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Effect of correlation on the traffic capacity of time-varying communication network

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The network topology and the routing strategy are major factors to affect the traffic dynamics of the network. In this work, we aim to design an optimal time-varying network structure and an efficient route is allocated to each user in the network. The network topology is designed by considering addition, removal and rewiring of links. At each time instant, a new node connects with an existing node based on the degree and correlation with its neighbor. Traffic congestion is handled by rewiring of some congested links along with the removal of the anti-preferential and correlated links. Centrality plays an important role to find the most important node in the network. The more a node is central, the more it can be used for the shortest route of the user pairs and it can be congested due to a large number of data coming from its neighborhood. Therefore, routes of the users are selected such that the sum of the centrality of the nodes appearing in the user's route is minimum. Thereafter, we analyze the network structure by using various network properties such as the clustering coefficient, centrality, average shortest path, rich club coefficient, average packet travel time and order parameter.

Keywords: Time-varying communication network; routing; congestion; centrality.

1. Introduction

The structure and dynamics of complex networks attracted much attention from the researchers of different areas in recent years. It has been widely accepted that the topology and degree distribution of networks have intense effects on the process dynamics on these networks, including disease spreading,[1] information diffusion,[2]

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traffic movement.[3–5] Due to the increasing traffic volumes on the networks, e.g. road networks, social and data communication networks, fulfillment of user's demand and minimization of traffic congestion is a challenging task. The performance of the data communication networks strongly depends on its data forwarding capacity which is determined by the structure of the underlying network. In this context, an optimal time-varying communication network (TVCN) model is designed to avoid congestion in the network and the user's route is selected based on centrality information especially, betweenness centrality (BC).

It is found that the communication networks are scale-free (SF)[6] and are more susceptible to traffic congestion than some homogeneous networks.[7] In SF networks, large degree nodes posses a large volume of data, hence, congestion usually starts at these nodes and then spreads to the whole network. Therefore, researchers proposed various strategies,[8] which can be classified into hard and soft strategies in order to handle traffic congestion and enhance network capacity. The restructuring of network topology comes under hard strategies. Zhao *et al.* redistributed a load of heavily loaded nodes to others,[5] some connections are removed between large degree nodes,[9] high BC nodes are removed first[10] and links are added between the nodes with long distance.[11] Jiang *et al.*,[12] assigned capacity dynamically to each link proportional to the queue length of the link. Some fraction of links is rewired based on node's degree information and BC.[4] Chen *et al.*[13] rewired the link against traffic congestion and proved that the network should have a core-periphery structure.

Sometimes it is impossible to modify the network topological structure and it also incurs a high cost to change the structure of the network. Hence, a soft strategy based on finding a better routing strategy is preferable to enhance the network capacity. Yin *et al.*[14] chose an efficient path (EP) for routing. Zhao *et al.*[15] assigned different routes with different traffic flow priorities and it is shown that traffic capacity is enhanced by approximately 12% compared with the initial EP approach. In communication networks, two rates are associated with each node: packet generation rate, λ and packet forwarding (delivery) rate, C. Tang *et al.*[16] considered the λ as a periodic function of time and proposed a mixed routing strategy to enhance transportation efficiency. For small λ, the shortest paths (SPs) are used to deliver the packets and when λ is large, an efficient routing method is used and loads are redistributed from central nodes to others. The capacity of the network is maximized using a routing strategy based on the minimum information path and average routing centrality degree of the node is calculated to analyze the traffic load on nodes of different degrees.[17] Some of the researchers studied transport processes on multilayer[18] or multiplex networks[3] with emphasis on optimizing the network capacity and transmission efficiency. Yang *et al.*[19] established a relationship between traffic congestion and network lifetime for the network with moving nodes in a defined area and it is concluded that the network lifetime is inversely related to traffic congestion.

The previous researches demonstrate the underlying network topologies and routing approaches have significant impacts on the overall network performance. The strategies for optimizing network topology can be divided into two parts: restorative and proactive strategies. Restorative strategies include methods to do some changes in existing networks such that congestion is minimized.[4,9–11,13] Through proactive strategies, new links are added in such a way that the optimal network structure is formed.[12,20] A proactive strategy like[20] converts the network into the homogeneous network but most of the real-world networks are SF networks. Therefore, the problem statement for the proposed work may be categorized under the following categories. (i) Design an optimal network structure by considering both the proactive and the restorative strategy. A TVCN model is proposed in such a way that the addition of new links are based on a proactive strategy while removal and rewiring of links follow restorative strategy. The probability that the new node will be attached to the node in the existing network is proportional to the degree of the existing node and inversely proportional to the correlation of the existing node with its neighbor. Few links of the congested nodes are rewired and connected with the nodes with preferential attachment (PA) and having less correlation with its neighbor. Some correlated and anti-preferential links are also removed from the network. (ii) The novelty of the proposed network structure is checked by studying different network parameters such as the clustering coefficient (CC), centrality, average path length (APL) and rich club coefficient (RCC). (iii) The route of each user is selected with the help of centrality of the node in the network. The BC is used to measure the extent to which a node lies on (SPs) between other node pairs. If a node is more betweenness central then it may appear in a large number of users' route. The nodes with maximum BC values are the most congested nodes in the network.[5] Therefore, routes of the users are selected such that the sum of the BC of the nodes appearing in the user's route is minimum. As a result, it is found that the path constructed through small betweenness central nodes is least congested than the other SPs. Simulation results show that the proposed routing strategy effectively enhances the transmission capacity and reduce the load of the networks.

In Sec. 2, some existing network models and proposed network model are described. Section 3 discusses some rewiring strategies. The traffic flow model is provided in Sec. 4. Section 5 presents the simulation results, and in Sec. 6, conclusions and future research plan are discussed.

2. Network Models

The concept of an evolving network is given by Barabási–Albert[6] (BA) where a new node attaches with an existing node through PA. In the BA model, only addition of nodes and links are considered and a new link will appear only when new node arrives. But, in the real scenario, links may appear or disappear at any time. Hence, two models are discussed; TVCN model and disassortative TVCN (DTVCN) model.

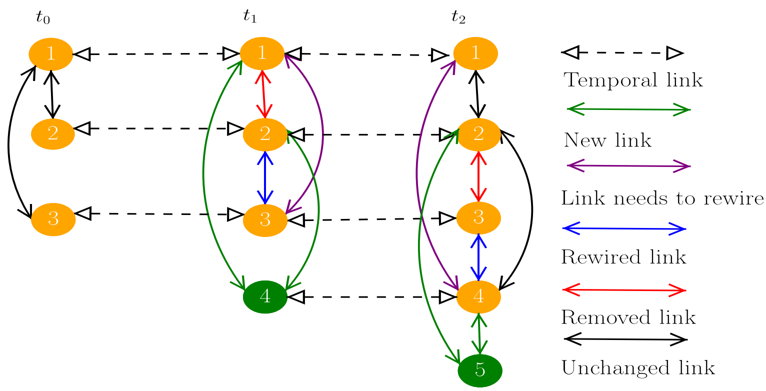

Fig. 1. (Color online) A TVCN at t_0, t_1 and t_2 time instants.

2.1. *TVCN model*

TVCN model can be represented as $G = (V, E, T)$, where V is the set of nodes, T is the set of time instants for which the TVCN is defined, and $E \subseteq V \times T \times V \times T$ is the set of links. The size of the network is considered as N. A dynamic link, e_{ij} between source node, i and destination node j in the TVCN is defined as an ordered quadruple $e_{ij} = (i, t_i, j, t_j)$, where $t_i, t_j \in T$ are the time instants of the appearing nodes, i and j, respectively. In Fig. 1, a network is shown at different time instances; t_0, t_1 and t_2. At each time instant, any link e_{ij} may appear or disappear but nodes will appear only in the network.

A TVCN model is proposed where at each time instant, t_i, a new node i, is added to the network (expansion) and a number $M(\leq n_0)$ is selected for network expansion, rewiring and removal, where n_0 is initial number of nodes present as the seed network. Links are divided into three categories; newly added, rewired and removed links. Fractions, α and γ are chosen for newly added and rewired links. Steps involved in the formation of TVCN model[21] are as follows:

(1) Total number of newly appeared links are

$$f_{\text{add}}(t) = \alpha M \,.$$

A new node i, to connect with an existing node v, is based on PA and the probability, Π_v to attach with node v in the existing network on the basis PA may be defined as

$$\Pi_v = \frac{k_v}{\sum_{u \in V} k_u} \,,$$

where k_v is degree of node v.

(2) Few links are rewired in the existing network;

$$f_{\text{rewire}}(t) = \gamma(M - f_{\text{add}}(t)) = \gamma(1 - \alpha)M \,.$$

A node s is chosen with probability, Π_s, and it will remove a connection from a node $t \in Ne(s)$, where $Ne(s)$ is a neighboring set, with an anti-PA probability Π'_t and it can be defined as

$$\Pi'_t = \frac{1}{N-1}\left(1 - \frac{k_t}{\sum_{u \in V} k_u}\right)$$

and connect with another node w in the existing network, with probability, Π_w.

(3) Final fraction of the remaining segment for deletion is

$$f_{\mathrm{delete}}(t) = M - f_{\mathrm{add}}(t) - f_{\mathrm{rewire}}(t) = (1-\gamma)(1-\alpha)M\,.$$

A node m is chosen with probability, Π'_m, and it will remove a connection with its neighboring node $p \in Ne(m)$, with probability, Π'_p.

The SF network (BA model) and TVCN model assume that the new node will prefer to attach with the nodes in the existing network based on the value of the degree of the existing node. But, in most of the networks, this assumption may not be true, as nodes cannot acquire links unconditionally. There is a limit on packet forwarding rate, i.e. the capacity of the node. If more links are attached to a node, then it may happen that the node will be a part of a large number of user's SPs and leads to congestion in the network. Therefore, we modified the probability to account for the congestion and introduced degree–degree correlation (DDC) as a multiplicative factor to the PA probability. DDC is a network parameter in which nodes with similar attributes, such as degree, tend to be connected. DDC is used to divide networks into three types: assortative, disassortative and neutral networks.[22] For assortative networks, hubs (or small degree nodes) tend to link to other hubs (or small degree nodes). In a disassortative network, hubs (or small degree nodes) connects with small degree nodes (or hubs). While in the neutral network, there is no preference for the connection between two nodes and the links between nodes are created randomly.

2.2. *DTVCN model*

In the TVCN, a node v, may generate packets with a packet generation rate, λ_v and may forward packets according to its capacity, C_v. Here, in this paper, the packet generation rate of the nodes are kept same in the network, i.e. $\lambda_v = \lambda$, $\forall v \in V$. For the smaller value of the packet generation rate, λ, system remains in free flow state as every packet is getting delivered. But, with the increasing value of λ, a point is reached where system converts into congested phase and this point of phase transition is known as critical packet generation rate, λ^*. The value of λ^* is affected by the topology of the network. DDC has an important influence on the structural properties of the network and is one of the deciding parameters to find congestion in the network[23] as well. Communication network comes under disassortative network. For that reason, a DTVCN model is proposed to achieve a

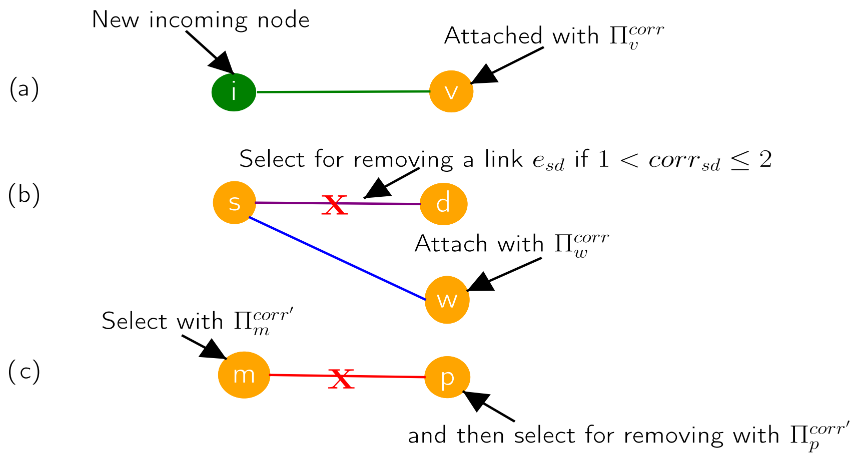

Fig. 2. (Color online) For selecting a node for (a) addition, (b) rewiring and (c) deletion. Green color node is the new incoming node and the orange color nodes are the existing nodes in the network.

higher value of λ^*. DDC between two nodes u and v can be defined as

$$\mathrm{corr}_{uv} = \frac{\mathrm{cov}(u,v)}{\mathrm{sd}(u) * \mathrm{sd}(v)}\,,$$

where $\mathrm{cov}(u,v)$ is the covariance between nodes, u and v and sd denotes the standard deviation. The steps involved in the formation of DTVCN model are as follows:

(1) A new incoming node i will establish a new connection with a node v in the existing network (Fig. 2(a)), by preferring the higher degree of the node v, and normalized disassortativeness, ζ_v, of node v with its neighbor set, $Ne(v)$, in the network. The probability, Π_v^{corr} of selecting a node v through PA and normalized disassortativeness with its neighbors may be defined as

$$\Pi_v^{\mathrm{corr}} = \frac{k_v}{\sum_u k_u}\zeta_v\,, \tag{1}$$

where $\zeta_v = \frac{D_v}{\sum_{n \in Ne(v)} \mathrm{corr}_{nv}}$, $D_v = \min_n\ \mathrm{corr}_{nv}$, $\forall n$: $n \in Ne(v)$. The value of corr_{nv} lies in the range of $[-1,1]$. If $-1 < \mathrm{corr}_{nv} < 0$, then the nodes, n and v show disassortativeness. The value of $0 < \mathrm{corr}_{nv} < 1$ shows the nodes, n and v are assortative. Here, in this paper, the value of corr_{nv} is scaled from the range of $[-1,1]$ to $[0,2]$. The value of ζ_v is dependent on the correlation of node v with its neighbors. The maximum disassortativeness of a node v with its neighbors is denoted by, D_v. If a node v is more disassortative to its neighbors, then the probability to get a new connection will be increased.

(2) A link e_{sd} between nodes s and d is removed if the node s shows assortativeness with node d (Fig. 2(b)). The node s will rewire its connection and connects with a node w, with probability, Π_w^{corr}.

(3) Final fraction of the remaining segment for deletion is $f_{\text{delete}}(t)$ (Fig. 2(c)). The probability, $\Pi_m^{\text{corr}'}$ of selecting a node m, with anti-PA and high correlation with its neighbors is given by

$$\Pi_m^{\text{corr}'} = \left(1 - \frac{k_m}{\sum_u k_u}\right)(1 - \zeta_m)\,.$$

A node m, is chosen with probability, $\Pi_m^{\text{corr}'}$, and it will remove a connection with its neighboring node p, with probability $\Pi_p^{\text{corr}'}$.

3. Routing Strategy

The communication network is shared by a large number of users. But, the user's information is not available at the time of design of network structure. If a node appears in the path of multiple users, then the capacity of the node will be divided equally among the users. Let us consider, a set of R users who want to access the network and each user, r, can pick any source and destination pair. There exists multiple SPs σ^r for each user $r \in R$ from the source node to the destination node. The set of the SPs, Ω^r, of user, r, can be written as

$$\Omega^r = \{\sigma_l^r \mid l\text{th SP for user } r\text{'s source destination pair}\}\,.$$

σ_l^r contains set of nodes those will appear in the SP of the user r and can be represented as

$$\sigma_l^r = \{u \mid \text{ nodes appear in the } l\text{th route of user } r\}\,.$$

Since the value of λ^* of the network is affected by the node with maximum BC and sometimes, it may happen that the node with maximum BC appears in user's route which leads to congestion in the route. Hence, the probability of selecting the SP, σ_l^r, depends on the value of sum of BC ($W_g(\sigma_l^r)$) of the nodes appearing in the route of user, r, and may be defined as

$$W_g(\sigma_l^r) = \sum_{u:u\in\sigma_l^r} g_u\,, \tag{2}$$

where g_u is the BC of node u. All the $W_g(\sigma_l^r)$ are added into the set W_g^r and can be denoted as

$$W_g^r = \{W_g(\sigma_l^r) \mid \forall l \in \Omega^r\}\,.$$

After calculating $W_g(\sigma_l^r)$, we assign weight on each SP. The SP, σ^{*r} is found as optimal SP if it provides minimum value from $W_g(\sigma_l^r)$ and it can be represented as

$$W_g(\sigma^{*r}) = \min_l W_g(\sigma_l^r)\,. \tag{3}$$

Similarly, the maximum value of $W_g(\sigma_l^r)$ of user r can be denoted as $W_g(\hat{\sigma}^r)$ where $\hat{\sigma}^r$ is the SP which provides maximum value of $W_g(\sigma_l^r)$. The $W_g(\sigma_l^r)$ of user r

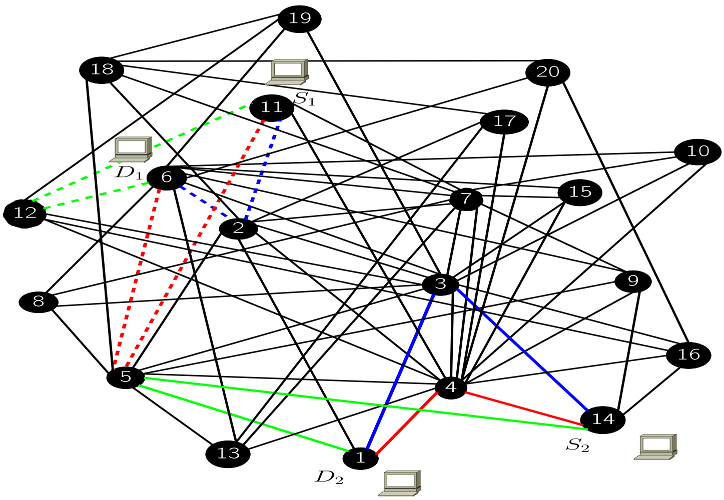

Fig. 3. (Color online) A SF network generated through the BA model with $N = 20$ and $\langle k \rangle = 4$. Red, green and blue color solid lines show route of User 1 and dashed line is for the route of User 2 under different routing strategies; $W_g^{\max}$, $W_g^{\min}$ and a random SP, respectively.

through any SP, $\tilde{\sigma}^r$ is denoted as $W_g(\tilde{\sigma}^r)$. A set of optimal SPs for all the users can be represented as

$$\Omega^* = \{\sigma^{*r} \,|\, \forall r \in R\}\,.$$

The set of $W_g(\sigma^{*r})$ is represented as

$$W_g^{\min} = \{W_g(\sigma^{*r}) \,|\, \forall r \in R\}\,.$$

Similarly, we can represent $W_g^{\max}$ and W_g^{SP}. The topological structure of the BA model is shown in Fig. 3. Different routing strategies ($W_g^{\min}$, $W_g^{\max}$ and a random SP) are applied for assigning SPs to each user. The sum of BC, $W_g(\sigma_l^r)$, of the nodes appearing in the SPs for different routing strategies is computed. In Fig. 3, two users, 1 and 2, want to access the network where $1, 2 \in R$. The value of $W_g(\sigma_l^1)$ for user, for the SP through green, red and blue color solid lines, is $0.0756, 0.2020$ and 0.1197, respectively. The SP is chosen through green, red and blue color dotted line for User 2 gives the value of $W_g(\sigma_l^2)$ as $0.0198, 0.0756$ and 0.0350, respectively.

At a particular time instant, only R users want to access the network and few nodes will be their point of interest. Therefore, instead of considering the whole network to calculate λ^*, a subnetwork consisting all the nodes appear in the users' route is only considered. With the increase in the size of the network, packets are more likely to be routed to the nodes with higher BC and packets are more likely to be accumulated at these nodes, resulting in traffic congestion. But, the proposed routing strategy avoids larger BC nodes and we may get a higher value of λ^*. Hence, there will be less congestion on the nodes those are the part of the subnetwork.

4. Traffic Model

The traffic flow model is based on different routing algorithms in communication networks. The topologies of various networks are different hence, data delivery capacity of each node is considered as different for different nodes, depending on the effect of the node on the other nodes in the network. Some nodes are endorsed by the nodes which are already congested and cause an increase in load at that node. The aim of the proposed approach is to assign more capacities to the congested node in order to reduce data traffic in the network. Eigenvector centrality is used to define the impact of the node on the other nodes in the network and is considered in the computation of capacity of the node. Therefore, data forwarding capacity, C_v of a node v, may be defined as

$$C_v = \beta \hat{x}_v N, \tag{4}$$

where N is size of the network, $\hat{x}_v$ is Eigenvector centrality of node v, $\hat{x}_v = \frac{1}{\kappa}\sum_{u\in V} A_{u,v}\hat{x}_u$. κ is maximum eigenvalue of the matrix A, where A is the adjacency matrix and the value of $A_{u,v} = 1$ if there is a link between the nodes, u and v, else it is 0. The term, β is a considerably modest fractional value and is a controlling parameter for the capacity of the nodes. Packets are forwarded through the SPs from the source node to the destination node into the network. Therefore, the probability to pass through a node v is provided as $\frac{g_v}{\sum_{u\in V} g_u}$, where g_v is the BC of node v. At each time step, the average number of packets generated is λN. Hence, the average number of incoming packets, Q_v, at node v is defined as

$$Q_v = \lambda \mathcal{D} N \frac{g_v}{\sum_{u\in V} g_u}, \tag{5}$$

where $\mathcal{D}$ is the average SP length of the network. The term, λ is a small fractional value and is a controlling parameter for Q_v for the node v. The capacity of a node increases with increase in the value of β. The sum of the capacities of individual node $v \in V$ is known as the capacity, C of the network. Similarly, the sum of the accumulated packets, Q_v of each node $v \in V$ is termed as the traffic load, Q, 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 point at which the phase transition occurs from free flow state to congested flow state is known as the critical point as well as the critical packet generation rate (λ^*). There are three possible relationships between Q and C: (i) $Q < C$ implies the system in free flow state, (ii) $Q = C$ shows the boundary case for congestion and (iii) $Q > C$ allows a system in congestion. Local congestion of a node v is calculated according to its C_v and λ_v. If $Q_v > C_v$ of node v, then the node will be congested and these nodes increase overall network congestion.

The node with the maximum BC can be easily congested, hence, it is necessary to consider only the traffic load of this node. The maximum number of packets that can be forwarded through a node, $v\_\max$ has capacity, $C_{v\_\max}$ and the total number of packets accumulated at maximum betweenness central node is

$$Q_{v\_\max} = \lambda^* \mathcal{D} N \frac{g_{v\_\max}}{\sum_{u\in V} g_u} ,$$

where $v\_\max \in V$. The value of λ in Eq. (5) is replaced by λ^* and theoretical estimation of critical packet generation rate is given by[5]

$$\lambda^* = \frac{C_{v\_\max}(N-1)}{g_{v\_\max}} .$$

The nodes with maximum packet forwarding capacity and maximum BC are denoted by $C_{v\_\max}$ and $g_{v\_\max}$, respectively. The average number of packets for a packet generation rate (λ) over a time window Δt can be calculated by using an order parameter $\theta(\lambda)$ and is given by

$$\theta(\lambda) = \lim_{t\to\infty} \frac{C}{\lambda} \frac{\langle \Delta \mathbb{P} \rangle}{\Delta t} ,$$

where $\Delta\mathbb{P} = \mathbb{P}(t+\Delta t) - \mathbb{P}(t)$, $\mathbb{P}(t)$ is number of packets at time t and $\langle . \rangle$ shows the average value over the time window Δt. $\langle \Delta\mathbb{P}\rangle = 0$ indicating that there is no packet in the network for $\theta = 0$, system is in free flow state. The ratio of C and λ provides the quantity of undelivered packet over Δt in the network.

In a network, if a packet is generated then it needs to be delivered. Once the packet is reached to its destination it is removed from the network. The average time, $\langle T\rangle$, to deliver all the packets to the destination nodes are dependent on the route of the user. Each node v, generates packets with rate λ_v. If $\lambda_v < C_v$, then all the packets will be forwarded to the next node toward its destination otherwise it needs to wait at the end of the queue. After that, packets will be processed on a first come first serve basis. From this, we can infer that the packets waiting in the queue increase $\langle T\rangle$ and θ as well. The $\langle T\rangle$ through $W_g^{\min}$ strategy can be formulated as

$$\langle T\rangle^{\min} = \sum_{\sigma^{*r}:\sigma^{*r}\in\Omega^*} \sum_{u:u\in\sigma^{*r}} Q_u / y_{\sigma^{*r}} , \tag{6}$$

where $y_{\sigma^{*r}} = \min_{u:u\in\sigma^{*r}} C_u$. Similarly, we can calculate $\langle T\rangle^{\max}$ and $\langle T\rangle^{\mathrm{SP}}$ for the routes with $W_g^{\max}$ and W_g^{SP}, respectively.

5. Simulation and Result

For the dynamics of DTVCN model, the simulation starts by establishing the infrastructure of the network. In this paper, the parameters are set with the value as seed node $n_0 = 5$, number $M(\leq t)$, fraction of newly added links α range in $(0, 1)$, fraction of rewired links γ is in the range of $(0.5, 1)$, with network size ranging from $N = 10^2$ to $N = 5\times 10^3$. Any node can be included in the user's source–destination pairs or may participate in routing also. The capacity of each node is proportional to the Eigenvector centrality of the node. Here, the range of DDC is scaled from $[-1, 1]$ to $[0, 2]$. The value of the controlling parameters, λ and β may be any small fractional value.

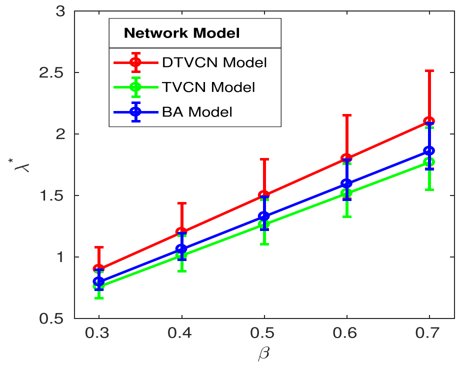

Fig. 4. (Color online) The value of λ^* for different values of β. Each result value is the average of 10 independent realizations of BA model, TVCN model and DTVCN model.

In Fig. 4, critical packet generation rate, λ^* is evaluated for the networks designed through different strategies. β is the controlling parameter for capacity C. The value of λ^* is proportional to the capacity of the maximum BC node hence, it increases with β. DTVCN model considers congestion at the time of topology design hence, it gives the higher value of λ^*. In the TVCN model, addition and rewiring strategies are based on PA and it will increase the degree of higher degree nodes which leads to increased congestion in the network. Therefore, the model gives least value of λ^* for different β.

Network topology and routing strategies both are deciding parameters for the load at the network. If we increase the flow of packets through the congested node, then the total number of undelivered packets will increase accordingly. Multiple SP exists for the different source node and the destination node. If the packets are sent through the path with $W_g^{\min}$, then the total number of accumulated packets θ is lower for distinct values of λ. The random SP offers the value of θ in between $W_g^{\max}$ and $W_g^{\min}$. The network designed through DTVCN model and routes selected through $W_g^{\min}$ give least value of θ for different λ and the network designed through TVCN model and the route selected through $W_g^{\max}$ gives highest value of θ. As a result, it is inferred that the network designed through DTVCN model outperforms than other models for all routing strategies (Fig. 5).

Congestion increases the number of the accumulated packet in the route of the user and the average packet travel time, $\langle T \rangle$. In Fig. 6, $\langle T \rangle$ is maximum when the routing strategy, $W_g^{\max}$ is applied on the network designed through all the models (DTVCN model, TVCN model and BA model) while $\langle T \rangle$ is minimum for $W_g^{\min}$ routing approach. The value of $\langle T \rangle$ for the random SP lies in between $W_g^{\min}$ and $W_g^{\max}$ routing approaches. The performance of the network designed through TVCN model for all routing approaches is lower than the other models. $\langle T \rangle$ for BA model and DTVCN model are approximately the same for their respective routing strategies.

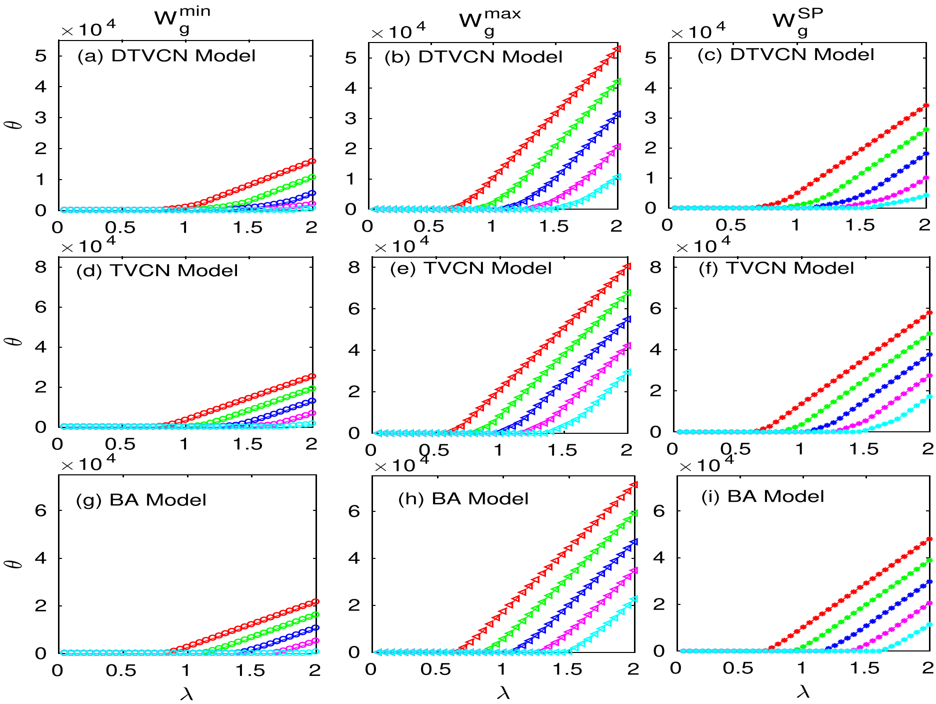

Fig. 5. (Color online) The order parameter, θ versus the packet generating rate, λ under different routing strategies ($W_g^{\min}$, $W_g^{\max}$ and SP) and the network designed through DTVCN model, TVCN model and BA model. Red, green, blue, magenta and cyan color blocks correspond to the simulations of $\beta = 0.3$, 0.4, 0.5, 0.6, 0.7, respectively. Each result value is the average of 10 independent realizations.

In Fig. 7, various network properties such as maximum BC ($g_{v\_\max}$), APL, RCC and CC are studied. All these are the properties of the network as a whole and not just of the individual node. This allows for the analysis of how the whole network changes and not just the structure around some particular node. Rich club (RC) phenomenon is characterized when the hubs are on average more intensely interconnected than the nodes with smaller degrees. When the nodes are with a large degree, then k tends to be more connected than the nodes with the smaller degree. The RC phenomenon refers to the tendency of hub nodes to connect with other higher degree nodes than the nodes with a smaller degree. Presence of RC increases load and congestion on the connecting link between two hubs. Most of the users want to send data through SPs, i.e. through hub nodes and congestion at hub nodes will reduce C and efficiency of the networks. The proposed DTVCN model takes care of congestion and offers the lowest value of RC than the other two models; the BA model and TVCN model. The value of $g_{v\_\max}$ for DTVCN model is minimum and TVCN model is maximum for different value of N. The APL of the network structured through all the models lie between 2 to 3. The clustering coefficient, CC decreases with increasing value of N and the CC of BA

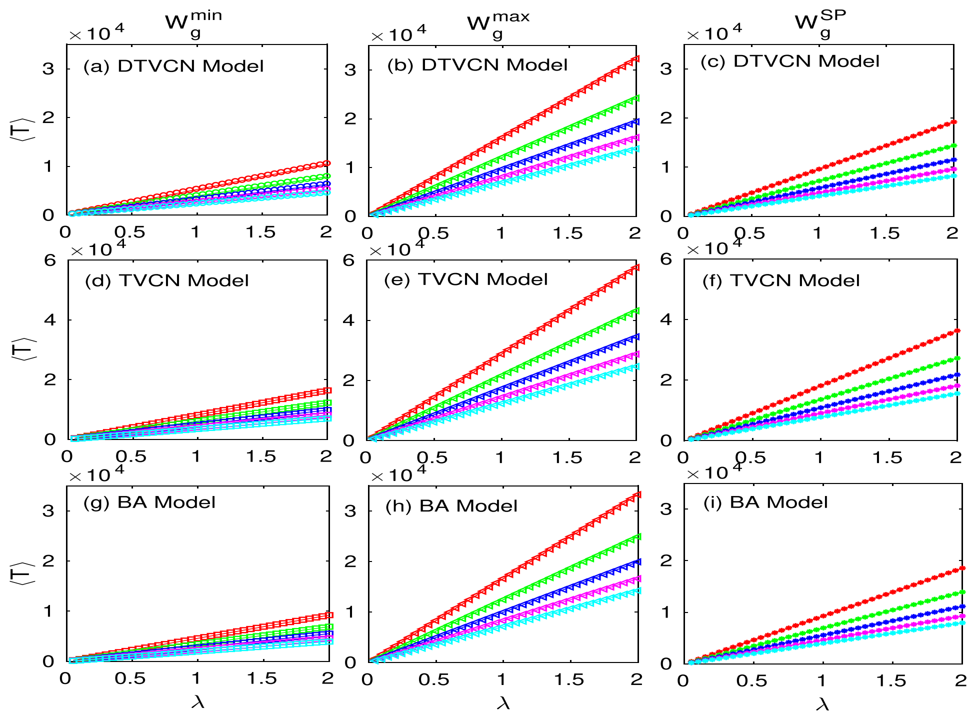

Fig. 6. (Color online) Average packet travel time, $\langle T \rangle$ versus packet generating rate λ for different value of controlling parameter, β under different routing strategies ($W_g^{\min}$, $W_g^{\max}$ and SP) and the network designed through DTVCN model, TVCN model and BA model. Red, green, blue, magenta and cyan color square blocks correspond to the simulations of $\beta = 0.3$, 0.4, 0.5, 0.6, 0.7, respectively. Each result value is the average of 10 independent realizations.

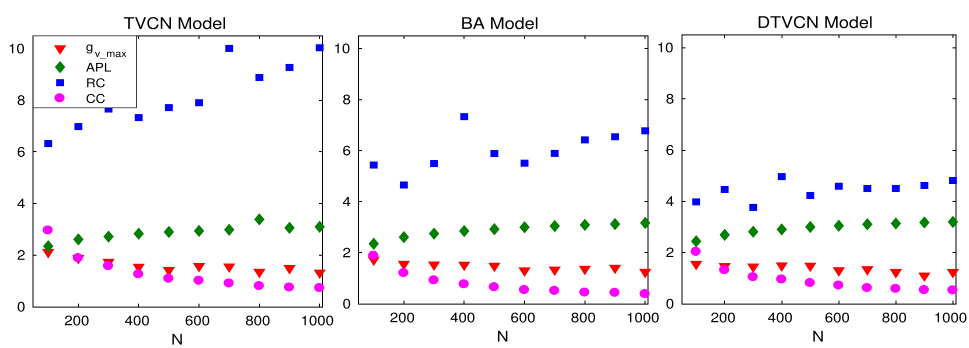

Fig. 7. (Color online) Study of the network parameters for all the models; DTVCN, TVCN and BA when N varying from 10^2 to 10^3. Each result value is the average of 20 independent realizations.

model is minimum and TVCN model is maximum. The length of the average SP of all the models increases with increasing value of the N. The quantitative value of the network properties is shown in Table 1.

Table 1. Study of the network parameters for all the models when N is varying from 10^2 to 10^3.

N	Network model	$g_{v\_\max}$	APL	RCC	CC
200	DTVCN	0.1466	2.6938	4.4639	0.1316
	TVCN	0.1890	2.6154	6.9843	0.1890
	BA	0.1562	2.6140	4.6577	0.1208
400	DTVCN	0.1495	2.9076	4.9605	0.0955
	TVCN	0.1551	2.8362	7.3350	0.1264
	BA	0.1530	2.8538	7.3302	0.0770
600	DTVCN	0.1305	3.0502	4.5967	0.0719
	TVCN	0.1576	2.9438	7.9056	0.1015
	BA	0.1307	3.0027	5.5156	0.0544
800	DTVCN	0.1237	3.1391	4.5039	0.0589
	TVCN	0.1352	3.3902	8.8899	0.0808
	BA	0.1369	3.0942	6.4224	0.0446
1000	DTVCN	0.1238	3.1983	4.8072	0.0528
	TVCN	0.1323	3.1029	10.0394	0.0730
	BA	0.1249	3.1712	6.7765	0.0386

6. Conclusion and Future Direction

In this paper, a time-varying network topology is designed by using PA and correlation of the nodes in the network. The network structure considers rewiring of some links of the congested node and also the removal of some anti-preferential and correlated links in the network. The correlation helps to mitigate traffic congestion in the network and provides a higher value of the critical packet generation rate, λ^*. After that, users' data are sent through three types of SPs; the SP with a minimum value of $W_g(\sigma^r)$, the SP with a maximum value of $W_g(\sigma^r)$ and a randomly selected the SP of user r. The proposed routing approaches are applied to the network designed through different models, namely, the BA model, the TVCN model, and the proposed DTVCN model. Simulation results show that traffic capacity can be increased considerably and traffic loads are also reduced by sending data through the SP with $W_g^{\min}$. Moreover, the average packet travel time, $\langle T \rangle$ is reduced compared with the routing approach through the SP with $W_g^{\max}$ and by choosing a random SP. Further, we analyzed various network properties and found that existence of higher BC, $g_{v\_\max}$ and RC phenomenon have a negative impact on the performance of the networks.

In future work, we would like to expand our work to the more realistic environment and those can be created using network simulators. Network congestion can be studied for varying packet generation rate on the network designed through some other strategies.

Appendix. List of Symbols

Symbols	Meaning
V	Set of nodes.
E	Set of links.
T	Life span of the networks.
λ_v	Packet generation rate of node v.
C_v	Packet forwarding rate of node v.
Π_v	Probability of a node v will be selected through PA.
Π'_v	Probability of a node v will be selected through anti-PA.
Π_v^{corr}	Probability of a node v will be selected through PA and least correlated with its neighbor.
$\Pi_v^{\text{corr}'}$	Probability of a node v will be selected through anti-PA and highly correlated with its neighbor.
corr_{uv}	Correlation between nodes u and v.
λ^*	Critical rate of packet generation.
g_v	Betweenness centrality of a node v.
e_{ij}	A link connects node i with node j.
α	Fraction of the links establish a new connections from the new node at time t , $0 < \alpha < 1$.
γ	Fraction of the links rewired in the existing network, $0.5 < \gamma \leq 1$.
n_0	Number of nodes in the seed networks.
$\hat{x}_v$	Eigenvector centrality of node v.
$W_g(\sigma^r)$	Aggregate value of the BC of the SP for user r.
$W_g^{\min}$	The set of $W_g(\sigma^{*r})$.
$g_{v\_\max}$	A node with maximum BC.
σ^r	SPs of user r.
Ω^r	The set of the SPs of user r.
σ_l^r	The set of nodes those will appear in the SP of the user r.
$W_g(\sigma_l^r)$	Sum of BC of the nodes appearing in the route of user r.
W_g^r	Set of all the $W_g(\sigma_l^r)$ of user r.
σ^{*r}	Optimal SP of user r.
$\hat{\sigma}^r$	The SP which provides maximum value of $W_g(\sigma_l^r)$ of user r.
$\tilde{\sigma}^r$	Any random SP of user r.
$W_g(\hat{\sigma}^r)$	The maximum value of $W_g(\sigma_l^r)$ of user r.
$W_g(\tilde{\sigma}^r)$	The $W_g(\sigma_l^r)$ of user r through any SP, $\tilde{\sigma}^r$ of user r.
Ω^*	A set of optimal SPs for all the users.
Q_v	Total number of accumulated packets at node v.
$v\_\max$	A node with maximum BC.
$\langle T \rangle$	Average packet travel time.
$\theta(\lambda)$	An order parameter to describe the network traffic.
CC	Clustering coefficient.
RC	Rich club.
APL	Average path length.

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