Network capacity enhancement with various link rewiring strategies

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Abstract—The structure of the network has a great impact on its traffic dynamics. Most of the real world networks follow heterogeneous structure and exhibit scale-free feature. In scale-free network, a new node prefer to connect with hub nodes and the network capacity is curtailed by smaller degree nodes. Therefore, we propose rewiring a fraction of links in the network, to improve the network transport efficiency. In this paper, we discuss various link rewiring strategies and perform simulations on scale-free networks, confirming the effectiveness of these strategies. The rewiring strategies actually reduce the centrality of the nodes having higher betweenness centrality. After the link rewiring process, the degree distribution of the network remains the same. This work is beneficial for the enhancement of network performance.

Index Terms—Rewiring strategies, centrality, capacity.

I. INTRODUCTION

Traffic dynamics of the time-varying networks have attracted the attention of a large number of researchers in recent years [1]–[3]. The ever-growing demand for the network resources has ineluctably led to traffic congestion in many real-life networks such as communication, transportation and so on. Most of the network structures are evolving and scale-free in nature where hubs and small degree nodes coexist. Congestion usually initiates from these hubs and then gradually propagate in the whole network. For that reason, we propose some rewiring strategies to maximize the traffic capacity of the hub nodes and the network performance as well.

The traffic capacity is critical to networks, especially the communication network in the era of bursty traffic generation. Therefore, the research of the enhancement of the network capacity is vital to us and has been studied extensively. The network capacity can be improved either by implementing various routing strategies [1], [4] or by optimizing the underlying network structure [2], [3]. Implementation of optimal routing strategies are respectively easy and incurs a low cost. But the finding of a global optimal route is an NP-complete problem [5]. Although network restructuring incurs more cost, the effect of changing the network structure on the traffic capacity and the load at the network is essential for the study of traffic dynamics on complex networks.

Network structure may be optimized by redistributing the traffic of heavily loaded [6], removing some congested nodes or links [7], adding some network resources [8] and so on. In real networks, the resources such as capacity, queue size are finite. Addition of new resources incur cost hence, rewiring strategies may be more suitable to improve network capacity. Rewiring strategies depend on numerous network parameters such as degree, centrality, queue length etc. Jiang et al. [7] improved the network capacity by removing the connection between two nodes with the maximum sum of the degree together with betweenness centrality (BC) and by adding a connection between two unconnected nodes with the minimum sum of the degree in addition to BC. Alweimine et al. [9] prioritized the packets according to the destination node and found that the prioritization of nodes with hubs is always more efficient than the prioritization of nodes with a small degree or a random prioritization. Ma et al. [10] worked on a two-layer network model and proposed a delivery capacity allocation strategy based on the degree distributions of both the layers. Jiang et al. [11] assigned capacity dynamically to each link proportional to the queue length of the link. Larger delivery capacities can be assigned to the hub nodes and a tunable parameter is introduced to optimize network capacity. Gong et al. [12] found that the network capacity can be improved significantly if the local resources of information processing are allocated optimally under certain routing strategy.

All the above researchers considered degree and centrality as the network parameters for rewiring and removal of links and nodes as well. Assortativity (disassortativity) is another network property which measures the tendency of a node to connect with other node having similar (dissimilar) attributes, such as the degree. It can also be used to enhance traffic capacity based on similarity or dissimilarity of an individual node. Fronczak [13] discussed the effect of assortativity on the properties of transport in complex networks and calculated critical packet generation rate $\lambda_c$ in traffic based on routing strategy with local information. Xue et al. [2] found that transport on scale-free random networks vary significantly and tuned the transport efficiency on scale-free networks through the disassortative or assortative topology. Chen et al. [3] rewired the link against traffic congestion and proved that the network should have a core-periphery structure and disassortative in nature.

Networks can be represented using a combination of local (degree, assortativity), global (BC, closeness centrality (CC)),
and intermediate (meso)-scale perspectives. Intermediate level study helps to discover some features not covered either at the local level or at the global level (e.g., summary states of algorithmic identification). In meso-scale, we focus on a group of nodes instead of focusing on an individual node or the whole network. Core-periphery structure [14] is a kind of meso-scale representation in which some nodes constitute a densely connected core and some make up the sparsely connected periphery. A core structure in a network also tends to be central to the network (e.g., in terms of short paths, distance). Apart from all these parameters, rich club (RC) phenomenon is also a network property which is characterized when the hubs are on average more intensely interconnected than the nodes with smaller degrees. RC as a function of degree k is defined as $\Phi(k) = \frac{e_{>k}}{N_{>k}(N_{>k}-1)}$ where, $N_{>k}$ is the number of nodes with degree greater than k, and $e_{>k}$ is the number of links connecting the $N_{>k}$ nodes [13]. Presence of RC increases load and congestion on the connecting link between two hubs. Inspired by the importance of all these parameters, we have considered all the perspectives for the restructuring of the network. The objectives of the proposed work are as follows. First, to obtain the optimal network structure for maximizing the network capacity using various rewiring strategies on a scale-free network. Then, we analyze the networks by studying several network parameters, such as maximum betweenness centrality, clustering coefficient, average path length (APL), assortativity, rich-club phenomenon, core-periphery structure. In this work, a relationship between these parameters and the traffic performance of the networks is established, by fixing the degree distribution.

Section 2 discusses about the traffic flow models. In Section 3, some rewiring strategies are described. Section 4 presents the simulation results, and in Section 5, conclusions and future research plan are discussed.

II. TRAFFIC MODEL

Traffic flow model is based on different routing algorithms in communication networks. Network has variable data capacity for individual node. Each node is endowed by its neighboring nodes recursively. If these neighbors are already congested then it will cause an increase in load at that node. Mostly the hub nodes are congested hence, a rational capacity allocation scheme is required for the hub nodes in order to reduce data traffic in the network. As Eigenvector centrality (EC) is used to define the impact of the node on the other nodes in the network hence, it is considered in the computation for the capacity of a node. Data forwarding capacity, $C_i$ of a node $i$ may be allocated as,

$$C_i = \beta \hat{x}(i) |N|.$$  

(1)

Where, $\hat{x}(i)$ is EC of node $i$, $\hat{x}(i) = \frac{1}{\kappa} \sum_{j \in N} a(ij) \hat{x}(j)$. $\kappa$ is largest Eigen value of the adjacency matrix $A$ of the network. The term, $\beta$ is a considerably modest fractional value and is a controlling parameter for capacity of the nodes. Packets are forwarded through the shortest paths from the source node to the destination node into the network. Therefore, the probability to pass through a node $i$ is provided as $\frac{q(i)}{\sum_{j=1}^{N} q(j)}$. At each time step, average number of packets generated is $\alpha |N|$. Hence, the probability of node $i$ to generate a packet, $\lambda_i$ [15],

$$\lambda_i = \alpha D |N| \frac{q(i)}{\sum_{j=1}^{N} q(j)}.$$  

(2)

Where, $D$ is the diameter of the network. The term, $\alpha$ is a small fractional value and is a controlling parameter for $\lambda_i$ for the node $i$. The capacity of a node increases with the increment in the value of $\beta$. The sum of the capacities $C_i$'s of each node $i$ is known as the capacity $C$ of the network. Similarly, the sum of the packet generation rates, $\lambda_i$'s of each node $i$ is termed as the traffic load, $\lambda$, of the network. If traffic load exceeds the traffic capacity of the network then the system will be in the congested state otherwise, it will remain in the free flow state.

The node with the maximum BC can be easily congested hence, it is necessary to consider only the traffic load of this node and theoretical estimation of critical packet generation rate, $\lambda_c$ is given by, $\frac{C_{max}|N|-1}{\sum_{i=1}^{g(max)}}$ [15]. The capacity of the node having maximum BC ($g(max)$) is denoted as $C_{max}$. An order parameter $\theta(\lambda)$ [16], is used to describe the traffic and is given by,

$$\theta(\lambda) = \lim_{\lambda \rightarrow \infty} \frac{\lambda \langle \Delta P \rangle}{\Delta t}$$

$\Delta P = P(t + \Delta t) - P(t)$, $P(t)$ is number of packets at time $t$ and $\langle \cdot \rangle$ shows the average value over the time window $\Delta t$. $\langle \Delta P \rangle = 0$ indicating that there is no packet in the network for $\theta = 0$, system is in free flow state.

III. PROPOSED REWIRING STRATEGIES

There exist various local, global and intermediate level network properties that affect the structure of the network. In rewiring, one link is removed and on the other side, a link is added to the network. The rewiring process may be random or by using some strategies. Here, in this paper, the parameters for rewiring are the degree, disassortativity, centrality measures, and core-periphery (CP) architecture.

(a) Original Network  
(b) k-core architecture

Fig. 1. Visualization of the core-periphery structure of a European airline network ($|N| = 106$). Note that the network has several layers of cores and a small dense innermost core. Best viewed in the various color schemes. Red, blue, green, yellow, pink and brown color represent subnetwork with 1-core, 2-core, 3-core and 4-core, 5-core and 6-core respectively.

The degree may be used to assign preference to a node; a higher degree increases the probability of the node to acquire a link in the network. In a disassortative network, hubs (small degree nodes) avoid each other, linking instead to small-degree
nodes (hubs). As the network is heterogeneous hence, the chances of congestion are more on hub nodes. If two congested hub nodes are connected then it will increase load on the network. For that reason, disassortativity has a positive effect on the traffic performance of the network [3]. Centrality measures are very helpful to find central and congested nodes in the network especially betweenness centrality (BC), closeness centrality (CC) and Eigenvector centrality (EC). The core-periphery structure can be formed with k-core decomposition, a method aimed to partitioned a network in layers from the external to the central ones [14]. A k-core of the graph $G$ is a maximal connected subgraph in which all nodes have the degree at least $k$. The k-core decomposition of a European airline is shown in Fig. [1]. The CP architecture can also be formed using the nodes those are part of k-core and having maximum CC. The identification of the nodes in the k-core is very helpful to find congestion in the network. By considering the importance of the above parameters, various rewiring strategies can be defined as follows:

1. **Disassortativity and preferential attachment (DPA) based rewiring strategy**: Disassortativity and preferential attachment are local parameters. In the preferential attachment, a node connects with another node having a higher degree in the existing network. In the rewiring strategy, the link $e_{ij}$ between nodes $i$ and $j$ is removed if the node $i$ shows assortativeness $0 < r_{deg} \leq 1$ with node $j$. The first node, $i$, will establish a new connection with node $v$ by preferring the higher degree of the node $v$ and normalized disassortativeness, $\zeta_v$ of node $v$ with its neighbors, $N_C(v)$ in the network. The value of $\zeta_v$ is dependent on the correlation $r_{deg}(v)$ of node $v$ with its neighbors. The $r_{deg}(v)$ measures maximum disassortativeness of a node $v$ with its neighbors. If a node $v$ is more disassortative to its neighbor then the selection probability will be increased. The probability $\Pi^g_i$ of node $i$ to attach with the node $v$ may be defined as,

$$\Pi^g_i = \frac{k_v}{\sum_v k_u \zeta_v}$$

Where, $\zeta_v = \frac{r_{deg}(v)}{\sum_u r_{deg}(v,u)}$, $r_{deg}(v) = \min r_{deg}(v,n), \forall n : n \in N_C(v)$, and the value of $r_{deg}(v,n)$ is scaled from the range $[-1,1]$ to $[0,2]$.

2. **Disassortativity and Eigen vector centrality (DEC) based rewiring strategy**: Here, rewiring is a combination of local and global parameters. In the proposed strategy, a link $e_{ij}$ between node $i$ and node $j$ is chosen randomly. The node $i$ will remove a connection with node $j$ if both the nodes show assortativeness. Further, node $i$ will prefer to connect with a new node $v$ if overall congestion at the node is lesser than other nodes in the network. As EC finds the impact of a node on the other nodes in the network, therefore, it is considered for rewiring. Higher the value of EC, lower the probability to get selected for a new connection. Thats why, the node $i$ will prefer to connect with a node $v$ having lower EC and higher disassortativeness with its neighbors. The probability $\Pi^{EC}_i$ of node $i$ to attach with node $v$ may be defined as,

$$\Pi^{EC}_i = (1 - \hat{x}(v))\zeta_v$$

Where, $\hat{x}(v)$ is Eigen vector centrality of node $v$ and $\zeta_v$ is same as explained in Eq. [3].

3. **k-core (degree) and Betweenness centrality (DKBC) based rewiring strategy**: The rewiring strategy is a combination of meso scale and global scale. The network is layered into k-cores on the basis of the degree of nodes [14]. The nodes in the inner cores are more central then the nodes in the periphery hence, nodes with higher k-core are preferred for a new connection. Apart from k-core, BC is used for rewiring of links. The BC of a node $i$ is equal to the number of shortest paths from all node pairs pass through the node $i$. Nodes with high BC may be easily congested as they lie on the most of the shortest paths. Hence, in the proposed strategy, we have preferred nodes with lower BC. By considering both parameters, the rewiring steps may be defined as follows. First, a link, $e_{ij}$ between the nodes, $i$ and $j$ is removed randomly. Then the node $i$ will connect with a node $v$ if it lies in higher core (i.e., $core(v) > core(i)$ and having less BC, i.e. $g(v) < g(i)$. Where, $core(v)$, $core(i)$, $g(v)$ and $g(i)$ represent k-core score of node $v$, k-core score of node $i$, BC of node $v$ and BC of node $i$ respectively. The detailed description is presented in Algorithm [1].

Algorithm 1 k-core (degree) and Betweenness centrality (DKBC) based rewiring strategy

1: **Input**: Initial Network ($G$), BC ($g$).
2: **Output**: Rewired Network ($G'$).
3: **core[n] = FindCore(G)** // Returns core number of each node $n \in N$
4: Remove a link $e_{ij}$ randomly.
5: Select a node $v$ randomly.
6: if $core(v) > core(i)$ AND $g[i] > g[v]$ then
7: Add a link $e_{iv}$ between the nodes $i$ and $v$.
8: end if
9: return $G'$

4. **k-core (closeness), Disassortativity and betweenness centrality (CKDKBC) based rewiring strategy** : As nodes in the innermost core are more central (in terms of distance) from all other nodes in the network [14]. Hence, the k-core is computed on the basis of the closeness of a node from all other nodes in the network. If the nodes are closest to all other nodes then they will be a part of the innermost core. Based on the value of closeness centrality (CC) of nodes, the network is divided into multiples cores. The total number of core is kept the same as the score of k-core through the degree of nodes. The interval of each core depends on the difference of the maximum and minimum value of CC of nodes. If the difference is more then multiple cores will be formed. Algorithm [2] provided detail description for the generation of k-core
structure. The nodes in the innermost core have higher CC hence, they can rewire their connections to reduce congestion in the network. A node \( i \) is chosen randomly from the innermost core and its connection with a node \( j \) is removed if the nodes \( i \) and \( j \) show assortativeness and the node \( j \) also holds higher BC value. A new node \( v \) is chosen if it shows disassortativeness with the node \( i \) and having less BC value. The detailed description is provided in Algorithm 3.

Algorithm 2 Formation of core through closeness centrality, \( C \) of the nodes

1. **Input:** Network \((G)\), NumCore.
2. **Output:** core[G].
3. \( C[n] \leftarrow \text{FindCloseness}(G) \) // Returns \( C \) of each node \( n \in N \).
4. \( \min = \text{FindMin}(C) \) // Returns minimum \( C \).
5. \( \max = \text{FindMax}(C) \) // Returns maximum \( C \).
6. \( CI \leftarrow \frac{\text{NumCore}}{\max - \min} \) // Returns interval of the cores.
7. for \( i \) in \( G\.nodes() \) do
8. \( \text{index} = \frac{C[i] - \min}{CI} \).
9. \( \text{core[\text{index]}.append}(i) \).
10. end for
11. return core

Algorithm 3 k-core (closeness), Disassortativity and betweenness centrality (CKDBC) based rewiring

1. **Input:** Initial Network \((G)\), BC \((g)\), assortativity \((r_{\text{deg}})\).
2. **Output:** Rewired Network \((G')\).
3. \( \text{CoreMax} \leftarrow \text{max}(\text{core}[G]) \) // returns core value of innermost core.
4. \( i \leftarrow \text{random}(\text{Core[CoreMax]}) \).
5. \( \text{Prod} \leftarrow \text{float}[n] \).
6. for \( n \) in \( G\.nodes() \) do
7. \( \text{Prod}(n) \leftarrow r_{\text{deg}}(n_1, n) + 1 \) * \( g(n) \).
8. end for
9. Select a node \( j \) randomly with probability proportional to \( \text{Prod} \) and \( \text{RemoveEdge}(i, j) \).
10. \( v \leftarrow \text{random}(N) \).
11. if \( \text{Prod}(v) < \text{random()} \) then
12. \( \text{AddEdge}(i, v) \).
13. end if
14. return \( G' \)

IV. SIMULATION AND RESULTS

The simulation of traffic capacity analysis is carried out in scale free networks (using BA model) with 50 nodes and some datasets i.e., CSA \([17]\), Karate \([18]\) and EuAir \([19]\). The initial BA network is generated from seed network with \( m_0 = 5 \) nodes, and each new node connects to \( m = 4 \) existed nodes. Some fraction of links, \( r_f \) is getting rewired in the existing network through all the rewiring strategies. The range of \( r_f \) lies between 5% to 50%. As the real world networks like communication networks are heterogeneous hence, the proposed rewiring strategies retain the degree distribution of the networks after each rewiring operation unlike some rewiring strategies \([7]\), \([12]\), \([16]\). After that, we have analyzed the efficiency of the proposed rewiring strategies on synthetic network and empirical datasets \([17]-[19]\).

The degree distribution after rewiring of 50% of the links is plotted through all the proposed rewiring strategies and we can infer that the rewired network is still following power law in spite of rewiring of large fraction of links (Fig. 2).

![Degree Distribution](image)

Fig. 2. Degree distribution of the network under (a) DPF, (b) DEC, (c) DKBC and (d) CKDBC rewiring strategies when \( r_f = 50 \).

The proposed rewiring strategies take care of congestion in the network by considering various network parameters. Traffic congestion occurs above the critical packet generation rate \( \lambda_c \), but below which the network traffic is free. The value of \( \lambda_c \) is proportional to capacity \((C)\) inversely proportional to the BC of the node with maximum BC value, \( g(\text{max}) \). Rich club phenomenon characterized when the hubs are on average more intensely interconnected than the nodes with smaller degrees. Presence of \( RC \) increases load and congestion on the connecting link between two hubs. Hence, the \( RC \) has a negative impact on the traffic capacity of the network. All these network parameters \((\lambda_c, g(\text{max}) \text{ and } R C)\) are plotted for increasing value of \( r_f \) (Fig. 3). We can infer that all the rewiring strategies give a higher value of \( \lambda_c \) and lower value of maximum BC, \( g(\text{max}) \) than the original network. The proposed rewiring strategies remove a link randomly from a randomly selected node. There exist a small fraction of links whose removal will affect the structure of the network drastically. The probability of selection of these nodes is very less. For that reason, rewiring of a large fraction of links will not alter the performance of the network in a considerable manner. \( RC \) of the network is calculated by using the rich club coefficient \( \phi(k) \) of the nodes with degree \( k \), and is written as \( \frac{k \phi(k)}{\sum_k k \phi(k)} \). Most of the users want to send data through shortest paths i.e., through hub nodes and congestion at hub nodes will reduce capacity \( C \) and efficiency of the networks. The proposed rewiring strategies take care of congestion and offer the lower value of \( RC \) than the initial network. The rewiring
strategy based on the consideration of k-core architecture (DKBC and CKDBC) enhances the network performance. Hence, rewiring of the network through the meso-scale perspective is comparatively desirable for the scale free network (using BA model).

Fig. 3. The X-axis represents the fraction of rewired links ($r_f$) and the Y-axis plots (a) $\lambda_c$, (b) $g(\text{max})$ and (c) RC for each rewiring strategy. Red, green, blue and magenta color lines correspond to rewiring strategies; DEC, DKBC, DPA and CKDBC respectively. Cyan color line gives the value of all the parameters for original network. Each result value is the average of 10 independent realizations.

Various network properties such as $g(\text{max})$, $\lambda_c$, assortativity coefficient ($r_{deg}$), average clustering coefficient ($\langle C_i C \rangle$), average node coreness (ANC), average path length (APL), average node betweenness (ANB) are studied for scale-free networks (Table I) and for some datasets (Table II). The reason behind selecting all these properties is because they are properties of the network as a whole and not just of the individual node. All the rewiring strategies reduce $g(\text{max})$ and enhance $\lambda_c$. The significance of the rewiring strategies is different. If someone is interested in the disassortative (or assortative) network then they will prefer CKDBC rewiring strategy as it provides a minimum value of $g(\text{max})$, the maximum value of $\lambda_c$, most disassortative (or assortative) in nature and having least clustering coefficient. The CKDBC makes communication (scale-free) and transportation (EuAir) networks more disassortative while social network (CSA) is converted into a more assortative network. As the network through DPA strategy provides maximum value of $\langle C_i C \rangle$ hence, more desirable for fast spreading process and robustness. ANC, APL, and ANB of the network designed through all the rewiring strategies are almost equal (Table I). But, the values of ANC, APL, and ANB are slightly changed for the empirical datasets (Table II).

**TABLE I**

| Measures | Original Network | DPA | DKBC | CKDBC |
|----------|-----------------|-----|------|-------|
| $g(\text{max})$ | 0.5554 | 0.5127 | 0.4904 | 0.4860 |
| $\lambda_c$ | 0.4977 | 0.6769 | 0.5008 | 0.4962 |
| $r_{deg}$ | -0.0092 | -0.4677 | -0.3141 | -0.2923 |
| $\langle C_i C \rangle$ | 0.1091 | 0.1227 | 0.0779 | 0.0897 |
| ANC | 2.2744 | 2.2440 | 2.4689 | 2.4697 |
| APL | 0.0338 | 0.0338 | 0.0339 | 0.0336 |
| ANB | 0.0338 | 0.0338 | 0.0338 | 0.0338 |

CSA dataset consists of social relationships (Facebook, Leisure, Work, Co-authorship, Lunch) between employees of computer science department at Aarhus. CSA contains 61 nodes and 620 links. EuAir consists of 450 nodes and 3588 links where nodes correspond to different airlines in Europe and the link shows the connection between them. Karate is a social network of friendships between 34 members of a karate club at a US university. $g(\text{max})$ of all the datasets are plotted against $r_f$ in Fig. 4. The value of $g(\text{max})$ obtained through all the rewiring strategies is lower than the original networks. CKDBC strategy outperforms than other strategies. DKBC performs better in all the datasets except EuAir. In

Fig. 4. The X-axis represents the fraction of rewired links ($r_f$) and the Y-axis plots the $g(\text{max})$ for each rewiring strategy for different datasets: (a) CSA [17], (b) Karate [18] (c) EuAir [19]. Red, green, blue and magenta color lines correspond to rewiring strategies; DEC, DKBC, DPA and CKDBC respectively. Cyan color line gives the value of $g(\text{max})$ of original network. Each result value is the average of 10 independent realizations.

Fig. 5 among all the values of $\lambda_c$, 95% values of the proposed rewiring strategies for all the datasets are higher than the $\lambda_c$ of the initial network. The DKBC routing strategy provides higher value of $\lambda_c$ for friendship network (CSA and karate) while CKDBC outperforms for the transportation network (EuAir). RC is plotted against $r_f$(Fig. 6). For all the datasets, CKDBC strategy provides lower value of RC except a few $r_f$s. For transportation (EuAir) network, RC for all the rewiring strategies are lower than initial datasets.

Core-periphery coefficient (CP) of the rewired datasets are evaluated for different values of $r_f$ (Fig. 7). All the rewiring strategies maintain core-periphery architecture. Most of the CP values are higher than the value of initial datasets. The performance of CKDBC rewiring strategy is better than others for all the datasets.

**TABLE II**

| Measures | Network | Original Network | DPA | DKBC | CKDBC |
|----------|---------|-----------------|-----|------|-------|
| $g(\text{max})$ | CSA | 0.5554 | 0.5127 | 0.4904 | 0.4860 |
| $\lambda_c$ | CSA | 0.4977 | 0.6769 | 0.5008 | 0.4962 |
| $r_{deg}$ | CSA | -0.0092 | -0.4677 | -0.3141 | -0.2923 |
| $\langle C_i C \rangle$ | CSA | 0.1091 | 0.1227 | 0.0779 | 0.0897 |
| ANC | CSA | 2.2744 | 2.2440 | 2.4689 | 2.4697 |
| APL | CSA | 0.0338 | 0.0338 | 0.0339 | 0.0336 |
| ANB | CSA | 0.0338 | 0.0338 | 0.0338 | 0.0338 |
packet generation rate, minimize congestion in the network by enhancing the critical datasets. The color scheme and dataset are same as Fig. 3. Each result value is the average of 10 independent realizations.

Fig. 5. The X-axis represents the fraction of rewired links ($r_f$) and the Y-axis plots critical packet generation rate, $\lambda_c$ for each rewiring strategy for different datasets. The color scheme and dataset are same as Fig. 2 Each result value is the average of 10 independent realizations.

Fig. 6. The X-axis represents the fraction of rewired links ($r_f$) and the Y-axis plots rich club coefficient $RC$ for each rewiring strategy for different datasets. The color scheme and dataset are same as Fig. 2 Each result value is the average of 10 independent realizations.

V. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, various rewiring strategies are proposed to minimize congestion in the network by enhancing the critical packet generation rate, $\lambda_c$ of the network. To mitigate traffic congestion, we have considered a combination of local, global and intermediate scale perspective for rewiring of the links in the network. As a result, it is found that the proposed rewiring strategies gives the higher value of $\lambda_c$ and minimize betweenness centrality ($g(max)$) along with rich club coefficient ($RC$) while maintaining core-periphery architecture. Further, we analyzed various network properties on some empirical datasets and find the same pattern as in scale free network (through BA model). Based on the significance of the routing strategies, CKDBC is more desirable for data communication.

While, DPA routing strategy can be preferred for fast spreading process and robustness.

In future work, we would like to expend our work to more realistic environment and those can be created using network simulators. Network congestion can also be studied for varying packet generation rate on different topologies of the networks.

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