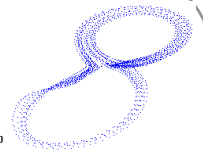
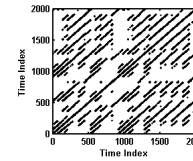


# Self-organized Topology of Recurrence-based Complex Networks

Gang Liu  
Hui Yang, Ph.D.

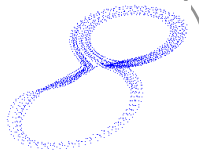
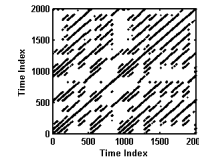
**Industrial & Management Systems Engineering**  
**University of South Florida**

# Relevant Publications



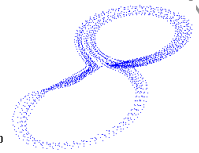
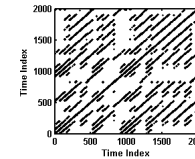
- ❑ **H. Yang\*** and G. Liu<sup>†</sup>, “Self-organized topology of recurrence-based complex networks,” *Chaos: An Interdisciplinary Journal of Nonlinear Science*, Vol. 23, No. 4, p043116, 2013, DOI: [10.1063/1.4829877](https://doi.org/10.1063/1.4829877)
- ❑ G. Liu<sup>†</sup> and **H. Yang\***, “Self-organizing network for group variable selection and predictive modeling,” *Annals of Operations Research*, 2017. DOI: [10.1007/s10479-017-2442-2](https://doi.org/10.1007/s10479-017-2442-2)
- ❑ C-B. Chen<sup>†</sup>, **H. Yang\***, and S. Kumara, “Recurrence network modeling and analysis of spatial data,” *Chaos: An Interdisciplinary Journal of Nonlinear Science*, Vol. 28, No. 8, p085714, 2018, DOI: [10.1063/1.5024917](https://doi.org/10.1063/1.5024917).
- ❑ G. Liu<sup>†</sup> and **H. Yang\***, “Self-organized recurrence networks,” *Proceedings of 2014 Industrial and Systems Engineering Research Conference (ISERC)*, May 31, 2014, Montreal, Quebec, Canada. (**Best Paper Award in Computer and Information Systems Track**)

# Outline



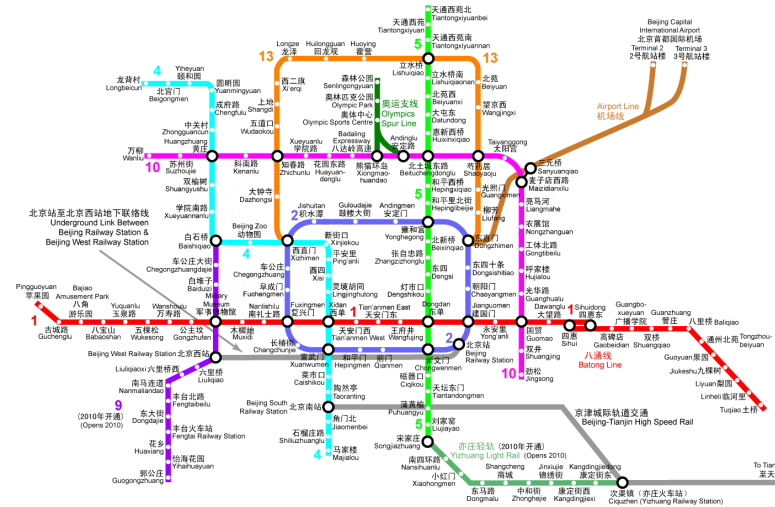
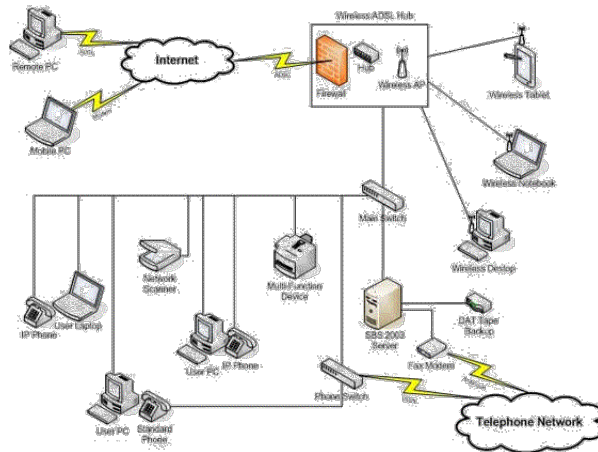
- ❑ Introduction
- ❑ Recurrence-based complex networks
- ❑ Force-directed recurrence networks
  - Spring-electrical model
  - Minimal-energy network
- ❑ Materials and experimental design
- ❑ Experimental results
- ❑ Conclusions

# Introduction



## Physical Network Analysis

### Known physical topologies

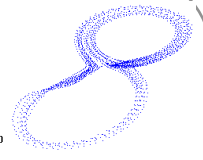
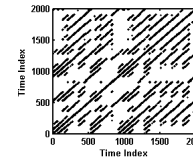


### Network representation – The adjacency matrix $A$ is a means of representing which nodes of a network are adjacent to other nodes.

$$A_{ij} = \begin{cases} 1, & \text{node } i \text{ and node } j \text{ are linked} \\ 0, & \text{otherwise} \end{cases}$$

### Network Statistics – statistical quantification of physical networks.

*Can we derive the physical topology from an adjacency matrix?*



## □ Background

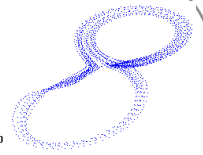
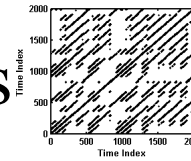
- Recurrence-based networks – investigate recurrence characteristics of dynamical systems from the perspective of *network theory*.
- Network-theoretic measures – new means to characterize the complexity of a nonlinear dynamical system.

## □ Gaps

- Most previous works focus on deriving the adjacency matrix to represent the complex network and extract network-theoretic measures.
- From the same adjacency matrix, the geometry/topology of a complex network can take variable forms.

## □ Objectives

- To develop a self-organizing approach to *derive the unique and steady geometric structure of a network from the adjacency matrix*
- To investigate the *factors affecting this self-organizing process*



## ❑ $K$ -nearest Neighbor Network

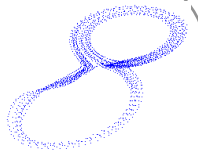
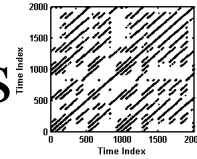
- Directed network
- Each node is connected to  $k$  nearest nodes in the network
- A fixed number of neighbors

## ❑ Recurrence Network

- Undirected network
- Each node may have a different number of links in the network
- A fixed size of the neighborhood

## ❑ Other Approaches

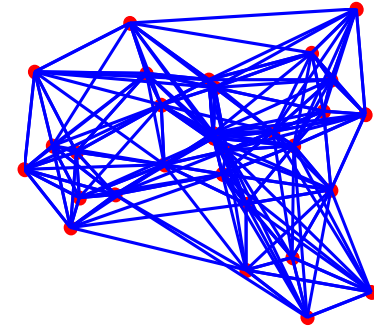
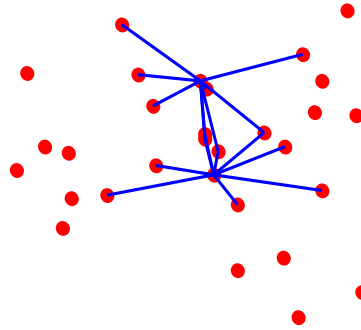
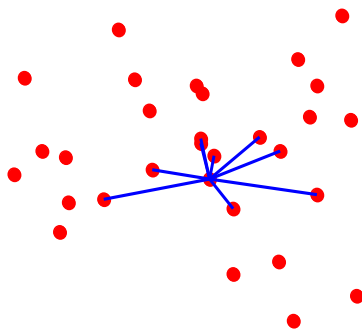
- Transition networks [Nicolis, 2005], cycle networks [Zhang, 2006], correlation networks [Yang, 2008], Visibility graphs [Lacasa, 2008].
- Donner, Marwan, *et. al* show that recurrence networks yield a unifying framework to transform nonlinear time series into complex networks.

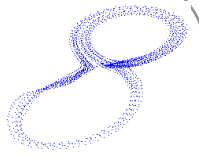
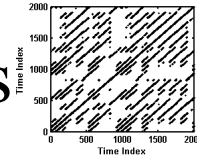


## □ K-nearest Neighbor Networks [Small, 2008]

- Given a time series:  $X = \{x_1, x_2, \dots, x_N\}^T$
- State space reconstruction:  $\mathbf{x}(i) = (x_i, x_{i+\tau}, \dots, x_{i+\tau(M-1)})$   
 $M$  is embedding dimension and  $\tau$  is time delay
- A node  $\mathbf{x}(i)$  is connected to its  $k$  nearest neighbors, but excluding the nodes in the same strand of the trajectory.

$$A_{ij} = \begin{cases} 1, & |j - i| > \Delta t \text{ \& } j \in \{k \text{ nearest neighbors of } i\} \\ 0, & \text{otherwise} \end{cases}$$





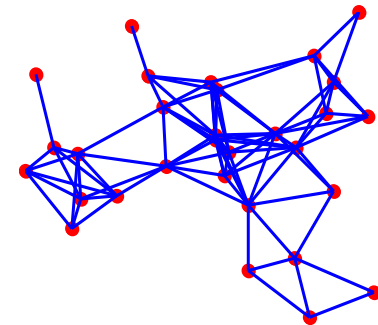
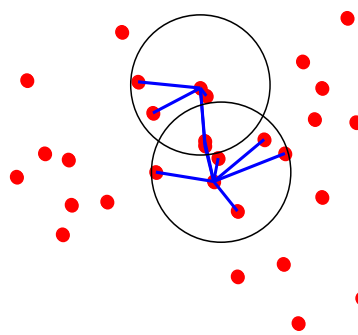
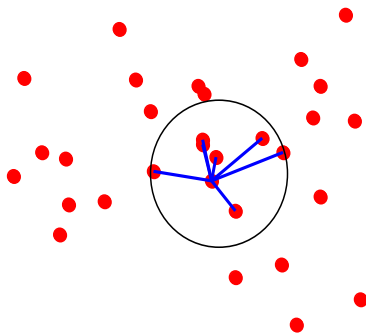
## □ Recurrence Networks [Marwan, 2008]

- Given a time series:  $\mathbf{X} = \{x_1, x_2, \dots, x_N\}^T$
- State space reconstruction:  $\mathbf{x}(i) = (x_i, x_{i+\tau}, \dots, x_{i+\tau(M-1)})$

$M$  is embedding dimension and  $\tau$  is time delay

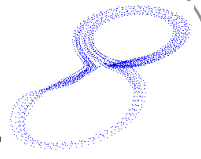
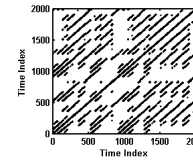
- The recurrences are treated as links in the network
- The adjacency matrix  $A$  is obtained from the recurrence matrix by removing the diagonal identities:

$$A_{i,j} = R_{i,j} - I_{i,j}$$





# Network-theoretic Measures



- Node degree  $k_i$  – the number of neighboring nodes of node  $i$

$$k_i = \sum_{j=1}^n A_{ij}, n \text{ is the number of nodes}$$

- Link density  $\rho$  – the ratio of the number of edges to the number of possible edges

$$\rho = \frac{1}{n(n-1)} \sum_{i,j=1}^n A_{ij}$$

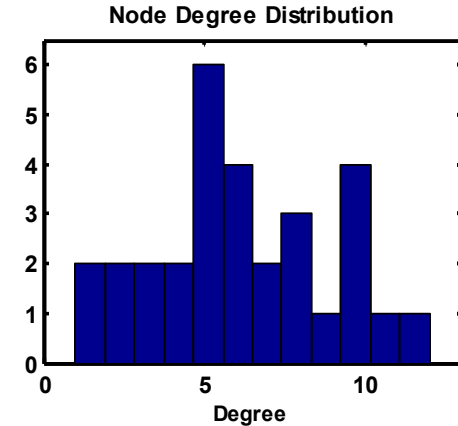
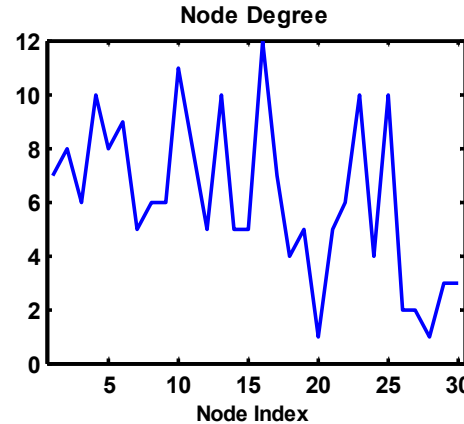
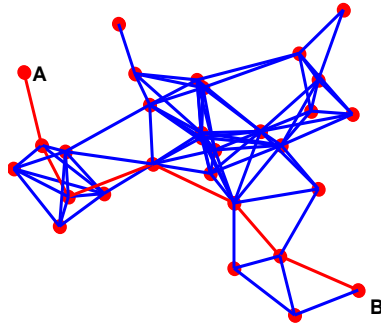
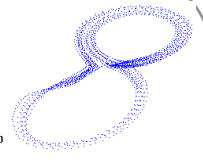
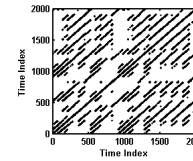
- Distance  $d_{i,j}$  – the minimal number of edges to travel from node  $i$  to node  $j$
- Average path length  $L$  – the average of all paired distances

$$L = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n d_{i,j}$$

- Diameter  $D$  – the longest of all shortest paths,  $D = \text{Max}\{d_{i,j}\}$
- Clustering coefficient of a node – the probability that two neighbors of a node  $i$  are also neighbors.

*Note that most of the metrics are calculated from the adjacency matrix*

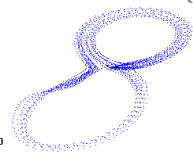
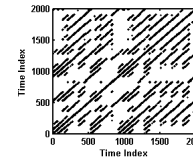
# Network-theoretic Measures



- The distance between node A and B is 6 - **# of links**.
- The average path length is 2.3210
- The clustering coefficients: 90.48% (node 1), 0 (node 20), 100% (node 27)
- The average clustering coefficient for the network: 62.71%

Network-theoretic measures – **actual node-to-node distances?**

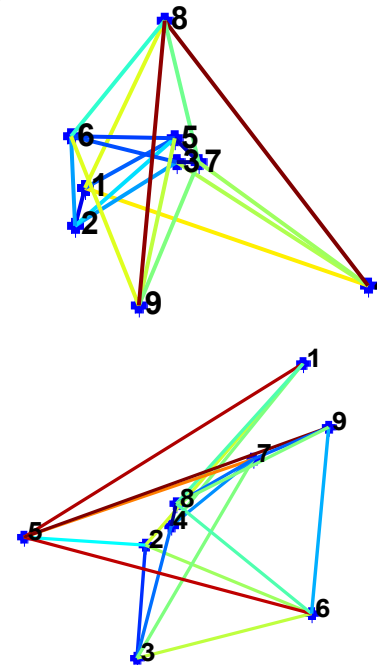
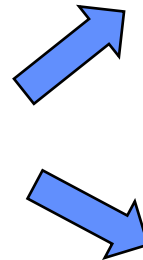
***How to derive the network topology from an adjacency matrix?***



## □ Adjacency Matrix → Network Topology

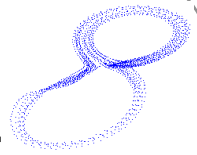
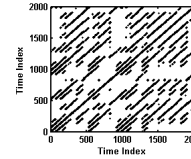
- From a recurrence adjacency matrix, we have a variety of possible topological structures for the network.

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$



?

- Is there a unique and stable topological structure for a recurrence-based network?



## □ Spring-electrical Model

- Nodes – electrically charged particles
- Edges – springs between nodes
- Note that **the repulsive force** exists between any pair of nodes  
**the attractive force** exists only between neighboring nodes



$$\text{Repulsive force: } f_r(i, j) = -\frac{CK^{1+p}}{\|x(i) - x(j)\|^p}, i \neq j$$



$$\text{Attractive force: } f_a(i, j) = \frac{\|x(i) - x(j)\|^2}{K}, i \leftrightarrow j$$

- Combined force at a node  $i$ :

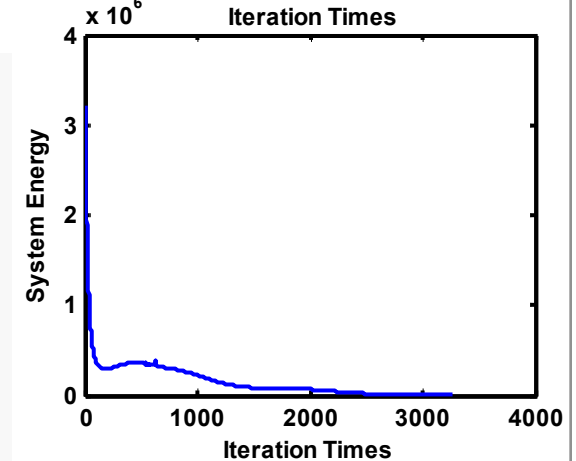
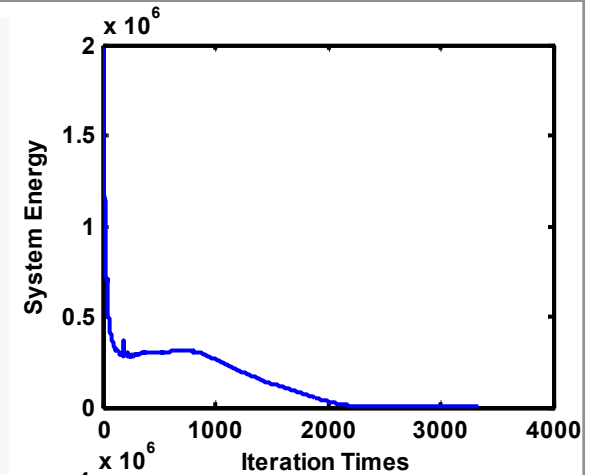
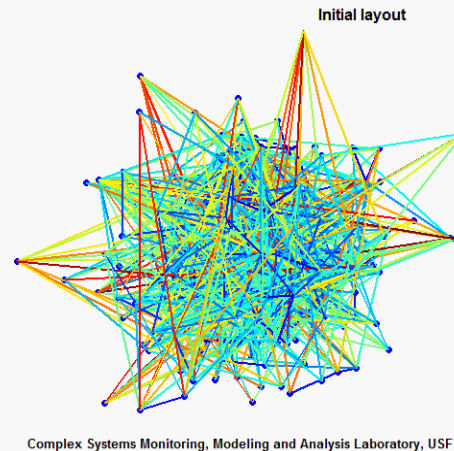
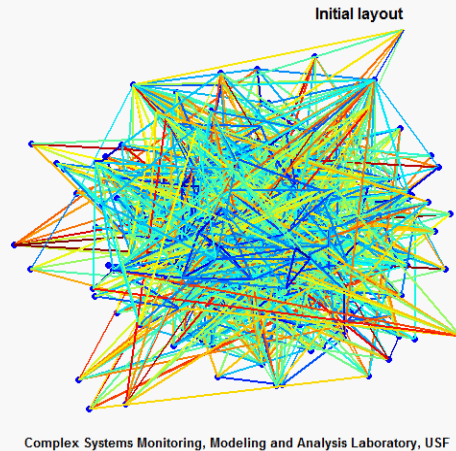
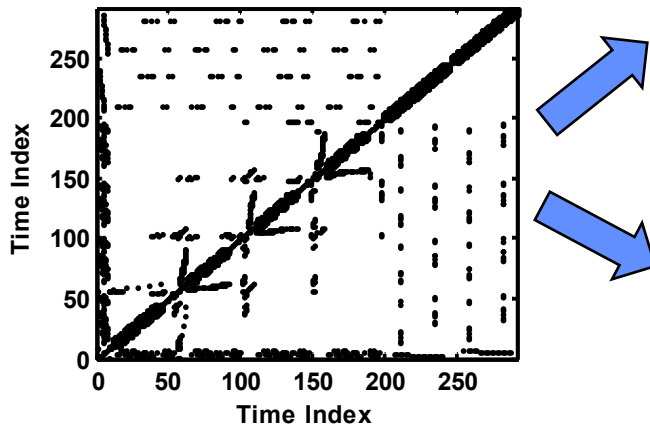
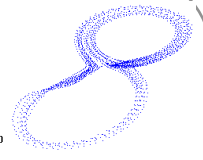
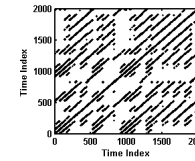
$$f(i, x, K, C)$$

$$= \sum_{i \neq j} -\frac{CK^{1+p}}{\|x(i) - x(j)\|^{p+1}} (x(i) - x(j)) + \sum_{i \leftrightarrow j} \frac{\|x(i) - x(j)\|}{K} (x(i) - x(j))$$

- Minimal Energy Network:

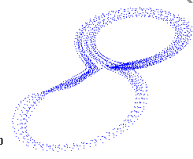
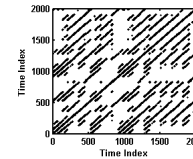
$$\min_{\tilde{x}} \{Energy_{se}(x, K, C)\} = \min_{\tilde{x}} \left\{ \sum_i f^2(i, x, K, C) \right\}$$

# An Example



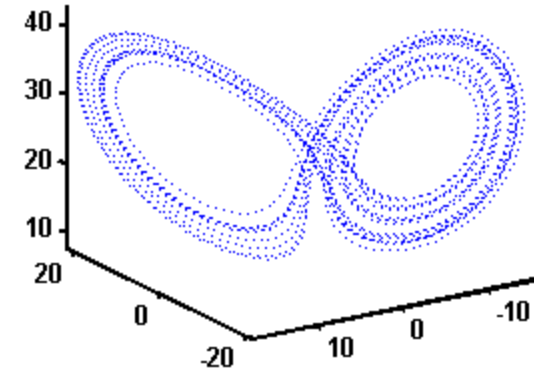
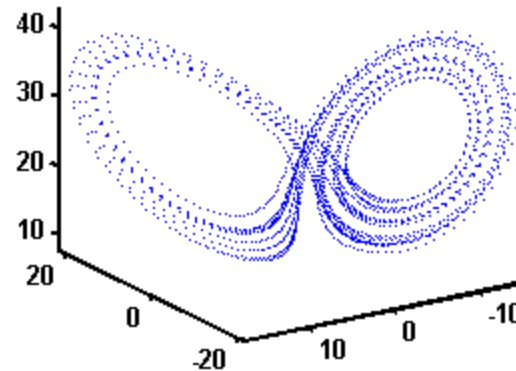
- For an adjacency matrix, the self-organizing approach yields a unique and stable network topological structure by minimizing the system energy, even from different initial settings.

# Nonlinear Dynamical Systems



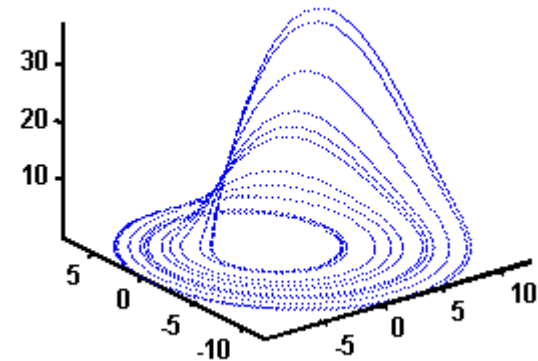
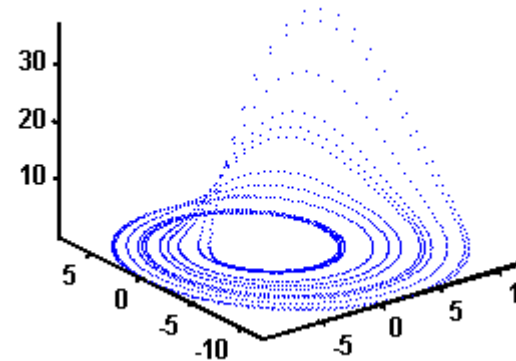
□ Lorenz system:

$$\begin{cases} x' = 10(y - x) \\ y' = x(28 - z) - y \\ z' = xy - 8z/3 \end{cases}$$



□ Rossler system:

$$\begin{cases} x' = -y - z \\ y' = x + 0.2y \\ z' = 0.2 + z(x - 5.7) \end{cases}$$

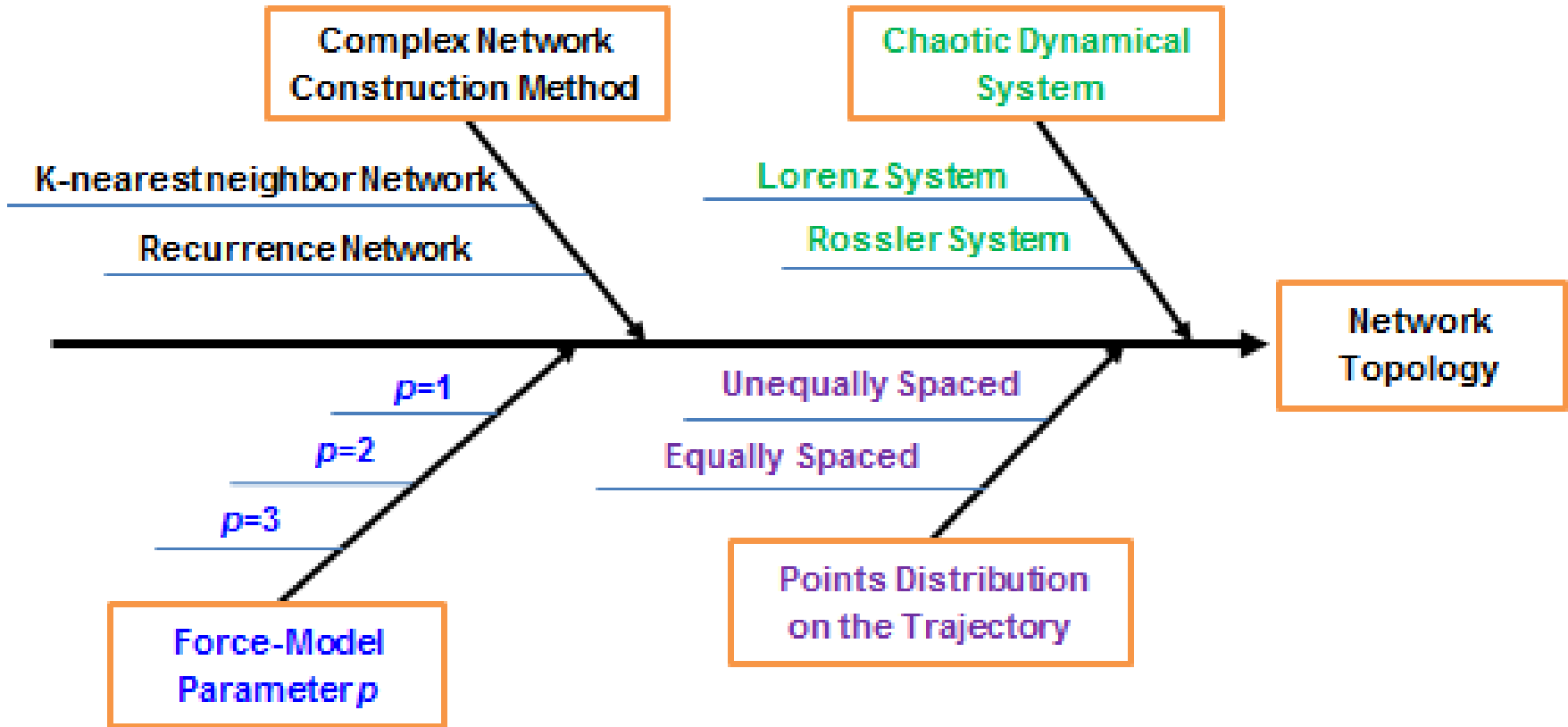
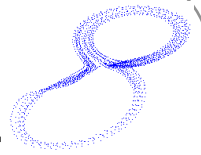
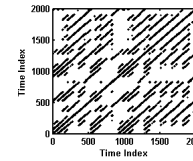


□ Continuous dynamical systems

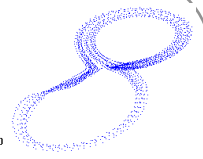
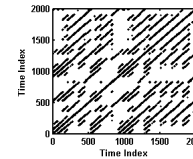
□ Discrete sampling

*Attractors with states unequally and equally spaced*

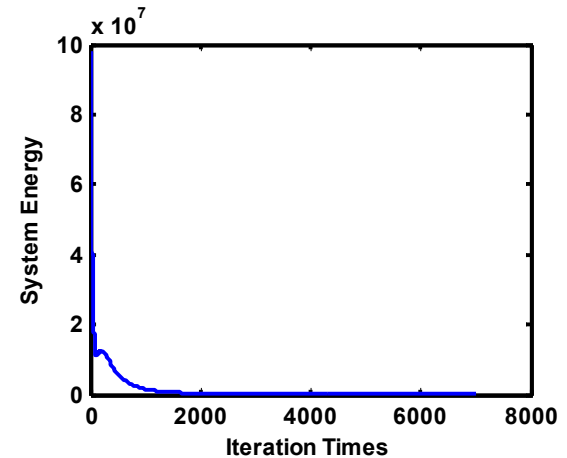
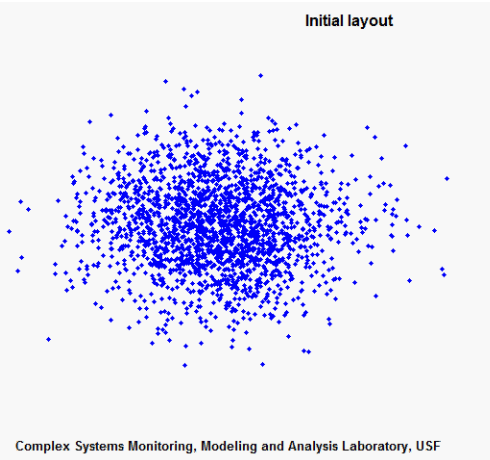
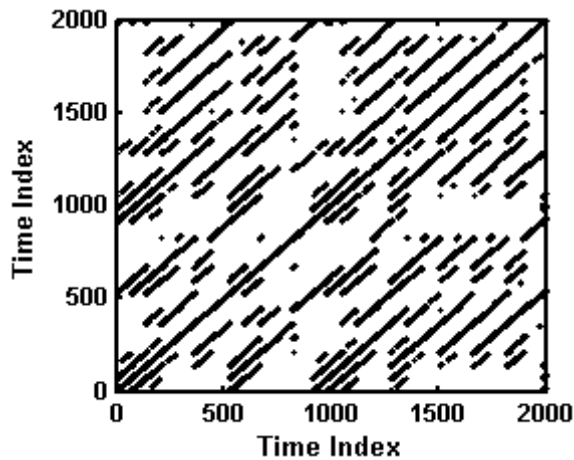
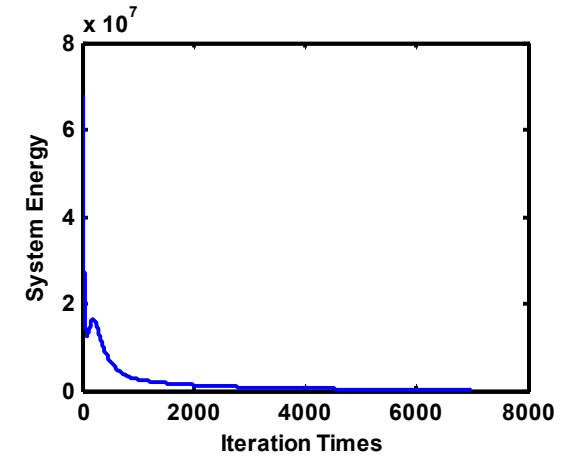
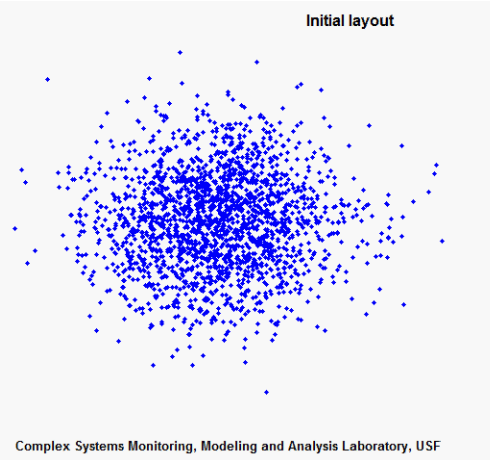
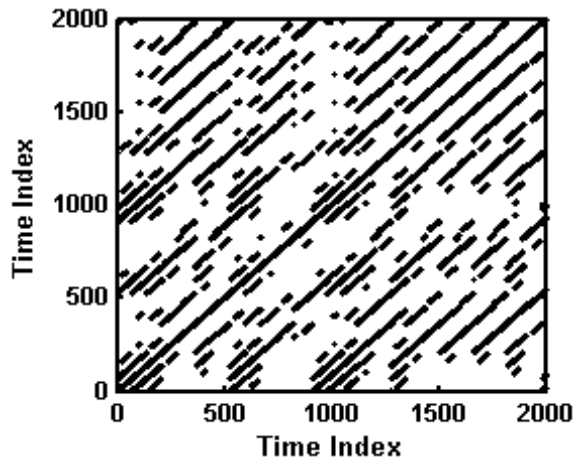
# Experimental Design



# Experimental Results

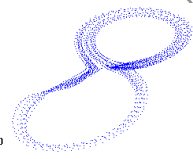
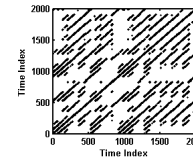


## □ *KNN Network vs. Recurrence Network* (Lorenz system)

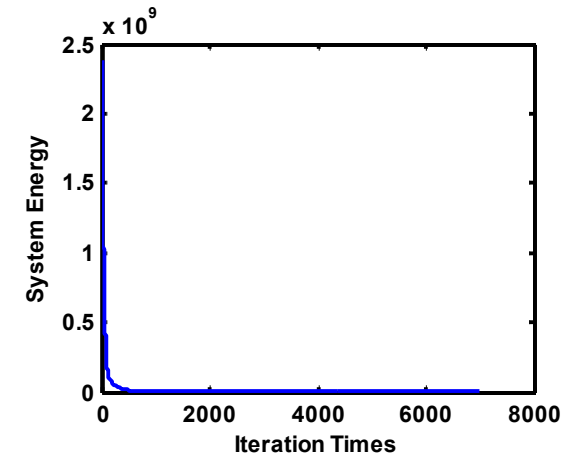
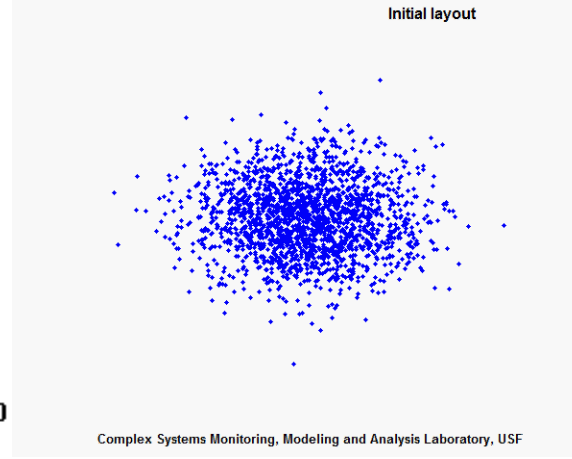
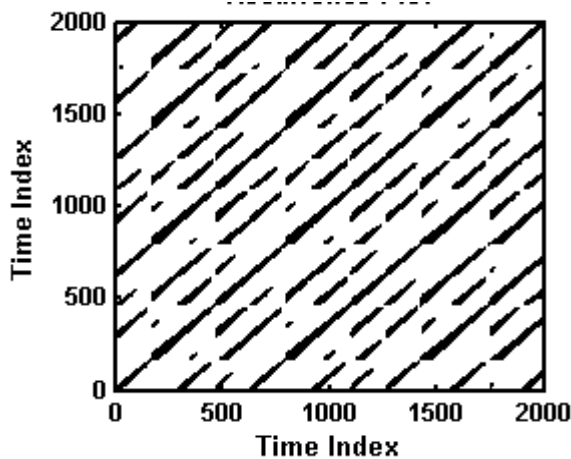
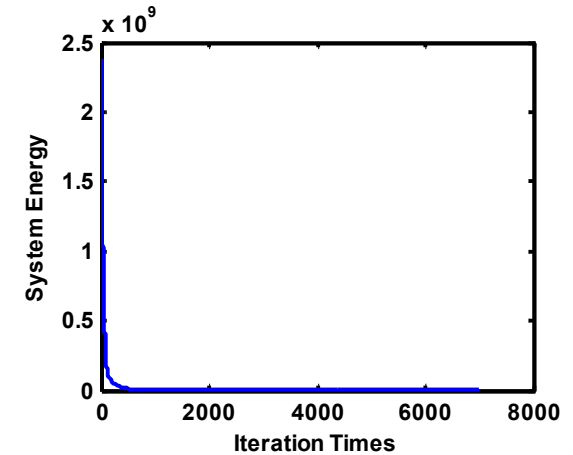
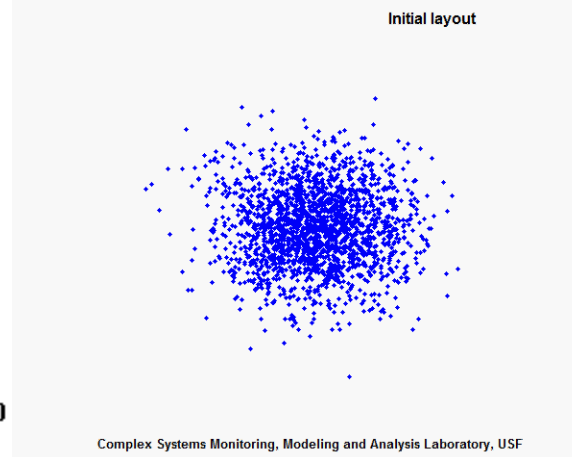
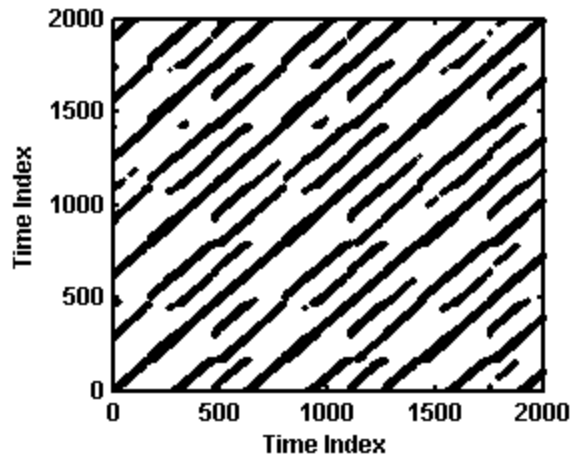




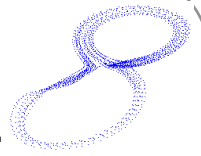
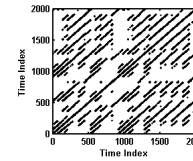
# Experimental Results



## □ *KNN Network vs. Recurrence Network* (Rossler system)

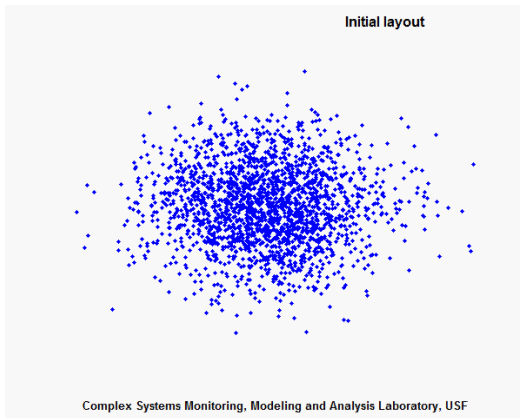


# Experimental Results

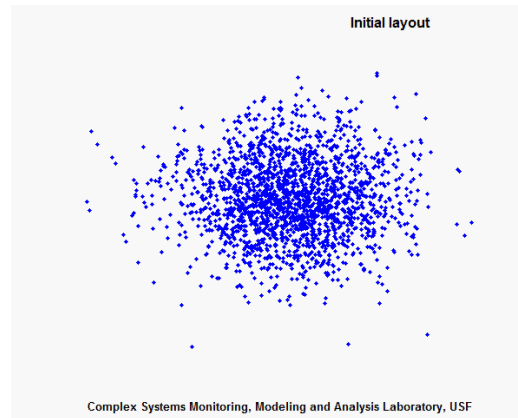


□ *Force-model parameter*  $p = 1, 2, 3?$

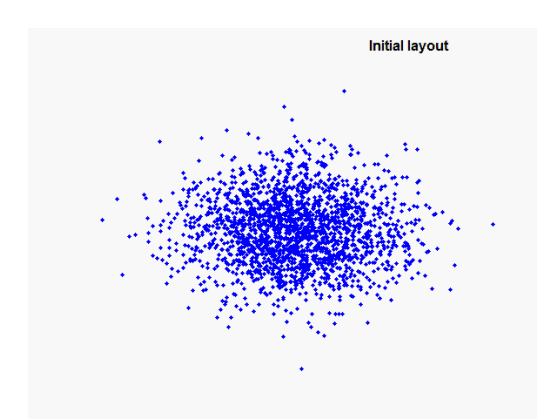
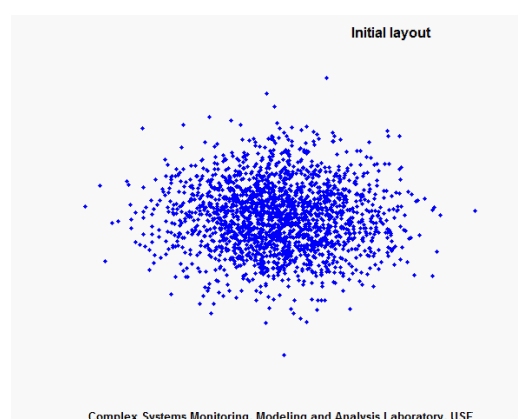
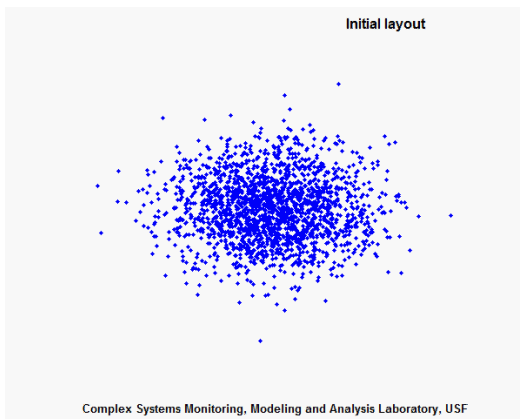
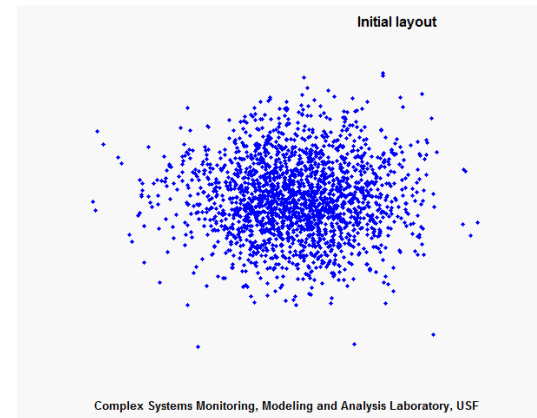
$p = 1$



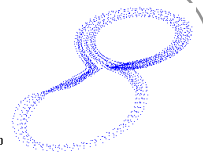
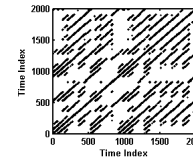
$p = 2$



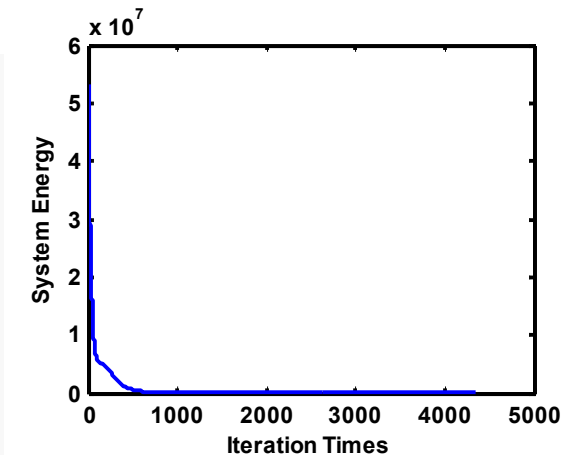
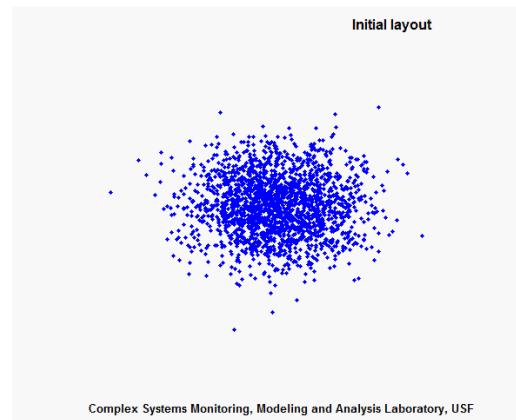
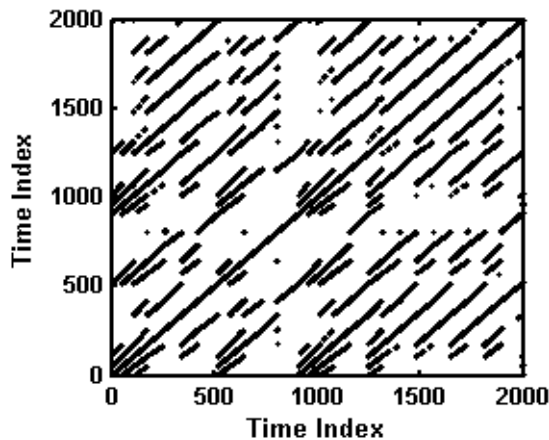
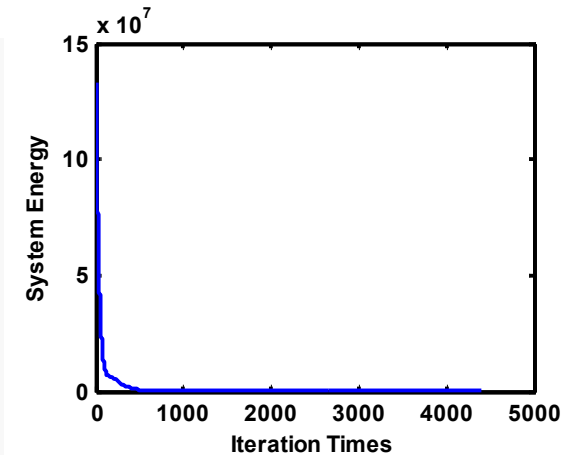
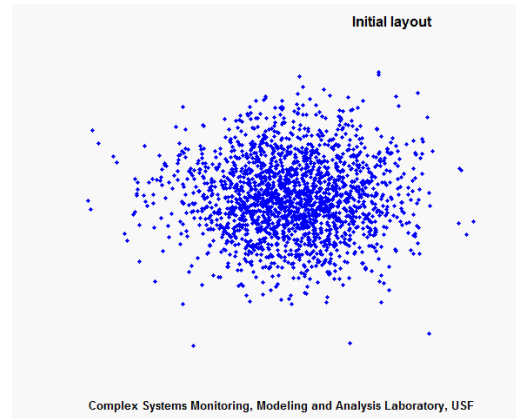
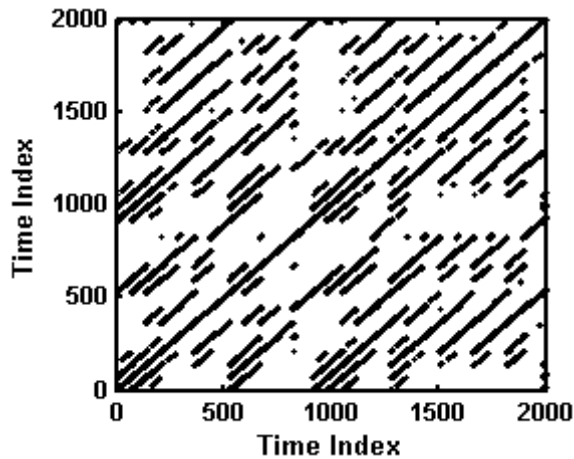
$p = 3$



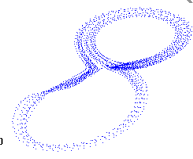
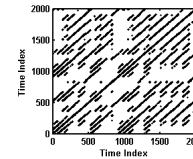
# Experimental Results



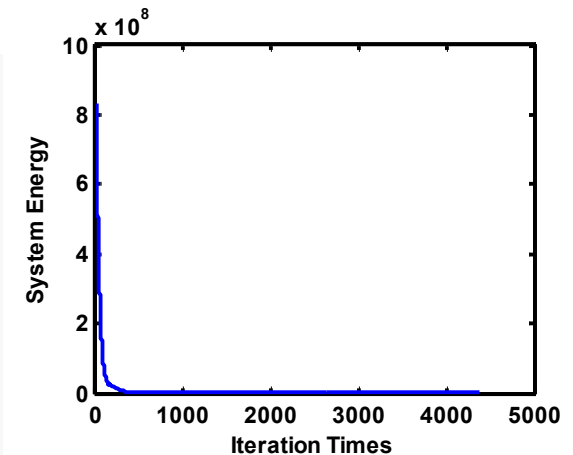
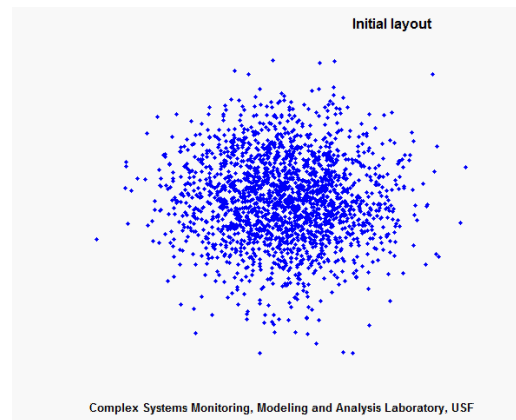
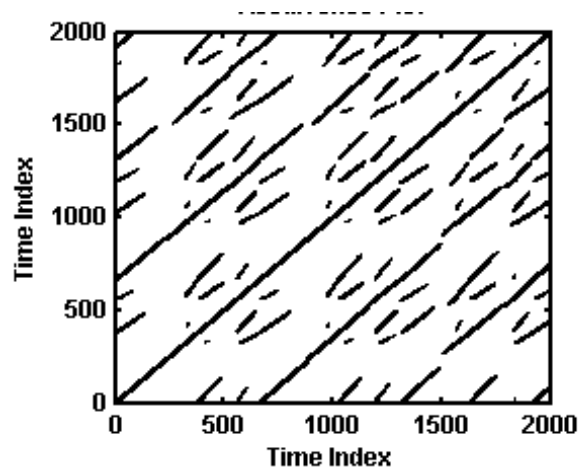
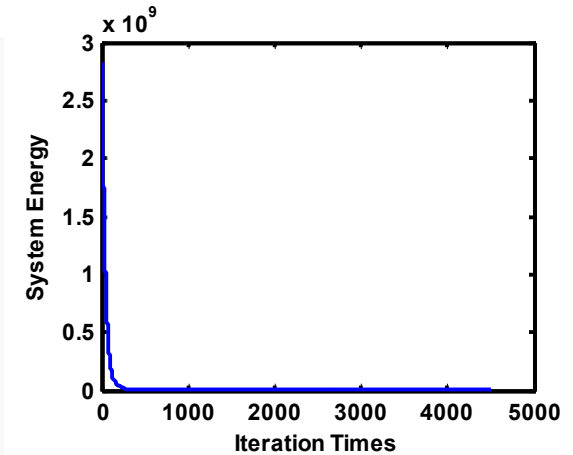
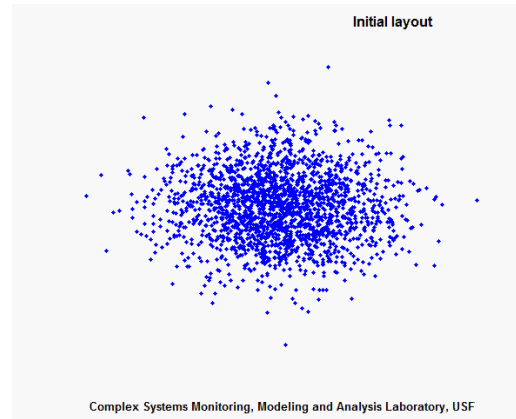
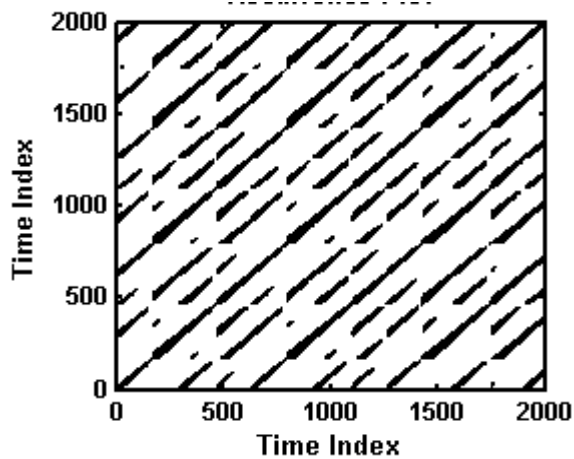
## □ *Unequally-spaced vs. equally-spaced* (Lorenz)



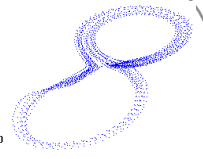
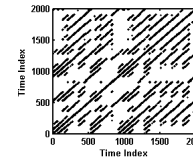
# Experimental Results



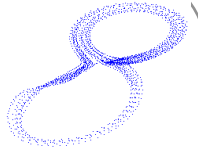
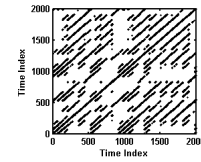
## □ *Unequally-spaced vs. equally-spaced* (Rossler)



# Conclusions



- ❑ Interestingly, the self-organizing geometry of a recurrence network recovers the attractor of the dynamical system.
  - Disclose the geometry of a recurrence network.
  - Provide a new way to reproduce the attractor or time series from the recurrence-based adjacency matrix.
- ❑ Important factors affecting the self-organizing process
  - *Network construction method* - The recurrence network shows a better performance to reconstruct the system dynamics.
  - *Force-model parameter  $p$*  - If the force-model parameter  $p$  is too small, the peripheral nodes tend to tightly cluster. Otherwise, the peripheral nodes are loosely distributed.
  - *Discrete Sampling* - Aliasing effects in the self-organized topology due to the distribution of sparse states in some local regions (e.g., the outer parts of the Rossler attractor). The self-organizing process performs better than the unequally-spaced attractors



END  
Questions?