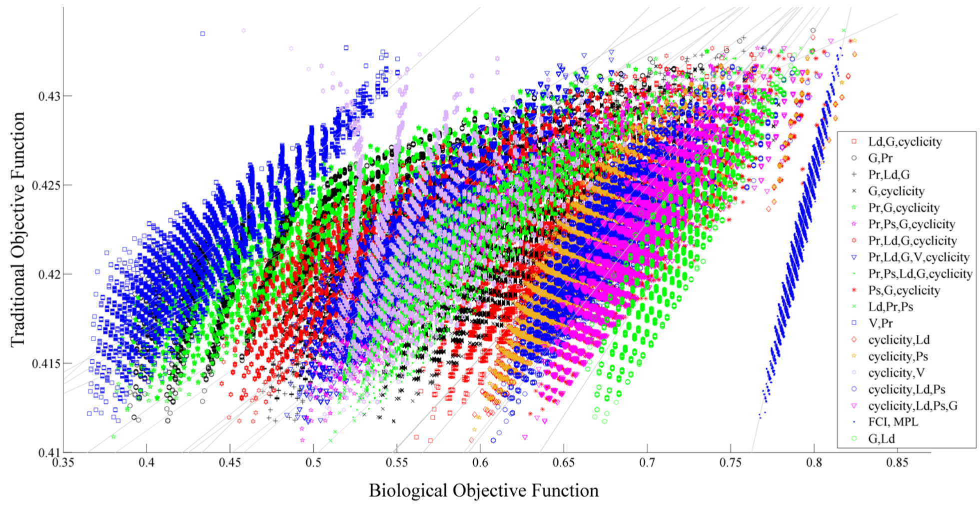

Figure 3. Relationship between the traditional and bioinspired objective function values for 100 000 random network designs for combinations of structural food web metrics when carpet flows were held constant at 8268 kg/year.

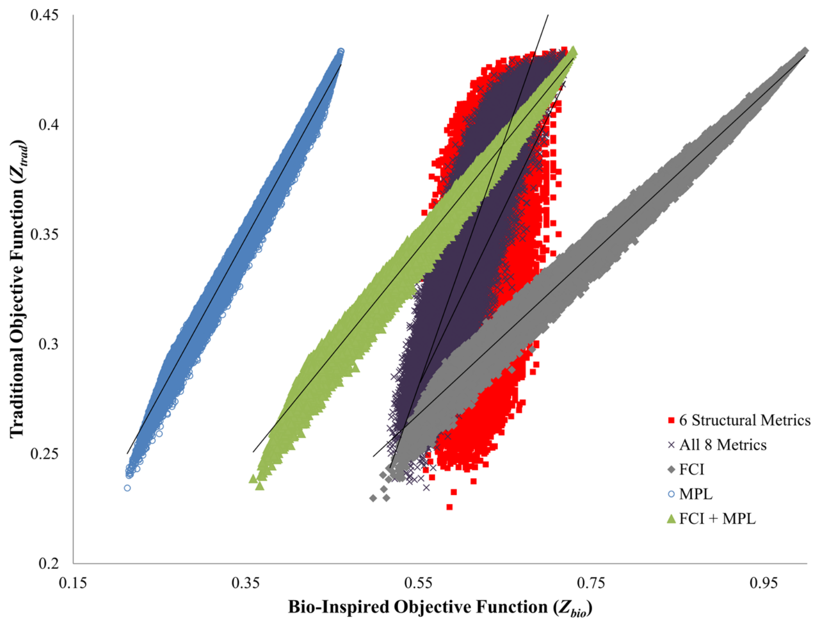

Figure 4. Relationship between the traditional and bioinspired objective function values when both structure and flows are allowed to vary.

Table 3. R^2 Values for Linear Relationships Between Z_{bio} and Z_{trad}

$Z_{bio} = f()$	R^2 for Z_{bio} vs Z_{trad}
MPL	0.9916
FCI and MPL	0.9914
FCI	0.9904
all eight metrics	0.7947
six structural metrics	0.2108

by each individual metric. However, the large correlations displayed by both MPL and FCI along with the relatively small difference between them do not argue strongly for one being superior to the other. The two flow based metrics MPL and FCI clearly control the positive correlation between ecological and traditional optimization approaches when they are used in conjunction with other metrics: the R^2 value with both structural and flow metrics is 0.7947 and is only 0.2108 when flow based metrics are excluded.

DISCUSSION

The founding hypothesis of eco-industrial parks (EIPs) is that a network structured like a natural ecosystem will inherit its other beneficial properties, including desirable network characteristics such as system robustness and sustainability. The analysis presented here validates this idea. Using specific ENA metrics to structure how individual components interact organizes the material and energy flows into that also satisfies the traditional economic goal of cost savings and the traditional environmental goal of emissions reduction. That is, the cycling within an industrial system is increased by adjustments to the system that decrease the number of specialized consumers, and increase the number of consumers receiving flows from a given producer or the number of producers contributing to material or energy to a particular consumer. Increasing the pathway proliferation rate and minimum path lengths also are beneficial. Thus, a given industrial network can be improved by determining how to configure specific consumer-producer links so as to make these

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network properties more convergent to median values in real ecosystems. Intuitively, this makes sense because natural ecosystems efficiently (re)cycle materials (biomass), which reduces both draws upon external energy (e.g., production of plant biomass via solar energy conversion) and waste (biomass that is exported outside the system). Industrial systems with low costs and emissions arguably also are more efficient because they use and waste fewer resources than systems with higher costs and emissions. Although robustness is not explicitly addressed in this work, the ability of ecologically inspired network designs to increase network cycling and waste reduction suggests a similar approach also could be used to examine this property in human systems.[28]

The analysis presented here indicates that the flow-based food web metrics FCI and MPL and a subset of food web structural metrics can be used to improve the performance of cyclic industrial networks where minimizing costs and emissions are important criteria. Four structural food web metrics in particular (λ_{max}, P_S, P_R, and G) account for nearly all of the correlation between biological and traditional objective function minimizations of the carpet network. A limited set of food web structural features results in a well-designed network structure under of constant and uniform flow conditions. Using the flow based metrics FCI and MPL both flow magnitudes and the network structure can be determined. The strongest correlation with the minimization of cost and emissions was found using mean path length (MPL), which resulted in a nearly perfect correlation with a R^2 of 0.9916, although both Finn cycling index (FCI) and the combination of FCI and MPL produced similarly high R^2.

The four structural metrics (Generalizability, Prey to Predator Ratio, Specialized Predator Fraction, and Cyclicity) that accounted for most of the correlation between the biological structure and traditional objective function optimization reveal potential design rules for EIPs. The target values for the first three of these metrics produce a system where each consumer interacts with a variety of producers; the number of producers and consumers is roughly equal, and only a small proportion of all consumers interact with only one producer. Industrial networks that converge on cyclicity values typical of ecological systems are strongly interconnected rather than having actors which, while connected, do not participate in loops. The importance of the parameter cyclicity in producing large correlations further emphasizes that cost and emission reductions occur when there is an opportunity for flows to pass through multiple and long paths within the system rather than the direct input-exit chain found in traditional industrial systems. Material cycling in natural systems is very strongly influenced by the presence of detritivores/decomposers; over half of all the material in a food web can transit through decomposer-type species such as fungi, which recycles unused material or dead matter (detritus) and returns this material and energy back to the system when it is consumed. Decomposers ensure the presence of food web pathways that include all other species in the system because the connections due to this consumption pattern contribute to many other existing cycles. Even limited connections to an actor that functions similarly in an industrial network would dramatically increase connectivity, and thereby efficiency. In an industrial context, a detritus-type actor is an actor that functions in waste treatment (i.e., composting), recovery, and recycling (i.e., repair, remanufacture, reuse, resale), or agriculture (i.e., farm, zoo, landscaping, green house, golf course). Additionally, to qualify as a detritus-type actor there must be at least one link entering and leaving said actor. This last criterion is based on the fundamental functional description of a detritus/decomposer in a food web and ensures that the detritus-type actor is an active participant of the network. Although it is not clear why the metric vulnerability (V) is less important in relation to cost and emission minimization, the lack of a strong effects of linkage density (L_D) again reinforces that the basic producer-consumer links, per se, are less important than links that allow a consumer or producer to interact indirectly (i.e., through intermediaries, known as indirect effects) with other actors,[20,21,33,50−52] particularly since this will allow increase input into the decomposer compartment.

The inclusion of flow based parameters allow for the possibility of better correlations with Z_{trad} because the flow magnitudes can be optimized in addition to the network structure. These metrics can route flows preferentially through strongly connected components, rather than regulating links in only a binary (on−off) manner. It is not surprising that network performance is proportional to MPL since a larger MPL means more actors participate in exchanges, keeping material flowing within the system for longer, reducing the amount of discarded usefulness of a material or energy flow. One industry design suggestion that emerges from understanding the positive role of MPL is to focus on the addition of industries and actors that can interact with *existing* material flows, increasing the average length of the route a material or energy flow will take through the network. Building a network based on existing material flows also adds some security for invitees into an EIP as the ability to meet their needs is already well established, a noted concern of industries when asked to participate in newly designed eco-industrial parks.[53,54]

The structural food web metrics are less indicative of desirable network performance than the flow based metrics. No set of structural metrics were as highly correlated with Z_{trad} as flow based metrics were, and adding the flow metrics to the structural metrics also improved their performance in the constant-flow scenarios. This indicates structural metrics must be combined with another method that can select flow magnitudes in order to find a complete solution for the network. However, these structural metrics still may be useful to network designers. First, there may be situations where flows cannot be altered; meaning that optimizing around structure is the only option. Second, a two-step process where optimization based on structure is followed by flow-based optimization appears to be the most effective method for producing the most cyclic EIP designs (Layton, Weissburg and Bras, unpub). Third, although flow based-metrics allow for more precise network representations, the trade-off is the effort associated with collecting this quantitative flow information. The cost of information is far less with structural metrics, which only require knowing a link exists between two actors. Based on what is seen here and the longstanding belief that form and function are inseparable, design criteria based on structure alone is certainly not without its own value. As was seen in Figure 2, even a structure only optimization correlates well with emissions and costs reductions (λ_{max}, P_S, P_R, and $G-R^2$ with an 0.876).

Despite long-standing interest in creating more cyclic production systems, there is still a shortage of design rules to guide the assembly of collections of interacting industries such as those found in an EIP. The design methods presented here result in industrial system structures and cycling that are closer

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to their natural analogs, and which exceed the values displayed by most industrial symbioses analyzed by Layton et al.[7] All food web metrics investigated in this paper except Vulnerability (V) show improvements from the worst to best designs (Tables 2 and 3), with associated benefits in system performance from a traditional standpoint.

That application of structural and flow metrics together seem to provide design guidance for networks that are both economically and biologically sustainable, through network cost and emissions reductions respectively, is a source of optimizm given the inevitable growth industrialization around the world. Using ecological network analysis as part of the design of industrial networks yields a set of quantitatively verifiable practices that can enable more sustainable production at a variety of scales. Water systems, industrial symbioses, and city scale economies all have been analyzed with these techniques developed for food webs, showing there are strong parallels between these human and biological systems.[6,7,9,28] Further, using design rules based on ecological networks also may result in industrial networks that embody other desirable food web features: ecological network analysis can be used to examine trade-offs between cycling efficiency[7,24] and resilience.[6,55] The methods described here would be amenable to these systems and other collections of colocated actors that exchange material and/or energy.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.6b03066.

> Three tables specifying the carpet manufacturing-recycling network (Table S1), the traditional objective function (Table S2), the biological objective function (S3). This material is available free of charge via the Internet at http://pubs.acs.org/ (PDF)

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Notes

The authors declare no competing financial interest.

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