A Grid-friendly Neighborhood Energy Trading Mechanism

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***Abstract*—More customers are tending to install batteries with photovoltaic (PV), so they can better control their electricity bills. In this context, customers may be tempted to go off-grid at a substantial up-front cost, leading electricity companies into a death spiral, thereby raising electricity price further on those remaining on grid. Neighborhood energy markets can promote the sharing of locally generated renewable energy and encourage prosumers to stay on grid with financial incentives. A novel neighborhood energy trading (NET) mechanism is developed using the topology of existing radial distribution network to encourage sustainable energy sharing in neighborhood and encourage prosumers to stay on grid. This mechanism considers loss, congestion management, and voltage regulation, and it is scalable with low computation and communication overhead. An IEEE test system is used to validate the NET mechanism. The simulation shows that the price and flow results are obtained with fast computation speed (within 10 iterations) and with loss reflected, flow limit reinforced, and voltage regulated. This study proves that the economic demand-supply-based pricing mechanism can be applied effectively in distribution networks to help encourage more renewable energy sharing in sustainable neighborhood and avoid energy network death spiral.**

***Index Terms*—Direct power flow, directional adjacency, local energy market, peer-to-peer, prosumer, solar community, sustainable building, transdisciplinary research.**

Nomenclature

A. Indices

j	Nodes in the network
k	Iteration number
l	Time interval
n	Node number at far end of line
t	Time index

B. Symbols

$\alpha(j,t)$	Intercept of demand-price curve at node j at time t
$\beta(j,t)$	Slope of demand-price curve at node j at time t
Γ_P	Adjustment of reactive power price constant in each iteration
Γ_{scale}	Scale factor for Γ_P
Γ_V	Price adjustment constant for voltage regulation
Φ	Price adjustment constant for losses
Θ	Price adjustment constant for flow constraint
η	Price adjustment constant for keeping prices within desired limits when there is no congestion
A	Branch current mismatch limit
$B(j,k,t)$	Branch current at node j in iteration k at time t
$B_{\max}(i)$	The maximum rating of branch i
$\boldsymbol{BIBC}$	Bus injection to branch current matrix of network
$\boldsymbol{BCBV}$	Branch current to bus voltage matrix of network

C. Scale Factor

$\cos\theta(j,k)$	Power factor at node j in iteration k
$i(j,k,t)$	Injected current from custom at node j in iteration k at time t
$Iter_{NET}$	Number of iterations for NET
$Iter_{P2P}$	Number of iterations for a generic P2P
MPg	Grid-supplied power price
MP^*	Desired maximum price level
$M_p(j,k,t)$	Market price of active power at node j in iteration k at time t
$M_{PT}(j,k,t)$	Total market price of active power for both consumption and voltage regulation at node j in iteration k at time t
$M_v(j,k,t)$	Nodal price for voltage regulation at node j in iteration k at time t
$M_{vp}(j,k,t)$	Nodal price of active power for voltage regulation at node j in iteration k at time t
$M_{vq}(j,k,t)$	Nodal price of reactive power for voltage regulation at node j in iteration k at time t
$p(j,k,t)$	Active power consumed/offered by customer at node j in iteration k at time t

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$q(j,k,t)$	Reactive power consumed/offered by customer at node j in iteration k at time t
R	Branch resistance
$T_p(j,k,t)$	Active power to node j in iteration k at time t
$V(j,k,t)$	Voltage at node j in iteration k at time t
$VD(j,k,t)$	Voltage deviation of node j from node 1 ($j>1$) in iteration k at time t
$\Delta V(j,k,t)$	Allowable limit of voltage deviation at node j in iteration k at time t
$\partial V(J)/\partial p(j)$	Voltage sensitivity of node J with respect to active power changes at node j
$\partial V(J)/\partial q(j)$	Voltage sensitivity of node J with respect to reactive power changes at node j

I. INTRODUCTION

AUSTRALIAN electricity prices have been doubled in the last eight years due to investments in distribution networks [1]-[3]. Network cost is about 50% of customers' electricity bills in Australia [4], while in many other countries with more dense networks, the factor is less than 20%. The present pricing method for most customers is based on the total energy use and the network charges are averaged across all customers. Hence, this pricing method does not effectively reflect the fact that peak demand is the main driver for the increased investment in networks.

Cost-reflective pricing for customers' use of distribution networks can play a key role in reducing peak load on networks through the promotion of non-network alternatives, such as photovoltaics (PVs), demand response, and energy storage at the right locations [5]. To design a cost-reflective pricing mechanism for the use of distribution networks, the desirable features of a distribution network pricing mechanism can be summarized as follows.

1) Local congestion should be solved by penalizing loading and reward generation downstream of a bottleneck. Repeated congestion should be relieved by driving investment by network or customers [6].

2) When the PV generation is plentiful, there should be a reduction of the energy cost [7].

3) Flows between neighbors or to/from the source should contribute to line maintenance.

4) Pricing should reflect a real network constraint [8].

5) Losses should be attributed to contributing customers with a benefit for relieving losses [9].

6) Voltage regulation can be an issue for networks with high PV penetration [10]. If there is a voltage violation, awards should encourage those with the strongest impact to contribute to the network-based correction [6].

7) Design reliability is a longer-term issue, and should reflect potential peak usage and seek to meet a local community standard. For example, there may be different targets for urban and rural customers considering costs [11].

One way to summarize these features is that pricing mechanisms need to consider the balance between local demand and supply, network flow management, losses, and voltage regulation [12], [13]. When evaluating pricing features, existing pricing mechanisms may include the following points.

1) Energy tariff (volumetric tariff) is one of the most widely-used mechanisms. Its network charges are averaged across all customers and not responsive to peak loading. It provides a maintenance and upgrade investment by scaling the energy charge; however, this charge does not address any of the above desirable features.

2) Time-of-use tariffs penalize the average expected congestions during a specific period (e.g., 4-8 p.m. on weekdays), which is not relevant to the actual loading of the network. Although this mechanism partly addresses the first feature, it is not directly related to the actual loading to reward responsive customers for the real peak demand events.

3) Tariffs with peak demand charge or energy charge with peak-demand-related line access fee (e.g., in Italy and France) attempt to avoid immediate local congestion. These tariffs partly address the first and fourth features with some impact on the sixth. However, these tariffs do not drive load to respond to the network peak.

4) Tariffs with coincident feeder congestion charge address the first and fourth features only.

None of these existing pricing mechanisms address all desirable features to reflect the real cost of network use for customers.

On the other hand, as the cost of PV and battery systems continue to decline, more customers intend to install PVs and pair them with battery storage to manage their electricity bills. In this context, customers may be tempted to go off-grid at a substantial up-front cost, leading electricity companies into a death spiral [14], thereby raising electricity price further on those remaining on grid. This dire scenario can be avoided by a mechanism, which encourages customers with PVs, energy storage or load flexibility to participate in energy markets [15], [16].

Energy markets in communities are clearly becoming more and more important, and existing studies often focus on the development of pricing mechanisms for the centralized, pairwise or a mix of centralized and pairwise energy trading. There are few developments with consideration of network losses in low-voltage decentralized peer-to-peer (P2P) networks [6], [17] and in blockchain-enabled P2P energy trading designs [9]. However, further investigations are needed for P2P energy sharing in communities as power flow and losses are not directly point-to-point [18], [19]. Communication overheads can be demanding for local energy markets when there are many participants [20], [21]. A lightweight blockchain framework has been developed for P2P energy trading with reduced level of communication overheads [22]. For a centralized market design, the scalability of communication or computation may be challengeable because of the sheer volume of customers in distribution networks [23], [24].

In this context, a new directional adjacency-based neighborhood energy trading (NET) pricing mechanism is proposed. This NET mechanism is based on a continually updated price and flow information of distribution market. Some features of the NET mechanism are similar to a centralized

P2P trading mechanism. For example, the NET mechanism has a head node as the system coordinator, which is similar to a market manager or mediator in a centralized P2P trading. This NET mechanism is not a P2P mechanism, but it is a centralized energy trading mechanism implemented in a decentralized form. By comparing general P2P mechanisms with this NET mechanism, the following conclusions can be achieved.

1) The NET mechanism works for radial feeders with the directional adjacency approach and the direct load flow approach. In the NET mechanism, nodes communicate with their adjacent nodes. For a generic N node radial network, as the number of nodes grows, the communication overhead of NET mechanism is expected to be less than that of the generic P2P mechanism. However, general P2P mechanisms work for all network topologies.

2) The NET mechanism aims to achieve a balance between the supply and demand by iteratively updating a head node market price. This is like a one-dimensional search, rather than multi-dimensional optimization in generic P2P trading among N nodes.

The main contributions of this study can be summarized as follows.

1) This NET mechanism uses the adjacency-based approach to communicate energy price and power flow information.

2) The NET mechanism uses the existing network topology. Compared with other P2P energy trading schemes, this NET mechanism requires less communication overhead.

3) The NET mechanism uses the demand and supply curves of prosumers as the energy trading basis. This economic approach, rather than optimization, ensures fast computation convergence.

4) The NET mechanism is scalable with its low communication overheads and fast computation convergence. Scaling up peer-based mechanisms can be challenging due to large numbers of communication links even for medium number of customers.

5) Local energy market trading schemes usually consider the economic aspects of energy without technical constraints satisfied. The NET mechanism has incorporated network loss correction, flow constraints, and voltage regulation into the energy trading inherently.

This new mechanism will facilitate an effective NET through correct pricing of energy and the network use. Thereby, this NET mechanism improves the utilization of the existing network assets and incentivizes customers (prosumers, e.g., solar households [25]) to stay on the network.

The remainder of this paper is organized as follows. Section II describes the NET mechanism. An IEEE test system is used as the case study in Section III. Finally, conclusion and future research areas are given in Section IV.

II. NET Mechanism

This section starts with the algorithm to determine the energy price for cases without grid supply and cases with grid supply under flow constraints. Gradually, price adjustments for network uses are introduced to reflect losses, limit flows, and regulate voltages. Network uses are for using network infrastructure to distribute electrical energy.

A. Energy Price

One of the most efficient ways to set energy prices is to use a market mechanism which reflects the actual and local economic conditions. The NET mechanism is based on demand and supply curves of the participants in the market.

As shown in Fig. 1, the process of NET mechanism starts from the head node of the feeder (or at the transformer). The price is broadcasted downstream to the next adjacent node one by one. According to the nodal price, customers generate or consume electricity. Then, the flow information is passed upstream one by one. Energy generation or consumption of each node and nodal prices are used to settle the payments or receivables of customers.

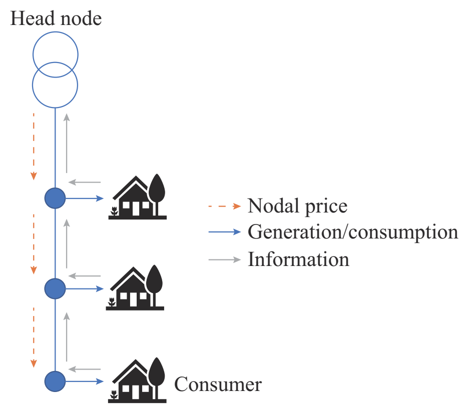

Fig. 1. Process of NET mechanism.

Based on the total supply and demand mismatch, and transformer constraining situation, the head node price is adjusted for the next iteration. This updating process of forward price and backward flow quantity continues until a convergence is reached. The algorithm for the iterative pricing process is given below.

B. Algorithm for Determining NET Energy Price

Step 1: let $k=1$ and denote the initial value for the price of active power at the head node (node 1) as $M_p(1,1,t)$.

Step 2: broadcast this price downstream, let $M_p(j,1,t) = M_p(1,1,t)$. Then, each consumer will decide how much they want to consume or sell depending on their demand or supply curves. The active power and reactive power consumed/offered by the customer are given by:

$$p(j,k,t) = \alpha(j,t) - \beta(j,t)\, M_p(j,k,t) \tag{1}$$

$$q(j,k,t) = p(j,k,t)\tan\theta(j,k) \tag{2}$$

The injected current from the customer at node j at time t can then be calculated as:

$$i(j,k,t) = \frac{p(j,k,t) - \mathrm{j}q(j,k,t)}{V(j,k,t)} \tag{3}$$

Step 3: customers will transmit the above current flow information from the end to the head node of the feeder. Branch current connecting each node can be calculated after summating injected currents from customers:

$$\left[B(i,k,t)\right]=\boldsymbol{BIBC}\left[i(j,k,t)\right] \tag{4}$$

The price for the next iteration is calculated as:

$$M_p(1,k+1,t)=\Gamma_P B(1,k,t)+M_p(1,k,t) \tag{5}$$

For cases without grid supply, the community power demands are met by local generation only and there is no power supplied from the main grid. Equation (5) will make sure that iterations are continued till $B(1,k,t)=0$.

For cases with grid supply, the community power demands are met by both local generation and the main grid. Also, when there is excess power from prosumers, it will be sent to the main grid. When the current through the transformer is within its limit, the energy price is settled at the desired grid-supplied power price MPg.

When the current through the transformer exceeds its maximum limit, the energy price for the customers supplied by the grid should be increased to reduce the flows through the transformer below its limit.

In (6), Γ_{scale} is used to scale Γ_P to limit the oscillation of the prices when the flows through the transformer are close to its maximum flow limits.

$$\Gamma_{scale}=\begin{cases}1 & B(1,k,t)>B_{\max}(1) \text{ or } \left|\left(B(1,k,t)-B_{\max}(1)\right)\right|>A\\ C & \text{otherwise}\end{cases} \tag{6}$$

When the current flow through the head node transformer towards downstream is above its maximum value, as given in (7), the energy price will be increased proportional to the flow mismatch to keep the flow within its limit in the next iteration. When the current flow is close to the maximum limit, the prices are slowly adjusted by using the scale factor Γ_{scale} to reduce the price oscillation. When the current flow through the transformer is within its limit, the energy price will be reduced to close to the desired price MP^* by using (8). If there is a reverse flow as shown in (9), prices are reduced for the next iterations to keep the reverse flow within the allowable limits. This process continues until no constraint is violated.

$$M_p(1,k+1,t)=\Gamma_{scale}\Gamma_P\left|B(1,k,t)-B_{\max}(1)\right|+M_p(1,k,t) \quad \forall B(1,k,t)>B_{\max}(1) \tag{7}$$

$$M_p(1,k+1,t)=M_p(1,k,t)-\eta\left(M_p(1,k,t)-MP^*\right) \quad \forall\left|B(1,k,t)\right|\le B_{\max}(1) \tag{8}$$

$$M_p(1,k+1,t)=-\Gamma_{scale}\Gamma_P\left|B(1,k,t)-B_{\max}(1)\right|+M_p(1,k,t) \quad \forall B(1,k,t)<-B_{\max}(1) \tag{9}$$

C. Adjustment to Energy Prices for Network Use

As the NET mechanism is carried out via the existing distribution network, in addition to the energy price, charges for network use should be considered for the efficient use of the network. Therefore, in each iteration, prices should be adjusted for network charges. For a cost-reflective pricing of network use, the energy price should be adjusted to incorporate desirable features listed in the introduction. In summary, the energy price in each iteration needs to be adjusted to incorporate losses, congestion, and voltage regulation. The formulation and details on the three aspects are provided as follows.

1) Algorithm for Updating Energy Price with Adjustments for Losses

Except for the changes in (10) and (11), the steps in Section II-B will be followed here. These changes are to ensure that the prices of each downstream node are adjusted for losses for the next iteration. As shown in (10), the losses in each branch are calculated using the branch current calculated by (4).

$$T_p(n-j+1,k,t)=T_p(n-j+2,k,t)+p(n-j+1,k,t)-B^2(n-j,k,t)R(n-j+1) \tag{10}$$

For $j=1$, the price for each iteration is calculated using (5)-(9). For nodes from $j=2$ to n, the price is adjusted for losses in (11).

$$M_p(j,k+1,t)=\frac{M_p(j-1,k+1,t)}{1-\Phi T_p(j,k,t)} \tag{11}$$

When there is no flow or voltage violation, the prices of the downstream nodes are reflected with (11). In general, the whole network would remain at constant prices.

2) Algorithm for Updating Energy Price with Adjustments for Losses and Congestions

Except for changes to adjust the nodal prices downstream of a congested line or equipment to alleviate the congestions, the steps in Section II-B will be followed here.

For node $j=J$, assume that the maximum limit of branch current is $B_{\max}(J)$. If $B(J,k)\ge B_{\max}(J)$, the price will not change for the upstream nodes $j=2$ to J. The price for nodes $j=2$ to J is calculated as:

$$M_p(j,k+1,t)=\frac{M_p(j-1,k+1,t)}{1-\Phi T_p(j,k,t)} \tag{12}$$

For the downstream nodes $j=J+1$ to n, the price will be increased, as calculated by (13).

$$M_p(j,k+1,t)=\frac{M_p(j-1,k+1,t)}{1-\Phi T_p(j,k,t)}+\Theta\left(B(J,k,t)-B_{\max}(J)\right) \tag{13}$$

In this case, there is a price difference between the upstream nodes and the downstream nodes of the constraint. For future network augmentation, a sinking fund can be established to reserve resources accumulated from the price differences.

3) Algorithm for Updating Energy Price with Additional Adjustments for Voltage Regulation

In addition to the energy charges, a voltage charge is imposed to each node based on the nodal voltage sensitivity/effectiveness to their net active or reactive injections on correcting the voltage problems in the network. The higher prices downstream of the line due to high-voltage charges are signals for active and reactive power changes, and at the same time, these higher prices can be costs or rewards for prosumers or the utility to invest on voltage regulation equipment.

The solution for voltage issues in the distribution networks is related to line characteristics. If the line reactance is much higher than the line resistance, the reactive power correction can improve the voltages more effectively than active power correction; if the line reactance is much lower than the line resistance, the active power correction can improve the voltages more effectively; if the line reactance and resistance are of the same size, the active and reactive power corrections have similar impacts on voltage regulation. The voltage sensitivities to active or reactive power reflect the effectiveness of their impact on voltage regulation. These voltage sensitivities are used to adjust energy prices, which in turn alter the consumption or supply of active or reactive power so that the voltage is regulated through an economic approach. The algorithm for adjusting these prices for voltage regulation is given below:

Step 1: use (14) and (15) to calculate the nodal voltages using the branch current calculated by (4).

$$\left[VD(j,k,t)\right] = \boldsymbol{BCBV}\left[B(j,k,t)\right] \tag{14}$$

$$V(j,k,t) = V(1) - VD(j,k,t) \tag{15}$$

Step 2: find the node with the maximum voltage deviation $VD_{\max}$ and mark it as node J. The voltage deviations of node J are calculated by:

$$\Delta V(J,k,t) = \begin{cases} VD(J,k,t) - VD_{\max} & \left|VD(J,k,t)\right| > VD_{\max} \\ 0 & \left|VD(J,k,t)\right| \le VD_{\max} \end{cases} \tag{16}$$

Step 3: for $j=1$, update M_v by:

$$M_v(1,k+1,t) = \Gamma_V\left|\Delta V(J,k,t)\right| + M_v(1,k,t) \tag{17}$$

Step 4: based on the maximum voltage deviation, and the voltage sensitivities of node J to active and reactive power at other nodes (denoted as $\partial V(J)/\partial p(j)$ and $\partial V(J)/\partial q(j)$, respectively), calculate the voltage charge for active and reactive power for each node with (18) and (19), respectively. The matrices of $\partial V(J)/\partial p(j)$ and $\partial V(J)/\partial q(j)$ need to be calculated first to estimate nodal price adjustments for voltage regulation.

$$M_{vq}(j,k+1,t) = \Delta V(J,k,t)\frac{\partial V(J)}{\partial p(j)}M_v(1,k+1,t) \tag{18}$$

$$M_{vp}(j,k+1,t) = \Delta V(J,k,t)\frac{\partial V(J)}{\partial p(j)}M_v(1,k+1,t) \tag{19}$$

Step 5: for the next iteration, calculate active and reactive power for each node using (20)-(22).

$$M_{PT}(j,k,t) = M_p(j,k,t) + M_{vp}(j,k,t) \tag{20}$$

$$p(j,k,t) = \alpha(j,t) + \beta(j,t)\, M_{PT}(j,k,t) \tag{21}$$

$$q(j,k,t) = p(j,k,t)\tan\theta(j,k,t) + \beta_q(j,t)M_{vq}(j,k,t) \tag{22}$$

To summarize, market prices $M_p(j,k,t)$ are to balance energy supply and demand as well as to reflect losses, using (5)-(13). Nodal prices $M_{vp}(j,k,t)$ and $M_{vq}(j,k,t)$ are calculated to regulate voltages, using (18) and (19).

III. Case Study

To validate the NET mechanism, a modified IEEE 13-bus test system is used, which is a radial distribution network [26]. As shown in Fig. 2, the test system consists of three generator nodes and six load nodes. The same set of line data is considered as in [26]. The base parameters of the supply curves of generators and demand curves of loads are given in Table I and Table II. These base parameters α are multiplied by different scale factors to represent demand and supply curves during different time periods.

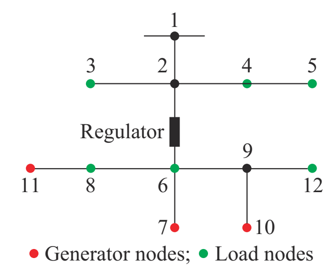

Fig. 2. Test system network.

TABLE I
VALUES OF α AND β OF CASE STUDY

Node	α	β	Node	α	β
1	0	0	7	0	−7113
2	0	0	8	1000	838
3	1200	1500	9	0	0
4	800	1022	10	0	−3277
5	800	1170	11	0	−3527
6	3465	8900	12	2000	5975

TABLE II
PARAMETERS OF CASE STUDY

Γ_P	C	Φ	Θ	Γ_V	β_q
9.5×10^{-4}	7×10^{-1}	3×10^{-4}	9.5×10^{-3}	1×10^{-5}	1×10^{-3}

A. Case Without Grid Supply

1) No Energy Price Adjustments for Network Use

In this case, community power demands are met by local generation only (i.e., $B_{\max}(1)=0$). First, the proposed price algorithm is applied neglecting price adjustments for network use (i.e., relax the regulator current constraint, the upper and lower voltage limits, and no price adjustment are made for line losses in the initial step).

Figure 3 presents how the market clearing energy price changes with the loads over ten intervals. In this case, the intercept values α of load demand curves are scaled to represent different loading levels for different intervals. The scale factors used for α over ten intervals are 0.7, 0.9, 1.2, 1.6, 0.8, 0.6, 0.7, 0.9, 1.1, and 1.4, respectively. In Fig. 3, the energy price varies from 16 ₵/kWh during off-peak hours to 43.9 ₵/kWh during peak hours. There is no price separation between the upstream nodes and the downstream nodes. So, the green and red lines on Fig. 3 are overlapped.

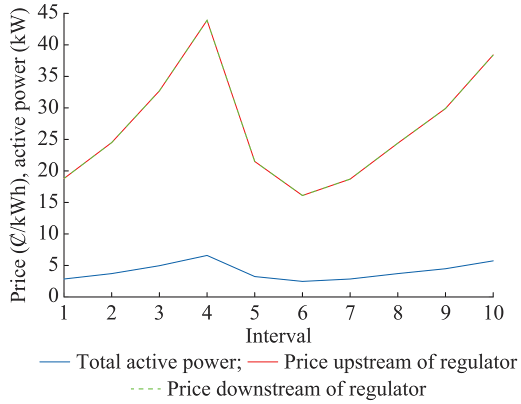

Fig. 3. Variation of demand and energy price in case without grid supply.

2) *Case with Energy Price Adjustments for Line Losses*

Figure 4 shows the variations of M_p at interval 4 when the price adjustments are made to reflect line losses. As a result, the price downstream tend to be slightly higher than the price at node 1 because electricity losses tend to be higher as it travels longer distances.

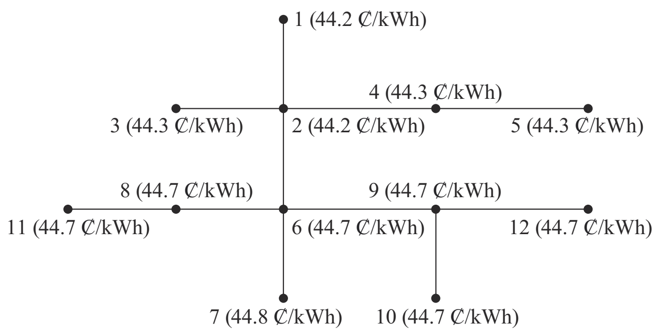

Fig. 4. Nodal prices at interval 4 with adjustments for line losses.

3) *Case with Energy Price Adjustments for Line Losses and Regulator Current Constraint*

In this case, the maximum current carrying capacity of the regulator between node 2 and node 6 is 6 A. When the current through the regulator reaches its limit, the prices of all nodes downstream the regulator branch is increased considering flow directions. Figure 5 shows the nodal prices at interval 4 when the prices are adjusted to reflect the line losses and the regulator current constraint. In this example, as all generators are on the nodes below the regulator branch and no supply is from the main grid, the direction of the current through the regulator is from node 6 to node 2.

Therefore, when the current through the regulator reaches its limits, the prices at nodes 2, 3, 4, and 5 are increased. In Fig. 5, the price at the transformer node is 43.9 ₡/kWh, however, the prices at nodes 2, 3, 4, and 5 are increased to 50.1 ₡/kWh to give price signals to customers downstream the regulator to adjust their consumptions. In addition to that, a small increase is observed for nodal prices at nodes 6-12 compared with the transformer node. This small price increase is to reflect the losses. Figure 6 shows how the nodal prices vary with time. The market price separation takes place due to a network constraint violation as the system demand increases.

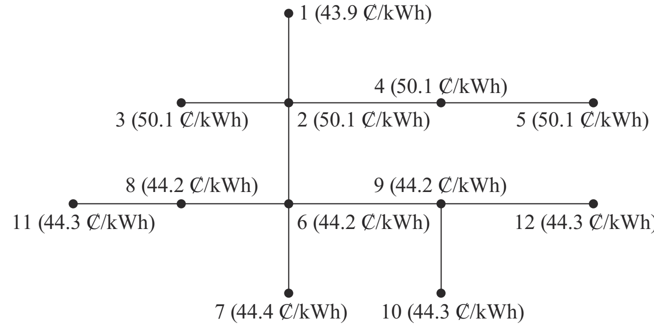

Fig. 5. Total nodal prices at interval 4 with price adjustment for line losses and regulator current constraint.

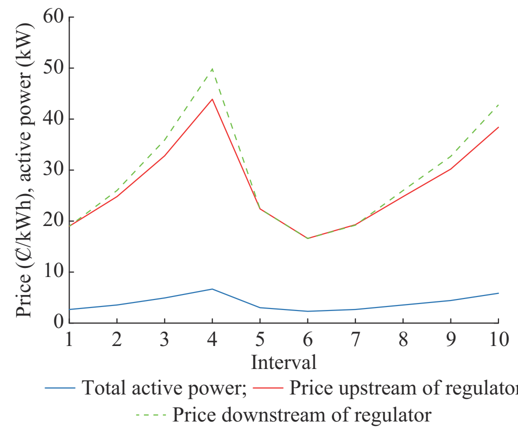

Fig. 6. Nodal market prices at ten intervals with price adjustment for line losses and regulator current constraint.

4) *Case with Additional Energy Price Adjustments for Voltage Regulation*

In this case, the maximum allowable voltage deviation of any node from the nominal voltage is 4 V. When the voltage of any node reaches this limit, the price for voltage regulation is implemented for each node based on their effectiveness in correcting the voltages, e.g., its voltage sensitivity to active and reactive power at the node with the highest voltage deviation above the limit.

Figure 7 shows the total price for energy balancing and voltage regulation at interval 4. It shows price variations among nodes at interval 4 with high demand due to different prices imposed at different nodes including losses, flow limit, and voltage regulation prices.

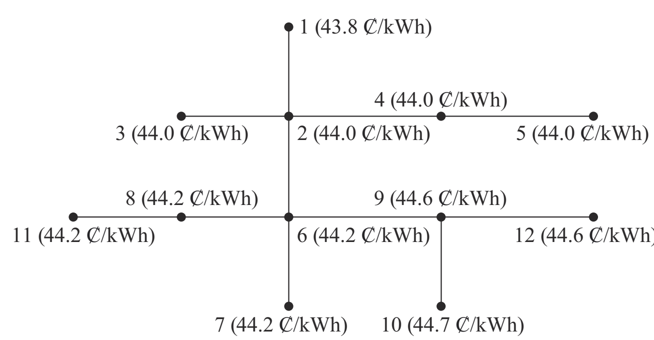

Fig. 7. Total energy prices for energy balancing and voltage regulation at interval 4.

Figure 8 shows the nodal voltages at interval 4. As can be seen in Fig. 8, the voltages of nodes 7, 9, 10, and 12 are above the allowable voltage limits with the maximum deviation at node 10.

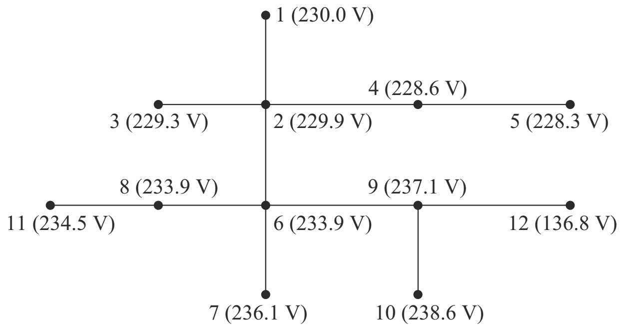

Fig. 8. Nodal voltages at interval 4.

Figure 9 illustrates how $M_{vp}(j,k,t)$ and $M_{vq}(j,k,t)$ are applied to different nodes to correct the voltage violation, which are plotted for interval 4. As shown in Fig. 9, both $M_{vp}(j,k,t)$ and $M_{vq}(j,k,t)$ for voltage regulation are the highest at node 10.

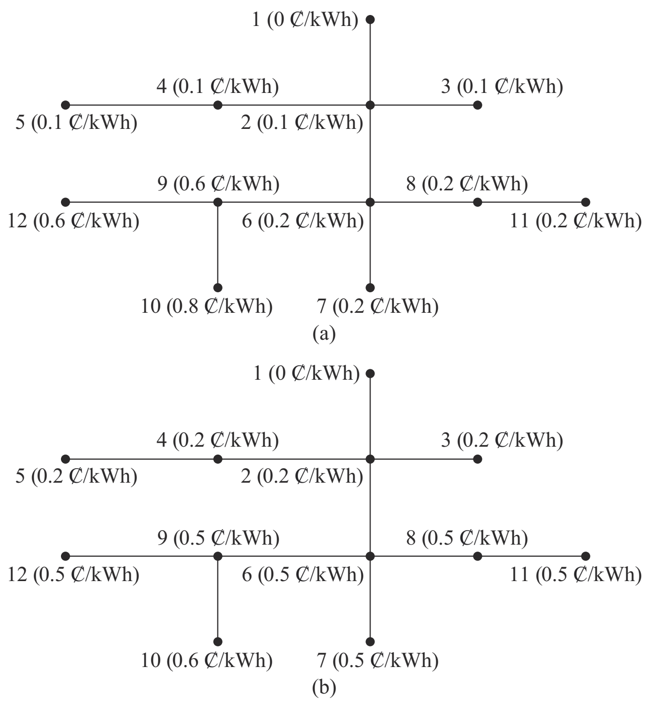

Fig. 9. Nodal prices for voltage regulation at interval 4. (a) $M_{vp}(j,k,t)$. (b) $M_{vq}(j,k,t)$.

B. Case with Grid Supply

In this case, the community power demands are met by both local generation and the main grid. The maximum current carrying capacity of the feeder line is 25 A (i. e., $B_{\max}(1)=25$ A).

1) No Adjustments to Energy Price for Network Use

To examine how the grid supply would change the market price, the NET algorithm is applied without price adjustments for the network use.

Figure 10 presents how the market energy price would change over ten intervals when the grid supply is available. As shown in Fig. 10, the energy price varies from 20 ₡/kWh during off-peak hours to 32.63 ₡/kWh during peak hours. The energy price during the peak period is 11.27 ₡/kWh less than that in case without grid supply.

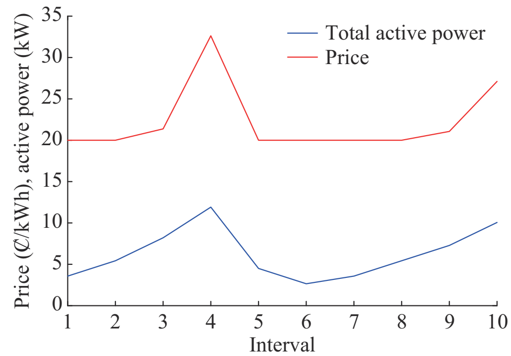

Fig. 10. Nodal prices for case with grid supply.

The energy price during intervals with low demand is settled at 20 ₡/kWh, which is the desired price for energy supplied from the main grid. However, during intervals with high demand, the price increases above the desired price to limit the flows through the transformer.

Figure 11 shows how price converges over iterations for different intervals. At intervals 4 and 10 with high demand, at the initial price of 20 ₡/kWh, the initial flows from the grid are much higher than the transformer capacity of 20 A. Therefore, the price is increased in the subsequent iterations until the flows from the grid fall below 20 A, which takes 10 iterations during the peak intervals.

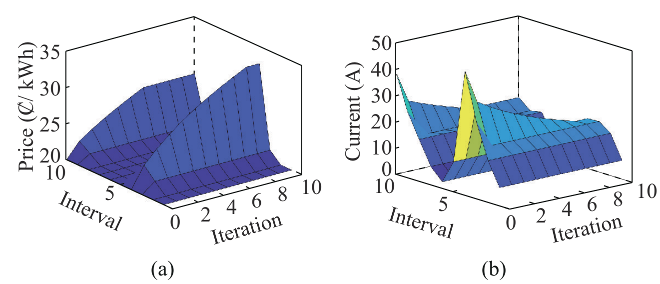

Fig. 11. Price and current over iterations to limit grid flows. (a) Price. (b) Current.

Figure 12 shows how the price converges and the flow from the grid changes over the ten iterations at interval 4.

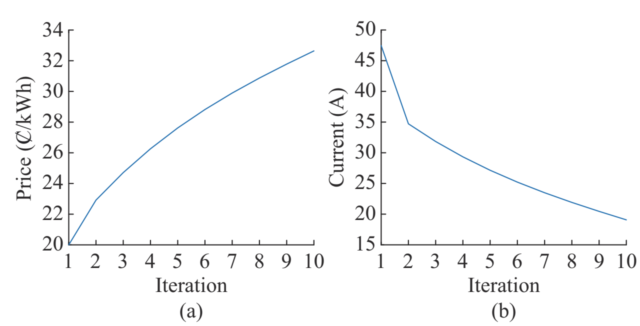

Fig. 12. Price and current over iterations to limit flows at interval 4.

2) Case with Energy Price Adjustments for Line Losses

Figure 13 shows the total nodal price during the peak period with adjustments for line losses. Nodal prices tend to be higher when the nodes are further away from node 1 because there are more losses when the electricity distribution path is longer.

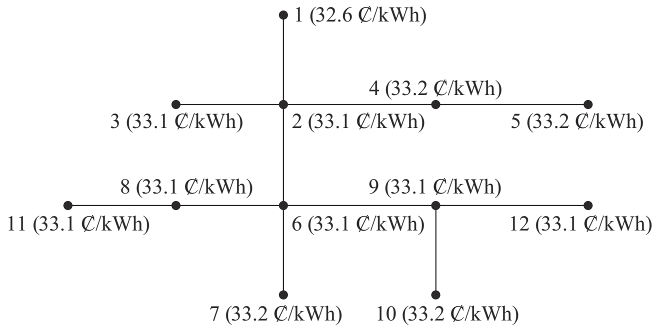

Fig. 13. Total nodal prices at interval 4 with line losses.

3) Case with Energy Price Adjustments for Line Losses and Voltage Regulation

Figure 14 shows the total price for energy and voltage regulation at interval 4 with the peak demand. Nodes 9, 10, and 12 have higher voltages and slightly higher prices than other nodes due to additional cost to manage voltage deviation (similar to the case without grid supply). Compared with Fig. 13, the price increasements of nodes 9, 10, and 12 are higher than those of other nodes, which is mainly from price adjustment to regulate voltage.

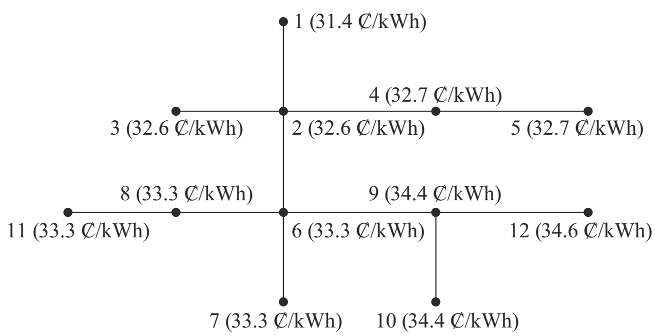

Fig. 14. Total nodal prices at interval 4 with losses and voltage regulation.

4) Case with Energy Price Adjustments for Line Losses, Regulator Current Constraint, and Voltage Regulations

Figure 15 shows the total nodal prices at interval 4, with the consideration of line losses, regulator current constraint and voltage regulations. Compared with Fig. 14, the nodes upstream of the regulator have similar prices; however, the nodes downstream of the regulator have slightly higher prices due to the regulator current constraint.

C. Scalability and Computation Time

To further test the scalability and demonstrate the results of the NET mechanism, the IEEE test system has been augmented to a 130-bus system. Out of 10000 simulations, the average computation time for simulating the NET mechanism over 10 intervals is 0.0038 s for the original case and 0.0228 s for the augmented 130-bus system.

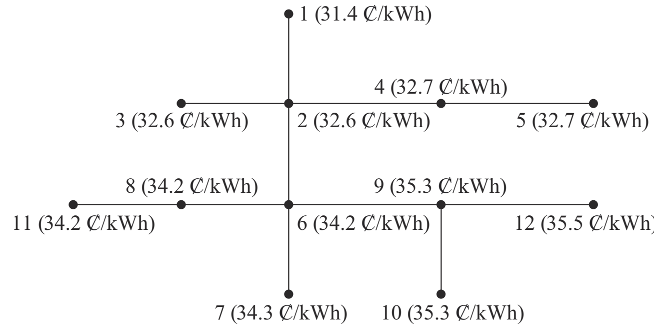

Fig. 15. Total nodal prices at interval 4 with losses, voltage, and current management.

The computation time is increased by 6 times for the 130-bus system. The increasement of computation time is lower than anticipated because the NET mechanism is mainly based on matrix computation such as (4) and (14). Matrices with more rows may not necessarily need much more time to calculate.

This comparison result shows that the NET mechanism is scalable and computationally efficient. Another evaluation is that the computation time of the NET mechanism is very small compared to the 5 min trading interval in Australian energy wholesale market.

IV. Conclusion

The communication overhead can be quite high in the existing distributed energy trading mechanisms, e.g., pair-wise communication in a full P2P market [24], [27]. With the unique adjacency-based communication design of NET mechanism, the low communication is needed to pass price information from upstream to downstream or pass flow information from downstream to upstream. Through a cost reflective pricing design, the NET not only has a scalable communication process and fast pricing convergence rates, but also could reflect losses and manage network constraints in the pricing mechanism.

Another advantage of the NET mechanism is that the existing network infrastructure can be used for the information flow (a realistic example is storage water heater, which has been controlled over decades with the existing electricity wires as the communication media). A limitation of the NET mechanism is that it works with radial feeders in distribution network when direct load flow approach is applicable [1]. However, generic P2P mechanisms may work in any electrical network topology. Further study includes a detailed financial evaluation for the NET impact on network planning.

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