Centrality Based Algorithms for Controller Placements in Software Defined Wide Area Networks

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Abstract. Most controller placement algorithms require as input the estimated number of controllers to be placed in software defined wide area networks (SD-WANs). However, determining the correct number of controllers is NP-hard, as it requires selecting the set of nodes whose propagation capabilities exceed a given threshold. To this end, we propose in this study, a number of centrality based algorithms for estimating the capability of nodes to propagate end-to-end traffic flow. Specifically, we explore the Dempster-Shafer (D-S) Theory of evidence as a framework for estimating the capability of nodes by combining the properties of multiple centralities together to derive new joint properties. Nodes whose estimated capabilities exceed a given probability threshold are then selected as controllers. Based on the set of selected controller locations, we evaluate the performance of each joint evidential centrality (JEC) algorithm in terms of latency-related metrics. Experimental results show the superior performance of the combination of degree, node-strength and betweenness centralities in estimating the number of controllers required when worst and average case latencies are to be minimized.

Keywords: Centrality · Controller placements · D-S theory of evidence · Latency · Propagating capability

1 Introduction

Until recently the management and configuration of computer networks was mostly conducted manually because of the rigid manner networking devices were wired. However, with the emergence of software defined networking (SDN), the underlying infrastructure has been split into two planes namely the control and data planes. The control plane contains the network's control logic responsible for managing and con-trolling traffic as well as several decision-making tasks [1, 14]. An important aspect of the decision-making tasks for control plane is the selection of the appropriate number of controller locations required for optimal performance. To this end, several algorithms have been proposed in the literature for estimating the number of controllers required. However, most of these algorithms require as an input the number of controllers to be placed beforehand. Thus,

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making the procedure cumbersome and computationally intensive due to the curse of dimensionality when the number of controllers to be placed is unknown [2, 3]. Therefore, we consider in this study, centrality measures for estimating the propagation capability of nodes with the aim of selecting the set of nodes that minimizes average and worst case latencies simultaneously. However, given the numerous centralities proposed in the literature for identifying significant nodes in social networks, there is the need to explore centralities relevant to controller placement optimization [4–6]. More so, given the number of available latency related optimization metrics, finding a balanced trade-off is a gap that re-quires further investigation. We envisage that one way to address the issue of multi-objective optimization in controller placements is to sort and rank nodes based on estimated significance using several centralities. Hence, in this study, we evaluate the selection of controller locations based on multiple centralities with the aim of determining the propagation capability of nodes in minimizing both average case (AC) and worst case (WC) latencies.

Essentially, in SD-WANs, minimizing worst and average case latencies is critical to the responsiveness of the control plane to different applications [7, 8]. More so, for a consistent and global view of the network's state both latencies need be optimized simultaneously. Hence, a strategy that offers balanced trade-offs between both latencies needs to be developed. One way to do this is to explore the centralities of net-works with the view of drawing inferences for determining the appropriate number of controllers. To this end, we explore in this study, the Dempster-Shafer's theory of evidence as a framework for combining multiple centralities with the view of estimating the propagation capability of nodes.

The rest of the paper is structured thus. The related centralities relevant to controller placements is presented in Sect. 2. The formulation of the joint evidential centrality algorithm is described in Sect. 3. Results evaluation are discussed in Sect. 4 with conclusions drawn in Sect. 5.

2 Related Works

In this section, we discuss six centrality based algorithms that has been used to ad-dress the problem of significant node identification for social networks which is similar to the controller placement problem. Hence, the algorithms used for determining the most significant set of nodes in social networks can also be explored for selecting the set of nodes suitable for hosting controllers in SD-WANs. However, given the NP-hardness of both problems requires that an efficient algorithm be developed for large instances of the problem. Therefore, we consider using centrality measures as an alternative and efficient method for identifying suitable nodes for controller placements in SD-WANs.

Centrality is a term used to describe the significance of nodes in social networks [9]. To this end, the literature is replicate with algorithms designed for evaluating the propagating capability of nodes in complex networks. These algorithms can be classified based on the scope of the network properties used to measure the significance of each node in the network. Whilst centralities such as degree (D) and step-neighborhood (N) only utilize local properties, centralities such as betweenness (B), closeness (C), eccentricity (E), average current flow (A) use global properties. Specifically, within the context of controller placements few scholars have adopted the use of centrality measures for determining the set of nodes in SDNs that are suitable for hosting controllers [4–6]. We provide a brief description of centralities that are relevant to controller placements in the sub-sections below drawing inspiration from the study carried out in [10]:

2.1 Local Centralities for Controller Placements

2.1.1 Degree Centrality (D)

This is the measure of the number of nodes directly connected to a given node. The degree centrality of node i is defined mathematically as follows:

$$\mathrm{D}_{(\mathrm{i})} = \sum_{j}^{N} v_{i,j} \tag{1}$$

where (vij) shows connectivity between a pair of observed nodes i and j in the network. Generally, to indicate connectivity, vij = 1 otherwise vij = 0. The degree of a node shows its ability to propagate information to its immediate neighboring nodes. Hence, the higher the degree centrality of a node, the greater its capability to propagate flows in the network. In this study we consider degree centrality as a measure for estimating the probability of each node's propagating capability with regards to its immediate neighboring nodes.

2.1.2 Weighted Neighborhood Centrality (N)

This is the measure of the sum of weights associated with each link L connected to a node to the kth degree. The weighted neighborhood centrality of node i is defined mathematically as follows:

$$\mathrm{N}^{\mathrm{k}(\mathrm{i})} = \sum_{i=1}^{N} L_i^{(k)} * W_i \; \forall i \; \in L \tag{2}$$

where $L_i^{(k)}$ denote the set of links connected to the observed node i to the kth step degree. For example, when k = 1, the set of nodes covered equals the value returned by the degree centrality without considering the weights on the links. The weighted neighborhood centrality is indicative of the clustering capacity of each node. Hence, the higher the weighted neighborhood centrality of a node, the greater its capacity to be a cluster head. In this study we consider this centrality as a measure for estimating the probability of each node's clustering capability.

2.2 Global Centralities for Controller Placements

2.2.1 Betweenness Centrality (B)

This is the measure of the number of times a node i lies between the shortest path of other nodes in the network. The betweenness centrality of node i is defined mathematically as follows:

$$\mathrm{B}_{(\mathrm{i})} = \sum_{j \neq l \neq i} \frac{n_{jl}(i)}{n_{jl}} \tag{3}$$

where n_{jl} denotes the set of binary shortest paths between nodes j and i, and $n_{jl}(i)$ denotes the subset of those paths that pass through node i. The betweenness centrality is indicative of the nodes in the network that are bridges or servers between nodes. Hence, the higher the betweenness centrality of a node, the greater its capacity to serve as hotspots. In this study, we consider this centrality as a measure for estimating the probability of each node's capability to serve as a bridge between nodes in the network.

2.2.2 Closeness Centrality (C)

This is the measure of the proximity of node i to every other node in the network. The closeness centrality C of node is defined mathematically as follows:

$$\mathrm{C}_{(\mathrm{i})} = \frac{1}{\sum_j^N d_{ij}} \tag{4}$$

where dij denotes the distance between nodes i and j in the network. It is indicative of nodes with efficient propagating capability. Where efficiency is a function of average case latency. Hence, nodes with higher closeness centrality have higher efficient propagating capability. In this study, we consider this centrality as a measure for estimating the timeliness with which a node can propagate flows across the network.

2.2.3 Eccentricity Centrality (E)

This is the measure of a node's proximity to the furthermost node in the network. It is similar to closeness centrality. However, the difference being that whilst closeness centrality caters for average distance, eccentricity takes care of longest distance. The eccentricity centrality of node i is defined mathematically as follows:

$$\mathrm{E}_{(\mathrm{i})} = \frac{1}{\max\{dist(i, j)\}} \forall i, j \in N \tag{5}$$

where max (dist (i, j)) is the maximum distance between the node i and its furthermost node. It is therefore also a function of latency and determines to a large extent the efficiency of a node to propagate flows with regards to worst case latency. Hence, nodes with higher eccentricity have lower efficiency whilst those with lower values have higher efficiency. In this study, we consider this centrality as a measure for estimating the timeliness with which a node propagates flows with regards to the further most node.

2.2.4 Approximate Current Flow Betweenness Centrality (A)

This is the measure of the amount of traffic flowing through node i with regards to source to target pair nodes. The average traffic flow centrality of node i is defined mathematically as follows:

$$\mathrm{A}_{(\mathrm{i})} = \frac{\sum_{j \neq l \in n} I_n^{(jl)}}{\frac{1}{2} n(n-1)} \tag{6}$$

where (n-1) is the number of reachable nodes from node i and n(n-1)/2 is the normalizing constant and $I_n^{(ij)}$ is the traffic flowing through node i from nodes j and l. Although a variant of betweenness centrality, it however, allows for traffic estimation in networks. Hence, the higher the approximate average flow betweenness centrality of a node the greater its utilization in the network. In this study, we consider this centrality as a measure for estimating the significance of nodes with regards to traffic flowing across all pairs of source to target nodes in the network.

3 Joint Evidential Centrality

In this section, we present new centrality measures called joint evidential centralities (JECs) for estimating the propagating capability of nodes in SD-WANs. With JECs, the attributes of multiple centralities are combined together to enable the provision of new insights for the estimation of node significance. Thus making it possible for nodes with high propagating capability to be selected as controllers. The steps for developing JEC algorithms are given below and follows the steps shown in [11–13].

3.1 Input Indicators of Centrality

To input indicators of centrality we consider the topological layout of SD-WANs which is here represented as a weighted graph:

$$G = \left(V_{|n|}, E_{|m|}, W\right) \tag{7}$$

where V = {v1, v2, v3…, v|n|} represents the set of switches and n = |n| the total number of switches present in the network. Conversely, E = {e1, e2, e3…, e|m|} represents the set of links connecting nodes and |m| the total number of links. W = {vi, vj} represents a weighted adjacency matrix. In this study, the entries of the weighted adjacency matrix show the shortest path distance between connected nodes.

3.2 Determine the Reference Value

Based on the indicators of centralities inputted in the first step, reference values are determined for each network. These values are simply the maximum and minimum centrality values of nodes in the network. For this study, we consider six centralities namely degree (D), node-strength (N), betweenness (B), closeness (C), eccentricity (E) and average traffic flow (A). Given that n = number of nodes in a network, this means that for each considered centrality, the maximum and minimum value of n number of nodes in the network is to be determined.

Let $D_{Max} = \max \{D_1, D_2, D_3, \ldots, D_{|n|}\}$ and $D_{Min} = \min \{D_1, D_2, D_3, \ldots, D_{|n|}\}$ represent the maximum and minimum reference values for degree centrality respectively. In like manner, $N_{Max} = \max \{N_1, N_2, N_3, \ldots, N_{|n|}\}$ and $N_{Min} = \min \{N_1, N_2, N_3, \ldots, N_{|n|}\}$, $B_{Max} = \max \{B_1, B_2, B_3, \ldots, B_{enn|}\}$ and $B_{Min} = \min \{B_1, B_2, B_3, \ldots, B_{|n|}\}$, $C_{Max} = \max \{C_1, C_2, C_3, \ldots, C_{|n|}\}$ and $C_{Min} = \min \{C_1, C_2, C_3, \ldots, C_{|n|}\}$, $E_{Max} = \max \{E_1, E_2, E_3, \ldots, E_{|n|}\}$ and $E_{Min} = \min \{E_1, E_2, E_3, \ldots, E_{|n|}\}$, $A_{Max} = \max \{A_1, A_2, A_3, \ldots, A_{|n|}\}$ and $A_{Min} = \min \{A_1, A_2, A_3, \ldots, A_{|n|}\}$ represent the maximum and minimum reference values for node-strength, betweenness, closeness, eccentricity and average current flow centralities.

3.3 Ascertain the Domain of Influence

With the reference values for each network determined a domain for evaluating the level of each centrality's influence with regards to the propagation capability of nodes is to be ascertained. In this study, the domain of influence θ indicates the level of uncertainty associated with each node's propagation capability. However, since the propagation capability of a node is a function of the reference values an estimate of the level of uncertainty associated with each centrality needs to be ascertained. Specifically, there are two possible evaluation indices for estimating the propagation capability of a node with regards to considered centralities. These indices are denoted as high (h) and low (l).

$$\theta = \{\text{High, low}\} \tag{8}$$

Thus the evaluation indices estimate the probability of a centrality's influence as either high or low. Hence, pD(i) (h) and pD(i) (l) denotes the probability that the influence of degree centrality in finding the propagation capability of nodes is considered high and low respectively. In like manner, pN(i) (h) and pN (i) (l), pB(i) (h) and pB(i) (l), pC(i) (h) and pC(i) (l), pE(i) (h) and pE(i) (l), pA(i) (h) and pA(l) shows that the probabilities that the influence of node-strength, betweenness, closeness, eccentricity and average current flow centralities in finding the propagation capability of nodes is considered to be high as well as low. Where i = |n|. Next, we normalize for both high and low probabilities the influence each centrality exerts on each node i in the network.

$$p_{D(i)}(h) = \frac{|D_i - D_{Min}|}{\mathrm{D}_{Max} - \mathrm{D}_{Min} + \alpha} \tag{9}$$

$$p_{D(i)}(l) = \frac{|D_i - D_{Max}|}{\mathrm{D}_{Max} - \mathrm{D}_{Min} + \alpha} \tag{10}$$

$$p_{N(i)}(h) = \frac{|N_i - N_{Min}|}{\mathrm{N}_{Max} - \mathrm{N}_{Min} + \alpha} \tag{11}$$

$$p_{N(i)}(l) = \frac{|N_i - N_{Max}|}{\mathrm{N}_{Max} - \mathrm{N}_{Min} + \alpha} \tag{12}$$

$$p_{B(i)}(h) = \frac{|B_i - B_{Min}|}{\mathrm{B}_{Max} - \mathrm{B}_{Min} + \alpha} \tag{13}$$

$$p_{B(i)}(l) = \frac{|B_i - B_{Max}|}{\mathrm{B}_{Max} - \mathrm{B}_{Min} + \alpha} \tag{14}$$

$$p_{C(i)}(h) = \frac{|C_i - C_{Min}|}{\mathrm{C}_{Max} - \mathrm{C}_{Min} + \alpha} \tag{15}$$

$$p_{C(i)}(l) = \frac{|C_i - C_{Max}|}{\mathrm{C}_{Max} - \mathrm{C}_{Min} + \alpha} \tag{16}$$

$$p_{E(i)}(h) = \frac{|E_i - E_{Min}|}{\mathrm{E}_{Max} - \mathrm{E}_{Min} + \alpha} \tag{17}$$

$$p_{E(i)}(l) = \frac{|E_i - E_{Max}|}{\mathrm{E}_{Max} - \mathrm{E}_{Min} + \alpha} \tag{18}$$

$$p_{A(i)}(h) = \frac{|A_i - A_{Min}|}{\mathrm{A}_{Max} - \mathrm{A}_{Min} + \alpha} \tag{19}$$

$$p_{A(i)}(l) = \frac{|A_i - A_{Max}|}{\mathrm{A}_{Max} - \mathrm{A}_{Min} + \alpha} \tag{20}$$

where α is a user defined parameter within the range [0 to 1]. The value of α has proven to be negligible with respect to the sorting orders of nodes in networks.

3.4 Estimate Propagation Capability of Nodes

To estimate the propagation capacity of nodes we consider a triple set:

$$\mathrm{P_{(k)}(i)} = \left\{\mathrm{p_{(k)}(h)},\ \mathrm{p_{(k)}(l)},\ \mathrm{p_{(k)}(\theta)}\right\} \tag{21}$$

where k is the kth centrality considered and p(k) (θ) = 1 – (p(k)(h) + p(k)(l)). In this instance θ = {high, low} captures the level of uncertainty associated with the propagation capability of each node with regards to multiple centralities. Hence the propagation capability value of the ith node is derived by combining the elements of Eq. (15) using the Dempster-Shafer's combination rule. For each node i the joint centrality is denoted as:

$$\mathrm{P(i)} = \left(\mathrm{p_i(h)},\ \mathrm{p_i(l)},\ \mathrm{p_i(\theta)}\right) \tag{22}$$

However, the complexity of the algorithm is affected by the number of centralities combined together. We illustrate the combination of three and four centralities in the following sub-sections. For simplicity in this section, let a = degree centrality, b = node-strength centrality, c = betweenness centrality, d = closeness centrality, e = eccentricity and f = average current flow centricity.

3.4.1 Estimating the Propagation Capability Based on Three Centralities

We consider the combination of degree (a), node-strength (b) and betweenness (c) in this section to illustrate the Dempster-Shafer's combination rule for three centralities.

$$\mathrm{p_i(h)} = \frac{a(h)\cdot b(h)\cdot c(h) + a(h)\cdot b(\theta)\cdot \mathrm{c}(\theta) + \mathrm{c(h)}\cdot \mathrm{b(h)}\cdot \mathrm{a}(\theta)}{1 - [a(h)\cdot b(l)\cdot c(l) + a(l)\cdot b(h)\cdot c(h)]} \tag{23}$$

$$\mathrm{p_i(l)} = \frac{a(l)\cdot b(l)\cdot c(l) + a(l)\cdot b(\theta)\cdot \mathrm{c}(\theta) + \mathrm{c(l)}\cdot \mathrm{b(l)}\cdot \mathrm{a}(\theta)}{1 - [a(h)\cdot b(l)\cdot c(l) + a(l)\cdot b(h)\cdot c(h)]} \tag{24}$$

$$\mathrm{p_i}(\theta) = \frac{a(\theta)\cdot b(\theta)\cdot c(\theta)}{1 - [a(h)\cdot b(l)\cdot c(l) + a(l)\cdot b(h)\cdot c(h)]} \tag{25}$$

3.4.2 Estimating the Propagation Capability Based on Four Centralities

We consider the combination of degree (a), node-strength (b), betweenness (c) and closeness (d) centralities in this section to illustrate the Dempster-Shafer's combination rule for four centralities.

$$\mathrm{p_i(h)} = \frac{a(h)\cdot b(h)\cdot c(h)\cdot d(h) + a(h)\cdot b(\theta)\cdot \mathrm{c}(\theta)\cdot \mathrm{d}(\theta) + \mathrm{d(h)\cdot c(h)\cdot b(h)\cdot a}(\theta)}{1-[a(h)\cdot b(l)\cdot c(l)\cdot d(l) + a(l)\cdot b(h)\cdot c(h)\cdot d(h)]} \tag{26}$$

$$\mathrm{p_i(l)} = \frac{a(l)\cdot b(l)\cdot c(l)\cdot d(l) + a(l)\cdot b(\theta)\cdot \mathrm{c}(\theta)\cdot \mathrm{d}(\theta) + \mathrm{d(l)\cdot c(l)\cdot b(l)\cdot a}(\theta)}{1-[a(h)\cdot b(l)\cdot c(l)\cdot d(l) + a(l)\cdot b(h)\cdot c(h)\cdot d(h)]} \tag{27}$$

$$\mathrm{p_i}(\theta) = \frac{a(\theta)\cdot b(\theta)\cdot c(\theta)\cdot d(\theta)}{1-[a(h)\cdot b(l)\cdot c(l)\cdot d(l) + a(l)\cdot b(h)\cdot c(h)\cdot d(h)]} \tag{28}$$

To normalize the value of pi(h) and pi(l) for both three and four centralities, we divide Eq. (23) and Eq. (24) by Eq. (25) and Eq. (26) and Eq. (27) by Eq. (28). The normalized value is given as:

$$\mathrm{P_i(h)} = \mathrm{p_i(h)} + \frac{1}{2p_i(\theta)} \tag{29}$$

$$\mathrm{P_i(l)} = \mathrm{p_i(l)} + \frac{1}{2p_i(\theta)} \tag{30}$$

Equation (29) and Eq. (30) represents the probability of high and low for each node i with respect to the centralities being considered. In D-S theory, it is assumed that the significance of a node i is proportional to the probability that a set of centralities have high influence and inversely proportional to the probability that as a set of centralities have low influence. Hence, the propagation capability of each node i is given as (Table 1):

$$\mathrm{PC(i)} = \mathrm{P_i(h)} - \mathrm{P_i(l)} \tag{31}$$

Table 1. JEC algorithm illustrating steps explained in Sect. 3.

Algorithm 1 Joint Evidential Centrality Algorithm

Input: A weighted graph G with |V| nodes, |E| edges and weight on edges
Input: Number of centralities K
Output: Propagation capability $PC_{(i)}$ of each node
Output: Number of controllers C

1: $P_k(h) = \emptyset$; $P_k(l) = \emptyset$; $P(h) = \emptyset$; $P(h) = \emptyset$;
2: for i=1 to |V|
3: Find $P_k(h)$, $P_k(l)$ using equations (9) – (20);
4: for i=1 to |V|
5: Find $P_i(h)$, $P_i(l)$ using equation (23) to equation (28)
6: for i=1 to |V|
7: Find $PC_{(i)}$ using equation (31)
8: Select Number of nodes whose $PC_{(i)} > 0$.

4 Evaluation of Results

The essence of developing centrality based algorithms for controller placements is to identify the set of nodes capable of propagating traffic flow across networks within the shortest possible time. To this end, identifying the correct number of nodes suitable for hosting controllers depends on the considered centralities for determining each node's significance.

Table 2. Joint Evidential Centralities (JEC) considered

Symbol	Details of each JEC
DNB	Degree, weighted neighborhood & betweenness
DNBC	Degree, weighted neighborhood, betweenness & closeness
DNBE	Degree, weighted neighborhood, betweenness & closeness
DNA	Degree, weighted neighborhood & average current flow betweenness
DNAE	Degree, weighted neighborhood, average current flow betweenness & eccentricity
DNCA	Degree, weighted neighborhood, closeness & average current flow betweenness

Table 2 shows the details of each considered Joint Evidential Centrality (JEC) used for evaluating the placement of controllers in four SD-WANs with regards to average and worst case latencies.

Table 3. Indicators of centrality for network topologies

Network name	Indicators of centrality: number of nodes/links	Number of controllers selected by JEC: Minimum/maximum
Abilene	11/14	2/5
Agis	25/30	3/6
Internet2	34/42	8/9
Bell Canada	48/64	9/11

Table 3 gives a description of the properties of four of network topologies gotten from the internet topology zoo and used in this study. The networks are Abilene, Agis, internet2 and Bell Canada [15]. The JEC algorithms have been implemented in python using the evidential based controller placement (EBCP) framework.

4.1 Performance of JEC Based on Number of Controllers Selected

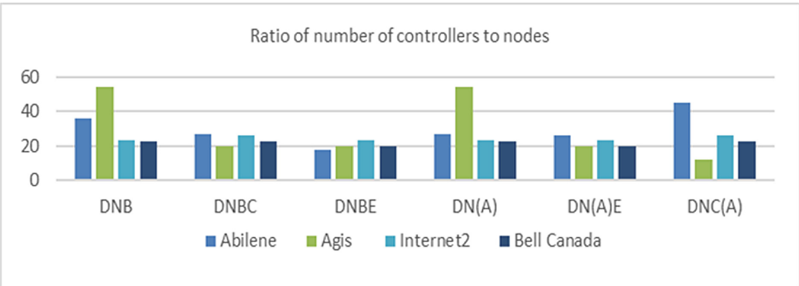

Fig. 1. Illustrates the cost of JEC algorithms with regards to number of selected nodes

Figure 1 shows how six variants of joint evidential centralities affect the selection of controller locations in SD-WANs. Determining the appropriate number of controllers is critical and infers different trade-offs between cost and performance of controller placement algorithms. To evaluate the cost of implementation, we find the ratio of controllers selected to the number of nodes present in the network. Specifically, DNBE out performs other JECs as it selects about 20% of the entire set of nodes as controllers thus reducing the search space by more than 75%.

4.2 Performance of JEC Algorithms in SD-WANs

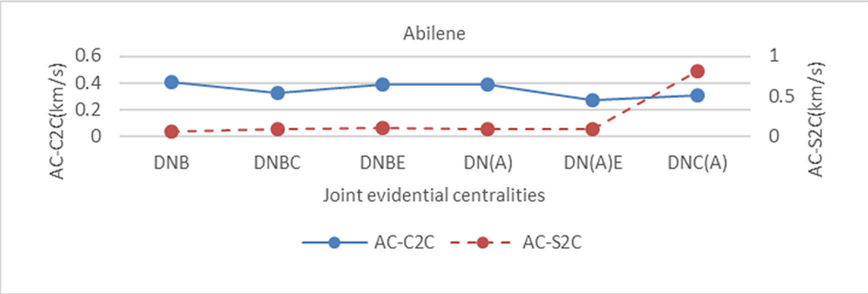

Fig. 2. Trade-off between average case controller to controller and switch to controller latencies in Abilene network.

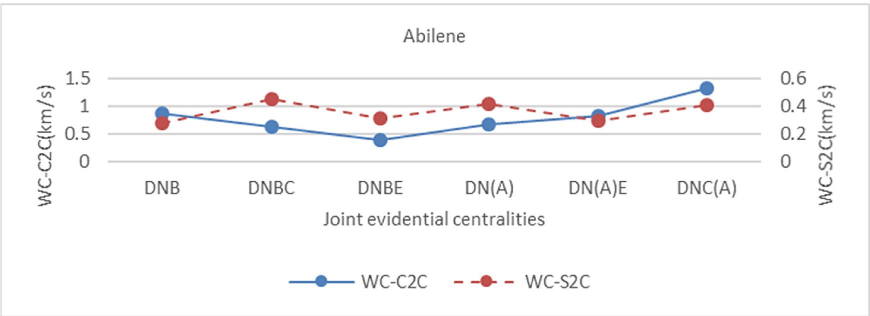

Fig. 3. Trade-off between worst case controller to controller and switch to controller latencies in Abilene network.

Figure 2 and Fig. 3 show the performance of six JEC algorithms in Abilene network. Here for average case controller to controller as well as switch to controller, DNAE and DNB have the least latencies of 0.27 km/s and 0.07 km/s respectively. Whilst for worst case controller to controller as well as switch to controller DNBE and DNB have the least latencies of 0.39 km/s and 0.28 km/s respectively.

Figure 4 and Fig. 5 show the performance of six JEC algorithms in Agis network. Here for average case controller to controller as well as switch to controller DNB, DNA and DNAE behave similarly with the least latencies of 0.33 km/s and 0.8 km/s respectively. Whilst for worst case controller to controller DNCA returns the least latency of 1.1 km/s closely followed by DNAE with 1.3 km/s. Conversely, for worst case switch to controller the first five algorithms have similar latencies of 0.84 km/s.

Figure 6 and Fig. 7 show the performance of six JEC algorithms in internet2 network. Here for average case controller to controller DNB returns the least latency of 0.19 km/s. Whereas for average case switch to controller DNB and DNA behave similar with a latency of 0.02 km/s. For worst case controller to controller DNB, DNBE, DNA and DNAE behave similarly with least latency of 1.35 km/s. Whereas for worst case switch

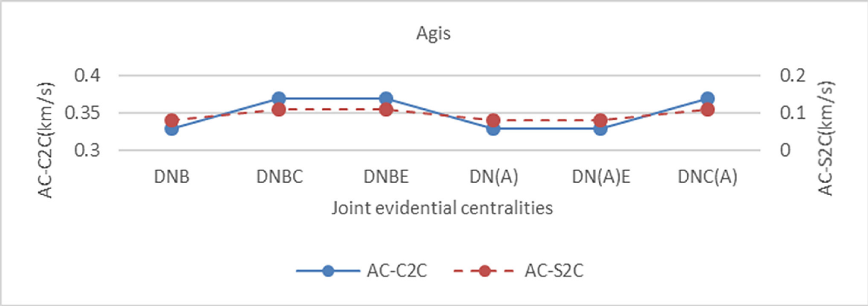

Fig. 4. Trade-off between average case controller to controller and switch to controller latencies in Agis network

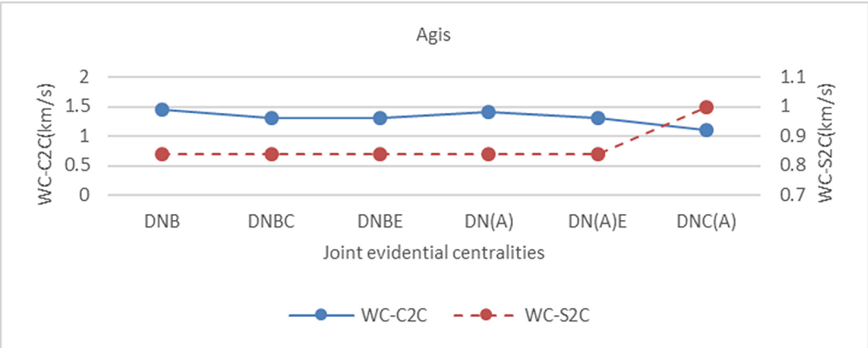

Fig. 5. Trade-off between worst case controller to controller and switch to controller latencies in Agis network

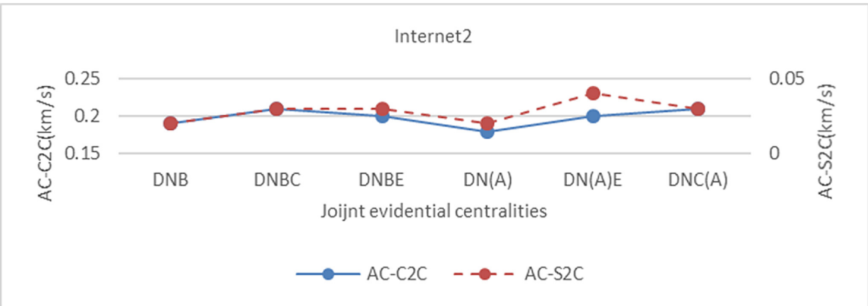

Fig. 6. Trade-off between average case controller to controller and switch to controller latencies in internet2 network

to controller DNCA returns the least latency of 0.27 km/s followed by DNB and DNA each having a latency of 0.31 km/s.

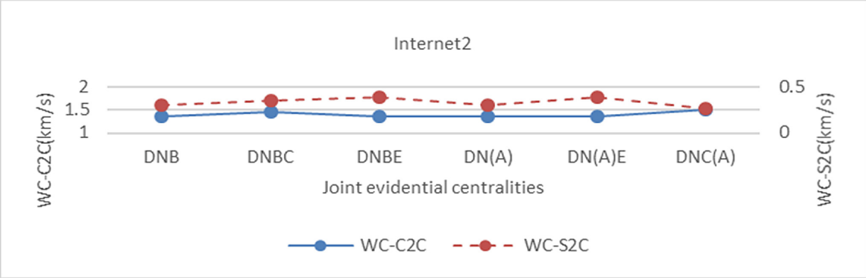

Fig. 7. Trade-off between worst case controller to controller and switch to controller latencies in internet2 network

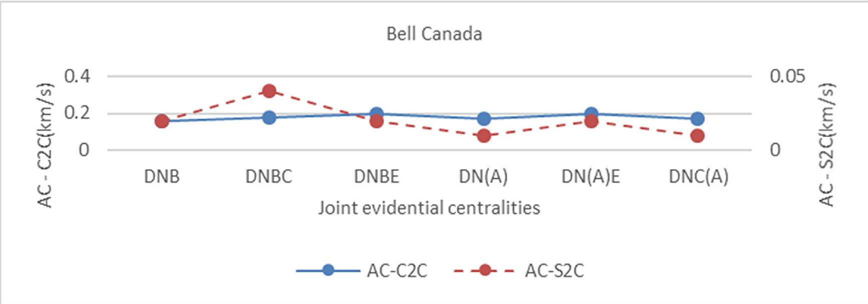

Fig. 8. Trade-off between average case controller to controller and switch to controller latencies in Bell Canada network

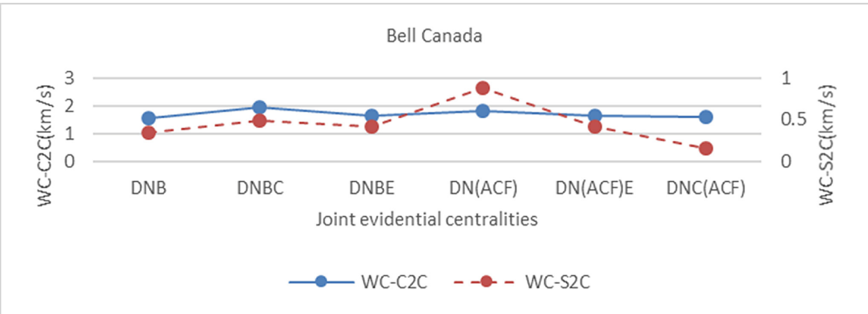

Fig. 9. Trade-off between worst case controller to controller and switch to controller latencies in Bell Canada network.

Figure 8 and Fig. 9 show the performance of six JEC algorithms in Bell Canada network. Here for average case controller to controller DNB returns the least latency of 0.16 km/s. Whereas for average case switch to controller DNA and DNCA behave similar with a latency of 0.01 km/s. For worst case controller to controller DNB outperforms other algorithms with the least latency of 1.55 km/s whilst for worst case switch to controller DNCA behaves better with the least latency of 0.16 km/s.

5 Conclusion

Determining the correct number of controllers to be placed is critical to the management of large scale networks like SD-WANs. In this study, we investigate the use of centrality measures to address controller placements in order to minimize average and worst case latencies between controllers as well as switch to controllers. We evaluate the performance of six joint evidential centralities on four real network topologies. To this end, we propose that combining multiple centralities together provides an opportunity for nodes to be sorted based on their propagation capability. This way, nodes capable of propagating traffic across the network can be identified as possible controller locations. Hence, based on the set of joint evidential centralities considered, we determine the appropriate number of controllers required for optimizing average and worst case latencies. Results gotten from experiments conducted indicate that combining the right set of centralities enhances optimal selection of controller locations to balance average and worst case latencies simultaneously.

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