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Adaptive Routing Algorithm for Information Management in Distributed Microgrids in Smart Grid

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Abstract: The increasing affordability of renewable energy resources is inspiring new interest in smart management techniques for the power grid. This paper presents an adaptive routing algorithm technique based on distributed dual-gradient update for facilitating communication among distributed energy resources (DER) units in smart grid. In particular, we consider the optimal message routing as a minimum cost flow problem among DER units in the network. The proposed technique employs a multi-commodity flow optimization, with the aim of minimizing the communication cost against network performances indicators such as throughput and delay. The results show that the proposed technique is able to route messages across the network in fewer processing steps than minimum spanning tree algorithm without any message drop. The algorithm is investigated for mesh, partial mesh and ring networks, with the result consistently showing potential cost savings and reduced complexity which can save significant amount of time when applied to a larger system.

Keywords: Distributed energy resources, prosumer, distributed algorithm, communication network, information flow management, optimal power flow.

1. INTRODUCTION

The power network is undergoing one of the major transformations in its history. The need for flexible, distributed energy management has given rise to new concepts such as *prosuming* (Jogunola et al. (2017)). To ensure optimal performance of the system, monitoring and control capabilities underpinned by reliable communication system are essential. Large scale integration of distributed generators brought new challenges with bidirectional power and information flows. From the power network perspective, the main challenge with adoption of distributed energy resources (DER) units is voltage control and power flow management (Lo and Ansari (2013)). In power flow management, excess power produced by DERs can be exchanged/shared/traded within the community or delivered to the neighboring distribution networks, thus leading to bidirectional power flow between the DER unit and the grid. Likewise, a communication network is required to transmit, analyze and coordinate the data traffic and control messages exchanged by the distributed DERs.

The traditional approach to information coordination and control is the centralized strategy (Liu et al. (2017)), where all control messages are directed to a single point that has complete knowledge of the whole network. In this approach, the DER units or microgrids (MGs) do not have the ability to interact among themselves, instead, they communicate via a central entity such as a virtual power

plant controller (Shaaban et al. (2017)). However, such reliance on a central entity reduces resilience against faults and unforeseen contingencies such as changes in link capacity or energy consumption caused by interference or other external events. Additional drawbacks include increase in power costs associated with power disturbance, congestion and loss, whereas the communications costs may include overheads, signal interference, and data packet loss (Lo and Ansari (2013)).

Considerable efforts have been made in the literature to address these limitations. For instance, utilizing the theory of multi-agent systems (MAS) and distributed control algorithm (Gomez-Sanz et al. (2014)). Distributed systems enhances power system health and safety with the capability to continue functioning after disturbances, damage or loss of equipment, etc. Meanwhile, in MAS, each DER can be modeled as an autonomous agent interacting through messaging to enable control and coordination (Marzal et al. (2018); Jogunola et al. (2018)). Rahman and Oo (2017) proposed a distributed MAS to manage power sharing in DERs, while Lo and Ansari (2013) proposed an overlay multi-tier communications infrastructure for the power network. The multi-tier communication infrastructure was designed to analyze the data traffic information and control message required for the corresponding power flow coordination. Also, Majumder et al. (2012) designed communications systems using wireless sensor network to manage power flow within MGs and adopted wired net-

work for data exchange among MGs. In Nguyen et al. (2010), the authors considered the optimal power flow (OPF) problem as a graph minimum cost flow problem by applying a cost-scaling push-relabel algorithm in a distributed agent environment, with the simulation implemented for both mesh and radial networks.

Lang et al. (2013) implemented agent-based communication using a minimum spanning tree (MST) algorithm for DER control. In MST, the communication process among the DERs commences after the formation of the tree network, which increases the number of steps and thus may not be suitable for a large network implementation or network with sensitive delay constraint. A peer-to-peer (P2P) communication scheme is proposed in Lakshminarayanan et al. (2016) for MAS and applied to economic dispatch problem with the aim of reducing complexity, as well as the communication steps of MST. However, the proposed scheme requires a supporting agent when the total number of agents in the network is odd, thus utilizing additional resources.

In contrast to Lang et al. (2013); Nguyen et al. (2010), and Lakshminarayanan et al. (2016), this paper proposes a min-cost adaptive routing solution for the exchange of data among the connected MGs. It considers with consideration of the communication link constraints for a more practical implementation. This shows potential application on optimal message routing in active distribution network (ADN) to facilitate efficient communication among the DER units.

The main contributions of this paper are:

- Formulation of a distributed dual-gradient algorithm for low-cost adaptive information routing among DER units with potential application in an ADN in smart grid;
- The proposed algorithm is applied to address congestion problem when routing the information among the DER units by directing the traffic to less congested alternate communication paths;
- While satisfying delay requirements for data delivery in smart grid, this study shows potential application of multi-commodity flow optimization to message routing among DER units in smart grid.

2. PROBLEM FORMULATION

Given a list of DER units, the anticipated size of information to route their energy control message with other DER units in the network, with aim of utilizing the minimum communication cost, whilst also ensuring data reliability, privacy and resilience. In the following, we present a distributed minimum cost routing algorithm to route the information by allocating link capacity and relying on only local information available at each unit for privacy and resilience.

2.1 Communication Network

Given a strongly connected undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, of $\mathcal{V} = \{1, \dots, \mathcal{N}\}$ interconnected nodes (i.e. DER unit) and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$, being the set of bidirectional arcs (links) as shown in Fig 1. A directed link from DER n_i to DER n_j is denoted by $(i, j) \in \mathcal{E}$. For simplicity, we denote e

as the connecting link i, j . Each e is characterized by its bandwidth capacity, u_e .

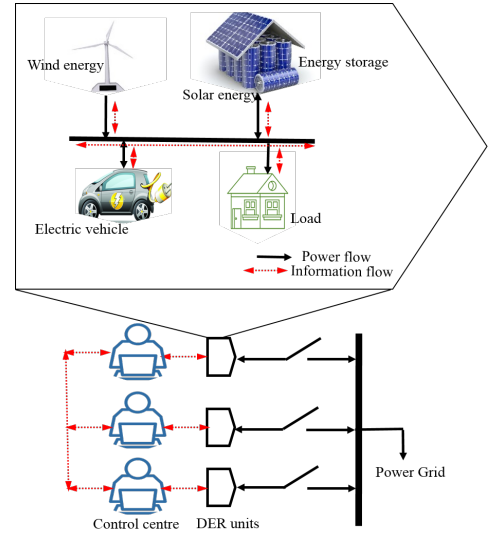


Fig. 1. IEEE 3-bus System showing the interaction among the DER units

In this paper, the communication topology is an overlay network different from the electrical network. Thus, the communication network is modeled as a time-varying network $\mathcal{G}(t) = (\mathcal{V}, \mathcal{E}(t))$, where each link set changes over time based on the state of the communication link at time, t . The set of message size, \mathcal{D} , required to be routed in the network is considered from source unit $n_i^d \in \mathcal{N}$, to destination unit $n_j^d \in \mathcal{N}$ with offered traffic or assigned bandwidth b^d to each data d_i .

2.2 Multi-commodity Network Flow Model

The network problem is modeled as a multi-commodity flow (MCF) optimization (Pióro and Medhi (2004); Trdlicka and Hanzalek (2012)), because of the flexibility it offers in analyzing the communication links to ensure the conservation law is observed, in order to eliminate incidence of dropped data packets. A MCF optimization accepts multiple traffic in \mathcal{G} and it models the average behaviour of the data transmissions across the network using transmission resources installed on the link. A MCF problem is expressed either through a link, path or destination-based formulation (Marino (2016)) depending on the optimization objective. For the purpose of consistency, we denote commodity as the control messages exchanged among the distributed DERs in the rest of the paper.

In this study, the flow-path formulation is considered, because the interest is in optimal message routing among the DERs. In the path-based formulation, \mathcal{P} is defined as the set of paths traversed by control message d_i , from source unit n_i^d , to destination unit n_j^d , and y_p as the number of links traversed by a path $p \in \mathcal{P}$. The objective of the optimization problem is to minimize the communication link cost by reducing the number of links traversed by a path in the network. This is expressed in flow-path based formulation as follows:

$$\min_{x_p: p \in \mathcal{P}} \sum_{p \in \mathcal{P}} y_p x_p \quad (1a)$$

$$\text{subject to: } \sum_{p \in \mathcal{P}_e} x_p \leq u_e, \quad \forall e \in \mathcal{E} \quad (1b)$$

$$\sum_{p \in \mathcal{P}^d} x_p = b_d, \quad \forall d \in \mathcal{D} \quad (1c)$$

$$x_p \geq 0, \quad \forall p \in \mathcal{P} \quad (1d)$$

where x_p is the flow traffic in the network. Constraints (1b) suggest that the individual traffic carried through path \mathcal{P}_e using the link e must not exceed its capacity u_e . Equation (1c) is the flow conservation constraint, i.e., as the data d flows through the link \mathcal{P}^d to the units, no data drop is allowed. Constraints (1d) represent non-negativity of the flow traffic x_p traversing the network.

3. PROPOSED ADAPTIVE ROUTING ALGORITHM

Without loss of generality, the optimal message routing problem in (1) can be rewritten into the linear optimization problem as

$$\min_x c^T x \quad (2a)$$

$$\text{subject to: } Ax = b \quad (2b)$$

$$x \geq 0. \quad (2c)$$

where x represents the vector of unknown variables, c and b are vectors of known coefficients, and A is a known matrix of coefficients. The linearity of the cost function c of (2) with both equality (2b) and inequality (2c) constraints would result in oscillations of the gradient algorithm without finding an optimal solution because of its non-strictly convex nature (Trdlicka and Hanzalek (2012)). Strict convexity of the objective function improves convergence of the dual algorithms (Marino (2016)). To enforce the convexity of the objective function $f(x)$, a regularization term (Marino (2016); Trdlicka and Hanzalek (2012)) can be added to $f(x)$, which in practice would still be equal to solving the original problem. In this model, a regularization term $\sum_j x_j^2$ is used to enforce strict convexity of the objective function. In addition, to minimize the weight of $\sum_j x_j^2$, a small value $0 \leq \epsilon \leq 1$ is added. Thus, the function becomes $f(x) + \epsilon \sum_j x_j^2$, where x_j is the j^{th} component of vector x . Other regularization methods exist in the literature, for instance, Trdlicka and Hanzalek (2012) used proximal point method to enforce strict convexity of the objective function by minimizing $f(x)$ over the proximal-point variable vector y , where $\epsilon \geq 0$. This regularization method translates to somewhat complex problem to solve compared to what is used in this study.

Therefore, the new objective function involves rewriting (1) in terms of (2) as follows

$$\min_x \sum_{p \in \mathcal{P}} \mathcal{B}_p(x_p) \quad (3a)$$

$$\text{subject to: } \sum_{p \in \mathcal{P}_e} x_p \leq u_e, \quad \forall e \in \mathcal{E} \quad (3b)$$

$$\sum_{p \in \mathcal{P}^d} x_p = b_d, \quad \forall d \in \mathcal{D} \quad (3c)$$

$$x_p \geq 0, \quad \forall p \in \mathcal{P} \quad (3d)$$

where $\mathcal{B}_p(x_p) = \sum_{p \in \mathcal{P}} y_p x_p + \epsilon \sum_{p \in \mathcal{P}} x_p^2$ is the term that translates the non-strictly convex routing model in (1) into a strictly-convex optimization problem. A unique minimizer, called the primal optimal solution, exist since $\mathcal{B}_p(x_p)$ is strictly convex. However, solving the primal problem (3) with constraints (3b)-(3d) directly, requires coordination among all units, which is impractical in real networks (Low and Lapsley (1999)). Rather, solving the optimization problem using its dual transformation would result in the desired decentralized and distributed solution.

3.1 Dual Lagrange Problem

To solve (3) over the flow variable, x_p , its dual problem is first presented, before presenting the distributed sub-gradient algorithm. The Lagrangian function for relaxing the link capacity constraints of problem (3) is

$$\mathcal{L}(x, \lambda_e) = \sum_{p \in \mathcal{P}} \mathcal{B}_p(x_p) - \lambda_e \left(\sum_{p \in \mathcal{P}_e} x_p - u_e \right) \quad (4a)$$

$$\text{s.t: } \sum_{p \in \mathcal{P}^d} x_p = b_d, \quad \forall d \in \mathcal{D} \quad (4b)$$

$$x_p \geq 0, \quad \forall p \in \mathcal{P} \quad (4c)$$

where $\lambda_e \geq 0$ represents the Lagrange multiplier associated with the flow constraint on link e transmitted to the DER units to ensure that the constraint conditions are not violated. In this study, λ_e can be explained as the dual variable representing the bandwidth cost per unit of control message flow on link e . While $\mathcal{B}_p(x_p)$ is the total cost per unit bandwidth for all links in the path x_p of message d_i . The dual decomposition results in each unit, n_i , solving,

$$x_{p: p \in \mathcal{P}^d} = \arg \min_{0 \leq x_p \leq b_d} \left(- \sum_{p \in \mathcal{P}_e} x_p \lambda_e + \mathcal{B}_p(x_p) \right) \quad (5)$$

which is unique due to the strict convexity of the cost function (Palomar and Chiang (2006)). Each flow adapts its routing to the current update using (5), thus each control message is conveyed through the shortest path using $\sum_{p \in \mathcal{P}_e} x_p \lambda_e + \mathcal{B}_p(x_p)$ as the link bandwidth cost and $\lambda_e u_e = 0$ as no cost is charged to self.

The dual function w is given as:

$$\begin{aligned} w(\lambda_e) &= \min_{x \in (4b, 4c)} L(x, \lambda_e) \\ &= \min_{x \in (4b, 4c)} \left[\sum_{p \in \mathcal{P}} \mathcal{B}_p(x_p) - \lambda_e \left(\sum_{p \in \mathcal{P}_e} x_p - u_e \right) \right] \end{aligned} \quad (6)$$

The Lagrange dual problem is the maximization of the Lagrange dual function,

$$w^* = \max_{\lambda_e \geq 0} w(\lambda_e) \quad (7)$$

3.2 Dual Optimization Distributed Algorithm

The Lagrange dual problem (7) can be solved using the gradient method (Terelius et al. (2011)). However, since the components of the model are decoupled, each sub-

problem can be solved as a sub-gradient of the main problem as follows;

$$\lambda_e(t+1) = [\lambda_e(t) - \alpha(t)g(t)]^+ \quad (8)$$

where $\alpha(t)$ is the step size at time t , and $g(t)$ is a sub-gradient to w at $\lambda_e(t)$, i.e. $g(t) = \frac{\partial w(\lambda_e(t))}{\partial \lambda_e(t)}$.

Remark 1. The objective function is strictly convex and $w(\lambda_e)$ is continuously differentiable (Bertsekas (1999)). When $w(\lambda_e)$ is differentiable, the sub-gradient $g(t)$ is $\nabla w(\lambda_e)$, which can be written as $g(t) = \partial w(\lambda_e)$. The partial derivative $\partial w(\lambda_e)$ in (6) is given by the slack variable of the relaxed link capacity constraints:

$$g(t) = \frac{\partial w(\lambda_e)}{\partial \lambda_e} = x_e - u_e \quad (9)$$

where $x_e \equiv \sum_{p \in \mathcal{P}_e} x_p$ is the aggregate demand messages rate at link e . Substituting (9) into (8), we obtain the (sub)gradient update of (7) along each dual variable,

$$\lambda_e(t+1) = [\lambda_e(t) - \alpha(t)(x_e - u_e)]^+, \quad \forall e \in \mathcal{E} \quad (10)$$

The dual variables are updated synchronously at discrete time $t = \{0, 1, \dots, \infty\}$, and only neighbours can communicate. At every time step, there is an upper bound on the optimal value of the optimization problem (3), which is obtained by evaluating the dual objective function (7). Each link computes its (sub)gradient coordinate using its capacity, u_e , and the schedules of the flows $\sum_{p \in \mathcal{P}_e} x_p$ that pass over it. From (10), if the bandwidth required for a control message $x_e(t) = \sum_{p \in \mathcal{P}_e} x_p(t)$ at link e exceeds the bandwidth capacity of that link $u_e(t)$, increase the link cost $\lambda_e(t)$, and vice versa. This control forces each unit to restrain from overloading the communication links thus reducing individual cost as well as reducing congestion on the links. The proposed routing algorithm is summarized in (Algorithm 1).

4. SIMULATION AND RESULT ANALYSIS

Simulations are performed using java (Net2plan (Sept. 2018); Marino (2016)) to observe the behaviour and convergence properties of the proposed distributed algorithm. An instance of a 5-bus network are connected as presented in the different network topology shown in Fig. 2. The required size of information (in bits) to be routed by each DER unit is given as $d_1 = 40kb$, $d_2 = 50kb$, $d_3 = 50kb$, $d_4 = 55kb$, $d_5 = 55kb$. The link capacities are set to $u_e \geq d_i$ with a total installed capacity of $800kb$. The step size, α , is set to a constant value of 1 (unless otherwise stated) for most of the cases considered.

The topmost plot of Fig. 3 shows the convergence of information routed by each of the DER units, while the bottom plot shows the total data routed and the capacity installed on the links for the mesh network topology. For this type of network, the cost functions settled around 2^{nd} time step (mean value), indicating just about a hop or communication step for each DER unit prior to convergence. This shows an improvement over the one proposed in (Lakshminarayanan et al. (2016)) which requires $\mathcal{O}(\mathcal{N})$ communication steps. Moreover, the

Algorithm 1. Proposed Adaptive Routing Algorithm

- 1: **Input:** The strongly connected time-varying graph $\mathcal{G}(t) = (\mathcal{V}, \mathcal{E}(t))$, the constant step-size, α , each link capacity, u_e , data, d_i , the initial link cost $\lambda_e(t) = 1$ for all $i \in \mathcal{N}$
- 2: **Output:** The optimal link cost, $\lambda_e(t)$, and the optimal routed data, $d_i(t)$.
- 3: $t > 0$,
- 4: Communicate λ_e to the DER units
- 5: n_i informs n_j , $j \neq i$, using

$$x_{p:p \in \mathcal{P}^d} = \arg \min_{x_p \geq 0, \sum_{p \in \mathcal{P}^d} x_p = b_d} \left(- \sum_{p \in \mathcal{P}^d} x_p \lambda_e + \mathcal{B}_p(x_p) \right) \forall n$$

- 6: Each link updates its cost, λ_e , $\forall d \in \mathcal{D}, \forall e \in \mathcal{E}$, using
$$\lambda_e(t+1) = [\lambda_e(t) - \alpha(t)(x_e - u_e)]^+$$
- 7: The link signals its updated link cost to the units, \mathcal{V}
- 8: Each unit adapts its traffic routing based on the updated link price
- 9: Go to next time slot until maximum time-step is reached

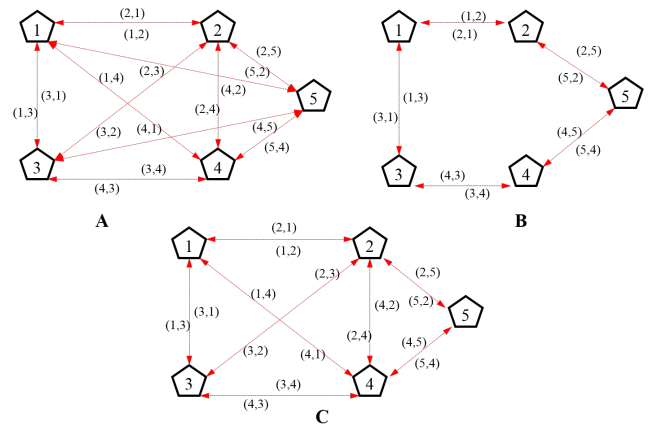


Fig. 2. Communication network topologies used for the test cases of the proposed algorithm (A: Mesh; B: Ring; C: Partial mesh)

number of units does not have to be parity dependent as in (Lakshminarayanan et al. (2016)), i.e., the algorithm proposed in (Lakshminarayanan et al. (2016)) works for an even number of agents, where a supporting agent is required each time the number of agents in the network is an odd number (see Table 1).

The behaviour of the three network topologies is assessed with the same installed link capacities as seen in Fig. 4. It is observed that the bandwidth cost for the ring network is higher than the partial-mesh and the mesh network. This behaviour resulted from the reduced number of links in the network thus some links were oversubscribed and their costs increased, while the costs of those links under-subscribed decreases. The adaptive nature of the routing algorithm resulted in redirecting the traffic through less subscribed links to both satisfy flow conservation

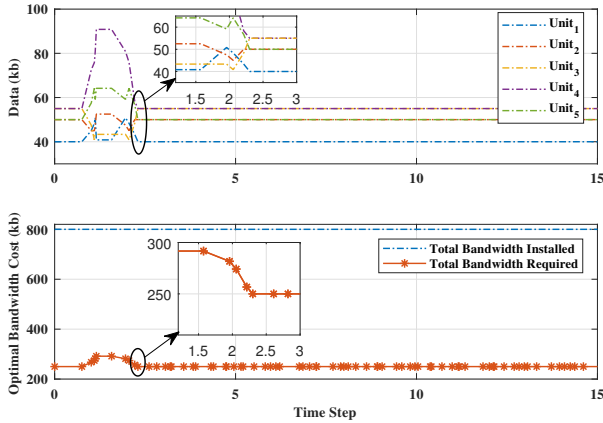


Fig. 3. Result for the mesh network showing convergence of the proposed Routing Algorithm

Table 1. Result comparison with related works Lakshminarayanan et al. (2016).

Description	MST	Ref. Lakshminarayanan et al. (2016)	Proposed
Number of communication steps for N agents	always $> N$	Odd, $N + 1$; Even, N	$< N$
Communication complexity	Less (one to one)	Less (one to one)	Less (one to one)
Pre-communication steps	Yes	Nil	Nil

constraints, and to ensure minimum routing cost to the connected units. However, the network delay for the ring topology is the lowest compared to other topologies. This is as a result of the less event that was processed in the network. Although the DER units in the mesh network are directly connected, the network complexity increases as a result of increased number of links. The behaviour of the three network topologies meet the required network delay for smart grid.

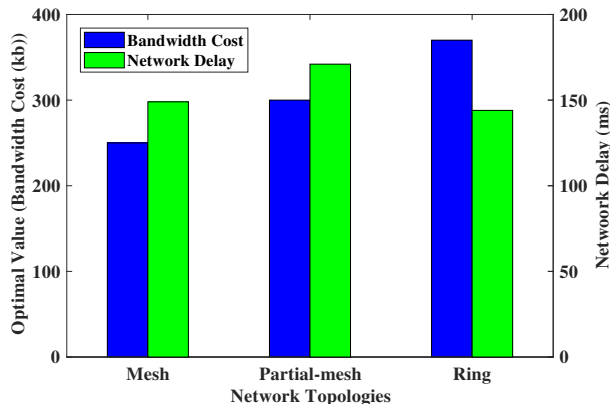


Fig. 4. Bandwidth cost and network delay for the three topologies

4.1 Varying Number of DER units from 3 to 15

To investigate the scalability of the proposed algorithm, we vary the number of DERs from 3 – 15 using the partial-mesh topology. The size of information for each unit is set between 10 – 15kb, the link capacities are varied up to a total network capacity of $U \geq D \leq 4D$. This is to validate the total link bandwidth capacity required to successfully route the traffic for the distributed units.

Fig. 5 corroborates the fact that as the number of units increases, so does the network delay. However, it is observed that the linearity tends to geometric growth as the number of the units increases. This implies that the messages in the network would be subjected to higher delays before being delivered. Depending on the size of the network and each unit’s message size, at some point, it is suggested that the network be grouped into clusters to minimize the network delay as presented in (Anoh et al. (2018)). The relationship between the message size, number of units and maximum acceptable delay is beyond the scope of this work.

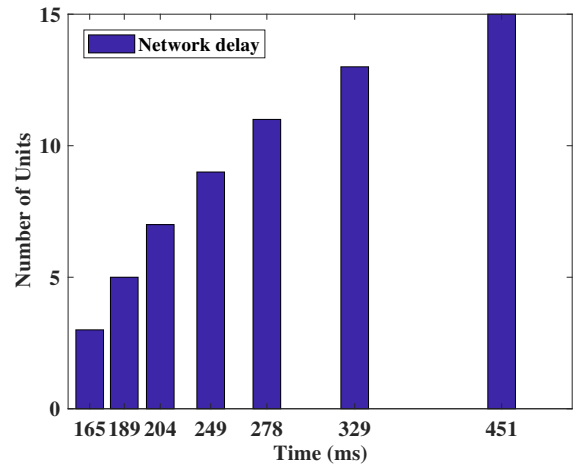


Fig. 5. Network delay for increasing number of DER Units in partial-mesh topology.

Furthermore, it is observed that the higher the network capacity installed, the lower the network delay, but this results in high network cost due to unused network capacity. As expected, increase in number of DER units would require more communication resources to be installed in the network, to achieve higher traffic throughput as shown in Fig. 6

Installing more communication links for increasing number of units could reduce the capacity required on each communication link. However, this would also result in higher installation cost. Using a full mesh topology where each unit is connected to every other unit results in increased number of links, higher installation cost and complexity. Two advantages of this topology are the reduced delay on individual link and the use of same communication capacity to transmit the message between peers. Finally, for distributed routing of messages, it is found that with increasing number of DER units, the communication link capacity required to effectively route the message and for the units to reach a consensus, could be in the order of 3 or more of the total information in the network.

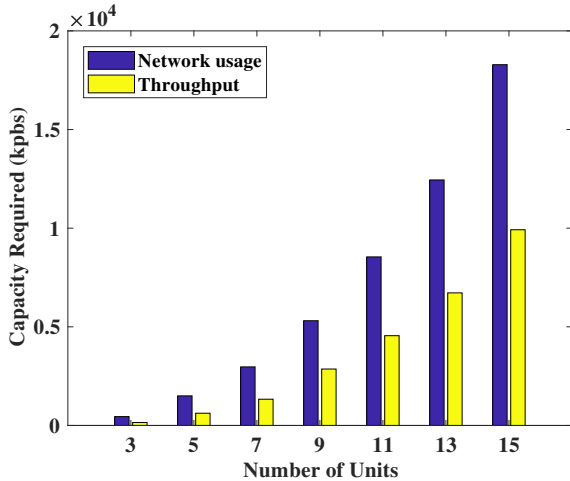


Fig. 6. Capacity required for increasing number of DER units.

5. CONCLUSION

In this paper, we proposed an adaptive routing algorithm for information coordination among DER units in smart grid. We showed that the proposed algorithm converges faster with fewer communication steps than previously proposed techniques including minimum spanning tree. This study can inform network planners on the average bandwidth capacity required and number of communication links to be installed for a particular number of DERs when considering bidirectional implementation. In the future studies, we shall evaluate the impact of each unit processing capacity on the adaptive routing algorithm.

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