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Distribution Locational Marginal Price Based Transactive Energy Management in Distribution Systems with Smart Prosumers—A Multi-Agent Approach

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Abstract: This work proposes a distribution locational marginal price (DLMP)-based transactive energy (TE) framework for distribution systems with enthusiastic or smart prosumers. The framework uses a multi-agent system (MAS) as the basis on which the proposed TE model, i.e., distribution locational marginal price (DLMP) based TE management system (DTEMS), is implemented. DTEMS uses a novel metric known as the nodal earning component, which is determined by the optimal power flow (OPF) based smart auction mechanism, to schedule the TE transactions optimally among the stakeholders by alleviating the congestion in the distribution system. Based on the individual contributions to the congestion relief, DTEMS ranks the prosumers and loads as most valuable players (MVP) and assigns the energy trading price according to the category of the player. The effectiveness of the proposed TE model is verified by simulating the proposed DTEMS for a modified 33 bus radial distribution system fed with various plug-able energy resources, prosumers, and microgrids.

Keywords: demand response; distribution locational marginal price; electricity markets; microgrids multi-agent system; transactive energy; renewable energy

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1. Introduction

The increased penetration of plug-able and distributed energy resources (DERs) that include electric vehicles EVs, microgrids, renewable energy sources and storages, as well as prosumers causes distribution system transformations. A promising solution represented as a coordination mechanism among all smart energy resources of the system is widely known as transactive energy (TE) [1]. TE is a new effective approach in providing control of energy flow and exchange of market-based standard values of the energy. TE improves system reliability, thus enables the optimal integration of green DERs using negotiation contracts among stakeholders and enhances the renewable-energy-hosting capacity of the distribution system [2]. However, TE systems must be reliable and transparent to all the players and stakeholders in the system. In the current literature, various TE approaches have been reported [3–10]. For instance, the authors of [3] have articulated the shortcomings of the existing methods and proposed a new framework to integrate TE optimally into a coupled natural gas and power system. For this, the overall system is modeled as an agent-based Virtual Power Plant which participates in day-ahead and real-time markets and regulates profit and energy imbalances [4,11].

Similarly, another article [5] proposes a framework for the day-ahead transactive market. In this framework, the distribution system operator DSO participates in wholesale electricity market operations to trade the TE and interact with distribution level prosumers, including microgrids, DERs, load aggregators, and demand response (DR) aggregators. Upon obtaining all the responses from local aggregations, DSO determines the distribution locational marginal prices (DLMPs) and payoffs. The work in [6] suggests a TE framework for the optimal scheduling of DERs in a virtual power plant. The schedule of DERs obtained as an offline solution is adjusted to minimize the real-time imbalance.

Reference [7] proposes a smart contract based on Ethereum blockchain. In this approach, the smart contracts enable energy producers to sell the excess of energy to the highest bidder through a Vickrey second price auction. The authors in [8] present a similar approach, where they introduce a different contribution metric to rank the prosumers by their energy production and consumption profiles. The TE is scheduled so that prosumers with a higher metric obtain more substantial benefits. A similar work dealing with assigning priorities to the prosumers is presented in [9], where the priorities were defined based on the energy shortage and game-theoretic strategy to maximise the profit for all parties.

It is important to note that the TE models strongly rely on a reliable communication network and require distributed computing environments such as a multi-agent system (MAS). Power system experts widely discuss the application of MAS to TE market management systems, and some significant approaches have been reported in [8–10,12–25]. For example, a TE management system to control flexible loads, EVs, generators, and energy storage systems was proposed in [10]. It uses a heuristic iterative multi-agent method for the TE management system, where the authority to make a decision is given to all customers. The work in [12] proposed a hybrid model for energy scheduling for multiple microgrids. Similarly, in [13], a comprehensive agent-based energy management system for multi-microgrid networks was presented, which aims at reducing the energy imbalances using DERs, such as DR and distributed energy storage systems (DESSs). Another approach in [14] utilized DLMP for TE management in distribution systems. Reference [15] presented a generalizable energy management method between microgrids in a grid-tied network based on multi-agent techniques. In a similar research work, renewable energy resources were integrated to an off-grid microgrid system, and economic cost optimization was performed [16]. A different approach to reduce the cost of community and peak demand by using a multi actor attention critic algorithm was used in [17]. Reference [18] performed stochastic dynamic-programming-based MAS to obtain an adaptive and offline self-learning system for uncertainty. For the decentralized management of MASs, an alternating direction method of multipliers was presented in [19]. Reference [20] proposed a decision support model for optimizing negotiations of small players in multiple markets. An agent-based platform for microgrid intelligent management with a peer-to-peer transaction model was applied in [21] for an office building. Reference [22] developed a comprehensive simulation-based TE valuation method which contains transmission, distribution, and building models. In another study, a bilateral energy trading mechanism for optimal power flow (OPF) to increase economic benefits was proposed and presented [23]. Similarly, a TE technique for optimum scheduling of DERs to obtain maximum microgrid profit was studied in [24,26].

Novelty and Contribution

Most of the proposed TE systems in the literature are based on decentralized power exchange and offer benefits for all market participants while utilizing the energy harvested from renewables efficiently. However, those TE systems are only feasible when the major parties such as DSO and TE service providers altruistically refuse to make a profit. Therefore, this work introduces a novel method by utilizing a special "nodal earn component" that supports building an effective TE framework. The nodal earn component indicates profit made by each node per one kWh of energy while participating in the electricity market. The node is usually supervised by one of the player agents: load agent (LA), generator agent (GA), and flexible agent (FA).

The work proposes a method of distributing this nodal earn component to satisfy major TE network stakeholders. In addition, individual risk-based bidding (RBB) strategies are developed for player agents. In addition, the concept of most valuable player (MVP) is proposed as an additional market regulation tool to discourage under-bidding and over-asking. This tool also supplements the idea of rescheduling the nodal earning component. The proposed TE system offers congestion management by utilizing DLMP metrics.

The major contributions of the work are listed below:

- Enhanced Multi-Agent-Based TE trading architecture with a high level of integration of the energy market to energy scheduling.
- A customized RBB strategy for trading agents such as consumers, distributed generators (DGs), and energy storage systems TE scheduling with congestion management and loss reduction;
- DLMP-based energy market with three cost components that encourage a fair process and loss and congestion reduction in distributed systems;
- A novel TE profit (earning) management, called MVP-based earning distribution, which includes the share of the TE stakeholders.

The rest of the paper is organized as follows. Section 2 details the proposed DLMP based TE management system (DTEMS) architecture and designated roles of various agents. The energy market structure and TE model followed by the DTEMS are described in Section 3. The case study system and simulation results are presented in Section 4. Lastly, Section 5 shows the insights of the overall work.

2. MAS Architecture of the DTEMS

Conventional supervisory control and data acquisition (SCADA) systems alone cannot handle the complexity added by the high penetration of pluggable DERs to the distribution system operation. To make complex decisions, MAS-based approaches are widely used. The combination of multiple intelligent agents, which are operating interactively, becomes a powerful tool to improve the performance of complex systems [27]. Since decentralized systems can compute tasks in parallel, they do not have a single point of failure, which is presented in centralized systems and can result in the failure of the whole system from the failure of one single point. Moreover, the systems built using MAS are independent, highly reactive, pro-active, and scalable. The proposed DTEMS also uses MAS as the underlying architecture over which the TE model is implemented.

The agent architecture of the DTEMS is presented in Figure 1. In this architecture, the pluggable resources, including prosumers are delegated and controlled by individual agents. These agents aim to achieve specific goals set by the owners, say prosumers and DERs. Therefore, as shown in Figure 1 the distinct loads, generators, and storage units are represented by load agents (LAs), generator agents (GAs), and flexible agents (FAs), respectively. These agents broadcast their bidding strategies to transactive energy (TE) market agent (TEMA), which is accountable for scheduling the TE in the system. TEMA consolidates the received data and passes them to the DSO to obtain required DLMPs.

The DSO determines the DLMP value for each node by solving the OPF described in detail in a latter section. Upon solving the OPF, the congestion (λ^{Con}) and loss (λ^{loss}) components of DLMP, including the nodal DLMPs, are determined and shared with TEMA. Upon receiving the data from DSO, TEMA implements the proposed TE mechanism in which it organizes the energy auction market using the bidding strategies collected from LAs, GAs, and FAs and determines the TE trading contracts. Figure 2 depicts the information exchange process in the proposed DTEMS. It is worth noting that all communication occurs through TEMA. The latter parts of the section detail the roles of the agents and their rational bidding strategies to interact with the TE market.

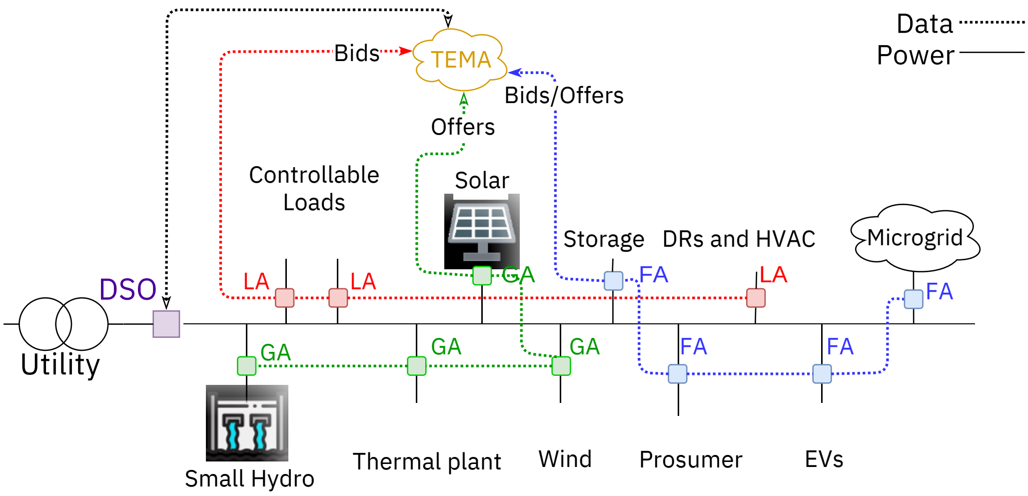

Figure 1. Multi-agent based transactive energy (TE) management framework with renewable energy sources.

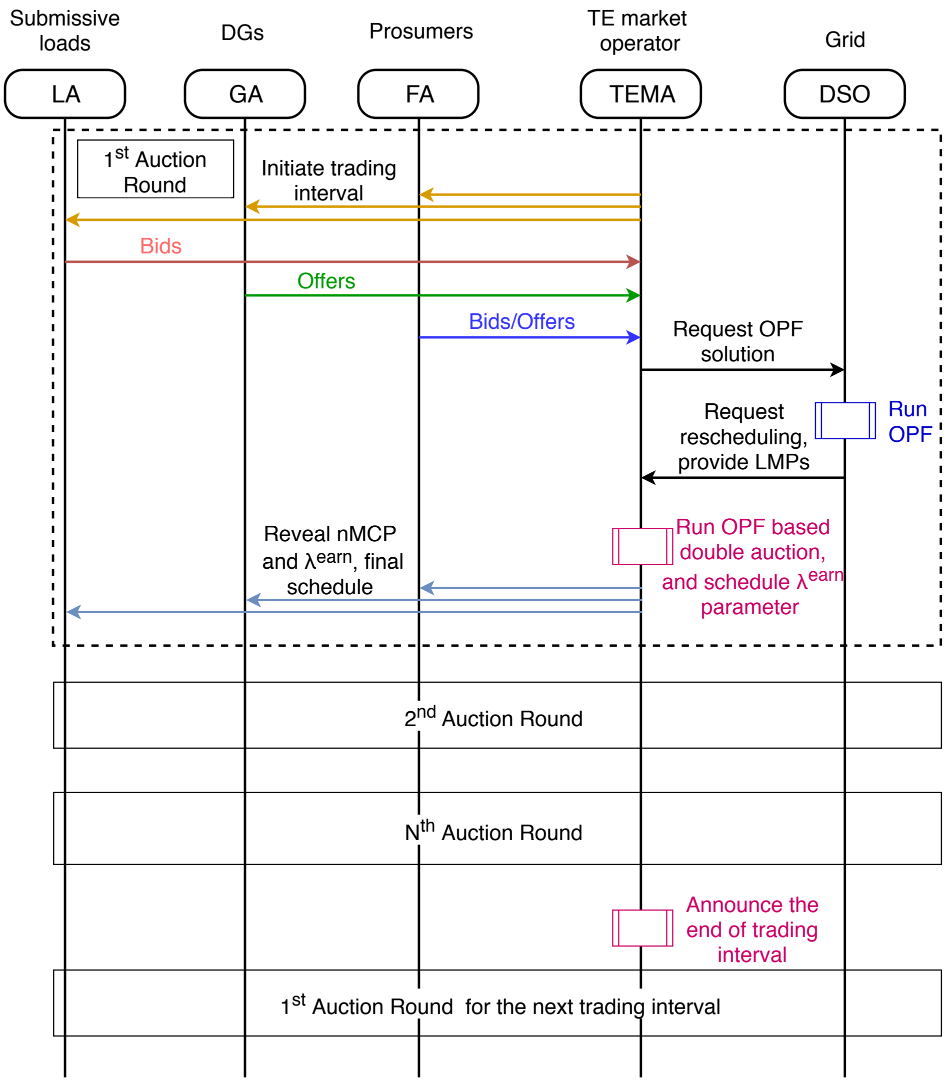

Figure 2. Data exchange layout for the agents in the proposed distribution locational marginal price (DLMP) based TE management system (DTEMS).

2.1. LA—Load Agent

LAs act as retailers or aggregators for the end-users with controllable low priority loads and without on-site generation. In general, there can be multiple LAs representing end-users across the distribution system. Examples of controllable loads might include: boilers, refrigerators, freezers, HVAC systems, etc. It is assumed that the end-users have a home energy management system (HEMS), such as the system proposed in [28], to coordinate with LAs for effective integration and trading of DR (NegaWatts). The HEMS of the corresponding end-user executes the load operation commands directed by LAs. Thereby, the load groups will be clustered and aggregated with the help of LAs. The end-users submit the information about their flexible loads to the LA via the HEMS.

Upon registering with an LA, the HEMS submits the sub-hourly load profile of the premises along with the flexible load information set by the owners. This information includes power ratings, operating time, and target time before which the device must be operated. Using this information, the LAs cluster the loads into high priority loads ($P_c(i,t)$), low priority or flexible loads ($P_f(i,t)$), and least priority or super flexible loads ($P_{sf}(i,t)$). Therefore, the total amount of power ($P_k(t)$) required by the LA is given by:

$$P_k(t) \;=\; \sum_{i=1}^{N} P_k(i,t); k \in \{c, f, sf\} \tag{1}$$

where N is the number of loads registered with the LA. After identifying the overall power requirement, LAs determine the bids for each load group by following the RBB strategy. The bids for each load category have different levels of risk, i.e., the bid for high-priority loads carries low risk, whereas the bid for the least-priority load group carries high risk. More detailed information about RBB is given in Section 2.4.

2.2. GA—Generator Agent

In the proposed DTEMS, GAs delegate the generators as energy sellers in the TE market. Based on the data provided by the DG owners, GAs develop energy offering strategies. In case of conventional generators, the energy generation is a quadratic function calculated as:

$$C_i(t, P_g) = A_{i,t} * P_g^2 + B_{i,t} * P_g + C_{i,t} \forall i \in \{1, 2, .., N_{DG}\} \tag{2}$$

where $C_i(t, P_g)$ is the cost of energy generation by DG in ($¢/kWh$) during the market interval t and $A_{i,t}$, $B_{i,t}$, and $C_{i,t}$ are the corresponding coefficients of the cost model. GAs convert the cost function into piece-wise linear form and submit data as (E_j, ask_j) pairs to TEMA at the beginning of each trading interval. In general, the energy offers may differ from the incremental costs of the generators as DG are profit motivated and the model of the market followed by DTEMS is a stable energy price market. Therefore, GAs change the offers using a strategy that maximizes the benefit for DG in the market. Similar to LAs, GAs are assumed to follow the RBB strategy explained in Section 2.4 to choose and revise the asks progressively in the proposed TE market.

2.3. FA—Flexible Agent

FAs represent the pluggable resources, which can draw the power from the distributed system or feed the power into the system. Therefore, these agents represent prosumers in the TE market. The prosumers include end-users with on-site energy generation, building-to-grid, DESSs such as vehicle-to-grid-enabled EVs, and smart microgrids. Prosumers such as EVs were found to be highly effective for DR programs in energy markets [29] and transactive systems [30]. In case of supplying energy to the grid, prosumers act as the energy sources, and the corresponding FA takes the role of a GA and calculates the energy offers based on the incremental costs provided by the end-users or the cost of accumulated energy in case of storage systems.

In case of drawing energy from the system, the FAs take the role of the LAs. If the prosumers have flexible loads then, accordingly, FAs choose the priorities and bids as described in Section 2.1. In the absence of flexible loads, the whole load demand is assigned high priority and placed in the market with the corresponding bid. In both cases, FAs follow the risk-based bidding strategy described in Section 2.4 to qualify the bids.

2.4. RBB—Risk-Based Bidding

The TE trading agents participate in continuous double auctions conducted by TEMA and use RBB as a bidding strategy. This strategy allows agents to place bids according to degree of risk [31]. In this strategy, player agents calculate the risk–return trade-off. Players that are looking for higher momentum profits have a lower probability of winning the transaction. This strategy is determined by target price τ, which is derived from the risk model and price estimate $p*$.

Each TE trading agent that participates in TEMA has two limit prices: l_{ik} indicates the maximum price the buyer is willing to pay, and c_{jk} indicates the minimum price seller is agreed to sell for. The first auction round starts when all agents submit their bids and asks. When the bid of the buyer is higher than the ask of a seller, the transaction pairs are formed. In every auction, round buyers and sellers submit bids according to Equations (3) and (4), respectively:

$$bid_i = \begin{cases} o_b + (\min\{l_{ik}, o_a\} - o_b)/\eta & \text{if first round} \\ o_b + (\tau - o_b)/\eta & \text{otherwise} \end{cases} \tag{3}$$

$$ask_j = \begin{cases} o_a - (o_a - \max\{c_{jk}, o_b\})/\eta & \text{if first round} \\ o_a - (o_a - \tau)/\eta & \text{otherwise} \end{cases} \tag{4}$$

where $\eta \in [1, \infty)$ is a constant that determines the convergence of bids toward transaction price, τ is the target price, o_a and o_b are outstanding ask and bid prices, respectively, which remained unresolved in the previous market's rounds and were used to determine current bid and ask prices.

In other auction rounds, LAs, GAs, and FAs estimate their target price τ for the loads based on risk—$r(t)$—and eagerness—Eag. The current risk factor for the next auction round $r(t+1)$ is estimated as:

$$r(t+1) = r(t) + Eag * (\delta(t) - r(t)) \tag{5}$$

$$\delta(t) = (1+\Delta)\rho, \Delta = (-k, k) \tag{6}$$

where $Eag \in (0,1)$ is the eagerness to secure the round. The ρ here is a risk factor for the last bid, $\delta(t)$ is the desired risk factor, and k is the step size.

In case a player fails to win transactions, he becomes more eager and raises the bid to increase the chance of winning in the next transactions. The proposed eagerness model (7) is subject to the current trading interval t_i, the deadline when the player must finalize bid/ask t_D, and the operation time for the load/generator t_{op}:

$$Eag = EF * \frac{t_i}{t_D - t_{op} + 1} \tag{7}$$

where $EF \in (0,1)$ is an eagerness factor indicating the trader's bias towards eagerness. Lower priority loads can raise priority when a load switches the state to a higher priority one as the deadline approaches, e.g., a low-priority load such as a washing machine that has to run for 3 h in any interval from 1:00 p.m. to 11:00 p.m. does raise its priority when a deadline (8:00 p.m.) is approaching. If the LA did not manage to win auction rounds for any period from 1:00 p.m. to 7:00 p.m., it automatically raises the priority of the load in auction rounds for the 8:00 p.m. to 11:00 p.m. interval.

Depending on controllable load type, the bids and risks of prosumers can be adjusted. In this work, three different load types are suggested, see Table 1. C1 loads are high-priority loads that should be served regardless of strategy; therefore, they can be cleared close to Grid Buying Price. On the other hand, lower priority loads C2 and C3, since they are flexible, might have higher risk appetite, and they are targeting the range of the Grid Selling Price.

Table 1. Bidding strategy for LAs.

Load	Bid in First Round	Risk	Eagerness Factor	Priority Rise
C1	High	Low	High	Impossible
C2	Medium	Medium	depends on load	Possible
C3	Low	High	depends on load	Possible

The target price τ is estimated based on the risk model, where the estimated price $p*$ is found according to the moving average method with regard to the history of past transactions. More details about the moving average method are presented in [32]. Target price adjustments reflecting past sales is given as follows:

For buyers:

$$\tau = \begin{cases} p^* * (1 - r * e^{\theta(r-1)}) & \text{if } r \in (0,1) \\ (l_{ik} - p^*) * (1 - (r+1) * e^{rk}) + p^* & \text{if } r \in (-1,0) \end{cases} \tag{8}$$

where $k = (p^* * e^{-\theta})/(l_{ik} - p^*) - 1$

For sellers:

$$\tau = \begin{cases} p^* + (a^{\max} - p^*)r * e^{\theta(r-1)}) & \text{if } r \in (0,1) \\ p^* + (p^* - c_{jk})r * e^{k(r+1)}) & \text{if } r \in (-1,0) \end{cases} \tag{9}$$

where $k = log[(a^{\max}) - p^*)/(p^* - c_{jk})] - \theta$.

The parameter $\theta \in [-1, \infty)$ indicates the rate of change concerning risk. A lower value of θ means a higher gradient of the cost.

3. Proposed TE Model

This section presents the novel TE scheduling method with a congestion management model. It also includes a DLMP-based auction algorithm for scheduling TE and the application of a nodal earning component.

3.1. Problem Formulation

The primary objective suggested to follow by the DSO for TE scheduling is to reduce costs by minimizing losses, maintaining power balance, and avoiding congestions and voltage drops. In addition, the network topology should be operating with a radial topology. The Optimal Power Flow (OPF) model is proposed as an optimization strategy. The objective function is given by:

$$F_{obj} = \min \sum_{i=1}^{N} C_i * P_{gi} \tag{10}$$

The constraints for the objectives are provided by expressions (11) to (20). The system balance constraints are as follows:

$$\sum_{i=1}^{Ns} P_i^D - \sum_{k=1}^{Nb} P_k^L - P_{loss} = 0 \tag{11}$$

Line limits constraints:

$$\sum_{i=1}^{N} S_{ki} * P_i \leq |PL_l| \tag{12}$$

The GA capacity constraints:

$$P_{i,\min}^{GA} \leq P_i^{GA} \leq P_{i,\max}^{GA} \tag{13}$$

The LA demand response constraints:

$$P_{i,\min}^{LA} \leq P_i^{LA} \leq P_{i,\max}^{GA} \tag{14}$$

The FA operation constraints:

$$0 \leq P_{i,t}^{FA,+} \leq P_{i,\max}^{FA,c} \tag{15}$$

$$0 \leq P_{i,t}^{FA,-} \leq P_{i,\max}^{FA,d} \tag{16}$$

$$E_{i,t} = E_{i,t-1} + \eta_i^c P_{i,t}^{FA,+} - \left(1/\eta_i^d\right) P_{i,t}^{FA,-} \tag{17}$$

$$E_i^R \cdot SOC_{i,\min} \leq E_{i,t} \leq E_i^R \cdot SOC_{i,\max} \tag{18}$$

$$E_{i,t=T} = E_{i,t=0} \tag{19}$$

The voltage constraint:

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{20}$$

For TE scheduling, it is necessary to ensure that physical constraints are not violated. Moreover, it is practical to support nodes that help to reduce losses and congestion in the network. Therefore, in this work, the DLMP components derived from the objective function outcome are integrated into the auction mechanism. More details are provided in Figure 2 and the following sections.

3.2. TE Scheduling

MAS collects strategies from LA, GA, and FA to conduct the electricity market by negotiating with DSO regarding nodal prices and running a double-sided auction.

For the proposed TE scheduling model, the first step is DSO conducting Economic Dispatch after receiving LA, GA, and FA strategies from MAS. After this step, the network is ready to respond to potential contingencies through utilizing obtained DLMP metrics by rescheduling LA, GA, and FA strategies. In the case of an uncongested network, the energy dispatch remains unaltered. In case of congestion, the proposed TE model deploys demand response through the rescheduling of resources of LAs, GAs, and FAs.

3.3. DLMP-Based Market Mechanism

From OPF results conducted by DSO, the Locational Marginal Prices for each node in the network can be derived. Locational marginal price modeling is used for economic scheduling of energy considering congestion and losses in a distribution network. When DSO identifies congestion in a system, it can request MAS to deploy a DR program by rescheduling LA, GA, and FA. Therefore, the energy for these agents is scheduled in a way to reduce congestions in lines according to their power transfer distribution factor (PTDF). PTDF identifies critical nodes that can assist in relieving congestion in the monitored line. The requested energy capacity-P^E from individual LA, GA, or FA used to relieve congestion by ΔPL_l is:

$$P^E = \Delta PL_l * PTDF_l \tag{21}$$

$$\Delta PL_l = |PL_l| - PL_l^{\max} \tag{22}$$

$$PTDF_l = \frac{\Delta P_{i,j}}{\Delta P_m} \tag{23}$$

where PL_l is the power flow on congested lines, and PL_l^{max} is the capacity of the branch l. ΔP_m is the power change at bus m caused by the power change on the branch $\Delta P_{i,j}$.

The proposed OPF-based auction algorithm utilizes DLMP, which is a nodal price model after including (1) λ_r—the cost of energy in the node; (2) λ_i^L—the price of losses paid by the node; and (3) λ_i^{Con}—the congestion price paid by the node:

$$\lambda_i^{DLMP} = \lambda_r + \lambda_i^L + \lambda_i^{Con} \tag{24}$$

$$\lambda_r = \frac{dC_p(P_p)}{dP_k} \tag{25}$$

where C_p are cost functions submitted by GAs and FAs, and P_k is energy received at bus k. The loss component of DLMP is derived as:

$$\lambda_i^L = -\lambda_r \times LF_k = -\lambda_r \times \frac{\partial L_t}{\partial PL_l} \tag{26}$$

$$L_t = \sum_{i=1}^{n} F_l^2 Z_l \tag{27}$$

$$F_l = \sum_{i=1}^{n} \alpha_{l,i} * P_{ti} \tag{28}$$

$$\alpha_{l,i} = \frac{z_{ni} - z_{mi}}{z_l} \tag{29}$$

where LF_k is the loss factor at bus k, and PL_l is the line flow at branch l. α is the line sensitivity factor of line l where z_{ni} and z_{mi} are the self-impedance of two ends of the line. The congestion component of DLMP can be derived as:

$$\lambda_i^{Con} = \sum_{i=1}^{n} (\alpha_{l,i} \times TL_l) \tag{30}$$

$$TL_l = \pi^+ - \pi^- \tag{31}$$

where TL_l is total cost variation with π^+ and without π^- line limits in line l, where π are Lagrangian multipliers of line limit constraints in (31).

To model the DLMP-based electricity market, a concept of nodal market clearing price (MCP) (λ_i^{Price}) is introduced where nodal MCP indicates the real price paid by the node to receive one unit of energy. This price is calculated by considering MCP and DLMP parameters such as loss and congestion components:

$$\lambda_i^{Price} = \frac{MCP}{\lambda_r} \lambda_i^{DLMP} \tag{32}$$

where λ_i^{Price} is MCP at node i, λ_i^{DLMP} is the DLMP at bus i, and λ_r is the cost of energy in bus r.

Market Clearing Rate—R—is a scale factor obtained by scaling prices until the last accepted ask equals to its nodal price:

$$R = \max_i \frac{o_i^{p,LA}}{\lambda_r} \tag{33}$$

where $o_i^{p,LA}$ is the price of last accepted energy ask from seller i, and λ_r is the marginal energy price at bus r.

3.4. Nodal Earning Component

MAS conducts the DLMP based double-sided auction (Figure 3), where buyers and sellers get earning through participation in the market. Nodal earning component—λ_i^{earn} represents the difference between nodal MCP and offer (or bid):

$$\lambda_i^{earn} = \frac{MCP}{\lambda_r} \lambda_i^{LMP} - \lambda_r \tag{34}$$

where λ_i^{LMP} is the locational marginal price at bus i, and λ_r is the energy price at bus r. The area of $Es_i * \lambda_i^{earn}$ in Figure 3 is additional revenue made by seller i after participating in the market. Therefore, in the proposed approach, these extra earnings can be used as a promotion tool for TE implementation. It is essential to encourage agents to contribute to system betterment by providing incentives to valuable contributors and depriving non-contributing agents. Therefore, the evaluation of the performance of agents is necessary to identify real contributors of the market. The λ_i^{earn} parameter evaluates individual contributions of LAs, GAs, and FAs to the whole system. In the proposed system, personal contribution is considered high when $|\ \lambda_i^{earn}\ |$ is relatively large compared to other inputs. There are five levels of agent's utility according to λ_i^{earn}: MVP, second valuable player (SVP), third valuable player (TVP), least valuable player (LVP), and non-valuable player (NVP).

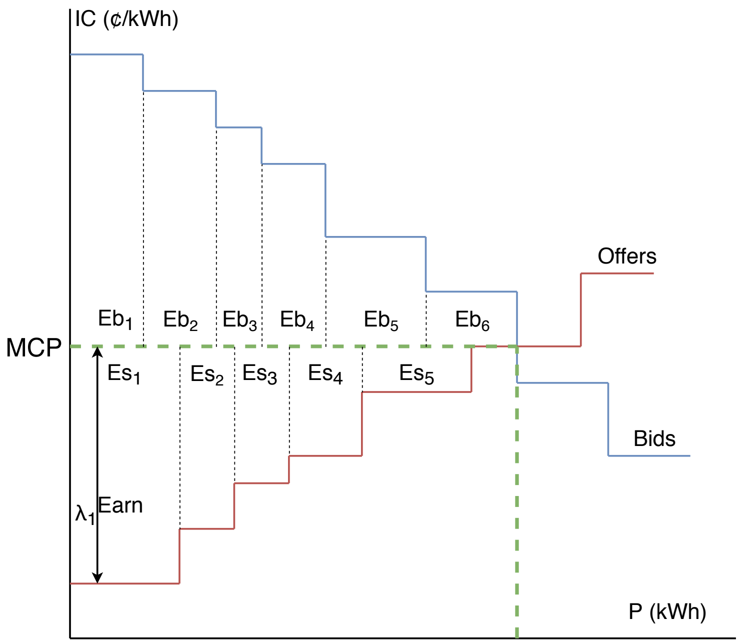

Figure 3. Market Clearing Price in Double Auction with earning component for each participant (Eb/Es).

The allocation of all agents is performed using the normal distribution to categorize the contribution (Figure 4):

$$z = \frac{(|\ \lambda_i^{earn}\ | - \mu)}{\sigma} \tag{35}$$

where z is a normally distributed random variable from the standard normal distribution function, λ_i^{earn} is the value that is being standardized, μ is the mean of the distribution, and σ is the standard deviation of the distribution.

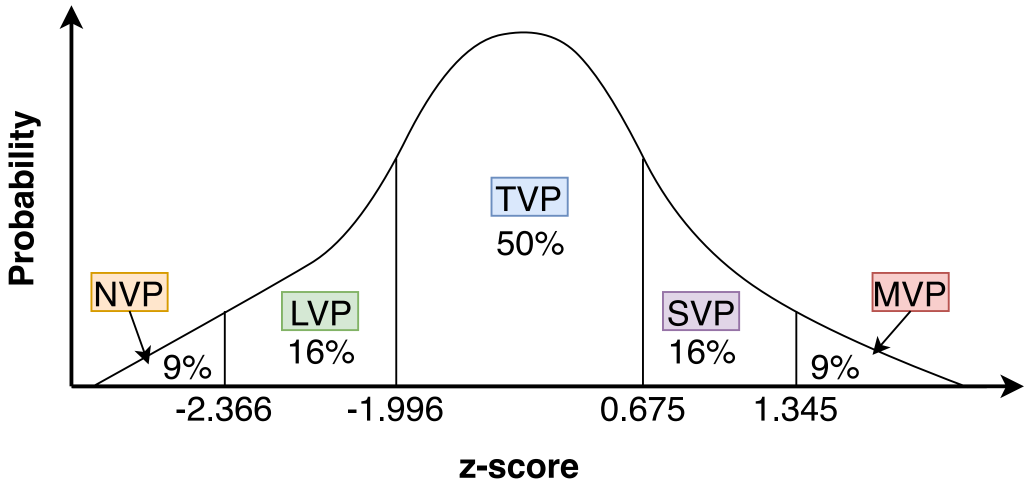

Figure 4. Allocation of agents to levels based on their contribution.

After ranking agents to a particular player value level, λ_i^{earn} are assigned as 100% honored for MVP, 75% for SVP, and with a decrease of 25% for every other player value level, so for agents located in NVP range, there is no extra profit. The ones who submitted low bids or help to clear congestion have a higher chance to obtain a high value of earning component and, thus, to be elected as MVP. Through this method, a system has money for stable TE framework operation due to an adequate amount of revenue to be distributed among stakeholders such as DSO and TE service providers. For nodal earning components, the share is decided individually by each node:

$$\sum_{i=1}^{n} \lambda_i^{earn} = \sum_{i=1}^{n} (a_i + b_i + c_i) * \lambda_i^{earn} \tag{36}$$

where $a_i, b_i, c_i \in [0.00, 1.00]$ with $a_i + b_i + c_i = 1$ are elements of TE stakeholders that have a share in earning (a is a share of players, b is a share of DSO, and c is a share of TE service providers). The primary objective is to build a reasonable and reliable TE framework that satisfies all sides. MAS is the governing agent for optimally scheduling incentives among stakeholders and executing the MVP algorithm.

4. Case Study

In the case study, the models described in the previous section will be simulated in a test distribution system with various loads, Distributed Generators, and Microgrids. For this purpose, the IEEE 33 bus feeder was selected as a topology of the system (Figure 5). The optimal locations for the generator and storage elements in the distribution feeder are determined using the autoadd command in OpenDSS. The distribution system in Figure 5 consist of 33 busses, 3 loads, and 5 prosumers (including DGs, and EVs, and Battery). The solid line represents distribution line in normal network state, tie lines are reserve lines used in case of emergencies, maintenance, and for alternative energy dispatch routes.

A wide variety of DERs with different power profiles that are comparable with the radial network were selected to demonstrate the feasibility of the TE framework. In the given system, some nodes have implemented MAS and are eligible to participate in the proposed TE framework. Player agents supervise renewable energy sources, in particular, LAs supervise EVs and various DESS, whereas GAs oversee HVAC and other controllable loads, and FAs manage microgrids. In the trading time interval Δt, LAs, GAs, and FAs are submitting bids and offers to MAS based on their strategy. Table 2 shows generator offers, and Table 3 shows bids submitted by loads. Based on the submitted bids and offers, TE runs an OPF-based smart market to determine winner and loser blocks.

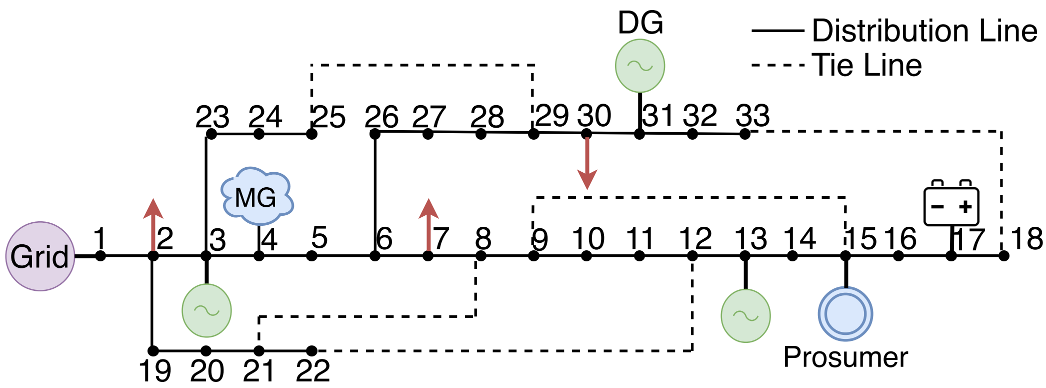

Figure 5. IEEE 33 bus feeder with optimal generation, flexible load, and storage locations.

Table 2. Generator Offers.

Bus	Type	Block 1 kW ‖ ¢/kWh	Block 2 kW ‖ ¢/kWh	Block 3 kW ‖ ¢/kWh
1	GSP	inf ‖ 5.0	-	-
3	Solar	96 ‖ 3.0	-	-
4	EV	12 ‖ 2.0	24 ‖ 4.2	24 ‖ 8.0
17	Battery	12 ‖ 2.0	24 ‖ 4.4	24 ‖ 9.0
13	Wind	96 ‖ 2.0	-	-
31	Controlable	50 ‖ 2.0	50 ‖ 6.0	50 ‖ 8.0

Table 3. Load bids.

Bus	Type	Block 1 kW ‖ ¢/kWh	Block 2 kW ‖ ¢/kWh	Block 3 kW ‖ ¢/kWh
7	HVAC	40 ‖ 10.0	30 ‖ 7.0	30 ‖ 6.0
15	EV	20 ‖ 10.0	20 ‖ 5.0	20 ‖ 2.0
30	Industry	100 ‖ 10.0	50 ‖ 6.0	50 ‖ 5.0
2	GBP	inf ‖ 3.0	-	-

In Table 2, there are six buses with prosumers and their corresponding offers were listed, GSP is representing the grid offer as Grid Selling Price, other prosumers might have single offer, such as Solar, or dynamic offers, such as EV or Battery. These offers are represented by blocks in kW ‖ ¢/kWh. In Table 3, all bids of the prosumers with controllable loads were submitted. GBP stands for Grid Buying Price and represents a virtual node 2. Other nodes are controllable loads or prosumers in consumption mode.

5. Results and Discussion

Following the topology and parameters from the case study section, the market simulation was conducted on the 33 bus radial feeder using Matlab. In the simulation, the parameter of Branch 2–3 (see Figure 5) is set to have capacity $PL_{2,3} = 3.06$ MW. The parameters of prosumers and controllable loads, as well as their market offers, are presented in Tables 2 and 3, respectively. Other network parameters were set to the default of the IEEE 33 bus distribution system. The OPF-based market results are shown in Table 4. From the table, we can observe all power injections from the proactive buses, including the grid. From Table 4, it can be noticed that by participating in Transactive Energy management system, all prosumers have benefited (see Earning). The simulation was carried out with a significant spread between grid buying and selling prices for one trading interval. The real economic impact can vary significantly depending on energy market conditions and adoption of Transactive Energy and Peer-to-Peer markets.

The breakdown of OPF in locational marginal components $\lambda_r, \lambda_i^L, \lambda_i^{Con}$ are presented in Table 5. The impact of congestion, network loss, and LMP can be observed and earning of each prosumer from participation in Transactive Energy markets can be estimated.

Table 4. Market Results.

Bus	Pg (kW)	λ^{Price} (¢/kWh)	Revenue (¢)	Cost (¢)	Earning (¢)	λ^{earn} (¢/kWh)
1	2760.7	5.000	13,803.5	13,803.6	0.0	0.000
3	96.5	5.671	547.2	289.5	257.7	2.671
4	36.0	5.715	205.7	120.0	85.7	2.382
17	36.0	6.056	218.0	120.0	98.0	2.722
13	96.5	6.019	580.9	193.0	387.9	4.019
31	83.9	6.000	503.4	471.5	31.9	0.381
7	−100.0	5.884	−588.4	−999.8	411.4	−4.114
15	−20.0	5.000	−100.0	−200.0	100.0	−5.001
30	−100.0	6.000	−600.0	−1000.0	400.0	−4.000
2	0.0	5.017	0.0	0.0	0.0	0.000

Table 5. Nodal Marginal Components.

Bus	λ_r (¢/kWh)	λ^{Con}	λ^L	λ^{LMP}	λ^{Price}	λ^{earn} (¢/kWh)
1	5.000	0.000	0.000	5.000	5.000	0.000
3	3.000	0.343	0.059	3.402	5.671	2.671
4	3.333	0.383	0.093	3.810	5.715	2.382
17	3.333	0.412	0.291	4.037	6.056	2.722
13	2.000	0.245	0.163	2.408	6.019	4.019
31	5.619	1.943	-0.819	6.743	6.000	0.381
7	9.998	1.186	0.582	11.766	5.884	−4.114
15	10.001	−0.001	0.001	10.001	5.000	−5.001
30	10.000	0.790	1.210	12.000	6.000	−4.000
2	3.000	0.000	0.010	3.010	5.017	0.000

The results show that the proposed Transactive Energy management system is effective when the spread between the grid buying and selling prices is large and there are enough market participants to arbitrage energy markets. In the existing literature, there are many models and simulations on the effect of Transactive Energy on distribution systems; however, this work integrated an economic model with network and conducted OPF-based simulations to determine optimal energy allocations of prosumers considering economics and physical network states. Unlike in other works, the complete breakdown of each marginal component, including congestion, network losses, and LMP, were included in the calculations. The results of the OPF-based market provide the optimal schedule for players. The earnings of market participants are considered as pure profit. However, in the real world, these earnings should be redistributed across multiple stakeholders.

The flowchart of the proposed Transactive Energy management model is presented in Figure 6. From the flowchart, it can be observed that there are multiple steps included in each trading interval to guarantee optimal market and network conditions to clear the market and allocate energy for prosumers. The significant stakeholders such as Players, DSO, and TE providers were selected as in Figure 7.

The schedule for distributed energy sources that have participated in the market includes a λ^{earn} component that is subject to rescheduling. When rescheduling the λ^{earn} parameter, players incentives were subject to the value of a player in the market. The player is considered as valuable when it has a relatively large λ^{earn} parameter according to Equation (34). A higher λ^{earn} parameter for GA indicates lower offers, and for LA, it is higher bids. Therefore, these players are considered valuable for the market and are eligible to become MVP. The scheduling λ^{earn} component is given in Figure 7. From these results. it is seen that Bus 15 is MVP and has 100% share of the profit, Bus 31 is LVP and has a 25% share, and other players are TVP with a share of 50%. Therefore, $a_{15} = 1, a_{31} = 0.25$, $a_i = 0.5; i \notin (15{,}31)$ are inserted into Equation (36).

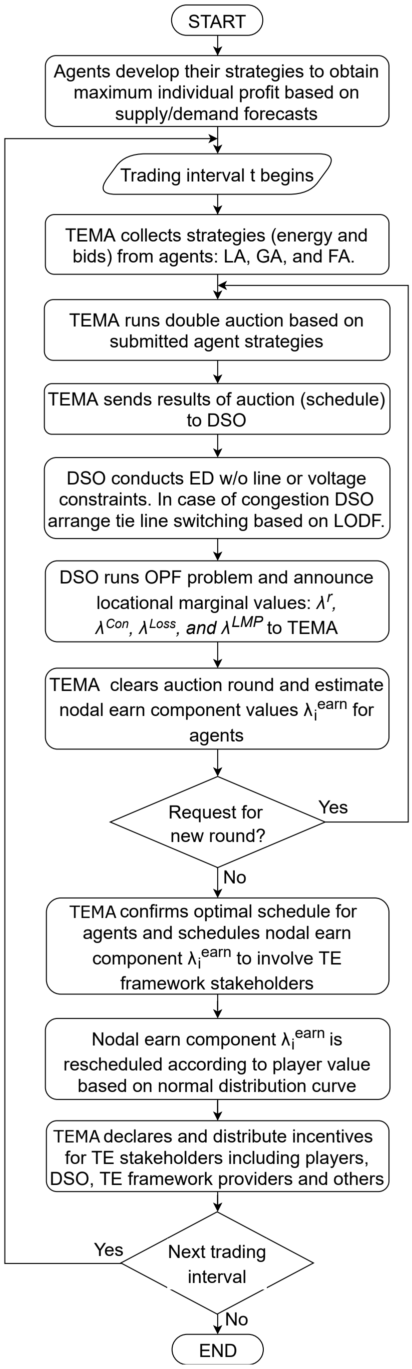

Figure 6. Flow Chart for entire framework.

The share of DSO and TE service providers were chosen as 80% and 20% of the remaining schedule: $b_{15} = c_{15} = 0, b_{31} = 0.6, c_{31} = 0.15, b_i = 0.4, c_i = 0.1; i \notin (15, 31)$.

The proposed TE framework is a feasible solution to implement within existing radial networks with the support of the DSO. The proposed player value management system attracts higher bids and lower offers that lead to an overall decrease in electricity prices. This TE framework ensures that agents submit an honest bid and offers since underbidding results in receiving an NVP status with 0% player-share for incentives.

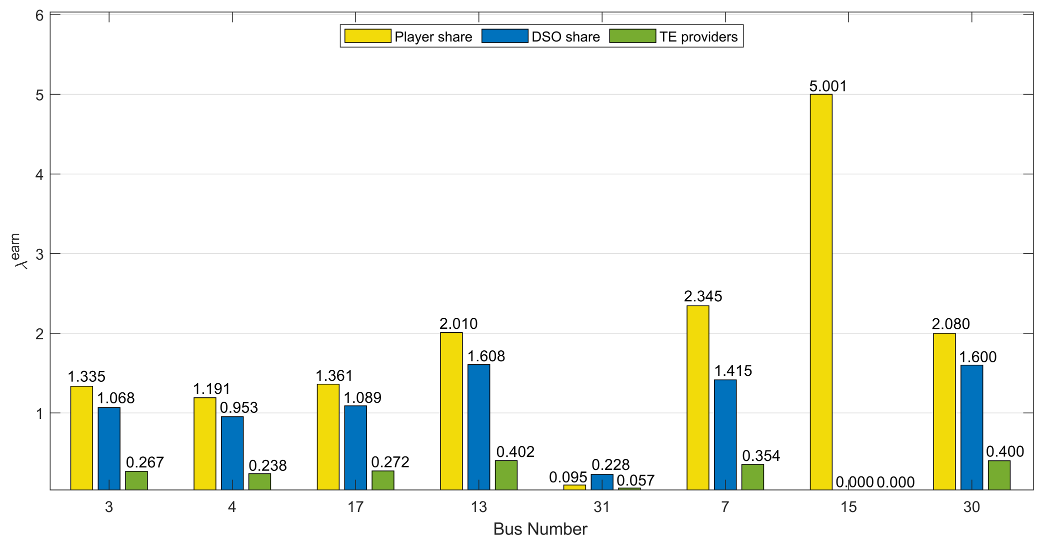

Figure 7. Scheduling Marginal Earn Component.

6. Conclusions

The proposed DLMP-based TE framework is simulated on a modified IEEE 33-bus radial feeder with renewable energy sources and DESS. The results have shown that locational marginal-price-based auction markets can be applied for optimal dispatch and can assist in congestion management and loss minimization for the system. A congestion-relieving method using agent-controlled DR was proposed. A novel approach of utilizing the λ^{earn} parameter is offered, which is developed in a way to promote TE in distribution systems. The proposed method considers incentives for major parties that are involved in the TE network.

To regulate the market operations, player value parameters were introduced to award the most valuable market participants. It was proven that dishonest players that practice underbidding are loosing due to the risk of becoming LVP or NVP with low λ^{earn} player-share. Punishing players in this format preserves the integrity of the auction and maintains the bid and ask prices in an adequate range. In addition, the results of the proposed framework have shown that MAS can assist DER owners to form on-site energy markets and participate.

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Abbreviations

DER	Distributed energy resource
DESS	Distributed energy storage system
DG	Distributed generator
DLMP	Distribution locational marginal price
DR	Demand response
DSO	Distribution system operator
DTEMS	DLMP based TE management system
EV	Electric vehicle
FA	Flexible agent
GA	Generator agent
HEMS	Home energy management system
LA	Load agent
LVP	Least valuable player
MAS	Multi-agent system
MCP	Market clearing price
MVP	Most valuable player
NVP	Non-valuable player
OPF	Optimal power flow
PTDF	Power transfer distribution factor
RBB	Risk-based bidding
SVP	Second valuable player
TE	Transactive energy
TEMA	TE market agent
TVP	Third valuable player

Nomenclature

E_{RL}	Requested energy capacity of aggregator (kWh)
$PTDF_L$	Power Transfer Distribution Factor of branch l
λ_r	Price of energy in the node (¢/kWh)
α	Line sensitivity factor
λ_i^{LMP}	Locational Marginal Price at bus i (¢/kWh)
λ_i^{L}	Nodal loss component at bus i (¢/kWh)
u_i^k	Uniform price at each bus k (¢/kWh)
$b_{i,t}$	Bid submitted by the load i in market interval t
R	Exchange rates of other uniform pricing rules
P_i^E	Requested energy injection from node i to relieve congestion
λ_i^{earn}	Nodal earning component at bus i
z	Normally distributed random variable
λ_i^{Con}	Congestion component of LMP/price MG i pay to responsive load to clear congestion (¢/kWh)
TL_l	Constraint cost a.k.a shadow price (¢/kW)
LF_k	Loss factor at bus k
PL_l	Line flow in branch l

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