Manuscript Title:
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Third institution, the second for Charlie Author

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(CLEO Collaboration)
(Dated: April 17, 2020)

An article usually includes an abstract, a concise summary of the work covered at length in the main body of the article.

Usage: Secondary publications and information retrieval purposes.

Structure: You may use the `description` environment to structure your abstract; use the optional argument of the `\item` command to give the category of each item.

I. INTRODUCTION

II. METHOD

A. Graph Generalization

Talk about how to map the original nanowire network on to a graph. Cite Zdenka here.

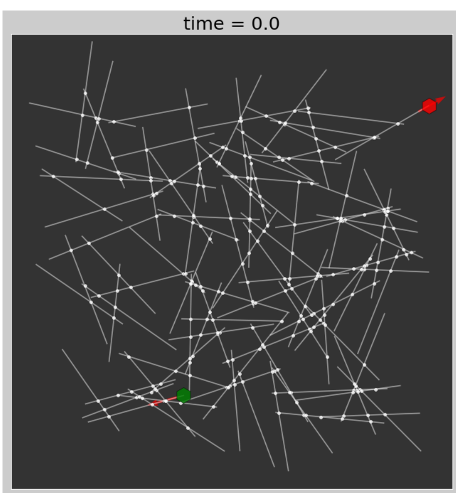

FIG. 1.

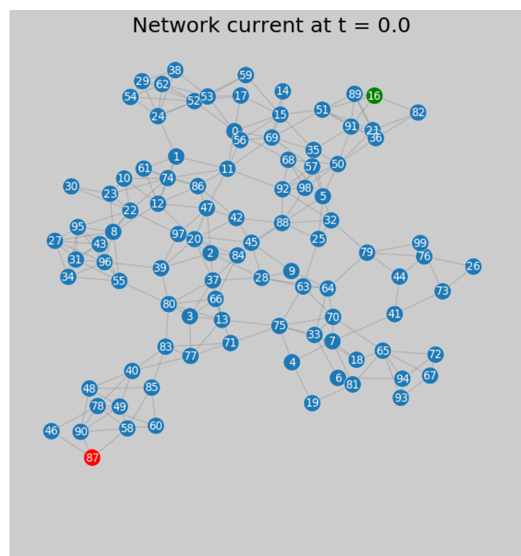

FIG. 2.

B. Simulation

When connected to external voltage biases, nanowire networks behave like traditional electrical networks. Each component in the network obeys Kirchhoff's law. Hence the voltage distribution across the network can be obtained by solving [1]:

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$$\mathcal{L}^{\dagger} V = I, \tag{1}$$

where $\mathcal{L}^{\dagger}$ is the expanded graph Laplacian of the network, composed as:

$$\mathcal{L}^{\dagger} = \left[\begin{array}{c|c} \mathcal{L} & C \\ \hline C^T & \mathbb{0} \end{array}\right], \tag{2}$$

in which $\mathcal{L}$ is the graph Laplacian and C represents the nodes (wires) connected to external electrodes.

$$\mathcal{L} = D - W. \tag{3}$$

Here W is the weighted adjacency matrix of the network. The weights on edges are determined based on their conductance:

$$W_{ij} = A_{ij} G(i,j). \tag{4}$$

And D is the weighted degree matrix generated from W:

$$d_i = \sum_{k=1}^{N} W_{i,k}, \tag{5}$$

$$D = \mathbf{diag}(d_i). \tag{6}$$

C. Centrality

Centrality **Put some reference here** is an important measure that helps understand the fundamental structures and connectivities of networks. Betweenness centrality of nodes and edges in networks can demonstrate .... Meanwhile, closeness centrality of nodes can be used to interpret the ..... [2].

A variation of centrality measures based on current flow model proposed by Brandes and Fleischer [3] is employed here. As the electrical dynamics in our networks fall in the class of **random walks** (not sure about here).

The betweenness centrality of a edge in the networks can be determined by:

$$c_{CB}(e) = \frac{\sum\limits_{s \neq t \in V} \tau_{st}(e)}{(n-1)(n-2)}, \tag{7}$$

where $\tau_{st}(e)$ is the current flow through edge e between nodes s and t, while n stands for number of nodes in the network.

The closeness centrality of a node in this context is structured in the same way as normal closeness centrality, with distance measured based on effective resistance rather than graphical distance. Therefore it is given by:

$$c_{CC}(v) = \frac{n-1}{\sum\limits_{v \neq w \in V} R(v,w)}. \tag{8}$$

In the context of a unit st-current in the network, $R(v,w)$ represents the effective resistance between nodes v and w.

D. Communicability

Communicability in a network represents .... [4].

In this work communicability is calculated based on the weighted connections [5]. A symmetric matrix M is generated to depict the communicability distribution, where $M_{i,j}$ represents the communicability between nodes i and j. Therefore, M reads:

$$M = \exp\left(D^{-1/2} W D^{-1/2}\right). \tag{9}$$

E. Modularity

Modularity is a network metric that ..... **talk about it here** [6].

Recent studies in neuro-science demonstrated that modularity plays an important role in .... **talk about it here** [7].

Modularity (Q^w) in a weighted network can be calculated by the Louvain method [8]:

$$Q^w = \frac{1}{D} \sum_{i,j} \left[W_{ij} - \frac{d_i d_j}{D} \right] \delta(m_i, m_j), \tag{10}$$

in which $w_{i,j}$ is the weight of the edge between nodes i and j, I^w represents sum of all weights in the network, k_i^w stands for the weighted degree of node i, m_i is the community where node i is located, and δ is the Kronecker delta function.

F. Transfer Entropy

Transfer entropy is an effective metric for information transduction ...... **cite Joe here**.

$$T_{Y \to X} = \sum_{u_n} p(u_n) \log \frac{p(x_{n+1} | x_n^{(k)}, y_n^{(l)})}{p(x_{n+1} | x_n^{(k)})}. \tag{11}$$

n is a time index, u_n represents the state transition tuple $(x_{n+1}, x_n^{(k)}, y_n^{(l)})$, $x_n^{(k)}, y_n^{(l)}$ represent the k and l past values of x and y up to and including time n. **rephrase here**.

The transfer entropy across an edge ($e_{i,j}$) is calculated by: **Have to write these equations in a better manner.**

$$TE_{i,j} = T_{V_i \to V_j} \tag{12}$$

And therefore the average outward TE and inward TE of a node can be calculated by:

$$\langle TEout_i \rangle = \frac{\sum\limits_{i,j,A_{i,j} \neq 0} TEout}{\#\text{ of edges connected to i}} \tag{13}$$

III. RESULTS

A. Centrality and Dynamics

100 nw is used here. Might have to use 700 nw for consistency.

As the network evolves, the edges close to sources and drains will be turned on first. A winner-takes-all current path will form, then branches out to the rest of the network. Among all sorts of metrics, voltage distribution on nodes $\vec{V_n}$ and on edges $\vec{V_e}$ would be the most important ones as they determine the network's state.

a. Voltage distribution Voltage distribution on edges at a specific time $\vec{V_e}(t)$ shows a clear correlation with edge current flow betweenness centrality. Meanwhile, since the filament states λ strongly rely on voltage distribution $\vec{V_e}(t)$, a correlation between λ and EBC as well. As plotted in fig. 3, for $V_e\vec{(t)}$ two linear groups

- **Rephrase here.**
- Two clustered groups (ON and OFF).
- Transition in between because of the continuity brought in by tunneling model.
- Maybe include power consumption here as well.

b. Current flow **Maybe try power dissipation of nanowire as well.**

The cumulative current flow through nanowires shows are linear relationship versus node current flow betweenness centrality. fig. 4.

B. Centrality and Functionality

a. Mean communicability Briefly Introduce the idea of communicability.

The communicability matrix (M) is generated based on W.... Each entry represents .... **might cite some Comm paper here**.

The row sum of M can somehow interpret how communicable a node is to the rest of the network.

The plot of comm vs node closeness cent shows something .....

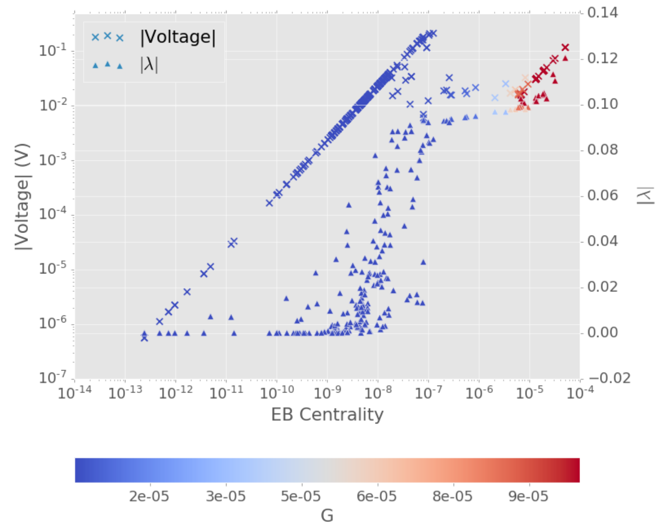

FIG. 3. T=2.9, around pathway formation. crosses are voltages and triangles are filament states.

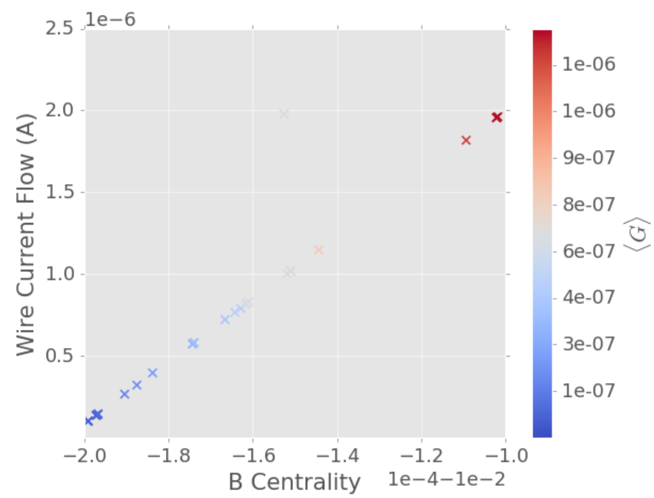

FIG. 4. Current flow on a nanowire vs node centrality

b. Node Transfer Entropy The wire closeness centrality also shows an interesting correlation with transfer entropy. More specifically, the capabilities of taking in and giving out information.

With 50 repetitions of different source/target pairing (while keeping the graphical distance between them constant), TE shows a close to linear relationship with centrality as well:

c. Node Active Information Storage **Not sure whether we need it here**.

C. Time-series analysis

a. ΔG The conductance time-series of the network reflects the activation stage of the network. Specifically,

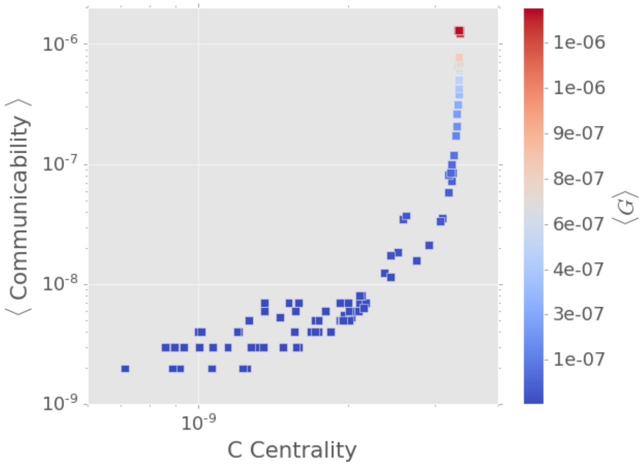

FIG. 5.

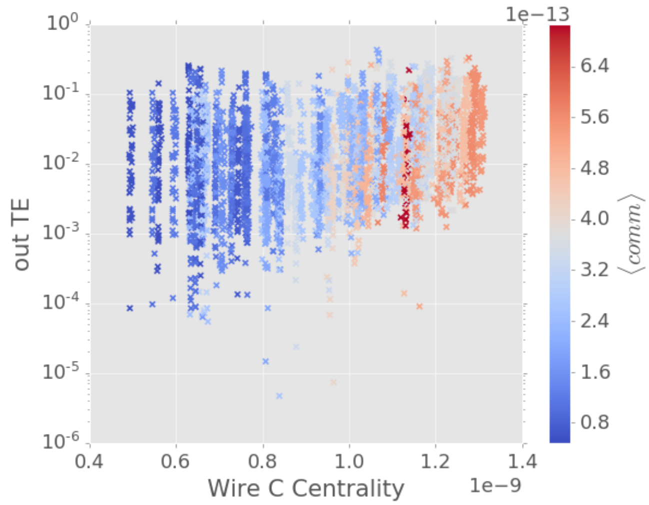

FIG. 7.

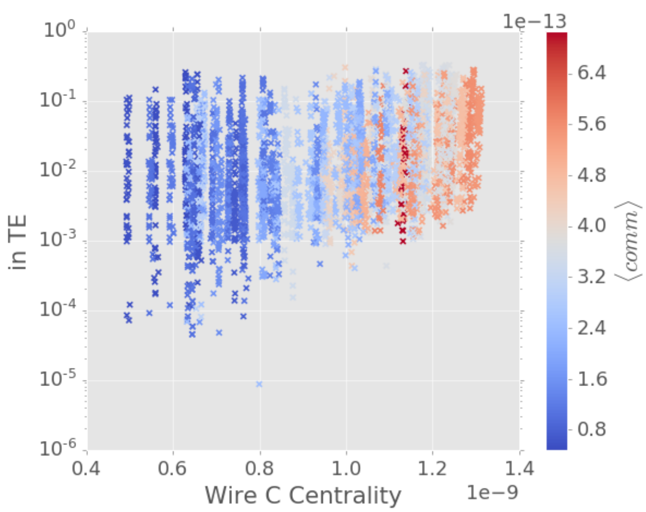

FIG. 6.

ΔG can help identify the avalanche behaviors of the network.

b. TE time series The transfer entropy across the whole network is calculated in the same way as before. The average is taken over the whole network the time series to obtain the time series.

Plotting TE time-series together with ΔG in the same figure, the spikes of both curves coincide.

Different amplitude of voltage biases are applied to the network. The activation time and TE peak time in these realizations line-up pretty well.

c. Modularity time series Modularity of the network is calculated throughout the activation. The drop of Modularity coincide with ΔG as well.

D. Dual task

Might change to a smaller amplitude. Here modularity peak at $t = 10$, too small to capture TE.

Pre-activate the network with Mackey-Glass signal, extract the state from different time-points. Then do a non-linear signal transform on it.

The Guimera **cite here** plots can be displayed as follow:

Have to match the color bars here.

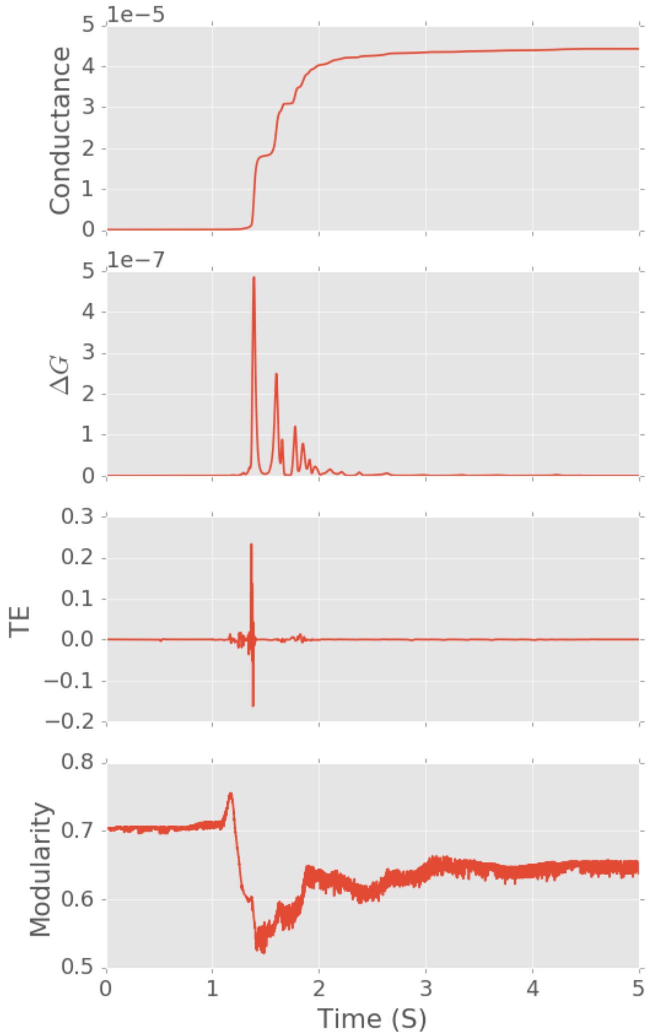

FIG. 8.

IV. DISCUSSION

V. CONCLUSION

ACKNOWLEDGMENTS

We wish to acknowledge the support of the author community in using REVTEX, offering suggestions and encouragement, testing new versions, ...

Appendix A: Appendixes

Appendix B: A little more on appendixes

[1] F. Dorfler, J. W. Simpson-Porco, and F. Bullo, Electrical Networks and Algebraic Graph Theory: Models, Properties, and Applications (2018).
[2] M. Newman, *Networks: An Introduction* (2010) pp. 1–784.
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[4] E. Estrada and N. Hatano, *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, Tech. Rep. 3 (2008).
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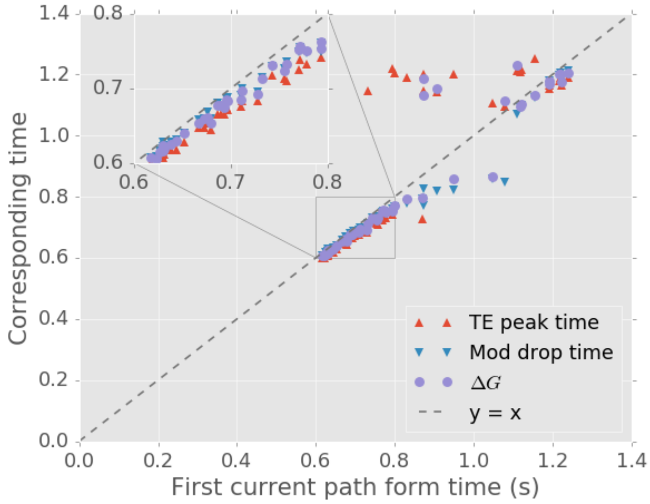
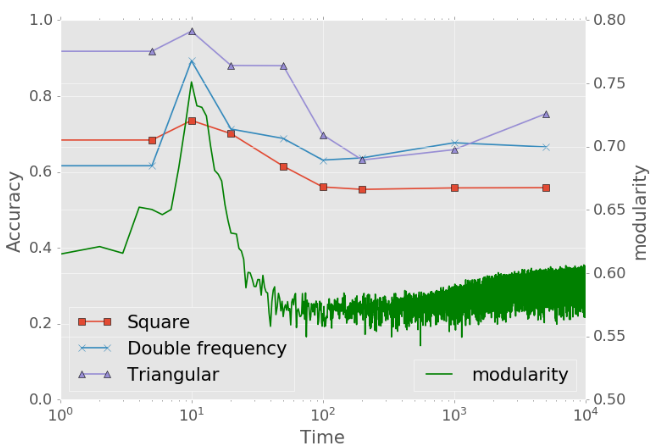


Corresponding time
First current path form time (s)
TE peak time
Mod drop time
ΔG
y = x

FIG. 9.



Accuracy
modularity
Time
Square
Double frequency
Triangular
modularity

FIG. 10.

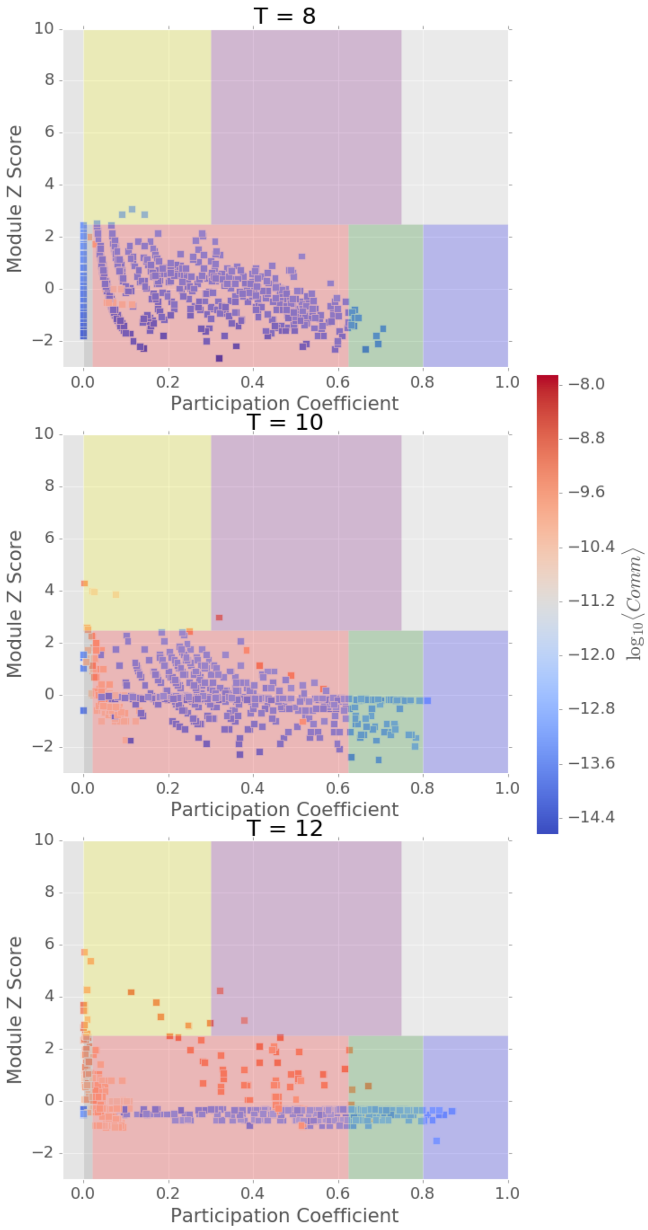

T = 8
T = 10
T = 12
Module Z Score
Participation Coefficient
$\log_{10}\langle Comm \rangle$
−8.0
−8.8
−9.6
−10.4
−11.2
−12.0
−12.8
−13.6
−14.4

FIG. 11.