Comparative Analysis of Connection Patterns in High-Unit Homeostat

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Abstract

The homeostat designed by William Ross Ashby takes longer to return to viability as the number of units increases. The aim of this project is to find the most efficient connection pattern among these patterns in high unit numbers by trying six different connection patterns. In this report, six different homeostats were created using six different connection patterns and the performances of these connection patterns in different numbers of units were analyzed. These analyzes were conducted in three different areas. These are adaptation time, complexity and robustness. Each homeostat was run ten times and data were obtained by averaging the results from these ten runs. In addition, the process of a homeostat whose single unit is subjected to an impulse disturbance to become stable again has been visualized and concretized with snapshots taken at regular intervals. According to the results, Sparse connectivity, importance-base connectivity and Watts-Strogatz model are very close to each other and are less complex than other patterns, and the most complex pattern is fully connected pattern. When the patterns are evaluated in terms of robustness, sparse connectivity is the most robust pattern in the number of 4,5,6,7 and 9 units, while importance-based connectivity is the most robust pattern in the number of 8 units, and Watts-Strogatz model is the most robust pattern in the number of 10 units. When the adaptation time was examined, sparse connectivity showed good performance in low unit numbers. In high unit numbers, importance-based connectivity is the most successful pattern.

1. Introduction

Adaptivity is the ability of a system to maintain or restore equilibrium by responding to environmental conditions or internal changes [1]. This definition of adaptivity was inspired by the definition of adaptivity by British psychiatrist and cybernetics theorist W. Ross Ashby, designer of Ashby's Homeostat. The homeostat can be defined in adaptive systems theory as a model that can reach and maintain a point of balance by adjusting its internal state in response to external influences or internal changes. This device was used by Ashby to embody the cybernetic principles of adaptation, automatic regulation and feedback mechanisms. Each unit of the homeostat is equipped with electrical connections and various control mechanisms. The connections between these units can be adjusted dynamically when it detects imbalances in the system. These settings enable the system to gain self-regulating feature. When the homeostat is in equilibrium, the system adjusts its parameters to maintain this balance, and when out of equilibrium, it adjusts its parameters to return to equilibrium. For this reason, the homeostat is an adaptive system. This is similar to homeostasis mechanisms observed in biological systems.

Ashby has very important works in the field of cybernetics and the understanding of adaptation in this field[2]. Homeostat is one of the most important of these studies. His book "An Introduction to Cybernetics" [3], published in 1956, is considered the first textbook in the field of cybernetics. In this book, he discussed topics such as feedback, control mechanisms and self-regulation. In addition, he introduced the concept of requisite variety, one of the basic concepts of cybernetics[4].

In addition to Ashby, Norbert Weiner is known as the founder of the field of cybernetics. He used the word cybernetics for the first time in his book Cybernetics: Or Control and Communication in the Animal and the Machine[5] and explained the basic principles of cybernetics in this book. At the same time, in this book, he defined the concept of feedback as "the chain of the transmission and return of information". They also worked together with Arturo Rosenblueth and Julian Bigelow in this field. In their article titled Behavior, Purpose and Teleology [6], published in 1943, they discussed how teleological concepts affect the behavior and control mechanisms of systems.

The adaptation time and stability of the homeostat are directly related to its complexity. Increasing the number of units, that is, making the homeostat more complex, will make it more difficult for it to stabilize and will prolong the adaptation time. This is equally true in larger and more complex systems. For example, the relationships between living things in the ecosystem and each other is an example of a complex system. It is a very complex situation that many different species can meet their needs such as food, water and shelter at the same time in balance. The extinction of any species from this state of balance will directly affect other species. To give a specific example, the loss of honey bees will cause a major disruption in the system. Pollination of plants will be greatly reduced and this may lead to a huge hunger crisis in the world. Since the structure is very complex, it will make it very difficult, perhaps impossible, for the system to become stable again. Ashby's homeostat studies allow us to simulate, understand and provide solutions to the challenges faced by these complex systems.

This study aims to examine the effects of different connection patterns on the stability of this system in different unit numbers of Ashby's Homeostat model. In the study, starting from the original four unit structure of the Homeostat, gradually increasing the number of units and the effects of changing connection patterns during this growth process on the system were experimentally tested. Six different patterns were used as connection structures. These are fully connected, random connectivity, sparse connectivity, importance-based connectivity, Wattz-Strogatz model and Barabási-Albert model. These patterns were compared using their complexity, robustness and adaptation time.

2. Methods

In this section of the report, the connection patterns, experimental setup, Sandbox and libraries used are explained in detail.

2.1. Connection Patterns

2.1.1. Fully Connected

In this connection pattern, all units are connected to each other and to themselves with random weights. Units are connected to themselves with negative weights, and these negative weights helps increase the stability of the system. This structure allows each unit to interact with all other units, which can result in numerous connections and complex feedback loops. The pseudocode of this connection pattern can be seen in Algorithm 1.

Algorithm 1 Fully Connected

```
n ← number of units
for i ← 1 to n do
    for j ← 1 to n do
        if i ≠ j then
            weight ← random value between − 1 and 1
            unit_i connects to unit_j with weight weight
        end if
    end for
end for
for i ← 1 to n do
    self_weight ← −random value between 0.5 and 1.5
    unit_i connects to itself with weight self_weight
end for
```

2.1.2. Random Connectivity

In the random connectivity model, units are connected to each other randomly and each connection is determined with a certain probability. Random connections give the system a wide range of possibilities, which can lead to unique behaviors.

Random graph was first used by Helen Hall Jennings and Jacob Moreno[7]. Paul Erdos and Alfréd Rényi did important work in the field of random graphs and introduced the Erdős–Rényi random graph model[9]. At the same time, Edgar Gilbert introduced the model known as the Erdős–Rényi–Gilbert model[10].

The random graph used in this study has a structure very similar to the Erdős–Rényi random graph model. Negative weight self-connections between units, which are added to increase stability, do not exist in the Erdős–Rényi random graph model. The pseudocode of this connection pattern can be seen in Algorithm 2.

Algorithm 2 Random Connectivity

```
n ← number of units
connection_matrix ←
random matrix of size n × n with probability <0.5
for i ← 1 to n do
    for j ← 1 to n do
        if connection_matrix[i, j] then
            weight ← random value between − 1 and 1
            unit_i connects to unit_j with weight weight
        end if
    end for
end for
for i ← 1 to n do
    self_weight ← −random value between 0.5 and 1.5
    unit_i connects to itself with weight self_weight
end for
```

2.1.3. Barabási-Albert Model

The Barabási-Albert model is a random network model used to create scale-free networks[11]. This pattern involves the tendency for new nodes to attach to nodes with more connections as the network grows, known as "preferential attachment". Preferential connecting results in some nodes having a large number of connections, while most nodes have fewer connections. Many networks, such as the World Wide Web, citation networks, and some social networks, include scale-free network features. Like the previous connection patterns, in this connection pattern the units are connected to each other with negative weight to increase stability. The pseudocode of this connection pattern can be seen in Algorithm 3.

2.1.4. Watts-Strogatz Model

The Watts-Strogatz model is a random network model used to model properties of real-world networks such as social networks, biological networks, and communication networks. This model was introduced by Duncan J. Watts and Steven Strogatz in 1998 [12] and developed to explain "small-world" characteristics such as high clustering and short average path length. The working principle is as follows. In the first step, the model is created as a regular structure in which each node is connected to a certain number of neighbors. In the second step, rewiring, new connections are established with a certain probability and the model acquires small-world features. The

Algorithm 3 Barabási-Albert Model

```
initial_connections ← 2
BA_graph ←
nx.barabasi_albert_graph(n_units, initial_connections)
for i ← 1 to n_units do
    for j ← BA_graph.neighbors(i) do
        if i ≠ j then
            weight ← random value between − 1 and 1
            unit_i connects to unit_j with weight weight
        end if
    end for
end for
for i ← 1 to n_units do
    self_weight ← −random value between 0.5 and 1.5
    unit_i connects to itself with weight self_weight
end for
```

rewiring process enables the network to reveal the characteristics of high clustering and short average path length.

In the initially created structure, the number of neighbors was determined as 2. The rewire probability is fixed at 0.3. All units are connected to themselves with negative weight to increase stability. The pseudocode of this connection pattern can be seen in Algorithm 4.

Algorithm 4 Watts-Strogatz Model

```
neighborhood ← 2
rewire_prob ← 0.3
sw_graph ←
nx.watts_strogatz_graph(n_units, neighborhood, rewire_prob)
for i ← 1 to n_units do
    for j ← sw_graph.neighbors(i) do
        if i ≠ j then
            weight ← random value between − 1 and 1
            unit_i connects to unit_j with weight weight
        end if
    end for
end for
for i ← 1 to n do
    self_weight ← −random value between 0.5 and 1.5
    unit_i connects to itself with weight self_weight
end for
```

2.1.5. Sparse Network

Sparse network is a type of network in which the connections between nodes or units are relatively few. Unlike other network structures, in sparse networks each node is connected to a small number of other nodes. These types of networks are used to transfer information efficiently, especially in large-scale systems. They offer advantages in terms of memory and computation due to their low connection density, especially in areas such as big data analysis, graph algorithms and network optimization.

In the sparse network created in this study, units connect with 30 percent of the other units. Units also create a negative weight self-connection with themselves. The pseudocode of this connection pattern can be seen in Algorithm 5.

Algorithm 5 Sparse Network Connection Pattern

```
num_connections ← int(n_units × 0.3)
for unit in self.units do
    possible_targets ←
    list of units excluding the current unit
    connected_units ← random.sample(possible_targets,
    min(num_connections, len(possible_targets)))
    for target in connected_units do
        weight ← random value between − 1 and 1
        unit.add_connection(target, weight)
    end for
end for
for i ← 1 to n do
    self_weight ← −random value between 0.5 and 1.5
    unit_i connects to itself with weight self_weight
end for
```

2.1.6. Importance-Based Connectivity

In this connection pattern each unit is randomly assigned an importance score, which determines their connection probability. A number of connections based on a Poisson distribution is calculated for each unit, then these connections are randomly selected based on normalized probabilities. Additionally, negative weight self-connection is added to each unit to increase stability.

The working principle is more specifically as follows. First, an importance score is assigned to each unit and total scores are calculated. Then, a random number of connections is created for each unit using the Poisson distribution. Afterwards, the connection probabilities are normalized according to the importance score of the units. Each unit is connected to other units according to normalized probabilities. Finally, self-connections are added. The pseudocode of this connection pattern can be seen in Algorithm 6.

2.2. Experimental Setup

In this section, the experimental setups created to find out the success of connection patterns in different numbers of units are introduced.

The coding of the experiment was done with Python. Compiled in Visual Studio Code and run on Macbook Pro with M1 chip, 32GB RAM configuration. In this study, Sandbox simulation created by Chris Johnson was used to run homeostat simulations. Sandbox is the latest version of a simulation framework for agent-based modelling which Chris Johnson created for teaching the Adaptive Systems module at Sussex, in 2020 [15]. The networkX library was used to visualize the

Algorithm 6 Importance-Based Connectivity

$importance\_scores \leftarrow$ random scores for each unit
$total\_importance \leftarrow$ sum of importance scores
$connection\_probabilities \leftarrow \frac{importance\_scores}{total\_importance}$
$num\_connections \leftarrow$ random Poisson values
$num\_connections \leftarrow \text{clip}(num\_connections, 1, n\_units - 1)$
for *unit* in self.units **do**
  $possible\_targets \leftarrow$ units except current unit
  $normalized\_probabilities \leftarrow \frac{connection\_probabilities}{\text{sum of probabilities}}$
  $num\_conns \leftarrow$ connections per unit
  $weights \leftarrow \text{random.uniform}(-1, 1, \text{size} = num\_conns)$
  $connections \leftarrow$ random.choice(possible_targets, size =
  num_conns, normalized_probabilities)
  for *target* in *connections* **do**
    unit connects to target with random weight
  end for
end for
for $i \leftarrow 1$ to n **do**
  $self_weight \leftarrow -$random value between 0.5 and 1.5
  $unit_i$ connects to itself with weight $self\_weight$
end for

created connection patterns and to create the Barabási-Albert graph and Watts-Strogatz graph [16].

Four different experiments were conducted in this study. In the first experiment, the time it took for homeostats with different connection patterns to become stable in different numbers of units, that is, their adaptation time, was calculated. In the second experiment, the complexity of homeostats with different connection patterns in different numbers of units was calculated. In the third experiment, the robustness of homeostats with different connection patterns in different unit numbers was calculated. In the fourth and last experiment, impulse disturbance was applied to the homeostat and snapshots were taken at certain times to embody the adaptability of the homeostat.

The fixed variables in the experiments are as follows.

- Number of units : [4,5,6,7,8,9,10]
- Number of runs : 10
- dt = 0.01
- duration = 1000
- upper_viability = 1
- lower_viability = -1
- Adapting function = random_val
- upper_limit = 20
- lower_limit = -20
- m = 1
- k = 1
- l = 1
- p = 2
- q = 1
- test_interval = 10

2.2.1. Experiment-1

In this experiment , the time for the homeostat to return to stable state was calculated to compare the performance of connection patterns in different numbers of units. In this experiment, no disturbance was applied to the homeostat. All connection patterns were run 10 times on all unit numbers in the initially specified ”number of units” array and a graph was created with the average of the obtained values. Initially the homeostat was not stable.

2.2.2. Experiment-2

In this experiment, the complexity of the homeostat was calculated to compare the performance of connection patterns across different numbers of units. In this experiment, no disturbance was applied to the homeostat. All connection patterns were run 10 times on all unit numbers in the initially specified ”number of units” array and a graph was created with the average of the obtained values. When calculating the complexity of the connection patterns, the total number of connections in the system was calculated. In this experiment, initially the homeostat was not stable.

2.2.3. Experiment-3

In this experiment, the robustness of the homeostat was calculated to compare the performance of connection patterns across different numbers of units. In this experiment, impulse disturbance was applied to the homeostat at time 200 and the recovery time, that is, the time for the homeostat to become stable after this disturbance, was calculated. Impulse disturbance has been applied to one unit of the homeostat. All connection patterns were run 10 times on all unit numbers in the initially specified ”number of units” array and a graph was created with the average of the obtained values. In this experiment, the homeostat was initially stable.

2.2.4. Experiment-4

In this experiment, impulse disturbance was applied to one unit of a stable homeostat and snapshots of the homeostat were taken every 25 cycles. The purpose of this experiment is to see how a disturbance applied to one of the units will affect the other units, then to observe the units returning to a viable state and thus to discuss the adaptability of the homeostat in a more concrete way. In this experiment, fully connected pattern was used as the connection pattern and the homeostat was initially stable.

3. Results and Analyses

In this section, the results obtained from the experiments are shown in graphs and these results are analyzed.

Figure-1 shows the results obtained from Experiment-1, that is, the time taken for homeostats using different connection patterns to return to stable state in different numbers of units. When we look at the graph in general, it is clear that the fully connected pattern gives the worst result. Except for homeostats, which consists of 4 and 5 units, it could not become stable within the specified duration in any number of units. Secondly, it can be said that the Barabási-Albert model gives a better result than the fully connected pattern, but worse than the remaining patterns. When looking at the random connectivity pattern, it clearly seems to give a better result than the Barabási-Albert model, but it has a weaker performance than the remaining three connection patterns. However, the fact that Barabási-Albert and random connectivity patterns become stable within the given duration for all unit numbers can be perceived as a positive result. If we then analyze the sparse connectivity pattern. It can easily be said that it gives a very impressive performance in homeostats consisting of 4, 5 and 6 units. Although it is seen that it gives a superior result compared to fully connected, Barabási-Albert and random connectivity patterns in homeostats consisting of 7,8 and 9 units, it is seen to be behind importance-based connectivity pattern. Looking at these results, it can be said that the sparse connectivity pattern loses performance quickly when the complexity of the homeostat exceeds a certain level, and is the best option for homeostats with low complexity. If we then examine the Watts-Strogatz model, we can say that it generally performs worse than sparse connectivity and importance-based connectivity. However, it generally provides a more consistent performance than sparse connectivity in all unit numbers. Finally, when we analyze importance-based connectivity, it can be said that it performs worse than sparse connectivity at low unit numbers, but performs better at high unit numbers. Compared to Watts-Strogatz, it showed better performance except for the homeostat consisting of 6 units. In general, when looking at all connection patterns, the pattern that gives the most consistent performance is importance-based. In addition, the performance of importance-based connectivity in 10 units is very impressive.

In Figure-2, the results obtained from Experiment-2 are shown graphically. In this graph, the complexity of homeostats using 6 different connection models can be seen in different unit numbers. Looking at the graph in general, it can be seen that the most complex model is fully connected. Since each unit is connected to itself and other units, its complexity, that is, the total number of connections, is the square of the number of units. When looking at other connection patterns, it would be logical to examine the unit numbers specifically because it is almost impossible to make a best-worst analysis among these connection patterns by looking at the graph in general. It is clear that sparse connectivity is the least complex connection pattern for units 4, 5 and 6. Although the patterns except fully connected and sparse connectivity are very close to each other, it can be said that random connectivity with 4 units and Watts-Strogatz with 6 units are the least complex patterns after sparse connectivity. When the number of units increases to 7 or more, random connectivity has a more complex structure than all patterns except fully connected. Although the Barabási-Albert model is less complex than random connectivity, it is more complex than the other patterns. Sparse connectivity, Watts-Strogatz and importance-based connectivity have almost the same complexity at 7, 8 and 9 units. With only 9 units, importance-based connectivity has a slightly more complex structure. At the number of 10 units, Watts-Strogats and importance-based connectivity have the least complexity, and sparse connectivity has a slightly more complex structure. This data also supports the poor performance of sparse connectivity at 10 units, as seen in Figure-1 and Figure-3.

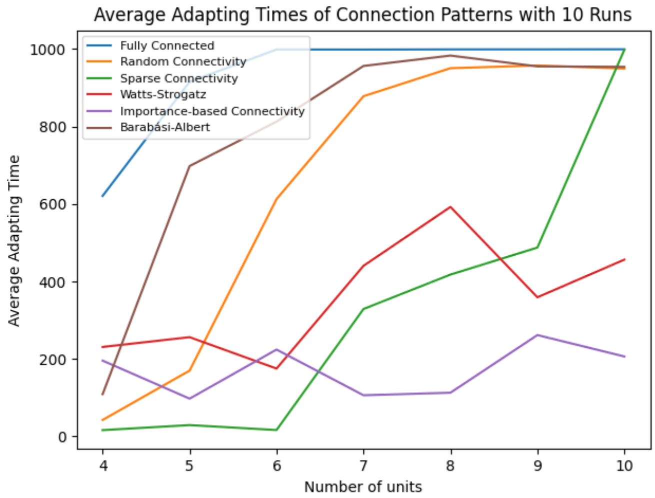


Figure 1: Average Adapting Times of Connection Patterns with 10 Runs

Figure-3 shows the graph created from the results obtained from Experiment-3. Looking at the graph, it can be seen that the fully connected connection pattern again gives the worst result. Only the homeostat consisting of 4 unit was able to return to stable state after the disturbance. The Barabási-Albert pattern is the worst performing pattern after fully connected. When the Barabási-Albert model and random connectivity are compared, it is seen that the random connectivity is more robust between 4 and 8 units, and the Barabási-Albert model is more robust at 9 and 10 units. Sparse connectivity performed best on homeostats with 4, 5, 6, 7 and 9 units. Watts-Strogatz managed to become stable after disturbance in all unit numbers, but its performance is generally worse than importance-based connection and sparse connection. Importance-based connection managed to become stable after the disturbance in all unit numbers. Although it gives worse performance than sparse connectivity in some unit numbers, it can be said that it gives a consistent and acceptable performance in general.

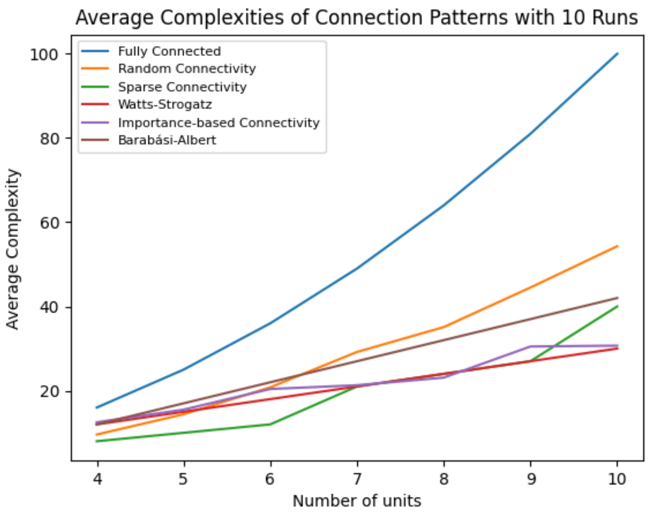


Figure 2: Average Complexities of Connection Patterns with 10 Runs

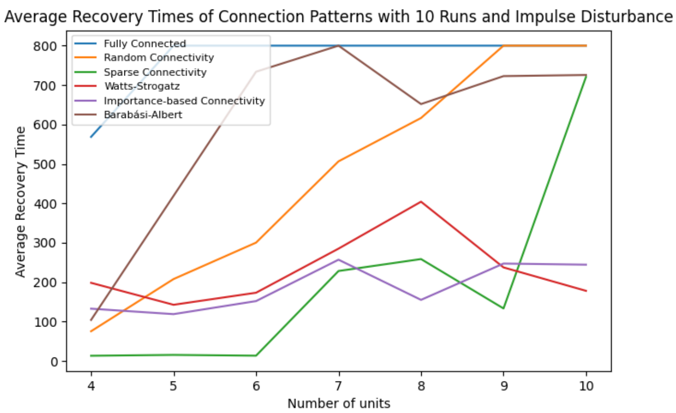


Figure 3: Average Recovery Times of Connection Patterns with 10 Runs

The graphs seen in Figure-4, Figure-5 and Figure-6 were obtained from the results of Experiment-4. Figure-6 shows snapshots taken at certain time intervals of a homeostat with a fully connected connection pattern with disturbance applied to a single unit. In Figure-6/a, the unit states of the homeostat before the disturbance is applied, and in Figure-6/b, the unit states after the disturbance is applied are shown. As we can see, the disturbance has been applied to Unit-0 and Unit-0 has left the viable state. Looking at Figure-6/c, the exit of a single unit from the viable state caused the other units to exit the viable state. The fact that all units of the homeostat are connected to each other plays an important role in this situation. This is less likely to occur with sparse connections. When we look at other graphs during the adaptation process of the homeostat, we can see that over time, some units came to the viable state and some units left the viable state, and as a result, all units entered the viable state between the moments t = 525 and t = 550. The weight changes of the units and the moments when they enter

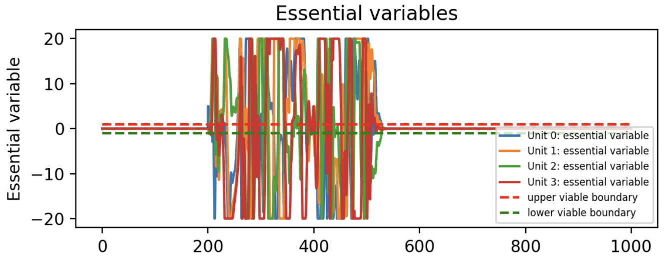


Figure 4: Fully Connected Homeostat Essential Variable Changes

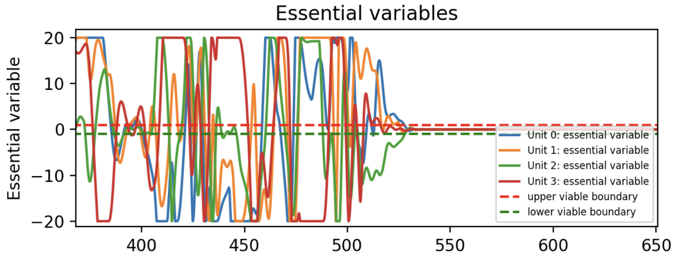
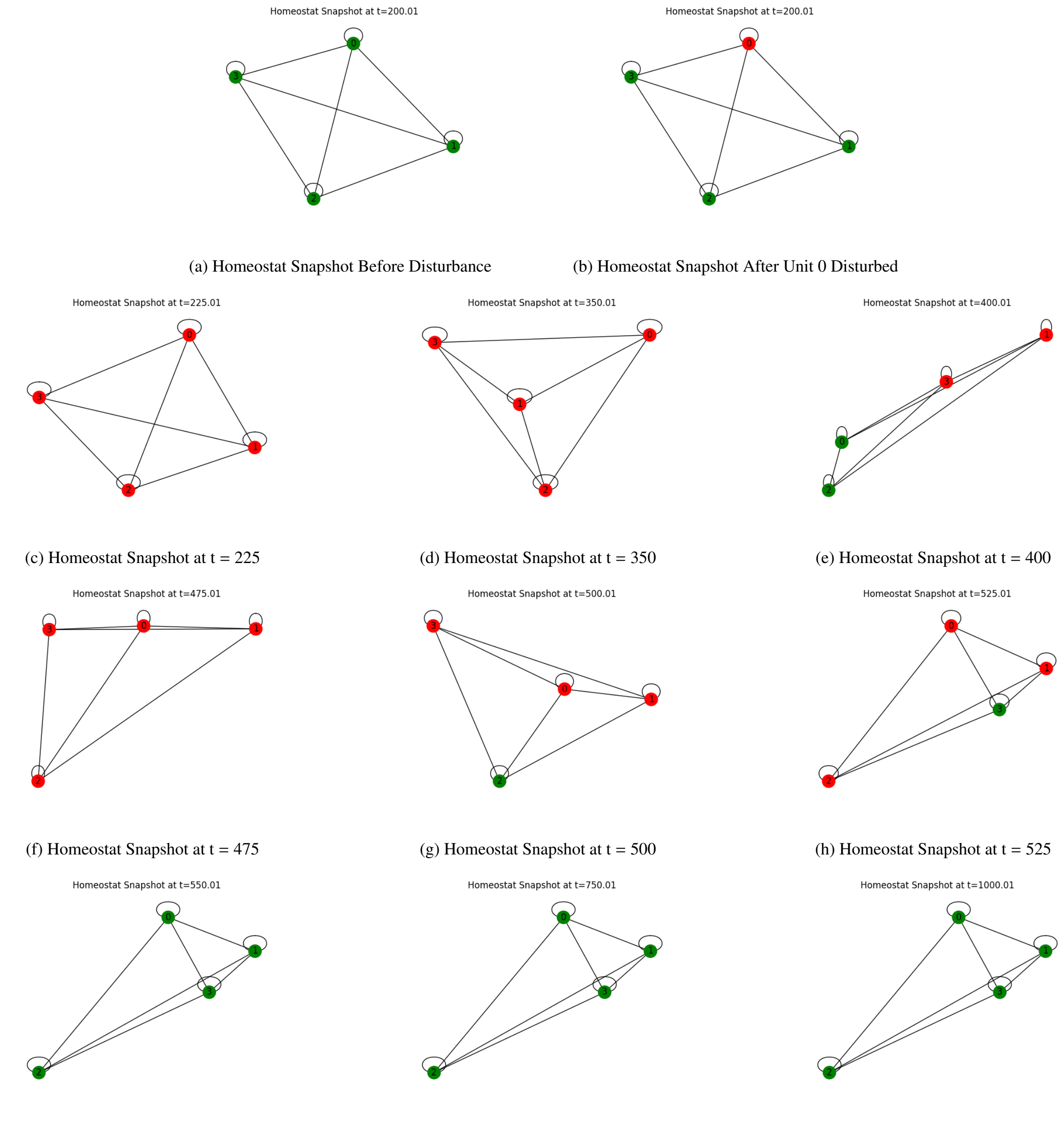


Figure 5: Fully Connected Homeostat Essential Variable Changes Closer

the viable state can also be seen in the graphs in Figure-4 and Figure-5.

It is possible to draw the following conclusions from all these analyses. There appears to be a negative correlation between complexity and robustness and a positive correlation between complexity and adaptation time. In other words, as complexity increases, robustness decreases and as complexity increases, adaptation time increases. In general, looking at this result, it would not be wrong to say that a simpler connection pattern will give better performance than a complex connection pattern. As can be seen in the graphs, there are exceptions to this. For example, the homeostat using sparse connectivity could never become stable within 10 units, 10 runs, and the given duration. Or, in number of 9 units, importance-based connectivity has a slightly more complex structure than the Watts-Strogatz model, but the homeostat using importance-based connectivity has become stable in a shorter time. However, these examples do not reflect the general situation of the system and are only exceptional cases.

When the connection patterns are compared in the light of these results, it is possible to say that the fully connected pattern is the most inefficient pattern, considering that it gave the worst results in all experiments. When random connectivity and the Barbasi-Albert model are compared together, it can be seen that random connectivity is generally more robust and has less adaptation time. Although it has a more complex structure than the Barabási-Albert model for 7 and more units, it would be more logical to use the random connectivity model when it is necessary to make a choice between the two. When the remaining 3 best-performing connection patterns are examined, sparse



(a) Homeostat Snapshot Before Disturbance
(b) Homeostat Snapshot After Unit 0 Disturbed
(c) Homeostat Snapshot at t = 225
(d) Homeostat Snapshot at t = 350
(e) Homeostat Snapshot at t = 400
(f) Homeostat Snapshot at t = 475
(g) Homeostat Snapshot at t = 500
(h) Homeostat Snapshot at t = 525
(i) Homeostat Snapshot at t = 550
(j) Homeostat Snapshot at t = 750
(k) Homeostat Snapshot at t = 1000

Figure 6: Homeostat Snapshots

connectivity stands out as the most efficient connection pattern in the number of 4 - 6 units and it is obvious that importance-based connectivity is the best performing pattern in the numbers of 7,8,9 and 10 units. Although the sparse connectivity model in 7 and 9 units and the Watts-Strogatz model in 10 units are a little more robust than the importance based connectivity, the adaptation time of the importance-based connectivity is much lower than other models and it would be logical to choose the importance-based connectivity. Watts-Strogatz model showed good performance in all number of units but it was not the pattern that gave the best performance in any number of units among the connection patterns selected in this study.

4. Discussion

In my definition of adaptability at the beginning of this report, I said that adaptability is the ability to maintain or restore equilibrium by responding to environmental conditions or internal changes. Looking at the results obtained from the experiments, it is seen that when a disturbance is applied to a homeostat with any connection pattern, that is, when an internal change occurs, all its units tend to go into viable boundries and act in accordance with this definition. However, although homeostats with all connection patterns discussed in this report meet this definition, not every connection pattern can achieve this purpose with the same efficiency. Considering the results obtained from the experiments, it is generally seen that it is more difficult for connection patterns with more complex structures to restore equilibrium, respond to internal changes and maintain equilibrium compared to simpler structures. However, if we consider that increasing the number of units of the homeostat automatically increases the complexity of the pattern, it would not be wrong to say that it becomes more difficult to restore and maintain equilibrium as the number of units increases.

Neuroplasticity is the functional and structural alterations in the brain that enable adaptation, learning, memory, and rehabilitation after brain injury [13]. The results obtained in this study can also be associated with the neuroplasticity feature of the brain. Restoring equilibrium after disturbance can be likened to neuroplasticity repairing itself after brain damage, or the functions that occur in the brain while learning something new can be likened to the homeostat changing the weights between units as it becomes stable. In addition, although the brain has a very complex structure, the fact that its adaptation speed is so high proves that much better results than the results obtained in this study can be achieved with a pattern similar to the connection pattern of the brain. In particular, more successful connection patterns can be created by taking inspiration from the brain's ability to create new connections and change connections.

In this study, six different connection patterns were used and compared. In future studies, the study can be further expanded by using connection patterns such as Modular Networks and Hierarchical Networks. Modular networks have dense and strong connections between nodes within the module and weaker and sparser connections between nodes in different modules. This structure allows modules to work independently and communicate with other modules when necessary. This structure ensures that other modules are minimally affected by disturbances within the modules and can produce a more robust result with higher adaptation potential. Also Meunier et al. (2010) [14] examined the impact of modular networks on brain functions and plasticity and noted that brain networks and many other complex systems exhibit hierarchical modularity or modularity at several topological scales. This shows that modular structures can provide successful results in complex networks. The use of hierarchical networks may also make sense in terms of the stability and efficiency of the system. Hierarchical networks are one of the examples of scale-free networks. It consists of top-level nodes and bottom-level nodes. This structure actually provides modularity to the network. Lower-level nodes can complete their tasks without ever communicating with higher-level nodes and can communicate with higher-level nodes when necessary. In this way, higher-level nodes can act as a buffer against disruptions in lower-level nodes and increase the stability of the system. In addition, it can be investigated whether using these connection patterns together in more complex systems will yield better results, and different adaptation functions that will increase performance can be studied. Finally, the most optimal connection densities of connection patterns can be investigated.

The results obtained from the systems and experiments created in this study can generally be used in all areas involving complex networks. The adaptation times of different connection patterns tried, their robustness, and the correlations of these parameters with complexity may help research in other fields. A clear view of how the system adapts can help understand how neural networks in the brain, such as gene regulatory networks and protein interaction networks, adapt. At the same time, information such as adaptation times and robustness can contribute to the understanding of functions in the brain such as learning and memory and to the understanding of diseases in the nervous system. In addition, it can contribute to studies in the fields of artificial intelligence and machine learning. Considering that adaptive networks play a very important role in the fields of artificial intelligence and machine learning, it is very critical that the adaptation speed of complex systems consisting of these networks be optimized and have a robust structure. This study can also provide insight into the selection of connection patterns of these networks. In addition to these areas, it can also be used in areas such as social networks and financial systems.

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