## V. Conclusion

Previous publications have suggested that a small error in the end-effector orientation does not decrease the quality of the paint job to a large extent. To guarantee uniform paint coating, it is far more important to maintain constant velocity throughout the trajectory. It is thus proposed to use the freedom that arises when we allow a small orientation error to increase the velocity of the end effector.

The preliminary work showed that one should be able to reduce the maximum torques and the energy needed to follow a specific path by about 50% by allowing a small orientation error in the specification of the end effector. The need to confirm these promising simulation results through experiments is thus apparent. In this paper, we have validated the theory and simulations presented previously and shown that we can substantially reduce the joint torques needed for a spray paint robot to follow a specific end-effector trajectory. We have shown that both the energy used and the maximum torques are reduced. This allows us to paint the surface considerably quicker than with the conventional approach.

In this paper, we have also investigated how the algorithm performs on curved surfaces. We are able to reduce the torques even more than for flat surfaces which shows that the approach is versatile and can be applied to a wide variety of problems.

## References

[1] P. J. From and J. T. Gravdahl, "A real-time algorithm to determine the optimal paint gun orientation in spray paint applications," *IEEE Trans. Autom. Sci. Eng.*, vol. 7, no. 4, pp. 803–816, Oct. 2010, doi: 10.1109/TASE.2009.2033567.

[2] V. Potkonjak, G. Dordevic, D. Kostic, and M. Rasic, "Dynamics of anthropomorphic painting robot: Quality analysis and cost reduction," *Robot. Autonomous Syst.*, vol. 32, no. 1, pp. 1493–1499, 2000.

[3] M. Buss, H. Hashimoto, and J. B. Moore, "Dextrous hand grasping force optimization," *IEEE Trans. Robot. Autom.*, vol. 12, no. 3, pp. 406–418, 1996.

[4] P. J. From and J. T. Gravdahl, "On the equivalence of orientation error and positive definiteness of matrices," in *Proc. Int. Conf. Control, Autom., Robot. Vision*, Hanoi, Vietnam, 2008, pp. 2089–2094.

# A Framework to Model the Topological Structure of Supply Networks

Qi Xuan, Fang Du, Yanjun Li, and Tie-Jun Wu, *Member, IEEE*

***Abstract*—Topological structure is considered more and more important in managing a supply network or predicting its development. In this paper, a new framework is proposed to model the topological structure of supply networks, where different types of supply networks can be created just by introducing different supplier-customer connecting rules. Generally, the networks created in the framework are much different from the random networks with the same degree sequences. The revealed phenomenon suggests that real-world supply networks may benefit from its intrinsic mechanism on flexibility, efficiency, and robustness to target attacks.**

***Note to Practitioners*—The topological structure of supply networks is considered more and more important in managing a supply network or predicting its development. In this paper, we introduce a framework to model and analyze the topological structure of supply networks. This work aims to characterize supply networks by statistical methods and can help researchers better understand the material dynamics on supply networks and further conveniently create their own supply networks by summarizing practical supplier-customer connecting rules or analyzing real-world supply network data. The work should be further expanded in other aspects, such as simulating material dynamics on supply networks, designing optimal structure by introducing proper supplier-customer connecting rules, rearranging local connections to enhance the competitiveness and further ensure the long-term benefit of a target firm, and so on, all of which are of much interest for governors, investors, and managers and can be studied in the present framework in the future.**

***Index Terms*—Complex network, logistics, modeling, self-organized system, supply network.**

## I. Introduction

PAST research on supply chains generally focused on optimizing the physical flow of materials [1]. However, nowadays, increasing product/service complexity, customer expectation, outsourcing and globalization lead to increasingly complex and dynamic supply networks. In such a situation, those exactly analytical approaches are losing their effects. Recently, several modern simulating methods, such as multiagent system (MAS) [2] and complex adaptive system (CAS) [3], [4] were introduced to model such increasingly complex supply networks. Provided with a set of proper rules, an artificial supply network can be dynamically created, then the coming state of real supply networks can be somewhat predicted and controlled by the model.

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In fact, a supply network, like a traffic [5] or social [6] network, has its topological structure which, as is widely believed, plays a very important role in transferring materials and information [7], [8]. Accordingly, the structure of a supply network can be viewed as the pattern of relationships among the involved firms, mainly including supplier-customer relationships (material flows) and information sharing relationships (information flows). Naturally, a single firm has the ability to shape the structure of a supply network by selecting different suppliers and customers [9]–[11] for some purposes, e.g., decrease cost and risk, increase flexibility and reactivity, and ensure on-time delivery [12], [13]. However, such ability seems to be limited as the supply network gets more and more complex, and thus the structure of a supply network are always considered emergent [3]. Therefore, in the future, a firm may benefit more from taking a right place in the supply network than from shaping its overall structure.

The role of structure has already been addressed by several supply network researchers. For example, Thadakamalla *et al.* [8] pointed out that some structural properties such as the average shortest path length and the average clustering coefficient may strongly correlated with the survivability of a supply network. Sun and Wu [14] discussed the robustness of supply networks created by their own scale-free model. Such works are for sure very interesting and build a bridge between complex network theory [15]–[17] and supply networks. In spite of that, it seems that such supply network models can be further improved by taking various types of products and directed flow between different firms into consideration. Besides, Meepetchdee and Shah [18] tried to design optimal supply network structure by considering robustness and complexity, which is of much practical value but is not the focus of this paper.

In this paper, we propose a new framework to model and analyze the topological structure of supply networks. In this framework, one can easily change the structure of a supply network by introducing different supplier-customer connecting rules. Such rules may be concluded from practical experiences or real-world supply network data. As examples, we introduce three very simple connecting rules and get three types of supply networks. Then several of their topological properties are carefully analyzed to illuminate which connecting rules may lead to supply networks of better performance.

## II. Framework

Here, a supply network is described by a directed network where each node represents an entity and each directed link denotes the material flow between two entities (from supplier to customer). A connecting rule then means a way that an entity selects its suppliers and customers in the supply network.

### *Definitions*

Generally, there are three types of products circulated in a supply network: raw materials, intermediate products between business entities and end products for customers. If we denote a product in a supply network by $a_j$, then all products in the network can be represented by a vector $G = [a_1, a_2, \ldots, a_n]$. Let $D^p$ be the supply-demand map matrix, whose rows and columns are both indexed by the products in the supply network. The elements of $D^p$ are 0s and 1s, with $D^p(j,k) = 1$ when $a_k$ is needed to produce $a_j$. The $j\mathrm{th}$ row of $D^p$, denoted by $D_j^p$, is called the demand vector of $a_j$. Denote with $D^e$ the demand matrix and with $S^e$ the supply matrix, whose rows are indexed by the entities and columns are indexed by the products in the supply network. The elements of $D^e$ and $S^e$ are also 0s and 1s, with $D^e(i,j) = 1$ when $a_j$ is a demand of entity $i$ and $S^e(i,j) = 1$ when $a_j$ is a supply of entity $i$. Denoting a matrix function $Y = F(X)$ satisfying that $Y(i,j) = 1$ if $X(i,j) > 0$ and $Y(i,j) = 0$ otherwise, it can be naturally deduced that

$$D^e = F(S^e D^p). \tag{1}$$

Denoting with $D_i^e$ the $i\mathrm{th}$ row of $D^e$ and with $S_i^e$ the $i\mathrm{th}$ row of $S^e$, and considering there are $N$ entities, the total demands $D$ and the total supplies $S$ of the supply network then can be calculated by (2) and (3), respectively

$$D = F\left(\sum_{i=1}^{N} D_i^e\right), \tag{2}$$

and

$$S = F\left(\sum_{i=1}^{N} S_i^e\right). \tag{3}$$

Naturally, there may be material flows between two entities if and only if one's supplies can partially satisfy the other's demands, that is, (4) must be satisfied

$$D_i^e (S_j^e)^T > 0. \tag{4}$$

### *A. Model*

Supply networks are growing as the circulated products are getting more and more diversified. There may be various ways to promote the evolution of a supply network. One way is *demand driven*, that is, new demands emerge first, then some entities are built to produce them, particularly, the modeling process is as follows.

1) Initially, there are $v$ raw materials and $m_0$ entities producing $n_0$ products by using some of these raw materials. So there are no links among these entities.
2) At each time $t$, with probability $p_d$, a new product $a_h$ is required and can be produced from raw materials and existent products. The circulated products in the supply network then is updated by $G = [G, a_h]$. Let $D_h^p(j) = 1$ if $a_j$ is needed to produce $a_h$ and $D_h^p(j) = 0$ otherwise, then the supply-demand map matrix is updated by $D_p = [D_p, 0; D_h^p, 0]$.
3) Create a new entity $i$, randomly select $w$ products (including materials) from the network's supplies as the entity's supplies $S_i^e$. If a new product is required at step 2), it is included in the $w$ selected products. The entity's demands $D_i^e$ then is determined by (1), i.e., $D_i^e = F(S_i^e D^p)$. Select some existent entities from those satisfying $\langle D_i^e, S_j^e \rangle > 0$ or $\langle D_j^e, S_i^e \rangle > 0$ by certain rule. It should be noted that raw materials and the supplies of the selected entities must cover the demands of the new entity. Then, connect these selected suppliers and customers to the new entity $i$, and turn to step 2).
4) Terminate the process after $T$ iterative times, and the supply network then has totally $N = m_0 + T$ entities.

Obviously, investors and managers can lead the evolution of the supply network to a certain extent by determining the outputs of their entities and selecting corresponding customers or suppliers, and these choices will certainly have impacts on the benefits of their entities.

## III. Examples

Without loss of generality, here, only two products are needed to produce a new product, and the suppliers are selected just to satisfy the demands of the new entity and one customer entity is selected if existed.

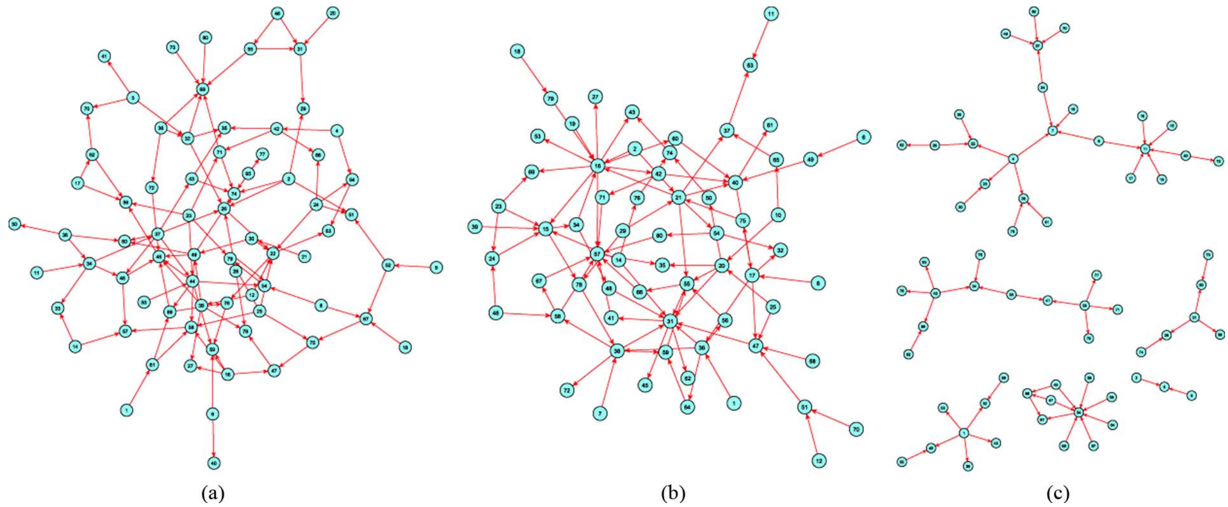


Fig. 1. Supply networks of (a) type I, (b) type II, and (c) type III. The parameters are set to be $v = 5, m_0 = 1, n_0 = 2, w = 2, p_d = 0.1, M = 3$, and $N = 80$. The isolated nodes are not shown here and each node is marked by a number representing its creating time.

Then, three types of supply networks are obtained by introducing different selecting rules in the framework.

### A. Supply Network With Random Rule (Type I)

In a society with no communication, a new entity $i$ can only randomly select its suppliers and customers from those entities satisfying $\langle d_i, s_j \rangle > 0$ or $\langle d_j, s_i \rangle > 0$. For convenience, the two products needed to produce the new product are also randomly selected from the raw materials and all the existent products. Such a supply network with parameters $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, and $N = 80$ is shown in Fig. 1(a).

### B. Supply Network With PA Rule (Type II)

The preferential attachment (PA) rule is first introduced by Barabási and Albert [19] to explain the scale-free property revealed in real-world networks: starting with $m_0$ (a small number) nodes, adding a new node at every time step, and connecting it to $m$ $(m \leq m_0)$ different existent nodes selected with probabilities linearly proportional to their degrees. For a supply network, the PA rule is consistent with *brand effect* [20] or *word-of-mouth effect* [21], which means that an entity with more suppliers and customers will have better chance to get a new partner. Such a supply network with parameters $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, and $N = 80$ is shown in Fig. 1(b).

### C. Supply Network Based on Product's Similarity (Type III)

In reality, a product is more likely to be a demand or supply of others with common materials, and thus industrial modules come into being. Particularly, here, if a new product $a_h$ is required at time $t$, this product is attached by a constant $\rho_h$ in order to measure how distinct it is from the others. The similarity between $a_i$ and $a_j$ may have various definitions [22]. Here, two products needed to produce $a_h$ are selected randomly from $M (M > w)$ closest products measured by $|\rho_h - \rho_i|$. Such a supply network with parameters $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, $M = 3$, and $N = 80$ is shown in Fig. 1(c).

## IV. Statistics

Fig. 1 provides a primary image that the supply network of type II has dominant entities with quite a large number of suppliers and customers, and the supply network of type III has many independent components representing different industries in the early stage. Such impressions can be further strengthened by quantitatively analyzing structural statistics which will be presented and discussed one by one as follows.

### A. Degree

In a supply network, each node has an incoming/outgoing degree representing the number of its suppliers/customers. The large degree of a node suggests the superior status of the corresponding entity over the others. The average incoming/outgoing degree can reflect the connection tightness among different entities and thus are always correlated to the robustness of the supply network, which is calculated by (5)

$$\langle k_{\text{in}} \rangle = \langle k_{\text{out}} \rangle = \frac{N_e}{N} \tag{5}$$

where $N_e$ is the total number of directed links in the supply network.

Three growing supply networks are created with parameters $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, and $M = 3$. When the supply networks grow to $N = 5000$ nodes, the degree related statistics are recorded in Table I, where we can see that the average incoming/outgoing degree $\langle k_{\text{in}} \rangle$ of the supply network of type III is much smaller than those of types I and II. This phenomenon suggests that the specialization may weaken the robustness of the supply network. One way to avoid such disadvantage is developing various products and materials of similar function. Fortunately, the average incoming/outgoing degree of each supply network increases as the network grows, i.e., more products and entities provide more chances for an entity to select its suppliers and customers, as is shown in Fig. 2(a). In other words, increasing complexity is always accompanied by increasing redundancy which is synonymous with robustness here.

As is widely believed, heterogeneous networks created by the PA rule are always robust to random failures but very sensitive to target attacks of nodes with large degree [8], [23]. However, in this paper, we find that the incoming/outgoing degree distribution of the supply network of type II seems not significantly more scalable than the other two types of supply networks, as is shown in Fig. 3(a), although its maximum incoming degree $k_{\text{in}}^{\max}$ and maximum outgoing degree $k_{\text{out}}^{\max}$ are indeed much larger. This is reasonable because the supply-demand map restricts the potential suppliers and customers of an entity, and such local-world restriction will prevent the quick formation of the dominant nodes, and lack of the dominant nodes consequently make the supply networks robust to target attacks.

### B. Directed Distance

Improving the material transferring efficiency in a supply network is one of the most important tasks for managers. Such property can be measured by the average directed distance of the supply network here.

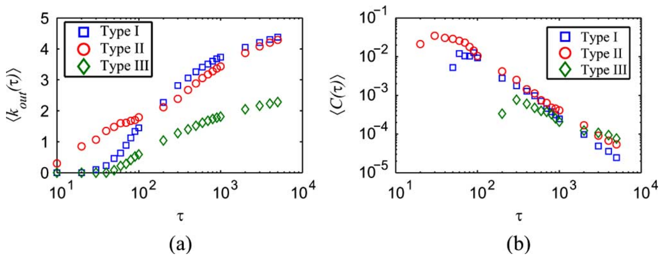



Fig. 2. (a) The average outgoing degree $\langle k_{\mathrm{out}}(\tau)\rangle$ and (b) the average clustering coefficient $\langle C(\tau)\rangle$ as functions of evolving phase $\tau = t + 1$ for the three supply networks of different types. The parameters are set to be $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, and $M = 3$.

TABLE I
THE BASIC STATISTICS OF THE SUPPLY NETWORKS WITH PARAMETERS $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, $M = 3$, AND $N = 5000$

| Networks | $\langle k_{in}\rangle$ | $k_{in}^{max}$ | $k_{out}^{max}$ | $\langle C\rangle$ | $\langle L\rangle$ | $\langle L_{sc}\rangle$ |
|---|---|---|---|---|---|---|
| Type I | 4.38 | 18 | 35 | $2.45 \times 10^{-5}$ | 7.30 | 4.61 |
| Type II | 4.29 | 27 | 93 | $5.38 \times 10^{-5}$ | 6.89 | 4.78 |
| Type III | 2.28 | 16 | 21 | $7.64 \times 10^{-5}$ | 4.70 | 5.96 |

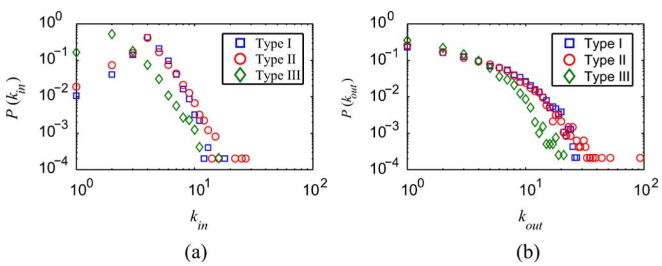



Fig. 3. (a) The incoming degree distribution and (b) the outgoing degree distribution for the three supply networks of different types. The parameters are set to be $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, $M = 3$, and $N = 5000$.

The directed distance $l(i, j)$ is defined by the minimum number of successive directed links from $i$ to $j$. As is presented in Table I, the smaller average directed distance $\langle L\rangle$ of the supply networks of type III suggests that the social division of labor and the resulting various industries indeed benefit for the whole supply network on efficiency. This is reasonable because there are fewer quite long value-added chains between different industries in the supply network of type III. In fact, if we consider only the average directed distance from the upper-stream entities with no suppliers to the downstream entities with no customer entities and neglect the extra value-added chains, the supply network of type III instead have the larger value of $\langle L_{sc}\rangle$ than the other two types of networks. Fig. 4 shows that there is a distinct difference between the two kinds of directed distance distributions for the supply networks of types I and II, while they are very similar with each other for the supply network of type III.

It seems that supply networks naturally have small-world property [24], i.e., for all the supply networks presented here, both kinds of average directly distances increase no faster than logarithmically as the networks grow, i.e., $L(\tau) \le \eta_1 \ln \tau$ and $L_{sc}(\tau) \le \eta_2 \ln \tau$, for certain values of parameters $\eta_1$ and $\eta_2$, as is shown in Fig. 5(a)–5(c). Especially, $L_{sc}(\tau)$ almost keeps the same when $\tau > 200$ for the supply networks of types I and II, which is a very beneficial property and suggests that upper-stream materials can be efficiently transferred to proper products satisfying downstream customers' requirements only by a very small number of intermediate links even if the supply network is quite large.

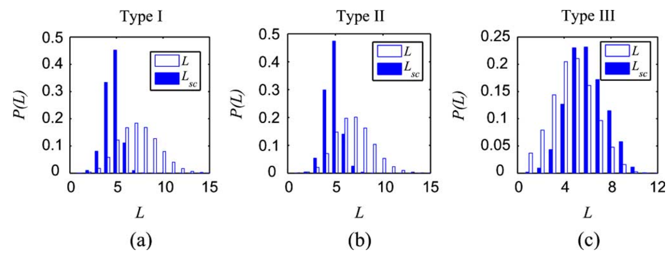



Fig. 4. The two kinds of directed distance distributions for the supply networks of (a) type I, (b) type II, and (c) type III. The parameters are set to be $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, $M = 3$, and $N = 5000$.

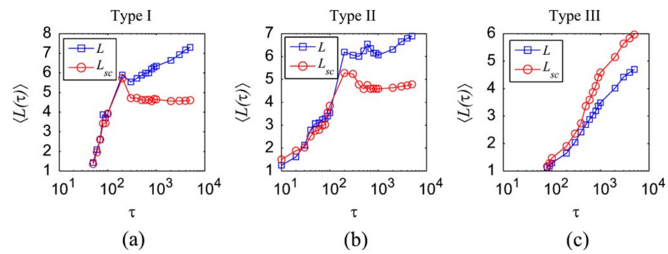



Fig. 5. The two kinds of average directed distances as functions of the evolving phase $\tau = t + 1$ for the supply networks of (a) type I, (b) type II, and (c) type III. The parameters are set to be $v = 5$, $m_0 = 1$, $n_0 = 2$, $w = 2$, $p_d = 0.1$, and $M = 3$.

### C. Motifs

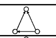
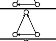
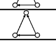
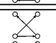
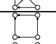
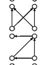
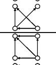
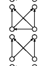
Generally, supply networks with a larger number of triangles (the fully connected triples) are always considered more flexible [8] when the total number of nodes are fixed. However, the chain essence of supply networks prevents the frequently emergence of the triangles, as a result, all the supply networks presented here have very small average clustering coefficients $\langle C\rangle$ and the values are getting even smaller as the supply networks grow, as is presented in Table I and Fig. 2(b). Here, the clustering coefficient of node $i$ is defined by the normalized form of the number of triangles involving the node $i$ by the number of connected triples with $i$ as the central node [17] in the corresponding undirected networks.

However, lack of triangles does not definitely mean that supply networks are lowly clustering and thus inflexible. In fact, triangle is just one motif of three connected triples, and in some special cases [25]–[27], the number of squares or larger loops is also used to measure the clustering degree of networks. Here, we use the FANMOD [28] to reveal several significant connected motifs [29], [30] with size equal to 3 or 4 in supply networks compared with random directed networks of the same incoming/outgoing degree sequences (for each supply network, 100 random networks are created for comparison). Several parameters are explained as follows.

- $F_o$: the frequency with which a motif occurred in the original supply network.
- $F_r$: the mean frequency with which the motif occurred in random networks.
- $D_r$: the standard deviation with which the motif occurred in random networks.
- Z-Score: the original frequency $F_o$ minus the random frequency $F_r$ divided by the standard deviation $D_r$.
- p-Value: the number of random networks in which the motif occurred more often than in the original network, divided by the total number of random networks. Therefore, p-Values range from 0 to 1.

A motif is considered more significant if it has larger Z-Score and smaller p-Value. In particular, the motifs with $F_o > 0.01\%$ and p-Value=0 are remained, and thereinto the motifs of the same size

TABLE II
SIGNIFICANT MOTIFS REVEALED IN THE SUPPLY NETWORKS

| M-Size | Networks | Motifs | M-Label | $F_o$ | Z-Score |
|---|---|---|---|---|---|
| 3 | Type I |  | $M_1^3$ | 0.0849% | 5.60 |
| | Type II |  | $M_1^3$ | 0.0995% | 5.89 |
| | Type III |  | $M_1^3$ | 0.560% | 71.8 |
| 4 | Type I |  | $M_1^4$ | 26.9% | 41.2 |
| | |  | $M_2^4$ | 0.0289% | 35.6 |
| | |  | $M_3^4$ | 0.0149% | 16.5 |
| | |  | $M_4^4$ | 0.0439% | 11.7 |
| | |  | $M_5^4$ | 0.0580% | 8.68 |
| | Type II |  | $M_2^4$ | 0.0296% | 38.8 |
| | |  | $M_1^4$ | 23.7% | 20.3 |
| | |  | $M_3^4$ | 0.0141% | 17.0 |
| | |  | $M_4^4$ | 0.0584% | 8.41 |
| | |  | $M_5^4$ | 0.0856% | 8.10 |
| | Type III |  | $M_6^4$ | 0.0102% | 431 |
| | |  | $M_2^4$ | 0.243% | 226 |
| | |  | $M_7^4$ | 0.0112% | 173 |
| | |  | $M_3^4$ | 0.0915% | 89.1 |
| | |  | $M_8^4$ | 0.222% | 78.1 |

and the same supply network are ranked by Z-Score and the top 5 are presented in Table II.

Generally, the motifs revealed in the supply network of type III have much larger Z-Score than those in the supply networks of types I and II, which suggests that, in the same situation (with same number of nodes and links), similarity based mechanism can strengthen the clustering and thus increase the flexibility of a supply network. It can be also found that, except $M_1^4$, all the other significant motifs contain at least one triangle or one square, which suggests that the supply networks may be more flexible than the compared random networks. Because both of the triangles and the squares are robust to random one-node and one-edge failures.

## V. CONCLUSION

By comparing the supply networks created in the framework and the random directed networks with the same incoming/outgoing degree sequences, we find that supply networks may benefit from its intrinsic mechanism on flexibility, efficiency, and robustness to target attacks. This work can help researchers better understand and further conveniently create their own supply networks by summarizing practical supplier-customer connecting rules or analyzing real-world supply network data. In fact, when an entity selects its partners from those satisfying supply-demand relationships, it will take into account many factors including finance, consistency, service, price, and so on. The work should be further expanded in other aspects, such as simulating material dynamics on supply networks, designing optimal structure by introducing proper supplier-customer connecting rules, rearranging local connections to enhance the competitiveness and further ensure the long-term benefit of a target firm, and so on, all of which are of much interest for governors, investors, and managers and can be studied in the present framework in the future.

## REFERENCES


[1] J. W. Forrester, *Industrial Dynamics*. Cambridge, MA: MIT press, 1961.

[2] J. M. Swaminathan, S. F. Smith, and N. M. Sadeh, "Modeling supply chain dynamics: A multiagent approach," *Decision Sci.*, vol. 29, no. 3, pp. 607–632, 1998.

[3] T. Y. Choi, K. J. Dooley, and M. Rungtusanatham, "Supply network and complex adaptive systems: Control versus emergence," *J. Oper. Manage.*, vol. 19, no. 3, pp. 351–366, 2001.

[4] S. D. Pathak and D. M. Dilts, "Simulation of supply chain network using complex adaptive system theory," in *Proc. IEEE Int. Eng. Manage. Conf.*, Cambridge, U.K., 2002, vol. 2, pp. 655–660.

[5] A. Barrat, M. Barthélemy, R. P. Satorras, and A. Vespignani, "The architecture of complex weighted networks," *Proc. Nat. Acad. Sci.*, vol. 101, no. 11, pp. 3747–3752, 2004.

[6] A.-L. Barabási, H. Jeong, Z. Néda, E. Ravasz, A. Schubert, and T. Vicsek, "Evolution of the social network of scientific collaborations," *Physica A: Statist. Mechanics Appl.*, vol. 311, no. 3-4, pp. 590–614, 2002.

[7] T. Y. Choi and Y. Hong, "Unveiling the structure of supply networks: Case studies in Honda, Acura, and Daimlerchrysler," *J. Oper. Manage.*, vol. 20, no. 5, pp. 469–493, 2002.

[8] H. P. Thadakamalla, U. N. Raghavan, S. Kumara, and R. Albert, "Survivability of multiagent-based supply networks: A topological perspective," *IEEE Intell. Syst.*, vol. 19, no. 5, pp. 24–31, 2004.

[9] T. Y. Choi and J. Hartley, "An exploration of supplier selection practices across the supply chain," *J. Oper. Manage.*, vol. 14, no. 4, pp. 333–343, 1996.

[10] L. de Boer, E. Labro, and P. Morlacchi, "A review of methods supporting supplier selection," *Eur. J. Purchasing and Supply Manage.*, vol. 7, no. 2, pp. 75–89, 2001.

[11] R. F. Olsen and L. M. Ellram, "Buyer-supplier relationships: Alternative research approaches," *Eur. J. Purchasing and Supply Manage.*, vol. 3, no. 4, pp. 221–231, 1997.

[12] C. Harland, R. Brenchley, and H. Walker, "Risk in supply networks," *J. Purchasing and Supply Manage.*, vol. 9, no. 2, pp. 51–62, 2003.

[13] T. Y. Choi and D. R. Krause, "The supply base and its complexity: Implication for transaction costs, risks, responsiveness, and innovation," *J. Oper. Manage.*, vol. 24, no. 5, pp. 637–652, 2006.

[14] H. Sun and J. Wu, "Scale-free characteristics of supply chain distribution networks," *Modern Phys. Lett. B*, vol. 19, no. 17, pp. 841–848, 2005.

[15] R. Albert and A.-L. Barabási, "Statistical mechanics of complex network," *Rev. Modern Phys.*, vol. 74, no. 1, pp. 47–97, 2002.

[16] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D.-U. Hwang, "Complex networks: Structure and dynamics," *Phys. Rep.*, vol. 424, no. 4-5, pp. 175–308, 2006.

[17] L. D. F. Costa, F. A. Rodrigues, G. Travieso, and P. R. V. Boas, "Characterization of complex networks: A survey of measurements," *Adv. Phys.*, vol. 56, no. 1, pp. 167–242, 2007.

[18] Y. Meepetchdee and N. Shah, "Logistical network design with robustness and complexity considerations," *Int. J. Phys. Distrib. Logistics Manage.*, vol. 37, no. 3, pp. 201–222, 2007.

[19] A.-L. Barabási and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, no. 5439, pp. 509–512, 1999.

[20] W. B. Dodds, K. B. Monroe, and D. Grewal, "Effects of price, brand, and store information on buyers' product evaluations," *J. Market. Res.*, vol. 28, no. 3, pp. 307–319, 1991.

[21] P. F. Bone, "Word-of-mouth effects on short-term and long-term product judgments," *J. Business Res.*, vol. 32, no. 3, pp. 213–223, 1995.

[22] Q. Xuan, Y. Li, and T.-J. Wu, "A local-world network model based on inter-node correlation degree," *Physica A: Statist. Mechanics Appl.*, vol. 378, no. 2, pp. 561–572, 2007.

[23] R. Albert, H. Jeong, and A.-L. Barabási, "Error and attack tolerance of complex networks," *Nature*, vol. 406, no. 6794, pp. 378–382, 2000.

[24] D. J. Watts and S. H. Strogatz, "Collective dynamics of 'Small-World' networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998.

[25] G. Caldarelli, R. Pastor-Satorras, and A. Vespignani, "Structure of cycles and local ordering in complex networks," *Eur. Phys. J. B—Condensed Matter and Complex Systems*, vol. 38, no. 2, pp. 183–186, 2004.

[26] P. G. Lind, M. C. González, and H. J. Herrmann, "Cycles and clustering in bipartite networks," *Phys. Rev. E*, vol. 72, no. 5, p. 056127, 2005.

[27] S. Porta, P. Crucitti, and V. Latora, "The network analysis of urban streets: A dual approach," *The Network Analysis of Urban Streets: A Dual Approach*, vol. 369, no. 2, pp. 853–866, 2006.

[28] S. Wernicke and F. Rasche, "FANMOD: A tool for fast network motif detection," *Bioinformatics*, vol. 22, no. 9, pp. 1152–1153, 2006.

[29] R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, and U. Alon, "Network motifs: Simple building blocks of complex networks," *Science*, vol. 298, no. 5594, pp. 824–827, 2002.

[30] X. Xu, J. Zhang, and M. Small, "Superfamily phenomena and motifs of networks induced from time series," *Proc. Nat. Acad. Sci.*, vol. 105, no. 50, pp. 19601–19605, 2008.