Payment Cost Minimization Auction for Deregulated Electricity Markets With Transmission Capacity Constraints

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***Abstract*—Deregulated electricity markets in the U.S. currently use an auction mechanism that minimizes total supply bid costs to select bids and their levels. Payments are then settled based on market-clearingprices. Under this setup, the consumer payments could be significantly higher than the minimized bid costs obtained from auctions. This gives rise to "payment cost minimization," an alternative auction mechanism that minimizes consumer payments. We previously presented an augmented Lagrangian and surrogate optimization framework to solve payment cost minimization problems without considering transmission. This paper extends that approach to incorporate transmission capacity constraints. The consideration of transmission constraints complicates the problem by entailing power flow and introducing locational marginal orices (LMPs). DC power flow is used for simplicity and LMPs are defined by "economic dispatch" for the selected supply bids. To characterize LMPs that appear in the payment cost objective function, Karush–Kuhn–Tucker (KKT) conditions of economic dispatch are established and embedded as constraints. The reformulated problem is difficult in view of the complex role of LMPs and the violation of constraint qualifications caused by the complementarity constraints of KKT conditions. Our key idea is to extend the surrogate optimization framework and use a regularization technique. Specific methods to satisfy the "surrogate optimization condition" in the presence of transmission capacity constraints are highlighted. Numerical testing results of small examples and the IEEE Reliability Test System with randomly generated supply bids demonstrate the quality, effectiveness, and scalability of the method.**

***Index Terms*—Deregulated electricity markets, electricity auctions, locational marginal price (LMP), mathematical programs with equilibrium constraints, payment cost minimization, surrogate optimization, transmission constraints.**

I. Introduction

In deregulated U.S. electricity markets (e.g., the day-ahead markets), independent system operators (ISOs) currently use an auction mechanism that minimizes total supply bid[1] costs to select supply bids and their levels for energy and ancillary services. This "bid cost minimization" problem is NP-hard due to its combinatorial nature, but because of its separability,[2] it can be effectively solved by using the Lagrangian relaxation technique or other mixed-integer programming methods for near-optimal solutions [1]–[7]. Furthermore with given demand, existing unit commitment and economic dispatch software can be readily adapted to solve the problem by replacing units with supply bids. After the auction problem is solved, markets are then settled where payments are calculated based on uniform market-clearing prices (MCPs) or congestion-dependent locational marginal prices (LMPs).[3] The above auction and settlement mechanisms are inconsistent and consumer payments could be significantly higher than the minimized total supply bid cost. This gives rise to "payment cost minimization," an alternative auction mechanism that minimizes consumer payments.[4] Illustrative examples have shown that with the same set of supply bids, payment cost minimization leads to reduced consumer payments as compared to bid cost minimization [8]–[15].

Disparate views are held for the two auction mechanisms. On the one hand, if supply bid prices represent true production

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[1]The term "supply bid" is used here instead of "supply offer" as in our previous paper [14] to comply with the recent FERC document [Docket Number: ER06-615-000 (02-1656-027, 029, 030, 031)].

[2]A problem is separable and can be decomposed into individual subproblems by using Lagrangian relaxation if both the objective function and the constraints that couple the subproblems are additive in subproblem variables.

[3]The issue of "pay-as-bid" versus "pay-at-clearing price" has been widely discussed in the literature, and many have concluded that under "pay-as-bid," suppliers may bid substantially higher than their marginal costs and "would do consumers more harm than good" [37]. Currently, all ISOs in the U.S. adopt "pay-at-clearing price" in their day-ahead energy markets. This paper focuses on U.S. electricity markets, and therefore also adopts the pay-at-clearing price scheme.

[4]This is different from minimizing the payments to supply bids, or producer payments. Consumer payments are the sum of producer payments and congestion revenues. From a different perspective, consumer payment minimization cares about LMPs at load nodes while producer payment minimization focuses on LMPs at supply nodes. If transmission capacities are sufficiently large, then minimizing consumer payments is equivalent to minimizing producer payments. Otherwise, the two problems are different and may not yield the same solution. The consumer payment minimization is used here since a major objective of deregulation is to "work for customers," i.e., to minimize consumer payments, not producer payments according to FERC white paper [38]. If congestion revenues were ultimately transferred into benefits to consumers, then minimizing producer payments might minimize the ultimate cost for consumers. This assumption, however, is questionable since there is no clear relation between congestion revenues and benefits to consumers under ISO's current practice involving financial transmission rights (FTR) auctions and load serving entities' billing policies.

costs, then the bid cost minimization auction maximizes social welfare. Whether supply bids represent true production costs, however, is questionable. On the other hand, the reported savings of payment cost minimization as compared with bid cost minimization are obtained under the same set of supply bids. However, suppliers may bid differently under the two auction mechanisms.[5] Regardless of these different views, the assessment of the two auction mechanisms hinges on the availability of their solution methodologies. While methods for bid cost minimization abound, few approaches for payment cost minimization have been reported. The difficulties of the latter result from its distinct feature that market-clearing prices explicitly appear in the objective function as decision variables in contrast to bid cost minimization where market prices are not involved but determined afterwards in an *ex post* manner. Consequently, market-clearing prices need to be appropriately defined in formulating the payment cost minimization problem and operationalized in the solution process.

Most of the payment cost minimization references cited above formulate the problem mathematically but do not provide effective solution methodologies. Also, most of these references consider uniform MCPs without transmission. A graph search algorithm is presented in [9] assuming simple bids with price-quantity curve only. A method based on forward dynamic programming is presented in [11] for small problems with MCPs defined as the maximum of amortized bid costs (the total energy and fixed costs divided by the total selected power). LMP and transmission constraints are considered in [13] and no solution methodology is provided. We have recently presented an augmented Lagrangian and surrogate optimization framework to solve payment cost minimization problems without considering transmission capacities [14]. MCPs were defined as the maximum prices of selected bids, and the definition was operationalized by inequality constraints on MCPs and bid prices. Augmented Lagrangian relaxation was used, and in view of the complex role of MCPs in the objective function and constraints, surrogate optimization was used to solve the relaxed problem by optimizing supply bids one at a time. In optimizing one bid, other decision variables were adjusted as needed to satisfy the "surrogate optimization condition." Also, it was shown that significant reduction of payment cost was obtained at a relatively small increase of bid cost by using payment cost minimization as compared to bid cost minimization.[6]

This paper formulates and solves the payment cost minimization problem with transmission capacity constraints for a day-ahead energy market in the U.S. with given demands by extending our work in [14].[7] The problem is mathematically formulated in Section II. The consideration of transmission complicates the formulation by entailing power flow and introducing location-dependent LMPs. For simplicity, transmission losses are ignored, and DC flow equations are included as constraints to model power flows. Based on marginal cost pricing, LMPs are defined by economic dispatch for the selected supply bids. To operationalize the definition, Karush–Kuhn–Tucker (KKT) conditions characterizing the economic dispatch are established and embedded as constraints, resulting in a mathematical program with equilibrium constraints (MPEC) [16], [17]. The reformulated problem contains complementarity constraints that are known to violate constraint qualifications, and involves cross-product couplings among bids, LMPs, and dual variables of economic dispatch such as transmission congestion prices and bid capacity prices.

Our solution methodology is presented in Section III. To satisfy constraint qualifications, complementarity constraints are replaced by the δ-complementarity ones. In view of the "pseudo-separability" caused by cross-product coupling among decision variables, the augmented Lagrangian relaxation and surrogate optimization framework of [14] is used, and supply bid subproblems are formed by taking the relaxed problem as a whole and solved one at a time. In optimizing one bid, other decision variables may have to be adjusted to satisfy the surrogate optimization condition. Specific methods for their adjustments in the presence of transmission capacity constraints are highlighted. LMPs, congestion prices, capacity prices, and bid levels are then approximately optimized within a bid subproblem based on first-order optimality conditions for the relaxed problem. Numerical testing results in Section IV demonstrate the quality of the method with small examples, and effectiveness and scalability of the algorithm based on the IEEE Reliability Test System with Monte Carlo simulations for ten randomly selected load profiles and supply bids.

II. Problem Formulation

In this section, the payment cost minimization problem with transmission capacity constraints is formulated for a day-ahead energy market with given demand and single-block supply bid curves. For simplicity, transmission losses are ignored and DC power flow is used to model the transmitted power. Also, since LMPs appear in the objective function as decision variables, they need to be appropriately defined and operationalized as opposed to being a byproduct of optimizations as in bid cost minimization. For simplicity, startup costs are assumed fully compensated and the minimum up/down time constraints are not considered. In the following, the problem formulation with LMPs defined by economic dispatch is presented in Section II-A. The KKT conditions characterizing the LMP definition are presented in Section II-B. These conditions are then embedded as explicit constraints in the formulation to form an MPEC.

A. Problem Formulation With LMP Definition

Consider a transmission network with I nodes indexed by $i = 1, 2, \ldots, I$, and L transmission lines indexed by $l = 1, 2, \ldots, L$. Let Ω_i denote the index set of nodes connected to node i. Line l connects node l_1 and node l_2 $(\in \Omega_{l_1})$ with the direction from l_1

[5] Suppliers' behaviors under the two auction mechanisms have been studied within a game theoretic context in our recent paper [36] without considering transmission capacity constraints.

[6] As a consequence of reduced payments, concerns are raised on the lack of incentives for new generation. Actually the lack of incentive is also discussed for the current bid cost minimization. We believe the short-term energy market alone is not sufficient to provide long-term incentive signals for new generation, and the issue should be addressed by considering capacity markets, long-term contracts, etc.

[7] This shall facilitate further study of the payment cost minimization auction, including comprehensive comparisons with bid cost minimization (which is not within the scope of this paper).

to l_2, and has reactance X_l and line capacity $f_{l\max}$. The transmitted power in line l at hour $t(1 \le t \le 24)$ is denoted by $f_l(t)$. The demand of node i at hour t is given as $P_i^D(t)$. There are K_i supply bids at node i. For the kth supply bid $(1 \le k \le K_i)$ at hour t, the minimum bid level is $p_{ik\min}(t)$, the maximum bid level is $p_{ik\max}(t)$, and the single-block bid price is $c_{ik}(t)$. The startup cost is denoted by $S_{ik}(t)$ and is incurred if and only if the supply bid is turned "On" from an "Off" state at hour t. The market price at node i and hour t is denoted by $LMP_i(t)$. The problem is to minimize the total consumer payment subject to power balance constraints, individual supply bid constraints, transmission capacity constraints, and the LMP definition as presented below.

Objective Function: With startup costs fully compensated, the total payment cost is the sum of MW payments and startup compensations across the system over a 24-h period, i.e.,

$$J \equiv \sum_{t=1}^{24} \left\{ \sum_{i=1}^{I} \left[LMP_i(t) \cdot P_i^D(t) \right] + \sum_{i=1}^{I} \sum_{k=1}^{K_i} S_{ik}(t) \right\}. \quad (1)$$

Power Balance Constraints: Power should be balanced for each node at each hour, i.e., the net power generation at a node should equal the net power transmitted out of the node as follows:

$$\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t) = \sum_{l:l_1=i} f_l(t) - \sum_{l:l_2=i} f_l(t), \quad \forall i, \forall t. \quad (2)$$

These local power balance equations at each node will be used to derive power flow equations and define nodal LMPs to be presented later in this subsection. By adding up (2) for all nodes at each hour, the following equations are obtained:

$$\sum_{i=1}^{I} \left[\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t) \right] = 0, \quad \forall t. \quad (3)$$

These system power balance equations with reduced number as compared to (2) will be used as constraints for the payment cost minimization problem to be presented at the end of this subsection.

Supply Bid Level Constraints: The power level of a supply bid is limited by its minimum and maximum values if the bid is selected. Otherwise, the power level should be zero. Denote the selection status of the kth bid of node i at hour t by an index variable $x_{ik}(t)$ with "1" representing "Selected" or "On," and "0" representing "Not Selected" or "Off." Then the supply bid level constraints are

$$p_{ik\min}(t) x_{ik}(t) \le p_{ik}(t) \le p_{ik\max}(t) x_{ik}(t), \quad \forall i, \forall k, \forall t. \quad (4)$$

Transmission Capacity Constraints: The transmitted power in a line cannot exceed the specified capacity of the line at any hour, i.e.,

$$-f_{l\max} \le f_l(t) \le f_{l\max}, \quad \forall l, \forall t. \quad (5)$$

For simplicity, the capacity limits for both directions take the same absolute value in (5).

DC Power Flow Equations: Following the power flow convention, a reference node is arbitrarily selected to have zero voltage phase angle. Then the voltage phase angle of node i at hour t relative to that of the reference node is denoted by $\theta_i(t)$. DC power flow assumes that the voltage magnitude is the same for all the nodes, line resistances are ignorable, and the phase angle differences among nodes are sufficiently small. With these simplifying assumptions, the transmitted active power in line l at hour t is given by [18]

$$f_l(t) = \frac{\theta_{l1}(t) - \theta_{l2}(t)}{X_l}, \quad \forall l, \forall t. \quad (6)$$

For each hour, (2) and (6) can be used to eliminate the phase angles, resulting in the system power balance equation (3) and the following representations of transmitted power as linear combinations of the net power generation at each node [18]:

$$f_l(t) = \sum_{i=1}^{I} \left[a_l^i \cdot \left(\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t) \right) \right], \quad \forall l, \forall t. \quad (7)$$

The coefficient a_l^i in (7) denotes the sensitivity of the transmitted power in line l with respect to the net generation at node i. It is also known as power transfer distribution factor (PTDF), and is determined by network topology, line reactance, and the selection of reference bus. Equations (3) and (7) are equivalent to (2) and (6), but with reduced numbers of equations and variables.

LMP Definition by Economic Dispatch: In view of LMPs' presence in (1) as decision variables, they need to be appropriately defined. In ISOs' current practices, LMPs are byproducts of the bid cost minimization auction and are determined in an *ex post* manner based on economic dispatch for selected bids. This is consistent with marginal cost pricing that the price of a product should reflect the cost for producing the last unit of the product. For the payment cost minimization auction, the LMPs are part of the decision variables and are to be optimized along with bid selections in the auction. To apply marginal cost pricing, LMPs are defined here as marginal costs for the *selected supply bids* at each hour, with bid selections to be determined during the payment cost minimization process. This definition is consistent with ISOs' current practices assuming bid selections have been determined. Based on the sensitivity theorem of Lagrangian relaxation [19], the LMPs at hour t are Lagrange multipliers associated with the local power balance constraints (2) in the following economic dispatch problem:

$$Min J^{ED}, \; with \; J^{ED} \equiv \sum_{i=1}^{I} \sum_{k \in \Psi_i(t)} (c_{ik}(t) \cdot p_{ik}(t)) \quad (8)$$

subject to (2) and (4)–(6) for hour t. In this economic dispatch problem, local power balance constraints (2) plus (6) instead of the equivalent ones (3) and (7) are used for LMP definition, $\Psi_i(t)$ is the index set of selected bids at node i and hour t, and the decision variables are $\{p_{ik}(t)\}$, $\{f_l(t)\}$, and $\{\theta_i(t)\}$. Then $LMP_i(t)$ is given by the multiplier $\pi_i(t)$ relaxing (2) for node i and hour t, i.e.,

$$LMP_i(t) \equiv \pi_i(t), \quad \forall i, \forall t. \quad (9)$$

The overall payment cost minimization problem is thus to minimize the total payment cost (1) subject to (3)–(5) and (7), and the LMP definition (9) obtained from the economic dispatch problem (8). Equations (3) and (7) are used for reduced numbers of equations and variables as compared to their equivalent pair (2) and (6).

B. Karush–Kuhn–Tucker Conditions for an MPEC Problem

Since economic dispatch itself is an optimization problem, the overall problem has a complex two-level structure: economic dispatch that defines LMP for selected supply bids at each hour at the low level, and selecting the bids to minimize the payment cost at the high level. To manage the complexity caused by this two-level structure, the KKT conditions that fully characterize the economic dispatch of the low level are established to operationalize the LMP definition (9) following the ideas of [16] and [17]. For simplicity of presentation, the time index t is omitted in deriving the following KKT conditions.

To completely characterize the economic dispatch problem, constraints (2) and (4)–(6) are relaxed by using multipliers $\{\pi_i\}$, $\{\beta_{ik\min}, \beta_{ik\max}\}$, $\{\gamma_{l\min}, \gamma_{l\max}\}$, and $\{\eta_l\}$, respectively. The Lagrangian of this economic dispatch problem is

$$\begin{aligned} L^{ED} = &\sum_{i=1}^{I}\sum_{k\in\Psi_i} c_{ik}p_{ik} \\ &+ \sum_{i=1}^{I}\left[\pi_i\cdot\left(p_i^D - \sum_{k=1}^{K_i} p_{ik} + \sum_{l:l_1=i} f_l - \sum_{l:l_2=i} f_l\right)\right] \\ &+ \sum_{i=1}^{I}\sum_{k\in\Psi_i}(\beta_{ik\min}(p_{ik\min}-p_{ik}) \\ &\qquad +\beta_{ik\max}(p_{ik}-p_{ik\max})) \\ &+ \sum_{l=1}^{L}(\gamma_{l\min}\cdot(-f_{l\max}-f_l)+\gamma_{l\max}\cdot(f_l-f_{l\max})) \\ &+ \sum_{l=1}^{L}[\eta_l(f_l-(\theta_{l1}-\theta_{l2})/X_l)]. \end{aligned} \tag{10}$$

The decision variables are $\{p_{ik}\}$, $\{f_l\}$, and $\{\theta_i\}$. The following KKT conditions are obtained [20]:

Primal feasibility:

(2) and (4)–(6) for the hour under consideration.

Dual feasibility:

$$\beta_{ik\min}, \beta_{ik\max}, \gamma_{l\min}, \gamma_{l\max} \geq 0. \tag{11}$$

Lagrangian optimality:

$$0=\frac{\partial L^{ED}}{\partial p_{ik}}=c_{ik}-\pi_i-\beta_{ik\min}+\beta_{ik\max},\ \forall i, \forall k\in\Psi_i \tag{12}$$

$$0=\frac{\partial L^{ED}}{\partial f_l}=\pi_{l1}-\pi_{l2}-\gamma_{l\min}+\gamma_{l\max}+\eta_l,\ \forall l \text{ and} \tag{13}$$

$$0=\frac{\partial L^{ED}}{\partial \theta_i}=-\sum_{l:l_1=i}\frac{\eta_l}{X_l}+\sum_{l:l_2=i}\frac{\eta_l}{X_l}, \quad \forall i. \tag{14}$$

Based on the economic interpretation of multipliers, $\beta_{ik\min}$ and $\beta_{ik\max}$ in (12), respectively, are minimum and maximum capacity prices of the kth bid at node i; and $\gamma_{l\min}$ and $\gamma_{l\max}$ in (13) are congestion prices of line l.

Complementarity slackness:

$$0=\beta_{ik\min}\cdot(p_{ik}-p_{ik\min}),\ \forall i, \forall k\in\Psi_i \tag{15}$$

$$0=\beta_{ik\max}\cdot(p_{ik\max}-p_{ik}),\ \forall i, \forall k\in\Psi_i \tag{16}$$

$$0=\gamma_{l\min}\cdot(f_l+f_{l\max}),\ \forall l \text{ and} \tag{17}$$

$$0=\gamma_{l\max}\cdot(f_{l\max}-f_l),\ \forall l. \tag{18}$$

The above KKT conditions (2), (4)–(6), and (11)–(18) with the time index t put back then replace the LMP definition (9) as part of the high-level constraints. After removing the redundant ones including (2) and (6) which are equivalent to (3) and (7), the constraints for the high-level payment cost minimization problem are (3)–(5), (7), and (11)–(18).

The above constraints are further simplified as follows. Equation (7) is removed after $f_l(t)$ is substituted out in (5), (17), and (18) to have

$$-f_{l\max} \leq \sum_{i=1}^{I}\left[a_l^i\cdot\left(\sum_{k=1}^{K_i}p_{ik}(t)-P_i^D(t)\right)\right] \leq f_{l\max} \quad \forall l,t \tag{19}$$

$$\gamma_{l\min}(t)\left[\sum_{i=1}^{I}\left(a_l^i\left(\sum_{k=1}^{K_i}p_{ik}(t)-P_i^D(t)\right)\right)+f_{l\max}\right]=0 \quad \forall l,t \tag{20}$$

$$\gamma_{l\max}(t)\left[f_{l\max}-\sum_{i=1}^{I}\left(a_l^i\left(\sum_{k=1}^{K_i}p_{ik}(t)-P_i^D(t)\right)\right)\right]=0 \quad \forall l,t. \tag{21}$$

Moreover, similar to the derivation of the power flow (7), (13), (14) can be reduced to the following equation with η eliminated and π_i replaced by LMP_i:

$$LMP_i(t)=LMP_{ref}(t)-\sum_l\left[a_l^i(\gamma_{l\max}(t)-\gamma_{l\min}(t))\right], \ \forall i,t. \tag{22}$$

The reference node for LMP in (22) can be arbitrary, and for convenience it is set to be the reference node for voltage phase angles in (6). It can be seen from (22) that LMPs degenerate to a uniform price if there is no transmission congestion, i.e., congestion prices γ are zero. Also, (22) is identical to the LMP decomposition formula currently used by ISOs when transmission losses are ignored [21]. This is a natural result of using economic dispatch to define LMP in payment cost minimization as done in bid cost minimization [22].

Since (12) is for selected bids only, it is generalized to the following for all the bids:

$$x_{ik}(t)\,(LMP_i(t)-c_{ik}+\beta_{ik\min}(t)-\beta_{ik\max}(t))=0,\ \forall i,k,t \tag{23}$$

where π_i has been replaced by LMP_i based on (9). Equation (23) describes the relationship among LMP, bid prices, and capacity prices at each node. According to (23), a bid at node i with selected power in-between its minimum and maximum generation levels (implying $\beta_{ik\min}=\beta_{ik\max}=0$) is a marginal bid whose price sets LMP, i.e., $LMP_i(t)=c_{ik}$. Also, if the bid is selected at its maximum generation level (implying

$\beta_{ik\,\min} = 0)$, $LMP_i(t) = c_{ik} + \beta_{ik\,\max}$, i.e., LMP is the sum of the bid price and capacity price. Similarly, if the bid is selected at its minimum generation level, $LMP_i(t) = c_{ik} - \beta_{ik\,\min}$, implying that the LMP could be lower than the price of a selected bid.[8] This is different from our MCP definition in [14] where MCP is defined as the highest price of selected bids. Similarly, (15) and (16) for selected bids are generalized to all the bids by defining zero capacity prices for those bids that are not selected as follows:

$$\beta_{ik\,\min}(t)\,(p_{ik}(t) - p_{ik\,\min}) = 0,\ \forall i,k,t \tag{24}$$

$$\beta_{ik\,\max}(t)\,(p_{ik\,\max} - p_{ik}(t)) = 0,\ \forall i,k,t. \tag{25}$$

As a result of the above simplification and generalization, the overall problem is to minimize the payment cost (1) subject to (3), (4), (11), and (19)–(25). The decision variables are $\{x_{ik}(t), p_{ik}(t)\}$ of bids, LMPs, capacity prices $\{\beta_{ik\,\min}(t), \beta_{ik\,\max}(t)\}$, and congestion prices $\{\gamma_{l\,\min}(t), \gamma_{l\,\max}(t)\}$, noting that except bid variables, the rest are in fact dual variables of the low-level economic dispatch. The problem is therefore an MPEC [16]. MPEC problems are known for their violation of the linear independence constraint qualification[9] at *any* feasible solution, causing difficulties in applying many nonlinear programming methods [17]. In addition, our problem with discrete variables is more complicated than those MPEC problems in the literature with continuous variables only. Furthermore, while the objective function (1) and constraints (3), (19), and (22) are additive in terms of bids and other decision variables, bids are coupled with LMPs, congestion prices, and capacity prices in "coupling" constraints (20), (21), and (23)–(25) through cross-product terms. As a result, the problem is "pseudo-separable" in terms of bids in contrast to the separable structure of a bid cost minimization problem, and cannot be directly decomposed into individual bid subproblems by using a traditional Lagrangian relaxation scheme.

III. Solution Methodology

To satisfy constraint qualifications for the above payment cost minimization problem, complementarity constraints (20), (21), (24), and (25) are replaced by δ-complementarity ones based on a regularization scheme of [28] to be presented in Section III-A. To manage combinatorial complexity and improve convergence, augmented Lagrangian is formed by relaxing coupling constraints and selectively adding quadratic penalty terms as presented in Section III-B. The non-decomposability difficulty caused by the pseudo-separable formulation is overcome by using "surrogate optimization" of [23] where approximate optimization of the relaxed problem is sufficient if the "surrogate optimization condition" is satisfied as presented in Section III-C. The relaxed problem is thus optimized with respect to a particular supply bid one at a time. In optimizing a bid, other variables may have to be adjusted to satisfy the surrogate optimization condition as presented in Section III-D. During the adjustment process, simple analytic solutions derived from first-order optimality conditions are used as presented in Section III-E. Multipliers are then updated by using a surrogate subgradient and an appropriate stepsize with issues on the estimation of optimal dual values discussed in Section III-F. Finally, heuristics are used to construct feasible solutions in Section III-G.

A. Regularization Methods

For an MPEC problem, the violation of constraint qualifications is caused by complementarity constraints, e.g., $x_1, x_2 \geq 0$ and $x_1 \cdot x_2 = 0$ [16], [17]. Two approaches have been developed to overcome the difficulties. The penalization approach replaces complementarity constraints by having penalty terms in the objective function [25]–[27]. The regularization approach replaces complementarity constraints by δ-complementarity ones, i.e., $x_1, x_2 \geq 0$ and $x_1 \cdot x_2 \leq \delta$, for a sufficiently small positive number δ [28]–[31]. The introduction of δ breaks the complementarity between x_1 and x_2, resulting in the satisfaction of the constraint qualifications. It has been shown that the solution of the regularized problem approaches the stationary point of the original MPEC problem as δ approaches zero under reasonable assumptions [32].

The above regularization approach is intuitively clear and easy to apply, and is adopted in this paper. Consequently, (20), (21), (24), and (25) are replaced by

$$\beta_{ik\,\min}(t)\,(p_{ik}(t) - p_{ik\,\min}(t)) \leq \delta,\ \forall i,k,t \tag{26}$$

$$\beta_{ik\,\max}(t)\,(p_{ik\,\max}(t) - p_{ik}(t)) \leq \delta,\ \forall i,k,t \tag{27}$$

$$\gamma_{l\,\min}(t)\left[\sum_{i=1}^{I}\left(a_l^i\left(\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t)\right)\right) + f_{l\,\max}\right] \leq \delta,\quad \forall l,t \tag{28}$$

$$\gamma_{l\,\max}(t)\left[f_{l\,\max} - \sum_{i=1}^{I}\left(a_l^i\left(\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t)\right)\right)\right] \leq \delta,\quad \forall l,t. \tag{29}$$

The same positive δ is used in (26)–(29) for simplicity and its value is iteratively reduced. The use of the above "δ-complementarity constraints" does not change the pseudo-separability of the problem since those cross-product terms remain in the formulation.

B. Augmented Lagrangian

The problem with δ-complementarity constraints will be solved by using the *augmented Lagrangian and surrogate optimization* framework of [14], with enhanced features to handle the complications caused by transmission capacity constraints, congestion-related LMPs, and δ-complementarity constraints. Let multipliers $\{\lambda(t)\}$ and $\{\mu_{l\,\min}(t), \mu_{l\,\max}(t)\}$ relax (3) and (19), respectively; $\{\rho_i(t)\}$ and $\{\varphi_{ik}(t)\}$ relax (22) and (23), respectively; and $\{\xi_{ik\,\min}(t)\}$, $\{\xi_{ik\,\max}(t)\}$, $\{\varsigma_{l\,\min}(t)\}$, and $\{\varsigma_{l\,\max}(t)\}$ relax (26)–(29). To have good algorithm convergence, quadratic penalty terms for (3), (22),

[8]This is caused by the "lumpiness" because of the existence of $p_{\min}$. As a result, the energy revenue $LMP_i \cdot p_{ik}$ may not cover the bid cost $c_{ik} \cdot p_{ik}$. The revenue shortage issue will not be discussed in this paper.

[9]The linear independence constraint qualification requires the gradients of active constraints to be linearly independent at an optimal solution [19]. Satisfaction of the constraint qualification implies the existence of a unique Lagrangian multiplier vector, and is important for many nonlinear programming methods including Lagrangian relaxation to work.

and (23) are added to the Lagrangian, resulting in quadratic terms for bids, LMP, β, and γ [19]. Let c be a positive penalty parameter, then the relaxed problem is (30) at the bottom of the next page, subject to (4) and (11). In contrast to the derivation of KKT conditions for economic dispatch in Section II-B, the simple individual bid level constraint (4) is not relaxed here but is enforced in the numerical optimization process. The above relaxed problem has mixed discrete/continuous bids (e.g., level p_{ik} of the kth supply bid at node i is either 0 or belongs to $[p_{ik\min}, p_{ik\max}]$ depending on the selection status) and other continuous decision variables. Its feasible region is thus made of a combinatorial number of discontiguous "sub-regions," each associated with a distinct selection of bids. This, combined with the fact that the relaxed problem cannot be decomposed into individual bid subproblems because of its pseudo-separability, results in difficulties in solving the relaxed problem optimally as required by a traditional Lagrangian relaxation scheme.

C. Surrogate Optimization

Our approach is not to solve the relaxed problem optimally. Rather, the relaxed problem is approximately optimized with respect to a particular supply bid one at a time within the surrogate optimization framework [23]. The algorithm can be summarized in three key steps, i.e., *initialization*, *solving the relaxed problem*, and *updating multipliers*, with conditions to be satisfied at each step for algorithm convergence and for surrogate dual costs to be lower bounds on the optimal feasible cost [23]. The above three steps for the payment cost minimization problem are presented below. For notational simplicity, let y represent the vector of the decision variables $\{x, p, LMP, \beta, \gamma\}$, and θ represent the vector of the multipliers $\{\lambda, \mu, \varphi, \rho, \xi, \varsigma\}$ within this subsection.

Initialization: Initial multipliers and decision variables are selected to satisfy the following "Surrogate Initialization Condition":

$$L_c^0 \equiv L_c(\theta^0; y^0) < L^* \tag{31}$$

where L_c is the augmented Lagrangian (30), L^* is the optimal dual value, and the superscript "0" indicates the 0-th iteration. Condition (31) states that the initial surrogate dual cost L_c^0 should be less than the optimal dual value as required for the induction of [23, Proposition 4.1].

Solving the Relaxed Problem: Given multiplier vector θ^m at the mth iteration, surrogate optimization does not require the

$$\min_{\{x,p,LMP,\beta,\gamma\}} L_c(\lambda,\mu,\varphi,\rho,\xi,\varsigma; x,p,LMP,\beta,\gamma), \text{ with}$$

$$\begin{aligned}
L_c \equiv \sum_{t=1}^{T} \Bigg\{ & \sum_{i=1}^{I} LMP_i(t)P_i^D(t) + \sum_{i=1}^{I}\sum_{i=1}^{K_i} S_{ik}(t) + \lambda(t)\left(\sum_{i=1}^{I} P_i^D(t) - \sum_{i=1}^{I}\sum_{k=1}^{K_i} p_{ik}(t)\right) + \frac{c}{2}\left(\sum_{i=1}^{I} P_i^D(t) - \sum_{i=1}^{I}\sum_{k=1}^{K_i} p_{ik}(t)\right)^2 \\
& + \sum_{l} \mu_{l\min}(t)\left[-f_{l\max} - \sum_{i=1}^{I} a_l^i \left(\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t)\right)\right] \\
& + \sum_{l} \mu_{l\max}(t)\left[\sum_{i=1}^{I} a_l^i \left(\sum_{k\in 1}^{K_i} p_{ik}(t) - P_i^D(t)\right) - f_{l\max}\right] \\
& + \sum_{i=1}^{I}\sum_{k=1}^{K_i} \Big[\phi_{ik}(t)x_{ik}(t)\left(LMP_i(t) - c_{ik}(t) + \beta_{ik\min}(t) - \beta_{ik\max}(t)\right) \\
& \qquad + \frac{c}{2}\cdot x_{ik}(t)\left(LMP_i(t) - c_{ik}(t) + \beta_{ik\min}(t) - \beta_{ik\max}(t)\right)^2\Big] \\
& + \sum_{i\neq ref} \Bigg[\rho_i(t)\left(LMP_i(t) - LMP_{ref}(t) + \sum_{l} a_l^i\left(\gamma_{l\max}(t) - \gamma_{l\min}(t)\right)\right) \\
& \qquad + \frac{c}{2}\cdot\left(LMP_i(t) - LMP_{ref}(t) + \sum_{l} a_l^i\left(\gamma_{l\max}(t) - \gamma_{l\min}(t)\right)\right)^2\Bigg] \\
& + \sum_{i=1}^{I}\sum_{k=1}^{K_i} \left[\xi_{ik\min}(t)\cdot\left(\beta_{ik\min}(t)\left(p_{ik}(t) - p_{ik\min}(t)\right) - \delta\right)\right] \\
& + \sum_{i=1}^{I}\sum_{k=1}^{K_i} \left[\xi_{ik\max}(t)\cdot\left(\beta_{ik\max}(t)\left(p_{ik\max}(t) - p_{ik}(t)\right) - \delta\right)\right] \\
& + \sum_{l} \varsigma_{l\min}(t)\left[\gamma_{l\min}(t)\left(\sum_{i=1}^{I} a_l^i\left(\sum_{k=1}^{K_i} p_{ik}(t) - P_i^D(t)\right) + f_{l\max}\right) - \delta\right] \\
& + \sum_{l} \varsigma_{l\max}(t)\left[\gamma_{l\max}(t)\left(f_{l\max} - \sum_{i=1}^{I} a_l^i\left(\sum_{k\in 1}^{K_i} p_{ik}(t) - P_i^D(t)\right)\right) - \delta\right]\Bigg\}
\end{aligned} \tag{30}$$

relaxed problem to be optimally solved. Rather, according to the "Surrogate Optimization Condition" [23, Eq. 28], solution y^m to the relaxed problem is only required to be "better than" the one in the previous iteration, i.e.,

$$L_c^m \equiv L_c(\theta^m; y^m) < L_c(\theta^m; y^{m-1}). \quad (32)$$

The satisfaction of (32) implies that the surrogate subgradient at the mth iteration forms an acute angle with the direction toward the optimal multiplier vector. Our relaxed problem is thus optimized with respect to a particular supply bid one at a time until (32) is satisfied. Since the augmented Lagrangian L_c (30) includes cross-product terms between $\{x_{ik}(t)\}$ and other decision variables, the relaxed problem has different structures over its discontiguous subregions. As a result, if other variables are fixed at their latest values in optimizing a bid, the solution may be trapped in one subregion and (32) cannot be satisfied. A similar situation has been illustrated by [14, Fig. 1]. Our approach is to adjust other decision variables as needed in optimizing a bid, with the goal to obtain lower surrogate dual cost L_c^m to satisfy (32).

Updating Multipliers: Once a subproblem solution satisfying (32) is obtained, a surrogate subgradient is used to update multipliers with a proper stepsize. The surrogate subgradient is a vector whose components are associated with corresponding multipliers. Similar to a traditional subgradient, these components are obtained as the levels of constraint violations, e.g., the components associated with $\lambda(t)$ and $\mu_{l\max}(t)$, respectively, are

$$\tilde{g}_\lambda(t)^m = \sum_{i=1}^{I} P_i^D(t) - \sum_{i=1}^{I}\sum_{k=1}^{K_i} p_{ik}(t)^m \text{ and} \quad (33)$$

$$\tilde{g}_{\mu_{l\max}}(t)^m = \sum_{i=1}^{I}\left[a_l^i\left(\sum_{k=1}^{K_i} p_{ik}(t)^m - P_i^D(t)\right)\right] - f_{l\max}. \quad (34)$$

The surrogate subgradient $\tilde{g}^m$ is then used to update multipliers as

$$\lambda(t)^{m+1} = \lambda(t)^m + s^m \tilde{g}_\lambda(t)^m \text{ and} \quad (35)$$

$$\mu_{l\max}(t)^{m+1} = \max\left(0, \mu_{l\max}(t)^m + s^m \tilde{g}_{\mu_{l\max}}(t)^m\right). \quad (36)$$

The stepsize s^m should satisfy the following "Surrogate Stepsize Condition" [23, Eq. 27]:

$$0 < s^m < \frac{(L^* - L_c^m)}{\|\tilde{g}^m\|^2} \quad (37)$$

where $\|\tilde{g}^m\|$ is the L2 norm of the surrogate subgradient. The satisfaction of (37) and (31), (32) guarantees a surrogate dual cost to be a lower bound on the optimal dual cost L^* [23, Proposition 4.1]), and therefore on the primal optimal cost f^* as a result of the weak duality theorem $(L^* \le f^*)$ [19]. Condition (37) utilizes the optimal dual cost L^*, which is unknown in general. The estimation of L^* and issues on the possible violation of (37) caused by overestimation will be discussed in Section III-F.

D. Forming and Solving Supply Bid Subproblems

Based on the above discussion, a supply bid subproblem, e.g., for the kth bid at node i, is formed by taking the relaxed problem as a whole and is optimized with respect to its bid variables $\{x_{ik}(t), p_{ik}(t)\}_{t=1,\dots,24}$. For simplicity of presentation, let ϕ_{ik}^t represent the collection of terms pertaining to hour t from the augmented Lagrangian (30) with the exception of $S_{ik}(t)$. Then the supply bid subproblem is

$$\min_{\{x_{ik}(t),p_{ik}(t)\}} L_c, \text{ with}$$

$$L_c \equiv \sum_{t=1}^{T}\left\{\phi_{ik}^t\left(x_{ik}, p_{ik}, \{x_{jr}, p_{jr}\}, LMP, \beta, \gamma\right) + S_{ik}(t)\right\}$$

$$(j \ne i \text{ or } r \ne k)$$

$$s.t.\ x_{ik}(t)p_{ik\min} \le p_{ik}(t) \le x_{ik}(t)p_{ik\max},\ \forall t. \quad (38)$$

In (38), except $\{S_{ik}(t)\}_t$ that depend on the bid's selection statuses at two consecutive hours $t-1$ and t, the rest of L_c are additive in hours. Therefore dynamic programming (DP) is used to solve this subproblem where hours are stages, bid status ("On" and "Off") for each hour are states, ϕ_{ik}^t is the stage-wise cost, and $S_{ik}(t)$ is the state transition cost. In view that ϕ_{ik}^t in (38) depends on p_{ik}, $\{x_{jr}, p_{jr}\}_{j\ne i \text{ or } r\ne k}$, LMP, β, and γ at hour t, these variables need to be determined to evaluate ϕ_{ik}^t for each state ($x_{ik} = 0$ or 1) at the hour. Since their latest available values may not lead to the satisfaction of surrogate optimization condition (32), these variables are tentatively adjusted as needed for each state to obtain low stage-wise costs so that (32) is likely to be satisfied. The optimal On/Off statuses $\{x_{ik}^*(t)\}_t$ are then determined by DP, and other variables are updated by using their values associated with $\{x_{ik}^*(t)\}_t$. Details are presented below.

To evaluate ϕ_{ik}^t for a particular state $x_{ik}(t)$ ("On" or "Off"), $\{x_{jr}(t)\}_{j,r}$ of other supply bids are first determined since continuous variables such as LMPs depend on the selection of bids through economic dispatch. These $\{x_{jr}(t)\}_{j,r}$ assume their latest available values, and are adjusted only when together with $x_{ik}(t)$ they do not form a feasible bid selection as detected by applying Phase I of the simplex method to the corresponding economic dispatch problem. To adjust $\{x_{jr}(t)\}_{j,r}$, simple heuristics are used to sequentially examine system power balance constraints (3) and transmission capacity constraints (19) as follows. For the system power balance constraint (3) at hour t, the minimum and maximum total generation levels under the selected bids are first calculated based on supply bid capacities (4). If the maximum level cannot meet the system demand $\sum_{i=1}^{I} P_i^D(t)$, then the least expensive bids in terms of amortized per MW costs (the sum of energy and startup costs divided by the bid capacity) that are currently off are sequentially selected until the demand can be met. Likewise, if the minimum total generation level exceeds the system demand, the most expensive "On" bids in terms of amortized costs will be sequentially deselected. For transmission capacity constraints (19) at hour t, the minimum and maximum power flows in line l under the selected bids are calculated based on (4) and (7). If the minimum flow exceeds $f_{l\max}$, some "On" bids with positive power transfer distribution factors (PTDF) in (7) are turned off and some "Off" bids with negative PTDFs are turned on. These are sequentially done in the descending order of the absolute values of PTDFs until the minimum flow is less than $f_{l\max}$. Similar adjustment is made if the maximum flow is less than $-f_{l\max}$. If the above procedure does not yield a feasible selection of bids, the cost ϕ_{ik}^t for the state under consideration is set to be a large number and the algorithm continues to evaluate remaining stage-wise costs.

With $\{x_{jr}(t)\}_{j,r}$ properly adjusted for the state $x_{ik}(t)$ under consideration, p_{ik}, $\{p_{jr}\}_{j,r}$, LMP, β, and γ at hour t can be determined by solving the corresponding economic dispatch problem. In view that these variables are continuous variables, they are approximately optimized by using first order optimality conditions for simple analytic solutions in the following subsection to reduce computational requirements. The corresponding stage-wise cost ϕ_{ik}^t associated with the state under consideration ($x_{ik} = 0$ or 1) is then calculated. With stage-wise costs for all states and all stages obtained, dynamic programming is used to determine the optimal selection $\{x_{ik}^*(t)\}_t$ following [2]. Variables p_{ik}, $\{x_{jr}, p_{jr}\}_{j,r}$, LMP, β, and γ are then updated by their values associated with $\{x_{ik}^*(t)\}_t$.

After solving the above bid subproblem, the surrogate optimization condition (32) is examined. If the condition is satisfied, then multipliers are updated. Otherwise, another bid subproblem is solved.

E. Adjusting Other Continuous Variables Within a Supply Bid Subproblem

In solving the above supply bid subproblems, bid levels, LMP, β, and γ are adjusted by using simple analytical results from first order optimality conditions of the augmented Lagrangian (30) as presented below.

Determining Bid Levels: Consider the rth bid at node j for hour t. If the bid is "Off," its level $p_{jr}(t)$ should be zero. Otherwise, $p_{jr}(t)$ is determined by projecting solution of the first order optimality condition $\partial L_c / \partial p_{jr}(t) = 0$ onto the feasible set $[p_{jr\,\min}, p_{jr\,\max}]$, i.e., see (39) at the bottom of the page.

Determining LMPs: To determine $LMP_i(t)$, the first order optimality condition $\partial L_c / \partial LMP_i(t) = 0$ is used to obtain

$$\begin{aligned} LMP_i(t) &= \Bigg[LMP_{ref}(t) - \sum_l a_l^i\left(\gamma_{l\,\max}(t) - \gamma_{l\,\min}(t)\right) - \frac{\rho_i(t)}{c} \\ &\quad + \sum_{k=1}^{K_i} x_{ik}(t)\left(c_{ik}(t) + \beta_{ik\,\max}(t) - \beta_{ik\,\min}(t)\right) \\ &\quad - \sum_{k=1}^{K_i} \frac{\phi_{ik}(t) x_{ik}(t)}{c} - \frac{P_i^D(t)}{c}\Bigg] \Bigg/ \left(1 + \sum_{k=1}^{K_i} x_{ik}(t)\right). \end{aligned} \tag{40}$$

Solution for $LMP_{ref}(t)$ is obtained in a similar way.

Determining β's and γ's: Bid capacity price $\beta_{ik\,\max}(t)$ is set to be zero if the corresponding bid is off, i.e., $x_{ik}(t) = 0$. Otherwise, $\beta_{ik\,\max}(t)$ is obtained by using $\partial L_c / \partial \beta_{ik\,\max}(t) = 0$ and (11) as follows:

$$\begin{aligned} \beta_{ik\,\max}(t) = \max\{0, &LMP_i(t) - c_{ik}(t) + \beta_{ik\,\min}(t) \\ &+ \left(\varphi_{ik}(t) - \xi_{ik\,\max}(t)\left(p_{ik\,\max}(t) - p_{ik}(t)\right)\right)/c\}. \end{aligned} \tag{41}$$

Solutions for $\beta_{\min}$, $\gamma_{\min}$, and $\gamma_{\max}$ are obtained in a similar way.

F. Updating Multipliers

As presented in Section IV-C, the surrogate stepsize condition (37) should be satisfied when multipliers are updated. Since the optimal dual value L^* in (37) is unknown in general, it has to be estimated during the solution process. In the following, a method for estimating L^* is presented, and the ramifications are discussed.

Based on the weak duality theorem [19], a primal feasible cost is an upper bound on L^*. Also, a surrogate dual cost is a lower bound according to [23, Proposition 4.1] if all the three conditions (31), (32), and (37) are satisfied. An estimated optimal dual value $\widetilde{L}^*$ is thus obtained as

$$\widetilde{L}^* = \left(f^m + L_c^m\right)/2 \tag{42}$$

where f^m and L_c^m are, respectively, the lowest primal feasible cost obtained thus far and the surrogate dual cost at the mth iteration. While L_c^m is readily available in the solution process, f^m needs to be calculated based on a primal feasible solution. Such a solution, however, cannot be easily obtained by using simple heuristics to satisfy all constraints. Our approach is to solve the economic dispatch problem (8) for the current set of selected supply bids by using the Simplex method. If there is no feasible solution, then the bid selection statuses are adjusted by using the heuristics of Section III-D. If the adjusted statuses are still infeasible, the value of f^m from the previous iteration is used. Also for computational efficiency, feasible solutions are constructed every few iterations instead of each iteration.

With a possibly overestimated optimal dual cost $\widetilde{L}^*$ from (42), the resulting stepsize may violate the surrogate stepsize condition (37). As a result, the surrogate dual cost is not guaranteed to be a lower bound on the optimal primal cost, leading to the difficulty of evaluating solution quality. No theoretical results have yet been developed to guarantee the satisfaction of (37). Our numerical testing experience on small problems suggests using small step sizes for large m and applying adaptive stepsize rules of traditional subgradient method [33]. Nevertheless, the surrogate dual costs cannot be used as lower bounds on f^* to evaluate the quality of a solution.

$$\begin{aligned} p_{jr}(t) = \max\Bigg\{p_{jr\,\min}, \min\Bigg\{p_{jr\,\max}, &\left(\sum_{i=1}^{I} P_i^D(t) - \sum_{i\neq j} \ \sum_{or\ k\neq r} p_{ik}(t)\right) + \frac{1}{c}\Bigg[\lambda(t) + \sum_l a_l^j\left(\mu_{l\,\min}(t) - \mu_{l\,\max}(t)\right) \\ &- \xi_{jr\,\min}(t)\beta_{jr\,\min}(t) + \xi_{jr\,\max}(t)\beta_{jr\,\max}(t) - \sum_l a_l^j\left(\varsigma_{l\,\min}(t)\gamma_{l\,\min}(t) - \varsigma_{l\,\max}(t)\gamma_{l\,\max}(t)\right)\Bigg]\Bigg\}\Bigg\} \end{aligned} \tag{39}$$

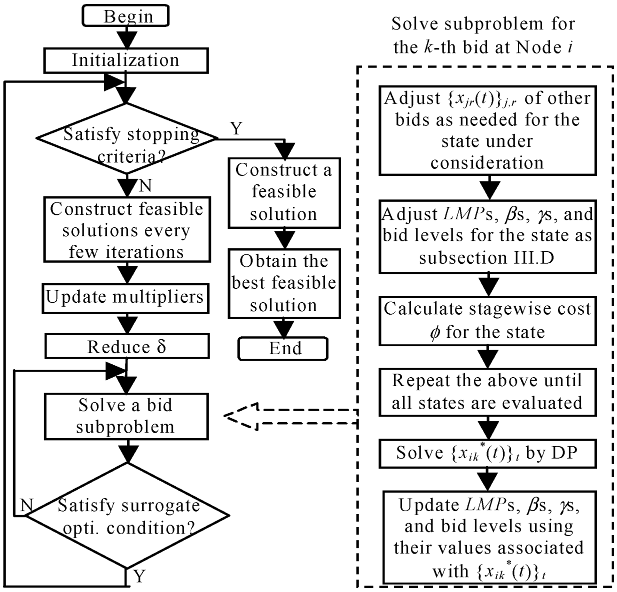

Fig. 1. Flow chart of the algorithm (spread update multipliers).

G. Obtaining Feasible Solutions

The overall algorithm is summarized in Fig. 1. The initialization assigns power to bids in the ascending order of their amortized per MW costs (the sum of energy and startup costs divided by the bid capacity). The regularization parameter δ in (26)–(29) is reduced by half every few iterations. The algorithm terminates when the level of constraint violation is less than a specified threshold over a few iterations, or when the number of iterations is greater than a specified value. A primal feasible solution is then constructed by the procedures used to obtain f^m in (42). This solution is compared to the solution associated with the lowest feasible cost obtained thus far, and the one with the lower total payment cost is chosen to be the problem solution.

To analyze the computational complexity of the algorithm, let N_1 be the number of outer loops in Fig. 1 required for convergence, N_2 be the number of inner loops required for the satisfaction of surrogate optimization condition, and t_b be the average computational time for solving a bid subproblem. Based on our testing experience, N_1 is more or less independent of the problem size,[10] N_2 is usually less than the total number of bids (i.e., $\Sigma_i K_i$), and t_b is the major contributor to the complexity based on our testing experience. By taking $\Sigma_i K_i$ as a conservative estimate for N_2, the algorithm complexity is approximately represented by

$$O\left(\sum_i K_i \times t_b\right). \tag{43}$$

The time t_b in (43) is then examined by analyzing the complexity of Dynamic Programming (DP) for solving bid subproblems. The DP process presented in Section III-D has T stages (e.g., $T = 24$), two states at each stage (i.e., "Off" and "On," with the bid's generation level optimized for the "On" state without discretization), and four state transitions between two consecutive stages, regardless of problem scale. The DP process therefore has a constant state space. However, the number of decision variables adjusted in evaluating a stage-wise cost as presented in Section III-D increases linearly with the problem size since these variables include bid levels (with the number of $\Sigma_i K_i$), LMP (I), $\beta(\Sigma_i K_i)$, and $\gamma(2L)$. Thus the complexity of DP including the adjustments is approximately proportional to the total number of these variables, i.e., $3\Sigma_i K_i + I + 2L$. As a result, (43) can be approximated as $O(\sum_i K_i \times (3\sum_i K_i + I + 2L))$.

[10] N_1 is affected by the tolerance level for terminating the outer loop. Here we assume that the same tolerance level is used for problems with different sizes.

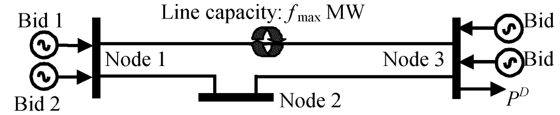

Fig. 2. Three-node transmission network.

IV. Numerical Results

The above algorithm for payment cost minimization has been implemented in C++ and run on a Pentium-4 2.79-GHz PC with 512 MB memory. In this section, three examples are presented. Example 1 examines the impact of transmission congestion, and compares the results of payment cost minimization with those of bid cost minimization. Example 2 uses a five-bus example based on ISO training document [21] to examine the solution quality of our algorithm by comparing results with optimal solutions obtained from exhaustive search, and verifies the effectiveness of the regularization approach. Example 3 then supports the analytical results for algorithm complexity in Section III by testing modified IEEE 24-bus, 48-bus, and 73-bus Reliability Test Systems [35] with Monte Carlo simulations for randomly selected load profiles and supply bids. Complete testing data and results are available at http://www.engr.uconn.edu/msl/.

Example 1: Consider a four-bid two-hour problem modified based on Example 1 of [14] without transmission. (The capacity of bid 3 at hour 2 is increased from 30 MW to 40 MW.) A three-node transmission network in Fig. 2 is assumed with equal reactance and zero resistance for all transmission lines. The line from node 1 to node 2 and the line from 2 to 3 are assumed to have sufficient capacities, e.g., 200 MW. For the line from node 1 to node 3, two cases are considered to compare the non-congested and congested situations. Since DC power flow calculation suggests that the result by using the MCP algorithm of [14] without transmission leads to 80 MW flow in that line at hour 2, the capacity of that line is considered to be 85 MW (>80) for the non-congested Case 1 and 75 MW (<80) for the congested Case 2.

Case 1: $f_{\max} = 85$ MW*:* The testing result shows that for both hours, bids 1 and 2 with the lowest bid prices and zero startup costs are selected at their maximum capacities (e.g., 60 MW for both bids at hour 2) and bid 4 provides the remaining power (e.g., 30 MW at hour 2). These results are identical to those under the MCP model in [14]. Also, the LMPs at each hour equal the MCP of that hour as a natural result of (22) with no transmission congestion. The CPU time is 0.38 s, close to 0.33 s obtained under the MCP model.

TABLE I
RESULTS FOR EXAMPLE 1, CASE 2

	Payment Cost Min.		Bid Cost Min.	
	Hour 1	Hour 2	Hour 1	Hour 2
Bid 1 (MW)	50	60	50	60
Bid 2 (MW)	40	52.5	40	52.5
Bid 3 (MW)	0	0	10	37.5
Bid 4 (MW)	10	37.5	0	0
LMP 1 ($/MWh)	30	20	65	20
LMP 2 ($/MWh)	30	25	65	42.5
LMP 3 ($/MWh)	30	30	65	65
Consumer Payment	$9300		$16300	
Total Bid Cost	$6475		$6387.5	

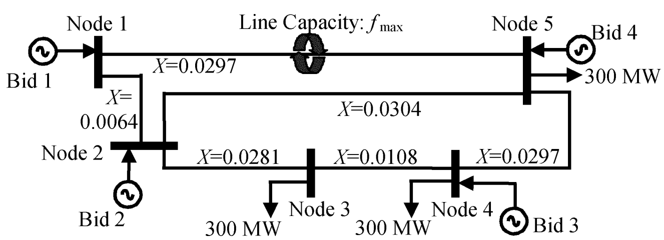

Fig. 3. Five-node transmission network.

Case 2: $f_{\max} = 75$ MW: The payment cost minimization solution is presented in Table I. Compared with the solution in the above non-congested case 1, bid 2 at node 1 generates less power at hour 2 (52.5 MW as compared to 60 MW) to serve the remote demand at node 3 through transmission while bid 4 at node 3 generates more at the hour (37.5 MW as compared to 30 MW) for its local demand. The transmitted power in the line from nodes 1 to 3 is thus kept within its capacity. For comparison, the bid cost minimization solution obtained by exhaustive search is also presented in Table I. This solution selects bid 3 (with high bid price but low startup cost) for its lower bid cost as compared to bid 4 (with low bid price but high startup cost). In contrast, payment cost minimization selects bid 4 for lower total payment as a result of lower LMPs because of the low bid price of bid 4. It can be seen from Table I that payment cost minimization, as compared to bid cost minimization, leads to a consumer payment reduction of $7000 ($16 300–$9300) at a relatively small increase of $87.5 ($6475–$6387.5) in the total bid cost.[11]

Example 2: Consider a five-node one-hour problem in Fig. 3 based on the transmission network of [21], with the transmission line reactance (under the per-unit system) and the demand shown in the figure. All lines except the one from node 1 to node 5 are assumed to have sufficient capacities, e.g., 400 MW. For the line from nodes 1 to 5, two cases are considered to compare the non-congested and congested situations. Since DC power flow calculation suggests that the result by using the MCP method of [14] without transmission leads to 267 MW flow in that line, the capacity of that line is considered to be 280 MW (>267) for the non-congested Case 1 and 240 MW (<267) for the congested Case 2. Single-block supply bids are described in Table II with bid 1 assumed on and other bids assumed off at hour 0.

[11]This can be interpreted as the tradeoff between consumer payment and production efficiency assuming bids represent true production costs, an assumption that does not hold in practice [39]. The tradeoff has been studied without that assumption, and preliminary results have been reported in [36].

TABLE II
SUPPLY BIDS FOR EXAMPLE 2

Bids	$P_{\min}$ (MW)	$P_{\max}$ (MW)	Bid Price ($/MWh)	Bid Startup ($/Start)
Bid 1	60	600	10	60000
Bid 2	15	210	15	30000
Bid 3	20	280	30	36000
Bid 4	10	200	30	15000

TABLE III
RESULTS FOR CASES 1 AND 2 IN EXAMPLE 2

	Case 1 $f_{\max} = 280$MW	Case 2 $f_{\max} = 240$MW
Bid 1 (MW)	600	600
Bid 2 (MW)	210	176
Bid 3 (MW)	0	0
Bid 4 (MW)	90	124
LMP 1 ($/MWh)	30	10.44
LMP 2 ($/MWh)	30	15
LMP 3 ($/MWh)	30	21.14
LMP 4 ($/MWh)	30	23.51
LMP 5 ($/MWh)	30	30
Total Payment	$72,000	$67,395

TABLE IV
COMPUTATIONAL TIME FOR CASES 1 AND 2 IN EXAMPLE 2

	Case 1	Case 2
Avg. Status Adjustment (%)	0	6.28
Number of Iterations	18	42
CPU Time (ms)	415	750

The solutions for both cases are presented in Table III. The 280 MW transmission capacity in Case 1 allows the two low-price bids 1 and 2 at nodes 1 and 2, respectively, to generate at their capacities to serve remote load at nodes 3–5 without creating transmission congestion. By contrast, the reduced transmission capacity in Case 2 causes a reduction of the generation of the low-price bid 2 at node 2 (from 210 MW to 176 MW) and an increase of the generation of the expensive bid 4 at node 5 (from 90 MW to 124 MW) to keep the transmitted power within its capacity. For each case, the solution was verified to be optimal by comparing payment costs of all the possible bid selections ($2^4 = 16$), demonstrating solution optimality for this small problem. An interesting observation is that the congested Case 2 has lower LMPs and consequently a lower payment cost as compared to those of the non-congested Case 1. An explanation for this is that the transmission congestion in Case 2 restricts the low-price bid 2 at node 2 from generating at its full capacity, making it a marginal bid to set low LMPs.

The average number of on-off status adjustments of other bids per evaluation of stage-wise cost in solving a bid subproblem (Section III-D), the number of iterations, and CPU time for the two cases are presented in Table IV. Their values for the non-congested case 1 are smaller than those for the congested case 2, implying that more computations are needed to obtain solutions with transmission congestion.

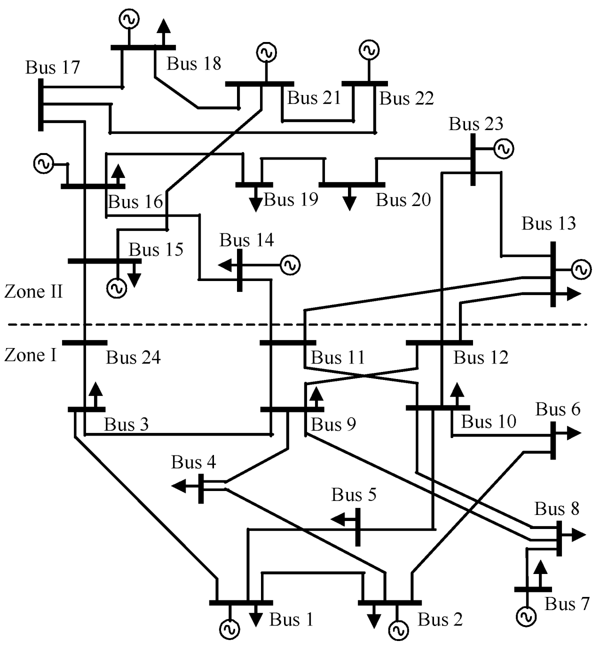

Fig. 4. IEEE one-area RTS-96.

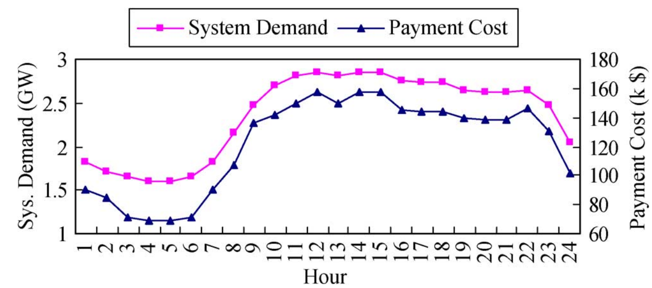

Fig. 5. System demand and payment costs for Example 3.

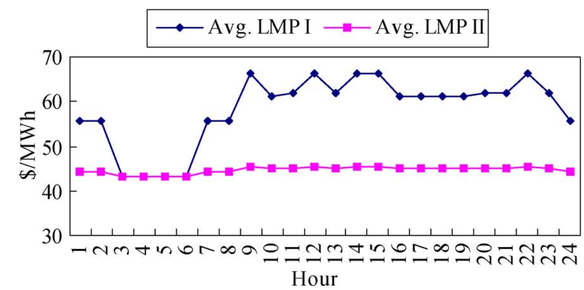

Fig. 6. Load-weighted average LMPs in zones I and II for Example 3.

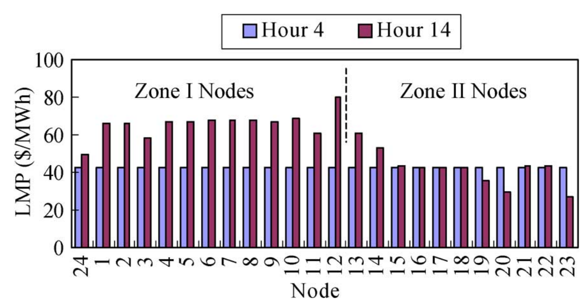

Fig. 7. LMPs at hour 4 and hour 14 for Example 3.

TABLE V
SUPPLY BIDS IN EXAMPLE 3

Unit Type	N. of Units	P_{min} MW	P_{max} MW	Mean Price	Stdev Price	Mean Startup	Stdev Startup
U12	5	3	12	67.15	9.2	247	56
U20	4	4	20	65.90	16.3	32.5	0
U50	6	0	50	15.00	0	0	0
U76	4	10	76	12.16	2.1	727.1	0
U100	3	15	100	56.60	5.1	1625	593
U155	4	20	155	10.42	0.6	317.2	244
U197	3	20	197	57.42	3.5	2880	623
U350	1	35	350	10.85	0.7	2336	899
U400	2	40	400	43.03	1.3	6000	0

Example 3: Consider a problem with 24 buses and 32 supply bids over a 24-h period based on the IEEE one-area Reliability Test System of 1996 (RTS-96) [35] depicted in Fig. 4. The system description includes reactance and capacities of transmission lines, hourly system load for a year, percentages of system load across the buses, and heat-rates of generating units. Following [4], the system is divided into two zones in Fig. 4, with 46.74% of system load but only 20.09% of total generation capacity located in zone I. Therefore, power flows from the export zone II to the import zone I. To demonstrate the impact of transmission capacity constraints, the five lines connecting the two zones are assumed to have a reduced 200 MW capacity each while other lines follow their capacity data in the test system. Ten test cases including one for the peak-load day of the year were run. For each case, its 24-h load data were selected from daily load profiles of the year of the test system, and thirty-two supply bids assuming identical over the 24 h were randomly generated with Gaussian distributions based on unit parameters presented in Table V.

Consider first the case for the peak-load day of the year. The result is analyzed below. The hourly system demand and payment cost are depicted in Fig. 5. Observe that the payment cost curve follows the demand curve, indicating higher payment cost for higher system demand in general. The hourly zonal prices (load-weighted average of nodal LMPs) for zones I and II are depicted in Fig. 6. It can be seen that for most hours, the price of import zone I is higher than that of export zone II. The only hours for which the two zones have equal zonal prices are hours 3–6 when system demands are the lowest of the day and there is no congestion in the lines connecting the two zones.

To examine the impact of transmission congestion, LMPs for peak hour 14 and off-peak hour 4 at various nodes are depicted in Fig. 7. Observe that LMPs at hour 14 vary across locations as a result of transmission congestion. By contrast, a uniform LMP is obtained for all nodes at hour 4 with a system load of only 56% of the peak load. It can also be seen that zone I receives higher LMPs at the peak hour 14 than the off-peak hour 4 as expected. However, nodes 19, 20, and 23 in zone II have lower LMPs during hour 14 as compared to hour 4. An explanation for this phenomenon is that transmission congestion at hour 14 restricts the low-price bids at these nodes from providing capacity power to other nodes, making them the marginal bids to set low LMPs for these nodes.

With ten test cases including the one for the peak-load day, the average N_1 and N_2 (defined in Section III-G), and the average and standard deviation of CPU time for the 24-bus problem are presented in Table VI. To test algorithm scalability

TABLE VI
COMPUTATIONAL TIME FOR 24-BUS AND 73-BUS PROBLEMS IN EXAMPLE 3

Problems	Avg. N_1	Avg. N_2	Avg. Time (s)	Stdev. Time (s)
24-Bus	227	2.4	141.1	27.5
48-Bus	181	3.0	791.6	219.5
73-Bus	283	4.5	1673.4	380.6

and to examine the analytical result for algorithm complexity in Section III, a 48-bus problem based on the IEEE two-area RTS [35] (interconnecting two duplicated Fig. 4) was also tested for ten cases. For each case, the demand profile and supply bids for one area were directly copied from the corresponding 24-bus case and those for the other area were created by using the same procedures as presented above. Similarly, a 73-bus problem based on the IEEE three-area RTS was tested for ten cases. Results for the 48-bus and 73-bus problems are also presented in Table VI.

It can be seen that the average CPU time for the 48-bus problem is about five times of that for the 24-bus problem. According to our analysis in Section III-G, the computational time should increase to four times of that for the 24-bus example since the numbers of nodes, lines, and bids are all doubled. The testing result (five times) is reasonably close to the analysis result (four times). For the 73-bus problem, the computational time is about twelve times of that for the 24-bus problem, which is also reasonably close to the analysis result (nine times) in view of the increase of the average N_1 as compared to the 24-bus example. While it is difficult for these testing results alone to conclude the polynomial algorithm complexity, they are roughly consistent with the complexity analysis in Section III, and therefore support the analytical result. For the three problems, the standard deviations of the CPU time are not small as a result of varying computational requirements for tests with low load (implying less congestion) and those with high load (implying more congestion).

V. CONCLUSION

Currently, most ISOs in the U. S. conduct bid cost minimization in auctions and settle the payments with market-clearing prices. An alternative auction mechanism that minimizes the consumer payment cost has been brought to recent discussions. In this paper, the payment cost minimization problem with transmission capacity constraints is formulated as an MPEC. A regularization method is first used to satisfy constraint qualifications. The resulting problem is pseudo-separable in terms of bids as a result of having LMPs in the formulation as decision variables. Surrogate optimization is thus used to overcome this difficulty so that the problem is solved by optimizing bids one at a time within the augmented Lagrangian relaxation framework.[12] Numerical results show that the method is promising to solve practical problems, and payment cost minimization leads to consumer payment savings as compared to bid cost minimization for the same set of supply bids. The method shall facilitate further study of the payment cost minimization auction, and open the door for solving other non-decomposable and NP-hard problems.

[12]While the method is still in its early stage and requires further development, we believe that it would gradually grow into a robust algorithm as many other algorithms have experienced in the past, e.g., mixed integer programming methods for solving bid-cost minimization.

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