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# CYCLICITY AND STRONGLY CONNECTED ACTORS AS A SET OF EARLY CIRCULAR ECONOMY DESIGN TOOLS FOR EMERGING TECHNOLOGIES

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## ABSTRACT

*The circular economy (CE) is a resource system in which byproducts and traditional end-of-life resource flows are fed back into the system to reduce virgin resource use and waste production. Emerging technologies offer an exciting opportunity to support circular economy efforts, especially in the early design phase when opportunities for incorporating these technologies are relatively easy. Traditionally, however, the early design phase has access to very little data about resource flows which makes the introduction of new technologies difficult to do, especially with respect to market-related design decisions. In the later design stages, this data is easier to obtain but is met with increased inflexibility and costs that make these types of changes less common. This paper proposes the use of cyclicity, also known as spectral radius, and NS* minimal-data input metrics that can direct designers to options with the greatest theoretical impact on routing commonly wasted resources back into value circulation. Cyclicity is a metric commonly used in ecology to assess the existence and complexity of cycles, or material/energy pathways that can start and end at the same node, occurring in a system. The metric uses a topological adjacency matrix of resource flows between potential circular economy actors, modeled as a directional graph, and is calculated as the largest absolute eigenvalue of an adjacency matrix and can be a value of zero (no cycles), one (basic cycles), and any value larger than one (increasing presence and complexity of cycles). This study also evaluates actors making up the network as to whether they are part of a strong cycle, a weak component of a cycle, or are disconnected from a cycle, quantified with NS*. In a strong cycle, all actors feed into the cycle and the cycle feeds back into the actors. Actors that are weakly connected to a cycle do not contribute to a cyclic pathway. Disconnected actors are not connected to any actor participating in cycling. This paper conducts two case studies on these design tools. The first, a survey of 51 eco-industrial parks (EIPs) and 38 ecological food webs to compare the presence and complexity of cycles in industrial resource systems to ecological resource systems. The latter, food webs, are very effective at retaining value inside the system boundaries. The former, EIPs, were built in support of circular economy principles to use waste streams from one industry as resource streams for others. The analysis shows that 46 out of 51 EIPs had cyclicity values of one or greater and an average of 54% of actors in an EIP are strong. The food webs all have a cyclicity greater than one and an average of 79% of actors in a food web are strong. These results can help decision makers consider CE-supporting pathways earlier in the design process, increasing the likelihood that emerging technologies are incorporated to maximize their CE impact. The second case study explores an emerging technology, Brine Miners, and how cyclicity and* $N_S^*$ *can be used to guide design decisions to impact the ability of this technology to aid in the creation of a circular economy. The exploration found that focusing on the creation of energy has the potential to add new actors to resource cycling and that diversifying the uses of byproducts creates more complex cycling within a hypothetical economy.*

Keywords: Circular Economy, Ecological Network Analysis, Cyclicity, Spectral Radius

## NOMENCLATURE

| | |
|---|---|
| CE | Circular Economy |
| ENA | Ecological Network Analysis |
| EIP | Eco-Industrial Park |
| FW | Food Web |
| $N$ | System Size (number of nodes) |
| $N_S$ | Number of Strong Nodes |
| $N_S^*$ | Normalized Number of Strong Nodes |
| $\lambda_{max}$ | Cyclicity or Spectral Radius |

## 1. INTRODUCTION

### 1.1 Circular Economy

Circular economy (CE) can be defined as a resource use system where resource streams move towards being closed

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loops, or cycles, thereby limiting virgin resource use and waste generation [1]. CE offers a sustainable alternative to the current linear economy model. In the linear model, resources are extracted, used to manufacture products, and then both the products and their byproducts are discarded at the end of their lifecycle [2, 3]. This system is inherently unsustainable: it creates significant pollution and drains finite resources. CE combats these negative impacts by emphasizing the use of recycling, reuse, and resource sharing [4].

One difficulty arising with CE implementation is that the information needed to make resource cycling decisions is often not available until a product or system is fully implemented. At this stage changes are difficult and expensive. Like most sustainability efforts, design changes made in the early design phases are cheap and relatively easy to implement. As a result, tools that can be used early in the design process that support later CE implementation are needed. This paper uses a low data metric (i.e. quantitatively cheap) called "cyclicity" as an early design tool for the introduction of new technologies in support of circular economy efforts. The metric quantitatively captures structural cycles in the network architecture. Designers and decision makers can use this information to ensure a product or system has built in pathways for CE. The hypothesis is that without this underlying cyclic structure resources cannot cycle and CE is severely limited. These decisions when made in the early design phases can shape how effective a technology can be at retaining resource value inside a system's boundaries. Three types of case studies, biological food webs (FWs), eco-industrial parks (EIPs), and a new developing technology called Brine Miners, are used here to highlight the effectiveness of cyclicity in supporting CE.

### 1.2 Ecological Network Analysis (ENA)

Biological ecosystems exhibit many traits that are desirable from an engineering perspective. These include resilience to unexpected disturbances, effective retention of resource value, and support for both individual species as well as system level functioning. Biological ecosystems when modeled as food webs highlight the effective retention of resources via cyclic pathways, primarily supported via detritivore-type species [5]. Detritivores are the recyclers of the ecosystem; species that feed on dead and decaying matter (detritus), turning it into usable energy for the rest of the food web. This enables energy to be cycled from higher trophic levels to lower ones. Trophic levels are a measurement of how far removed a predator is from primary producers in a food chain [5, 6]. Ecological food webs, especially more mature systems, have been found to have lots of cyclic pathways and a high proportion of resources that remain in the system via cycling [7, 8]. These characteristics can be quantified via the Ecological Network Analysis (ENA) metric cyclicity (also known as spectral radius, $\lambda_{max}$). This metric is combined here with the number of actors participating in cycles for its potential value as a low-data (i.e. quantitatively inexpensive) quantitative representation of available cyclic pathways that could be selected to best support CE in a new system design.

### 1.3 Case Studies

Three types of case studies are used to highlight the ability of cyclicity to capture a system's potential for CE-supportive cycling. Eco-Industrial parks (EIPs) are a network of industries that share resources via mutually beneficial interactions [9]. EIPs are intended to support circular economy principles, with interactions set up to reduce system-level environmental impacts and better utilize resources [10] (for example water is a common EIP motivator, with industries replacing freshwater use with greywater exchanges where possible [11]). The development of EIPs can also be driven by financial benefits for participating companies, allowing the generation of profits from residual waste and enabling access to more cost-effective material streams [12]. EIPs can be initiated by local communities, governments, and companies directly. Governmental support has been identified as a key factor in the successful creation of EIPs [10]. Once created, many factors contribute to their success: will they grow, stagnate, or fail. For example, research has indicated that more EIPs succeed in supporting resource sharing when the driving force comes from the companies themselves [13]. Tools to support the incorporation of pathways for resource sharing and reuse – especially during the initial design phases - would thus support EIP growth and avoid disconnectedness between industries. Although EIP cyclicity has already been investigated with respect to food webs [14], this work goes a step further by focusing on the ability of cyclicity to serve as a CE supporting tool.

Another cited barrier to EIPs' growth has been insufficient trust between companies. The utilization of noncompetitive waste streams has been proposed as a method to remove this barrier. These waste streams are associated with a negative environmental impact and costly disposal methods [10]. The second case study investigated here investigates this strategy: taking advantage of a noncompetitive waste stream. Brine Miners is a technology under development that has a novel approach enabling mineral extraction from brine waste [15]. The Brine Miners case study is an example of how cyclicity can be used to influence decisions in the *early* design phases of an emerging technology. During the early design phase of the Brine Miners' technology, the designers had four main design decisions regarding their targeted stakeholders and markets. The first was the *source of brine*. The choices were a) a natural source, like a highly saline lake, b) waste brine from desalination plants, or c) brine waste from industrial semiconductor plants. Each of these sources had different brine compositions and thus the technology would need to be designed based on their target market. The second was *what minerals* the technology would specifically extract and to what degree they would be refined. The third was what would *happen to the freshwater* produced via the mineral's extraction. The options were a) to use it for habitat rehabilitation by reintroducing it into the environment, b) to create green hydrogen, or c) for high value agriculture. The fourth was what would *happen to the green hydrogen* if produced. These options included a) the use of green hydrogen as an energy source for Brine Miners' operations, b) an energy source for desalination plant operations, c) an energy source to be sold back to the power grid, d) for agricultural uses in fertilizers, e) or to be sold outside of the system to generic green hydrogen customers. These design decisions and their various options made up the design variations tested in this work. Additional details about the model creation for Brine Miners can be found in Section 2.6.

## 2. METHODS

### 2.1 Directional Graph and Matrix Representations

Graphs are a type of data structure that represent relationships between entities. In this context, the nodes are industrial and environmental actors. Each actor is represented as a node, and the connections between them are represented as edges. A connection can be a transfer of materials, information, or any other interaction. A *directed* graph, or digraph, shows not only node connections but also the direction of the connections. These interactions represent predator-prey exchanges in food webs and the transfer of a resources from one actor to another in an EIP [16]. Network architecture information can be captured from the graph in a matrix form. An adjacency matrix [**A**] is a binary representation of a digraph, with a one indicating a connection from a column to a row and a zero indicating no connection.

Figure 1 shows how a biological ecosystem can be modelled as a directional graph, such as a food web. This graph captures the topology and flow magnitudes in a flow matrix [**T**]. The flows are directed from rows to columns, with the first row representing system imports, and the last two columns capturing useful outputs and dissipations, respectively. The structural adjacency matrix [**A**] is the transpose of the internal flow matrix, where a non-zero flow becomes a one and a zero remains a zero. Some ENA metrics are calculated from the structural matrix and some use the flow matrix. Cyclicity is of interest because it only uses structural information, making it ideal for the early design stages when a lot is still unknown about a design/product/system.

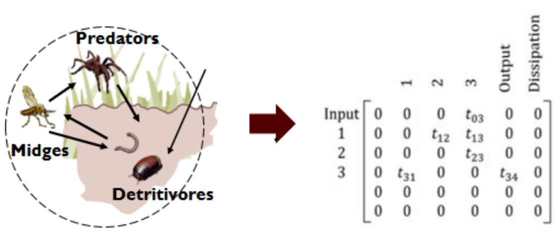


**FIGURE 1:** FLOW MATRIX FOR A HYPOTHETICAL FOOD WEB DIGRAPH MODEL. BASED ON [14]

### 2.2 Cyclicity

Cyclicity ($\lambda_{max}$) is a structural metric used in ecology, also known as *pathway proliferation* in ecological studies, and *spectral radius* in mathematical studies [5]. Cyclicity assesses the existence and complexities of structural cycles in a system. Cyclicity is calculated from the adjacency matrix [**A**] of a digraph and is calculated following Eq. 1 as the maximum real eigenvalue of the adjacency matrix.

$$\lambda_{max} = \text{maximum real eigen value solution to: } 0 = \det(\mathbf{A} - \lambda \mathbf{I}) \quad (1)$$

Cyclicity can be a value of zero, one, or greater than one – up to a maximum of $N^2$, where $N$ is the number of nodes or components in the system. A cycle occurs when a path can be followed starting and ending at the same node. A cyclicity of zero indicates that no cycles exist in a system, or that all flows are linear. An example of this is shown in Fig. 2a. A cyclicity of one indicates that a simple cycle exists in the system, meaning that there is a single path through the system that creates a cycle made up of nodes each with one input and one output, illustrated in Fig. 2b. Cyclicity values greater than one indicate that cycles contain multiple possible paths, illustrated in Fig. 2c where a two-way connection increases the complexity of the basic cycle in Fig. 2b. This added opportunity for cycling gives the system a cyclicity of 1.32.

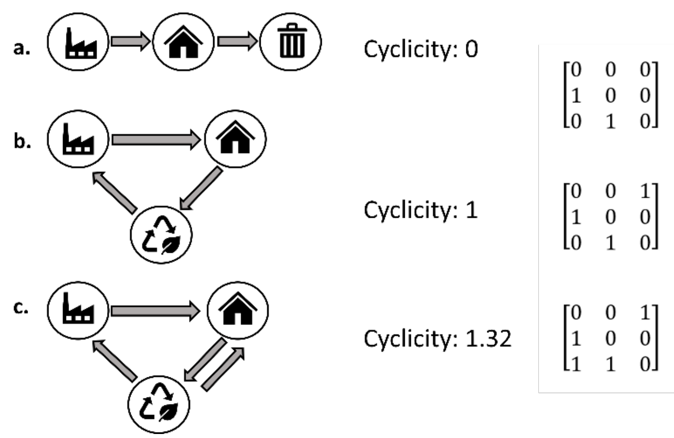


**FIGURE 2:** EXAMPLES OF CYCLICITY FOR A THREE NODE SYSTEM. THE DIGRAPH IS SHOWN ON THE FAR LEFT, IN THE CENTER IS THE CYCLICITY VALUE, AND THE FAR RIGHT SHOWS THE ADJACENCY MATRIX.

As the number of nodes in a system increases, so does the maximum potential value of cyclicity. Cyclicity does not need to be normalized for system size (normalizing distorts the meaning of cyclicity), however it is important to look at *more* than just cyclicity when assessing a system's cycles. Only the topological nature of cycles present in the system are indicated by cyclicity.

### 2.3 Strong vs. Weak Nodes

Another aspect of an adjacency matrix that can supplement cyclicity findings are the number of nodes connected by *strong* cycles in a system. Digraphs can be categorized in three ways, 1) disconnected, 2) strongly connected, and 3) weakly connected.

A *disconnected digraph* has one or more paths that do not connect with each other. Disconnected digraphs can be split into connected subdigraphs, where subdigraphs contain only nodes that are connected to each other but not to any node outside of the subdigraph. Once split from a disconnected digraph, subdigraphs are digraphs in themselves. These subdigraphs, as digraphs, can then further be categorized as strongly connected or weakly connected. Figure 3 shows an example of a *disconnected* graph with two subdigraphs. These subdigraphs are both weakly connected, however when placed together in a larger digraph, the digraph itself is disconnected. The first subdigraph (Subdigraph 1) consists of nodes 1-4. The second subdigraph (Subdigraph 2) consists of the nodes 5-7.

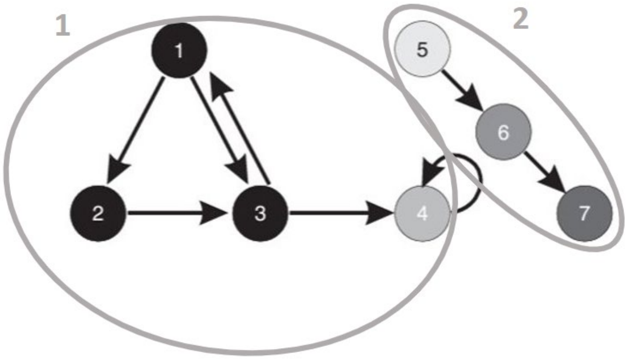


**FIGURE 3:** EXAMPLE OF A DISCONNECTED DIGRAPH MADE UP OF 2 SUBDIGRAPHS (NODES 1-4 AND 5-7) [17].

A *strongly connected digraph* has a path that connects every node to each other following the direction of the flows. Weakly connected sub-digraphs with a cyclicity of one or higher can be paired down to contain only nodes that are a part of the strongly connected cycle. These nodes, which only belong to a strongly connected cycle, are termed *strongly connected components*. Subdigraph 1 in Fig. 3 can be paired down to include only nodes 1-3 to create a strongly connected cycle [17].

A *weak digraph* is where all nodes are connected but if direction is followed not every node can be reached from every other node. A *weakly connected cycle* can have a cyclicity of zero and would contain only a linear path. A weak cycle with a cyclicity of one or higher indicates that there exist nodes in the system that either feed into a cycle or a cycle feed into them, for example Subdigraph 1 in Fig. 3 is a weakly connected cycle with a cyclicity of one, as node 4 does not feed back into the cycle of nodes 1-3. Subdigraphs 2 in Fig. 3 is also an example of a weakly connected subdigraph with a cyclicity of zero: its linear path connecting nodes 5-7 but using flow direction we cannot get from node 7 back to node 5.

The number of strongly connected nodes in the system $N_S$ and the *normalized* number of strongly connected nodes in the system ($N_S^*$ or Eq. 2, normalized by the total number of nodes e.g. 7 in the case of Fig. 3) are needed in addition to cyclicity to fully understand the *size* of cycles.

$$N_S^* = \frac{N_S}{N} \quad (2)$$

### 2.4 Case Studies

#### 2.4.1 Eco-Industrial Parks and Food Webs

Fifty-one EIPs were compared to 38 food webs (FWs) to investigate and compare their overall structure and functioning. Food web data collection in the early 1990s was becoming more standardized, thus the food web data set included in this study only uses those gathered after 1993 following major publications dates in the ecological FW literature [18, 19]. Although this reduces an initial dataset of 144 FWs [18] to only 38, the quality of these case studies is significantly higher and prior work has shown that trends between the pre and post 1993 FW data are significantly different[14]. These same EIPs and FWs are used here to further understand the roll of cycling in different networks.

#### 2.4.2 Brine Miners

Brine Miners is an example of how cyclicity and node strength can be used to guide design decisions in the early design phase of a technology. A hypothetical realistic industrial system model was created for the Brine Miners case study with twenty nodes representing system actors, such as the Brine Miners' patented technology, collaborating desalination plants, the environment, and lithium mining/production. Three hundred and thirty-six scenarios covered every combination of the 4 different brine donation cases, 4 different water use cases, 5 different green hydrogen use cases, and 7 different mineral extraction cases. The cyclicity and $N_S^*$ values were assessed for these cases and used to proposed the best CE supporting designs.

The four brine donation cases included Option 1) receive brine waste from desalination plants, Option 2) to extract brine from hyper saline lakes, such as the Great Salt Lake or Lake Albert, Option 3) to receive brine from a generic factory (this option accounted for any brine donation source which was not specifically modeled in the system), and Option 4) to receive brine from a semi-conductor factory.

The Brine Miners' technology extracts metals and salts from brine waste, resulting in the production of clean water as a byproduct. Water is a unique resource with respect to CE because its value does not get "used up." Water only changes forms but can always be cleaned to return to its original state. One option for using this water was to create green hydrogen using renewable energies. The second possible use case option involved habitat rehabilitation through reintroducing clean freshwater to environments affected by droughts or hyper-saline conditions resulting from human intervention. A third possible option was to both create green hydrogen and perform habitat rehabilitation and a fourth option being considered was to donate the clean water to high value agriculture.

Green hydrogen production also had five potential use cases. One option was to use green hydrogen as an energy reserve for the Brine Miners' technology. Brine Miners hoped to use only renewable and/or waste heat as energy for their processes. Hydrogen was proposed to store energy due to the inconsistent nature of renewable sources, enabling extraction as needed. This option resulted in a "cannibalistic" interaction in the digraph, where a node provides a resource flow to itself. Another option was to send green hydrogen to a power plant, which would use it as an energy source to send power to the grid.

A third option was for desalination plants to use green hydrogen as an energy source, creating a mutually beneficial interaction in the digraph. A fourth option was to send it to a fertilizer production plant to create fertilizer for agriculture and the final option being considered was to sell it to a generic hydrogen consumer.

The final set of Brine Miners design variables was related to the extraction of minerals, including lithium and selenium in brine or solid mineral form. Brine Miners' technology had the opportunity to extract these minerals in a hyper concentrated brine or to develop further technology to process these brines and output a refined form of these minerals. Brine Miners' could also extract multiple minerals at once. Seven different combinations of these minerals and concentrated brines make up the different mineral extraction options.

The total number of brine miners cases were 336, because not every use case involved green hydrogen being created and necessitating the additional design options for green hydrogen use. Two of the water use cases, the second and the fourth, did not generate green hydrogen and thus the number of cases without the design variable of green hydrogen were 56. The two water use cases that included the production of green hydrogen were the first and second. When combined with the brine donation, mineral, and green hydrogen use cases this led to 280 different cases. Summing the cases with and without the production of green hydrogen created 336 cases.

## 3. RESULTS AND DISCUSSION

### 3.1 Eco-Industrial Parks vs. Food Webs

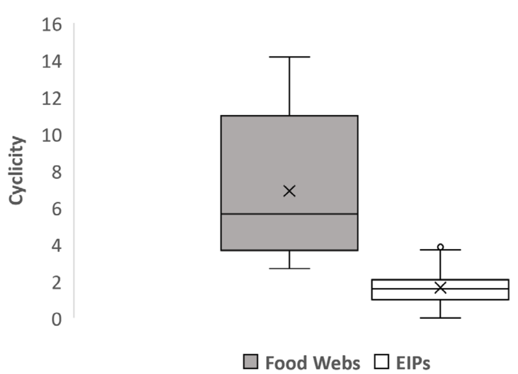


**FIGURE 4:** BOX AND WHISKER PLOT OF CYCLICITY FOR FOOD WEBS (GREY, LEFT) AND EIPS (WHITE, RIGHT) REITERATING PREVIOUS FINDINGS IN [18].

Figure 4 shows a box and whisker plot of cyclicity values for food webs (FWs) vs Eco-Industrial Parks (EIPs). The 51 EIPs had an average cyclicity of 1.65, with a minimum of zero and maximum of 3.85. The 38 FWs had an average cyclicity of 6.90, with a minimum of 2.68 and maximum of 14.17. The results of a two tailed unpaired t-test showed that these two data sets are statistically different with a p-value of $1.63 \times 10^{-15}$. This confirms and extends the findings of Layton *et. al.* [14, 18] including 3 additional newer EIPs [20] and down selecting to 38 post-1993 complete FWs available from [21], that the significantly higher cyclicity in ecosystems contributes to greater complexity in the connections between their components, ultimately facilitating better value retention. However, despite the intended aim of EIPs to promote these characteristics, they exhibit considerably lower values. Six EIPs had a cyclicity of zero, indicating that no resource cycles exist in these systems. This work adds to prior findings [14, 18] that deliberately designing EIPs to attain cyclicity values of one or higher can ensure that resources have the capability remain in circulation and support CE efforts.

A complex cycle provides multiple pathways for resources to travel between actors. More cyclic resource pathways provides more options for routing materials and material byproducts, helping industries reduce their waste outputs and raw material use. Figures 5 and 6 highlight that cyclicity ($\lambda_{max}$) is not enough alone to guide this design however. The plots show the impact of number of actors in the system and number of actors in the strongest subdigraph of FWs and EIPs against cyclicity. The linear $R^2$ values for FWs and EIPs between cyclicity and $N$ are 0.474 and 0.007, respectively, however when we look at the number of strongly connected nodes ($N_S$) vs. cyclicity we see a much stronger relationship, with an $R^2$ value for FWs of 0.603 and for the EIPs of 0.408. Lower $R^2$ values for cyclicity are not necessarily a surprise as the metric is a reflection of higher-order effects. Future work will investigate higher-order correlations. Figure 6 also highlights that in addition to a positive relationship between $N_S$ and $\lambda_{max}$, there also appears to be a lower bound for achievable $\lambda_{max}$ based on $N_S$. Thus, the number of strongly connected nodes in a system is an important factor for achieving higher cyclicity values, much more so than only the total *number of nodes*, i.e. how components of a networks are participating in the overall network is more important that just increasing the number of components. This is valuable as previously the connection between a network's maximum possibly cyclicity and its overall number of actors (maximum achievable cyclicity = $N^2$) was the primary focus in trying to achieve FW levels of cycling. Thus, when designing for CE it is important to focus on increasing the number of *strong nodes* in a system. This corresponds to an increased potential for resource cycling and value extraction.

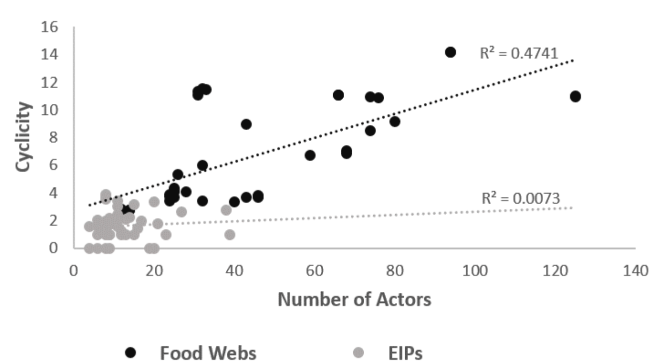


**FIGURE 5:** PLOT OF CYCLICITY VS $N$ IN FOOD WEBS AND EIPS

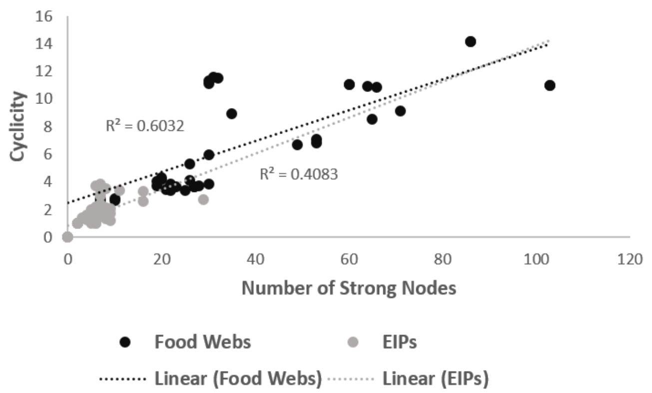


**FIGURE 6:** PLOT OF CYCLICITY VS $N_S$ IN FOOD WEBS AND EIPS

The box and whisker plot in Figure 7 illustrates the normalized number of strongly connected actors in a system ($N_S^*$) for FWs compared to EIPs. It reveals an average $N_S^*$ of 0.55 for EIPs and 0.76 for FWs, indicating a statistical difference between the two (a two-tailed unpaired t-test yielding a *p*-value of $5.22 \times 10^{-6}$). This indicates that a larger proportion of total FW actors are active participants in resource cycling as compared to EIPs. FWs also exhibit higher cyclicity values than EIPs for the same ratio of strong actors to total actors, as seen in Fig. 8. $N_S^*$ can thus be used to assess whether a system is taking advantage of the actors that are present and connected to the system. Increasing the proportion of strongly connected actors ($N_S^*$) supports two-way connections and circular economy initiatives. $N_S^*$ is potentially an important component for assessing designs for CE. Increasing the number of actors participating in cycling increases the potential for resources to be cycled and industries to extract value from byproducts. Figure 8 also indicates a potential upper limit to the possible cyclicity gained by increasing $N_S^*$, although additional work is needed to validate this.

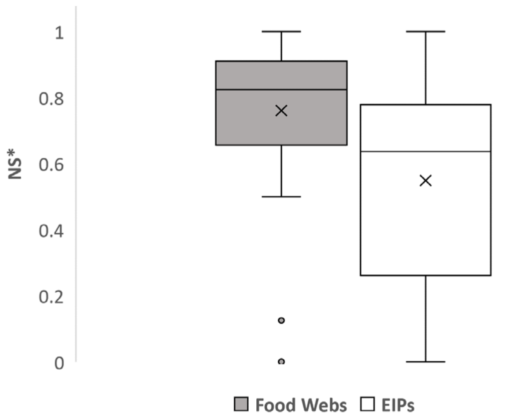


**FIGURE 7:** BOX AND WHISKER PLOT OF NS* VALUES FOR FOOD WEB AND EIP DATASETS.

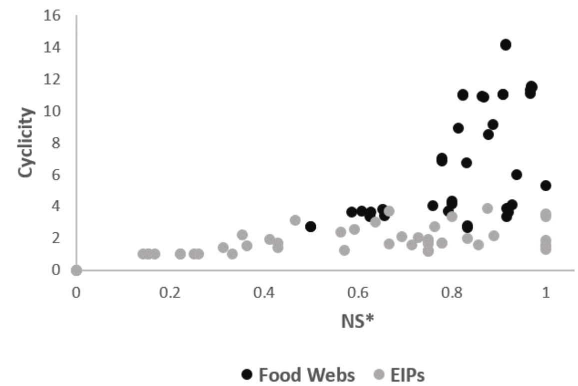


**FIGURE 8:** SCATTER PLOT OF CYCLICITY VS $N_S^*$ FOR THE FOOD WEBS AND ECO-INDUSTIAL PARKS.

Figure 8 also indicates that FWs are more opportunistic than EIPs when it comes to creating complex connections that effectively retain value inside the system boundaries. The strong actors in FWs create more complex cycles (i.e. higher cyclicity values). This is in contrast with EIPs, where Fig. 8 shows that even as the number of strong actors and their relative proportion in the network increase, cyclicity does not. Designing mutualistic industrial networks to be more opportunistic will push them to function more like biological food webs, more effectively retaining value and supporting circular economy initiatives.

### 3.2 Cyclicity for Early Design Decisions: Brine Miners

This work developed 336 theoretical design scenarios, calculating both cyclicity and $N_S^*$ for Brine Miners to consider in their selection of partners and next steps. The base scenario, without the incorporation of Brine Miners' technology, produced a cyclicity of zero (i.e. no resource cycling was occurring). Out of the theoretical scenarios, 244 yielded a cyclicity value of one or greater, i.e. Brine Miners created a 72.6% chance of pathways being introduced for resource cycling. When assessing the impact that the four design decisions (donor, water, green hydrogen, and mineral) had on the cyclicity of the system, some design decisions proved to be more crucial than others.

Figure 9 illustrates the breakdown of Brine Miners designs based on cyclicity values. The data is split into four different freshwater use cases, light grey for the production of green hydrogen, medium gray for habitat rehabilitation, black for the combination of green hydrogen and habitat rehabilitation, and striped for use in high value agriculture. The cyclicity analysis clearly shows that the use of the freshwater byproduct of Brine Miners' technology for habitat rehabilitation creates a greater than one cyclicity value. Additionally, diversifying the uses for the freshwater byproduct has the ability to yield cyclicity values of greater than 1.75. Water is a resource that always retains its value and therefore is a great way to support the goals of CE. While it is not always the most economically valuable resource, we found that it can have significant beneficial effects when introduced back into a habitat or reintroduced back into the system.

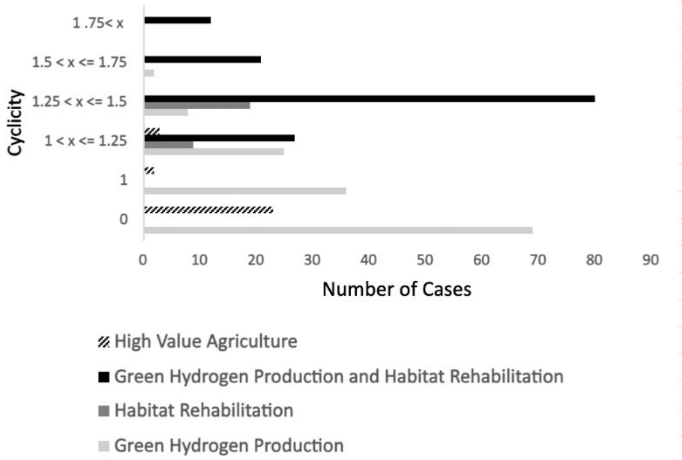


**FIGURE 9:** CYCLICITY FOR 336 BRINE MINERS SCENARIOS, GROUPED BY 4 WATER USE SCENARIOS.

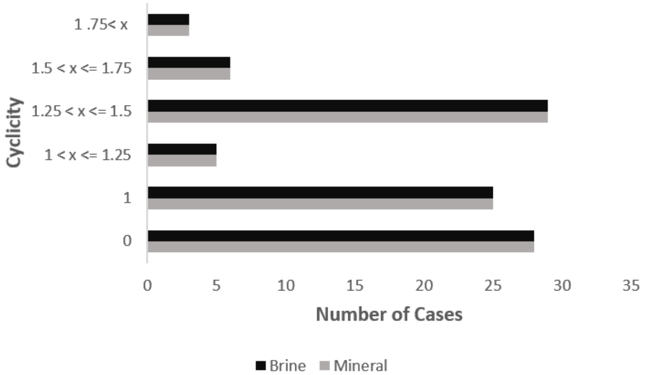


**FIGURE 10:** CYCLICITY FOR 96 CASES OF MINERAL EXTRACTION IN BRINE FORM (BLACK) OR PURIFIED MINERAL FORM (GRAY).

Figure 10 shows cyclicity values for the four mineral extraction cases Brine Miners was considering. The cases are broken up into the extraction of minerals in a concentrated brine form, or the extraction of minerals in conjunction with purification down to their solid forms. This was an important design decision as it would potentially require further research and resources to advance the technology to separate the extracted minerals in their solid forms. The cyclicity values for the cases remained unchanged, indicating that additional economic information may be necessary to inform this decision. Cyclicity indicated that this design decision was not crucial for maximizing the cycling in the final design.

Investigating $N_S^*$ revealed more information about the usage of green hydrogen in the proposed system. Figure 11 shows a box plot of the $N_S^*$ values for the five different green hydrogen use cases, 280 scenarios. Out of the five usage options, selling green hydrogen to be used as energy in the power grid (the white box) stood out, yielding on average much higher $N_S^*$ values. The average $N_S^*$ value for selling green hydrogen for energy use was 0.215, compared to averages ranging from 0.121 to 0.143 for other hydrogen use cases. This was further validated with a one way ANOVA test resulting in a *p*-score of $9.25 \times 10^{-5}$, meaning that there was a statistically significant difference in the average $N_S^*$ value between the case where energy was sold to the grid and the other four cases. These results indicate that using hydrogen as a grid-level energy source has the potential to connect a greater number of actors and create a more strongly connected system. Routing energy back into the power grid creates these higher $N_S^*$ values because energy is a resource used by almost every actor in an industrial system.

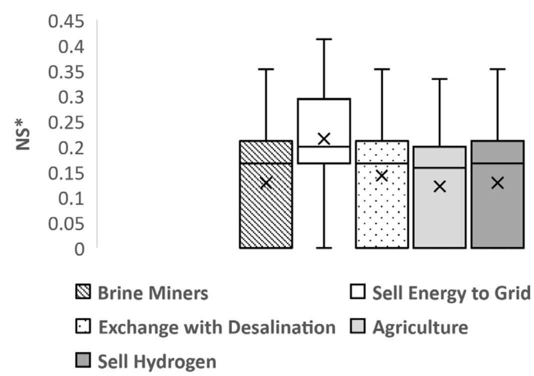


**FIGURE 11:** $N_S^*$ FOR 224 BRINE MINERS SCENARIOS, GROUPED BY 5 HYDOGEN USE SCENARIOS (56 BRINE MINERS, 56 EXCHANGE, 56 SELL, 56 AGRICULTURE, AND 56 SELL HYDROGEN).

Along with including more actors into the circular resource flow, using green hydrogen as an energy source has other circular economy benefits as well. A study conducted by the U.S. Environmental Protection Agency revealed a 6% rise in overall $CO_2$ emissions from the United States in 2021 [22]. This increase in emissions was driven in large part by $CO_2$ emissions associated with energy production via fossil fuel combustion [22]. Reducing an industrial ecosystem's dependency on energy sourced from finite natural resources not only aligns with the circular economy objective of minimizing raw material inputs to a system but also diminishes the environmental footprint of these systems.

While these case studies looked at comparing existing EIPs to natural systems and making early design decisions for new technology, the implications of this research extend much further. The principle of creating circular pathways and adding a greater percentage of actors to these pathways can be used to further the development of current EIPs. Future work for this project involves investigating case studies that assess the addition of actors and connections between actors in EIPs. This would help identify the actors capable of closing resource loops and determine which resources offer the greatest potential to connect new actors to an existing EIP. That work will also add flow magnitude data to illuminate the ratio of resource flows that are cycled within a system to the amount of resources passing through a system. Limitations of this current work include the lack of resource flow data for these EIPs. Cyclicity and $N_S^*$ have the potential to support the creation of more structural pathways for resource cycling in a system early in the design process when their implementation is still relatively cheap. These pathways are critical to the value retention that CE seeks to enhance.

## 4. CONCLUSION

Cyclicity and $N_S^*$ offer promise as set of system level circular economy supporting design tools, which can be used to set the foundation of a circular economy in the early design phases of a project. Understanding resource flows associated with design decisions will further illuminate which decisions can create a circular foundation in a larger industrial ecosystem. These decisions can work to connect more actors into a system, with the hopes that they will also be able to participate in the cycling and reuse of these resources.


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