

Article

The Role of Demand Flexibility in Addressing Inc-Dec Gaming in Electricity Markets

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Abstract

Zonal day-ahead (DA) electricity markets followed by redispatch (RD) markets for congestion management are vulnerable to the strategic bidding behavior known as Inc-Dec gaming. Although previous literature has demonstrated the effects of Inc-Dec gaming, it has neglected the participation of flexible demand in RD markets. This paper addresses this gap by developing a novel multi-period bi-level optimization model of a strategic producer participating in DA and RD markets, accounting for the inherent time-coupling operating characteristics of demand flexibility (DF) in the RD market. This model includes an upper level problem determining the optimal bidding decisions of the strategic producer in the DA and RD markets, and two lower level problems representing the clearing process of the two markets. The role of DF in addressing Inc-Dec gaming is demonstrated through a small-scale case study involving a 2-node system and a 2-period market horizon (showing peak/off-peak dynamics), as well as a large-scale case study involving a modified IEEE RTS 24-node system and a daily (24-h) market horizon.

Keywords: Bi-level optimization; demand flexibility; electricity markets; Inc-Dec gaming; redispatch markets



Academic Editor: Charisios Achillas

Received: 14 November 2025

Revised: 9 December 2025

Accepted: 15 December 2025

Published: 18 December 2025

Citation: Pozzi, L.; Papadaskalopoulos, D.; Trovato, V.; Qiu, D.; Strbac, G. The Role of Demand Flexibility in Addressing Inc-Dec Gaming in Electricity Markets. *Energies* **2025**, *18*, 6626. <https://doi.org/10.3390/en18246626>

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1. Introduction

1.1. Background and Motivation

Deregulated and highly renewable energy systems are characterized by more variable and less predictable power flows within the transmission network [1]. In this context, Transmission System Operators (TSOs) carry out the critical task of managing grid congestion. In the US, this is primarily addressed through the application of nodal pricing, which accounts for transmission constraints and varying costs of delivering electricity at different nodes across the network. In contrast, the EU target model relies on a zonal day-ahead (DA) market, followed by redispatch (RD) markets as the main ex-post remedial action used by TSOs to adjust DA schedules, resolve grid congestion, and maintain grid stability [2]. In 2023, Germany, Poland, and Spain each carried out RD activations corresponding to approximately 5% of their total electricity demand—a record level—in order to resolve transmission grid congestion. According to data from the EU Agency for the Cooperation of Energy Regulators (ACER), this costed £2 billion in Germany alone [3]. While this trend is in part driven by the ongoing large-scale integration of non-dispatchable renewable energy, in recent years, the European Commission has also highlighted [4] that the RD process is

vulnerable to the strategic bidding behaviour called Inc-Dec (or Incremental-Decremental) gaming—which could contribute to the observed rise in RD volume and cost.

Within the electricity markets literature, the terms strategic bidding and market power generally refer to a producer's ability to influence market prices (through economic withholding or capacity withholding) within a single market stage [5]. In [6] the concept of locational market power is discussed, which may arise even in the absence of congestion, as strategic producers can induce binding network constraints through their bids. The Inc-Dec game represents a (still largely unexplored) extension of this concept to a market framework with sequential stages, where producers exploit the interaction between DA and RD markets rather than a single-stage price effect. Through Inc-Dec gaming, producers can exploit the DA market to induce artificial scarcity or surplus in their node, to influence the subsequent RD market, ultimately increasing their profit [7]. Inc-Dec gaming played a crucial role in the U.S. transition to nodal pricing [8] and has been empirically evidenced in the UK [9], Italy [10], and Germany [11]. This mechanism therefore links strategic DA behaviour to redispatch outcomes rather than to single-market price manipulation, making it a distinct, inter-temporal manifestation of market power.

To address these concerns, several scholars have examined the issue, mainly through game theoretical analysis of simplified representations of the European network and markets' rules. The early contribution in [12] analytically derives the Nash equilibrium for a continuum of infinitesimally small producers under various market design scenarios. It demonstrates that a zonal DA market, followed by a pay-as-bid RD market, results in additional payments to producers in export-constrained nodes due to Inc-Dec gaming, thereby leading to inefficient investment signals. These results are confirmed in [13], which considers pay-as-clear pricing in the RD market, and [14], which also considers demand-driven uncertainty on network congestion. However, both analyses are limited to a 2-node system. Reference [15] introduces an Equilibrium Problem with Equilibrium Constraints (EPEC) model that is reformulated as a Mixed-Integer Linear Programming (MILP) model, enabling the study of larger networks. In [16], this approach is applied to investigate the impact of Inc-Dec gaming under two different RD pricing options: pay-as-bid and "optimal zonal" pricing, the latter proposed by the authors. By focusing on surplus nodes in a 6-node and a 24-node system, the analysis demonstrates that RD with pay-as-bid pricing is less efficient than optimal zonal pricing, where the geographical price granularity in RD matches that of the DA market (i.e., zonal). Rather than focusing on market equilibrium calculations, reference [17] introduces a bi-level model for the strategic bidding of a single producer. Authors consider grid congestion at both the distribution and transmission levels, carrying out analysis on a meshed 3-node transmission network linked to two branches of a radial distribution network.

Beyond the above challenges associated with managing transmission congestion, another fundamental feature of the emerging energy systems is the enhanced role of the demand side, whose flexibility (i.e., the ability of modifying its temporal patterns) is widely considered as a key enabler towards achieving cost-efficient decarbonization [18]. Currently in Europe, consumers are legally eligible to participate in RD markets in Austria, Finland, France, the Netherlands, Norway, Romania, and Sweden [19]. At the same time, TSOs can also access innovative platforms such as GOPACS [20] and NODES [21] to procure congestion management services. Previous studies have examined the participation of demand-side flexibility in DA energy markets (e.g., [22,23]) and balancing markets (e.g., [24,25]), but its explicit role within RD markets, where producers strategies interact with grid constraints, has not been addressed in the literature.

Therefore, a relevant research gap emerges in this context: previous literature on Inc-Dec gaming (as summarized in Table 1) has focused on generation-only RD markets, neglecting demand-side participation. Going further, existing studies have merely focused on

single-period models, thus being inherently unable to capture the time-coupled operating characteristics of demand flexibility (DF).

Table 1. Summary of Existing Literature on Inc-Dec Gaming.

Paper	Model	Examined Network	RD Participants	Time Frame	Time-Coupling
[12]	Analytical	No specific network	Producers	Single-period	No
[13,14]	Analytical	2-node	Producers	Single-period	No
[15]	EPEC	No specific network	Producers	Single-period	No
[16]	EPEC	24-node	Producers	Single-period	No
[17]	MPEC	3-node	Producers	Single-period	No
This paper	MPEC	24-node	Prod. and Demand-Side	Multi-period	Yes

1.2. Scope and Contribution

As indicated in Table 1, this paper aims to fill this knowledge gap by investigating for the first time the participation of DF in RD markets, while accounting for its time-coupling operating characteristics, and analyzing the impacts of such participation on Inc-Dec gaming. Specifically, the novel contributions of this paper are as follows:

- A multi-period bi-level optimization model of a strategic producer participating in DA and RD markets is proposed, accounting for network constraints and the time-coupling operating characteristics of DF participating in the RD market. The upper level problem determines the optimal bidding decisions of the strategic producer in the DA and RD markets, while the two lower level problems represent the clearing process of the two markets. This bi-level problem is solved by converting it into a Mathematical Program with Equilibrium Constraints (MPEC) and subsequently to a MILP through strong duality and binary expansion techniques.
- The role of DF in addressing Inc-Dec gaming, as well as the generic applicability of the proposed model, are demonstrated through two case studies: a simple 2-node, 2-period example, and a large-scale case study based on a modified IEEE RTS 24-node system over a daily market horizon.

1.3. Paper Structure

The rest of this paper is organized as follows. Section 2 details the developed bi-level optimization model. The application of the model to an illustrative small-scale case study and a large-scale case study is presented in Sections 3 and 4, respectively. Finally, Section 5 discusses conclusions and future extensions of this work.

1.4. Nomenclature

Indices and Sets

$t \in T$	Index and set of time periods
i	Index of strategic conventional producer
$i- \in I-$	Index and set of conventional producers other than i
$k \in K$	Index and set of renewable producers
$j \in J$	Index and set of demands
$n \in N$	Index and set of network nodes
$l \in L$	Index and set of network lines
$I_n \subseteq I$	Subset of conventional producers i connected to n
$I_n^- \subseteq I-$	Subset of conventional producers other than i connected to n
$K_n \subseteq K$	Subset of renewable producers k connected to n
$J_n \subseteq J$	Subset of demands j connected to n

Parameters

λ_i^G	Marginal cost of producer i [€/MWh]
λ_j^D	Marginal benefit of demand j [€/MWh]
$\lambda_{j,t}^{up}$	Discomfort cost of demand j for shifting demand away from t [€/MWh]
$\lambda_{j,t}^{dn}$	Discomfort cost of demand j for shifting demand towards t [€/MWh]
VoLL	Value of lost load [€/MWh]
g_i^{max}	Maximum power of conventional producer i [MW]
$g_{k,t}^{max}$	Maximum power of renewable producer k at t [MW]
$d_{j,t}^{max}$	Maximum baseline power of demand j at t [MW]
$GSF_{n,l}$	Generation Shift Factor between node n and line l
F_l^{max}	Transmission capacity of network line l [MW]
α_j	Load shifting limit of demand j [%]

Variables

$g_{i,t}$	Day-ahead market dispatch of producer i at t [MW]
$d_{j,t}$	Day-ahead market dispatch of demand j at t [MW]
λ_t^{DA}	Day-ahead market clearing price at t [€/MWh]
$k_{i,t}$	Day-ahead strategic bidding variable of producer i at t
$k_{i,t}^{up}$	Upward redispatch strategic bidding variable of producer i at t
$k_{i,t}^{dn}$	Downward redispatch strategic bidding variable of producer i at t
$r_{i,t}^{up}$	Upward redispatch provided by producer i at t [MW]
$r_{i,t}^{dn}$	Downward redispatch provided by producer i at t [MW]
$d_{j,t}^{up}$	Power of demand j shifted away from t [MW]
$d_{j,t}^{dn}$	Power of demand j shifted towards t [MW]
$d_{j,t}^{un}$	Unserved power of demand j at t [MW]

2. Modeling Approach

2.1. Modeling Assumptions

The proposed bi-level optimization model expresses the perspective of a strategic conventional producer i who aims at optimizing its bidding decisions in order to maximize its total profit in the DA energy and RD markets, while anticipating the clearing outcomes of the two markets and potential DF activations in the RD market. For clarity reasons, the main assumptions behind this model are outlined below:

1. The modeled DA market is a pool-based, energy-only, zonal market, cleared by the market clearing agent through the solution of a social welfare maximization problem which ignores within-zone network constraints and adopts pay-as-clear pricing.
2. The modeled RD market is a pool-based, pay-as-bid (as commonly implemented in the EU) market, cleared by the TSO, who also acts as the sole buyer, in order to resolve within-zone network congestion with the minimum RD cost. The TSO employs a DC power flow model and Generation Shift Factors (GSFs) to represent network constraints. The RD market clearing follows the DA market clearing.
3. Considering the focus of the paper, and for the sake of simplicity, the model considers a single bidding zone (the one where the strategic producer is located), and thus disregards market coupling.
4. For clarity, and without loss of generality, the model assumes that each producer owns a single generation unit and submits a single price-quantity bid for this generation unit for each time period t and in each of the two considered markets. For the same reasons, the model assumes that each demand participant submits a single bid for each time period t , including in the RD market when the unit provides flexibility.

5. The strategic producer's ability to adjust DA and RD bids to maximise profit across the two stages is an essential feature of the proposed model. Expanding the approach employed in [26], the strategic behavior of producer i is expressed through the decision variables $k_{i,t}$, $k_{i,t}^{up}$ and $k_{i,t}^{dn}$. Specifically, $k_{i,t}$ expresses its behavior in the DA market with $k_{i,t} = 1$ implying that it behaves competitively and reveals its actual marginal cost λ_i^G to the DA market, while $k_{i,t} > 1$ and $k_{i,t} < 1$ imply that it behaves strategically (overbids and underbids, respectively). In a similar fashion, $k_{i,t}^{up}$ and $k_{i,t}^{dn}$ express its behavior in the RD market (upward and downward, respectively), with $k_{i,t}^{up} = 1$ and $k_{i,t}^{dn} = 1$ implying that it behaves competitively.
6. DF is incorporated in the RD market clearing problem through a generic, technology-agnostic, and inter-temporal model, which follows the approach of [27–31]. Specifically, the load of the demand participant j at time period t can be reduced or increased relative to its dispatch in the DA market, but (a) this reduction/increase is subject to certain limits (prescribed by the relative parameter α_j), (b) it entails a quantifiable marginal cost of discomfort [30] which also constitutes the price offered by j in the RD market (i.e., strategic behavior of flexible demand participants is neglected), and (c) the total size of demand reductions is equal to the total size of demand increases within the considered daily market horizon, implying that demand shifting is energy neutral.

2.2. Bi-Level Optimization Model of Strategic Producer

The structure of the proposed bi-level optimization problem is illustrated in Figure 1 and involves three interdependent optimization problems; specifically, the upper level (UL) problem determines the optimal bidding decisions of the strategic producer i in the DA and RD markets, and is subject to two lower level problems, which represent the clearing process of the DA market (LL1) and the RD market (LL2). The detailed formulation of the bi-level problem is presented below:

(UL problem)

$$\max_{\Xi} \sum_t \left[(\lambda_t^{DA} - \lambda_i^G) g_{i,t} + (k_{i,t}^{up} \lambda_i^G - \lambda_i^G) r_{i,t}^{up} + (\lambda_i^G - k_{i,t}^{dn} \lambda_i^G) r_{i,t}^{dn} \right] \quad (1)$$

where:

$$\Xi = \{k_{i,t}, k_{i,t}^{up}, k_{i,t}^{dn}\} \quad (2)$$

(LL1 problem)

$$\min_{\Xi^{DA}} \sum_t k_{i,t} \lambda_i^G g_{i,t} + \sum_{i-,t} \lambda_{i-}^G g_{i-,t} + \sum_{k,t} \lambda_k^G g_{k,t} - \sum_{j,t} \lambda_j^D d_{j,t} \quad (3)$$

where:

$$\Xi^{DA} = \{g_{i,t}, g_{i-,t}, g_{k,t}, d_{j,t}\} \quad (4)$$

subject to:

$$\sum_j d_{j,t} - g_{i,t} - \sum_{i-} g_{i-,t} - \sum_k g_{k,t} = 0 : \lambda_t^{DA}, \forall t \quad (5)$$

$$0 \leq g_{i,t} \leq g_i^{max} : \mu_{i,t}^{G-}, \mu_{i,t}^{G+}, \forall t \quad (6)$$

$$0 \leq g_{i-,t} \leq g_{i-}^{max} : \mu_{i-,t}^{G-}, \mu_{i-,t}^{G+}, \forall i-, \forall t \quad (7)$$

$$0 \leq g_{k,t} \leq g_{k,t}^{max} : \mu_{k,t}^{G-}, \mu_{k,t}^{G+}, \forall k, \forall t \quad (8)$$

$$0 \leq d_{j,t} \leq d_{j,t}^{max} : \mu_{j,t}^{D-}, \mu_{j,t}^{D+}, \forall j, \forall t \quad (9)$$

(LL2 problem)

$$\min_{\Xi^{RD}} \sum_t \left[\left(k_{i,t}^{up} \lambda_i^G r_{i,t}^{up} - k_{i,t}^{dn} \lambda_i^G r_{i,t}^{dn} \right) + \sum_{i-} \left(\lambda_{i-}^G r_{i-,t}^{up} - \lambda_{i-}^G r_{i-,t}^{dn} \right) + \sum_k \left(\lambda_k^G r_{k,t}^{up} - \lambda_k^G r_{k,t}^{dn} \right) + \sum_j \left(\lambda_{j,t}^{up} d_{j,t}^{up} + \lambda_{j,t}^{dn} d_{j,t}^{dn} + d_{j,t}^{un} \text{VoLL} \right) \right] \quad (10)$$

where:

$$\Xi^{RD} = \{r_{i,t}^{up}, r_{i,t}^{dn}, r_{i-,t}^{up}, r_{i-,t}^{dn}, r_{k,t}^{up}, r_{k,t}^{dn}, d_{j,t}^{up}, d_{j,t}^{dn}, d_{j,t}^{un}\} \quad (11)$$

subject to:

$$\sum_{j \in J} (d_{j,t}^{dn} - d_{j,t}^{up} - d_{j,t}^{un}) - r_{i,t}^{up} + r_{i,t}^{dn} - \sum_{i \in I-} (r_{i-,t}^{up} - r_{i-,t}^{dn}) - \sum_{k \in K} (r_{k,t}^{up} - r_{k,t}^{dn}) = 0 : \lambda_{0,t}^{RD}, \forall t \quad (12)$$

$$-F_l^{max} \leq \sum_n \text{GSF}_{n,l} \left[g_{i \in I_n, t} + r_{i \in I_n, t}^{up} - r_{i \in I_n, t}^{dn} + \sum_{i \in I_n^-} (g_{i-,t} + r_{i-,t}^{up} - r_{i-,t}^{dn}) + \sum_{k \in K_n} (g_{k,t} + r_{k,t}^{up} - r_{k,t}^{dn}) - \sum_{j \in J_n} (d_{j,t} + d_{j,t}^{dn} - d_{j,t}^{up} - d_{j,t}^{un}) \right] \leq F_l^{max} : \mu_{l,t}^{F-}, \mu_{l,t}^{F+} \forall l, \forall t \quad (13)$$

$$0 \leq r_{i,t}^{up} \leq (g_i^{max} - g_{i,t}) : \mu_{i,t}^{up-}, \mu_{i,t}^{up+}, \forall t \quad (14)$$

$$0 \leq r_{i,t}^{dn} \leq g_{i,t} : \mu_{i,t}^{dn-}, \mu_{i,t}^{dn+}, \forall t \quad (15)$$

$$0 \leq r_{i-,t}^{up} \leq (g_{i-}^{max} - g_{i-,t}) : \mu_{i-,t}^{up-}, \mu_{i-,t}^{up+}, \forall i-, \forall t \quad (16)$$

$$0 \leq r_{i-,t}^{dn} \leq g_{i-,t} : \mu_{i-,t}^{dn-}, \mu_{i-,t}^{dn+}, \forall i-, \forall t \quad (17)$$

$$0 \leq r_{k,t}^{up} \leq (g_k^{max} - g_{k,t}) : \mu_{k,t}^{up-}, \mu_{k,t}^{up+}, \forall k, \forall t \quad (18)$$

$$0 \leq r_{k,t}^{dn} \leq g_{k,t} : \mu_{k,t}^{dn-}, \mu_{k,t}^{dn+}, \forall k, \forall t \quad (19)$$

$$\sum_t (d_{j,t}^{dn} - d_{j,t}^{up}) = 0 : \mu_j, \forall j \quad (20)$$

$$0 \leq d_{j,t}^{up} \leq \alpha_j (d_{j,t} - d_{j,t}^{un}) : \mu_{j,t}^{up-}, \mu_{j,t}^{up+}, \forall j, \forall t \quad (21)$$

$$0 \leq d_{j,t}^{dn} \leq \alpha_j (d_{j,t} - d_{j,t}^{un}) : \mu_{j,t}^{dn-}, \mu_{j,t}^{dn+}, \forall j, \forall t \quad (22)$$

$$0 \leq d_{j,t}^{un} \leq d_{j,t} : \mu_{j,t}^{un-}, \mu_{j,t}^{un+}, \forall j, \forall t \quad (23)$$

The objective function of the UL problem (1) lies in maximizing the total profit of the strategic producer i in the DA and RD markets, which is determined as the difference between its revenues from the two markets $\sum_t (\lambda_t^{DA} g_{i,t} + k_{i,t}^{up} \lambda_i^G r_{i,t}^{up} - k_{i,t}^{dn} \lambda_i^G r_{i,t}^{dn})$ and its operating cost $\sum_t (g_{i,t} + r_{i,t}^{up} - r_{i,t}^{dn}) \lambda_i^G$ and rearranging some terms. This objective is pursued by optimizing the strategic bidding variables (2).

The objective function of the LL1 problem (3) lies in minimizing the perceived negative social welfare of the DA market, by optimizing the market clearing decisions (4). This problem is subject to the demand-supply balance constraints for the considered (single) bidding zone (5)—whose associated dual variables λ_t^{DA} constitute the DA market clearing prices—and the minimum and maximum dispatch limits of the market participants (6)–(9).

The objective function of the LL2 problem (10), lies in minimizing the perceived total RD cost incurred by the TSO—including both upward and downward adjustments—by optimizing the RD market clearing decisions (11). This cost includes RD actions on both the generation side, captured by the first two rows of (10), and the demand side, represented by the last row of the same equation. On the demand side, we consider upward and downward RD offers from participants with DF, as well as the cost of involuntary load curtailment actions, which are priced at the Value of Lost Load (VoLL). Constraints (12) ensure that the demand-supply balance for the considered bidding zone is preserved after the RD

market clearing. Constraints (13) ensure that network congestion within the examined zone is resolved by the RD market i.e., the power flow on each line is lower or equal to its transmission capacity, employing a DC power flow model similar to [32], and GSFs. Constraints (14)–(19) express the minimum and maximum RD limits of the producers.

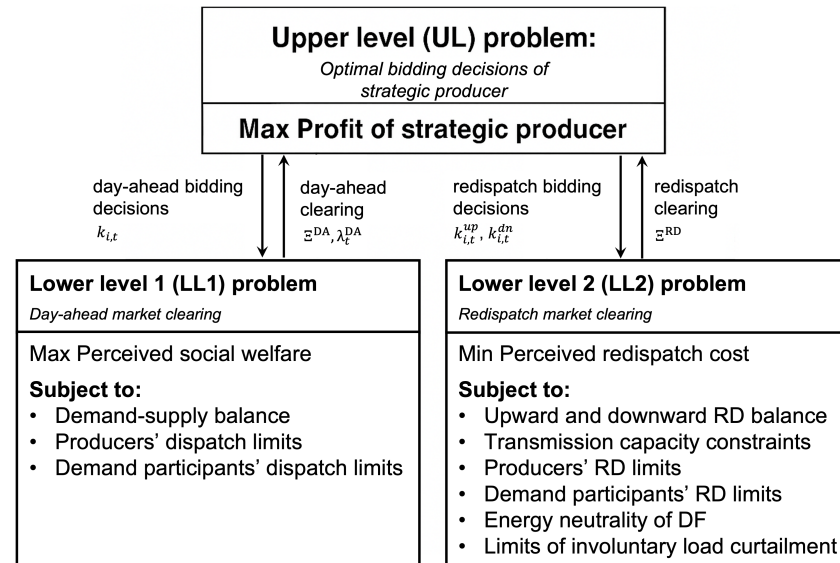


Figure 1. Illustration of the proposed bi-level optimization problem.

The DF of demand participant j in the RD market is expressed by constraints (20)–(22), following Assumption (6) of Section 2.1. Constraint (20) ensures that demand shifting is energy neutral within the examined daily horizon. Constraints (21) and (22) express the limits of demand reduction and increase, respectively, as a ratio α_j of the dispatch in the DA market, reduced by any required involuntary load curtailment; $\alpha_j = 0$ implies that participant j does not exhibit any DF while $\alpha_j = 1$ implies that its whole energy consumption can be shifted in time. Finally, constraints (23) express the bounds of involuntary load curtailments.

2.3. MPEC Model of the Strategic Producer

As a first step towards solving the above bi-level optimization problem, LL1 and LL2 problems are replaced by their Karush–Kuhn–Tucker (KKT) conditions and the bi-level problem is converted to a single level MPEC, which is formulated as follows:

$$\max_{\Xi^{MPEC}} \sum_t \left[(\lambda_t^{DA} - \lambda_i^G) g_{i,t} + (k_{i,t}^{up} \lambda_i^G - \lambda_i^G) r_{i,t}^{up} + (\lambda_i^G - k_{i,t}^{dn} \lambda_i^G) r_{i,t}^{dn} \right] \quad (24)$$

where:

$$\Xi^{MPEC} = \Xi \cup \Xi^{DA} \cup \Xi^{RD} \cup \Xi^{DUAL} \quad (25)$$

$$\Xi^{DUAL} = \{ \lambda_t^{DA}, \mu_{i,t}^{G-}, \mu_{i,t}^{G+}, \mu_{i-,t}^{G-}, \mu_{i-,t}^{G+}, \mu_{k,t}^{G-}, \mu_{k,t}^{G+}, \mu_{j,t}^{D-}, \mu_{j,t}^{D+}, \lambda_{0,t}^{RD}, \mu_{l,t}^{F-}, \mu_{l,t}^{F+}, \mu_{i,t}^{up-}, \mu_{i,t}^{up+}, \mu_{i,t}^{dn-}, \mu_{i,t}^{dn+}, \mu_{i-,t}^{up-}, \mu_{i-,t}^{up+}, \mu_{i-,t}^{dn-}, \mu_{i-,t}^{dn+}, \mu_{k,t}^{up-}, \mu_{k,t}^{up+}, \mu_{k,t}^{dn-}, \mu_{k,t}^{dn+}, \mu_{j,t}^{up-}, \mu_{j,t}^{up+}, \mu_{j,t}^{dn-}, \mu_{j,t}^{dn+}, \mu_{j,t}^{un-}, \mu_{j,t}^{un+} \} \quad (26)$$

subject to:

LL1 original equality condition: (5)

LL1 KKT optimality conditions:

$$k_{i,t} \lambda_i^G - \lambda_t^{DA} - \mu_{i,t}^{G-} + \mu_{i,t}^{G+} = 0, \forall t \quad (27)$$

$$\lambda_{i-,t}^G - \lambda_t^{DA} - \mu_{i-,t}^{G-} + \mu_{i-,t}^{G+} = 0, \forall t, \forall i- \quad (28)$$

$$\lambda_k^G - \lambda_t^{DA} - \mu_{k,t}^{G-} + \mu_{k,t}^{G+} = 0, \forall t, \forall k \quad (29)$$

$$-\lambda_j^D + \lambda_t^{DA} - \mu_{j,t}^{D-} + \mu_{j,t}^{D+} = 0, \forall t, \forall j \quad (30)$$

LL1 complementarity constraints:

$$0 \leq g_{i,t} \perp \mu_{i,t}^{G-} \geq 0, \forall t \quad (31)$$

$$0 \leq (g_i^{max} - g_{i,t}) \perp \mu_{i,t}^{G+} \geq 0, \forall t \quad (32)$$

$$0 \leq g_{i-,t} \perp \mu_{i-,t}^{G-} \geq 0, \forall t, \forall i- \quad (33)$$

$$0 \leq (g_{i-}^{max} - g_{i-,t}) \perp \mu_{i-,t}^{G+} \geq 0, \forall t, \forall i- \quad (34)$$

$$0 \leq g_{k,t} \perp \mu_{k,t}^{G-} \geq 0, \forall t, \forall k \quad (35)$$

$$0 \leq (g_{k,t}^{max} - g_{k,t}) \perp \mu_{k,t}^{G+} \geq 0, \forall t, \forall k \quad (36)$$

$$0 \leq d_{j,t} \perp \mu_{j,t}^{D-} \geq 0, \forall t, \forall j \quad (37)$$

$$0 \leq (d_{j,t}^{max} - d_{j,t}) \perp \mu_{j,t}^{D+} \geq 0, \forall t, \forall j \quad (38)$$

LL2 original equality conditions: (12), (20)

LL2 stationarity conditions:

$$k_{i,t}^{up} \lambda_i^G - \lambda_{0,t}^{RD} + \sum_l \text{GSF}_{(n:i \in I_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{i,t}^{up-} + \mu_{i,t}^{up+} = 0, \forall t \quad (39)$$

$$-k_{i,t}^{dn} \lambda_i^G + \lambda_{0,t}^{RD} - \sum_l \text{GSF}_{(n:i \in I_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{i,t}^{dn-} + \mu_{i,t}^{dn+} = 0, \forall t \quad (40)$$

$$\lambda_{i-}^G - \lambda_{0,t}^{RD} + \sum_l \text{GSF}_{(n:i- \in I_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{i-,t}^{up-} + \mu_{i-,t}^{up+} = 0, \forall t, \forall i- \quad (41)$$

$$-\lambda_{i-}^G + \lambda_{0,t}^{RD} - \sum_l \text{GSF}_{(n:i- \in I_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{i-,t}^{dn-} + \mu_{i-,t}^{dn+} = 0, \forall t, \forall i- \quad (42)$$

$$\lambda_k^G - \lambda_{0,t}^{RD} + \sum_l \text{GSF}_{(n:k \in K_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{k,t}^{up-} + \mu_{k,t}^{up+} = 0, \forall t, \forall k \quad (43)$$

$$-\lambda_k^G + \lambda_{0,t}^{RD} - \sum_l \text{GSF}_{(n:k \in K_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{k,t}^{dn-} + \mu_{k,t}^{dn+} = 0, \forall t, \forall k \quad (44)$$

$$\lambda_{j,t}^{up} - \lambda_{0,t}^{RD} + \sum_l \text{GSF}_{(n:j \in J_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) - \mu_{j,t}^{up-} + \mu_{j,t}^{up+} = 0, \forall t, \forall j \quad (45)$$

$$\lambda_{j,t}^{dn} + \lambda_{0,t}^{RD} - \sum_l \text{GSF}_{(n:j \in J_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) + \mu_{j,t}^{dn-} + \mu_{j,t}^{dn+} = 0, \forall t, \forall j \quad (46)$$

$$\text{VoLL} - \lambda_{0,t}^{RD} + \sum_l \text{GSF}_{(n:j \in J_n),l} (\mu_{l,t}^{F+} - \mu_{l,t}^{F-}) + \alpha_j (-\mu_{j,t}^{up-} + \mu_{j,t}^{up+} - \mu_{j,t}^{dn-} + \mu_{j,t}^{dn+}) - \mu_{j,t}^{un-} + \mu_{j,t}^{un+} = 0, \forall t, \forall j \quad (47)$$

LL2 complementarity constraints:

$$0 \leq -\sum_n \text{GSF}_{n,l} \left[g_{i \in I_n,t} + r_{i \in I_n,t}^{up} - r_{i \in I_n,t}^{dn} + \sum_{i- \in I-n} (g_{i-,t} + r_{i-,t}^{up} - r_{i-,t}^{dn}) + \sum_{k \in K_n} (g_{k,t} + r_{k,t}^{up} - r_{k,t}^{dn}) - \sum_{j \in J_n} (d_{j,t} + d_{j,t}^{dn} - d_{j,t}^{up} - d_{j,t}^{un}) \right] + F_l^{max} \perp \mu_{l,t}^{F+} \geq 0, \forall t, \forall l \quad (48)$$

$$0 \leq \sum_n \text{GSF}_{n,l} \left[g_{i \in I_n,t} + r_{i \in I_n,t}^{up} - r_{i \in I_n,t}^{dn} + \sum_{i- \in I-n} (g_{i-,t} + r_{i-,t}^{up} - r_{i-,t}^{dn}) + \sum_{k \in K_n} (g_{k,t} + r_{k,t}^{up} - r_{k,t}^{dn}) - \sum_{j \in J_n} (d_{j,t} + d_{j,t}^{dn} - d_{j,t}^{up} - d_{j,t}^{un}) \right] + F_l^{max} \perp \mu_{l,t}^{F-} \geq 0, \forall t, \forall l \quad (49)$$

$$0 \leq r_{i,t}^{up} \perp \mu_{i,t}^{up-} \geq 0, \forall t \quad (50)$$

$$0 \leq -r_{i,t}^{up} + g_i^{max} - g_{i,t} \perp \mu_{i,t}^{up+} \geq 0, \forall t \quad (51)$$

$$0 \leq r_{i,t}^{dn} \perp \mu_{i,t}^{dn-} \geq 0, \forall t \quad (52)$$

$$0 \leq -r_{i,t}^{dn} + g_{i,t} \perp \mu_{i,t}^{dn+} \geq 0, \forall t \quad (53)$$

$$0 \leq r_{i-,t}^{up} \perp \mu_{i-,t}^{up-} \geq 0, \forall t, \forall i- \quad (54)$$

$$0 \leq -r_{i-,t}^{up} + g_{i-,t}^{max} - g_{i-,t} \perp \mu_{i-,t}^{up+} \geq 0, \forall t, \forall i- \quad (55)$$

$$0 \leq r_{i-,t}^{dn} \perp \mu_{i-,t}^{dn-} \geq 0, \forall t, \forall i- \quad (56)$$

$$0 \leq -r_{i-,t}^{dn} + g_{i-,t} \perp \mu_{i-,t}^{dn+} \geq 0, \forall t, \forall i- \quad (57)$$

$$0 \leq r_{k,t}^{up} \perp \mu_{k,t}^{up-} \geq 0, \forall t, \forall k \quad (58)$$

$$0 \leq -r_{k,t}^{up} + g_{k,t}^{max} - g_{k,t} \perp \mu_{k,t}^{up+} \geq 0, \forall t, \forall k \quad (59)$$

$$0 \leq r_{k,t}^{dn} \perp \mu_{k,t}^{dn-} \geq 0, \forall t, \forall k \quad (60)$$

$$0 \leq -r_{k,t}^{dn} + g_{k,t} \perp \mu_{k,t}^{dn+} \geq 0, \forall t, \forall k \quad (61)$$

$$0 \leq d_{j,t}^{up} \perp \mu_{j,t}^{up-} \geq 0, \forall t, \forall j \quad (62)$$

$$0 \leq \alpha_j(d_{j,t} - d_{j,t}^{un}) - d_{j,t}^{up} \perp \mu_{j,t}^{up+} \geq 0, \forall t, \forall j \quad (63)$$

$$0 \leq d_{j,t}^{dn} \perp \mu_{j,t}^{dn-} \geq 0, \forall t, \forall j \quad (64)$$

$$0 \leq \alpha_j(d_{j,t} - d_{j,t}^{un}) - d_{j,t}^{dn} \perp \mu_{j,t}^{dn+} \geq 0, \forall t, \forall j \quad (65)$$

$$0 \leq d_{j,t}^{un} \perp \mu_{j,t}^{un-} \geq 0, \forall t, \forall j \quad (66)$$

$$0 \leq -d_{j,t}^{un} + d_{j,t} \perp \mu_{j,t}^{un+} \geq 0, \forall t, \forall j \quad (67)$$

The MPEC shares the same objective function as the UL problem. The set of decision variables (25) includes the decision variables of the UL, LL1, and LL2, along with the dual variables (26) associated with the constraints of LL1 and LL2. The KKT optimality conditions are expressed by (27)–(38) and (39)–(67), for LL1 and LL2, respectively.

2.4. MILP Model of the Strategic Producer

Since the above MPEC model is non-linear, we convert it to a MILP model which can be effectively solved through commercial solvers. Specifically, the MPEC model includes three different categories of non-linearities which we address through suitable linearization techniques. The first one involves the bi-linear term $\sum_t \lambda_t^{DA} g_{i,t}$ in the objective function (24). This term is linearized by applying the strong duality theorem to LL1 and exploiting the KKT conditions (31) and (32), as follows (full derivation provided in Appendix A):

$$\begin{aligned} \sum_t \lambda_t^{DA} g_{i,t} = & \sum_{j,t} \lambda_j^D d_{j,t} - \sum_{i-,t} g_{i-,t}^{max} \mu_{i-,t}^{G+} - \sum_{k,t} g_{k,t}^{max} \mu_{k,t}^{G+} - \\ & \sum_{j,t} d_{j,t}^{max} \mu_{j,t}^{D+} - \sum_{i-,t} \lambda_{i-}^G g_{i-,t} - \sum_{k,t} \lambda_k^G g_{k,t} \end{aligned} \quad (68)$$

The second non-linearity involves the bi-linear terms $\sum_t k_{i,t}^{up} r_{i,t}^{up}$ and $\sum_t k_{i,t}^{dn} r_{i,t}^{dn}$ in the objective function (24). These terms are linearized through binary expansion [33]. This technique requires introducing the auxiliary variables:

$$\Xi^{BE} = \{x_{b,i,t}^{up}, x_{b,i,t}^{dn}, z_{b,i,t}^{up}, z_{b,i,t}^{dn}\} \quad (69)$$

where $x_{b,i,t}^{up} \in \{0, 1\} \forall b, \forall t$ and $x_{b,i,t}^{dn} \in \{0, 1\} \forall b, \forall t$ are binary variables and $z_{b,i,t}^{up}$ and $z_{b,i,t}^{dn}$ are linear dummy variables. Let $\{k_{b,i}^{up}, b = 1, 2, \dots, B\}$ and $\{k_{b,i}^{dn}, b = 1, 2, \dots, B\}$ be two sets of B discrete values in the range $[k_i^{up,min}, k_i^{up,max}]$ and $[k_i^{dn,min}, k_i^{dn,max}]$, respectively. Then, the variables $k_{i,t}^{up}$ and $k_{i,t}^{dn}$ can be replaced with the following sums of binary variables:

$$k_{i,t}^{up} = k_i^{up,min} + \sum_{b=0}^{\log_2 B - 1} 2^b \Delta_i^{up} x_{b,i,t}^{up}, \forall t, \forall b \quad (70)$$

$$k_{i,t}^{dn} = k_i^{dn,min} + \sum_{b=0}^{\log_2 B-1} 2^b \Delta_i^{dn} x_{b,i,t}^{dn}, \forall t, \forall b \quad (71)$$

where $\Delta_i^{up} = (k_i^{up,max} - k_i^{up,min})/B$ and $\Delta_i^{dn} = (k_i^{dn,max} - k_i^{dn,min})/B$. Multiplying both sides of (70) and (71) by $r_{i,t}^{up}$ and $r_{i,t}^{dn}$, respectively, summing for every t , and defining the new dummy variables $z_{b,i,t}^{up}$ and $z_{b,i,t}^{dn}$, results in:

$$\sum_t k_{i,t}^{up} r_{i,t}^{up} = k_i^{up,min} + \sum_{t,b} 2^b \Delta_i^{up} z_{b,i,t}^{up}, \quad (72)$$

$$\sum_t k_{i,t}^{dn} r_{i,t}^{dn} = k_i^{dn,min} + \sum_{t,b} 2^b \Delta_i^{dn} z_{b,i,t}^{dn}, \quad (73)$$

$$z_{b,i,t}^{up} = x_{b,i,t}^{up} r_{i,t}^{up}, \forall t, \forall b \quad (74)$$

$$z_{b,i,t}^{dn} = x_{b,i,t}^{dn} r_{i,t}^{dn}, \forall t, \forall b \quad (75)$$

Therefore, the bilinear terms $\sum_t k_{i,t}^{up} r_{i,t}^{up}$ and $\sum_t k_{i,t}^{dn} r_{i,t}^{dn}$ can be replaced by their discrete approximation, on the right side of (72) and (73), respectively. The product of variables in (74) and (75) can be transformed into the following equivalent mixed-integer linear constraints:

$$0 \leq r_{i,t}^{up} - z_{b,i,t}^{up} \leq G(1 - x_{b,i,t}^{up}), \forall t, \forall b \quad (76)$$

$$0 \leq z_{b,i,t}^{up} \leq Gx_{b,i,t}^{up}, \forall t, \forall b \quad (77)$$

$$0 \leq r_{i,t}^{dn} - z_{b,i,t}^{dn} \leq G(1 - x_{b,i,t}^{dn}), \forall t, \forall b \quad (78)$$

$$0 \leq z_{b,i,t}^{dn} \leq Gx_{b,i,t}^{dn}, \forall t, \forall b \quad (79)$$

where G is a positive constant that is large enough for the constraints (76) and (78) to be relaxed when $x_{b,i,t}^{up} = 0$ and $x_{b,i,t}^{dn} = 0$, and for the constraints (77) and (79) to be relaxed when $x_{b,i,t}^{up} = 1$ and $x_{b,i,t}^{dn} = 1$, respectively.

The third non-linearity involves the bi-linear terms in the complementarity conditions (31)–(38) and (48)–(67), which can be expressed in the general form $0 \leq \mu \perp p \geq 0$, with μ and p representing generic dual and primal terms respectively. They are linearized using the Fortuny-Amat approach [34] (i.e., *big-M*). By introducing an auxiliary binary variable θ , each of these conditions is replaced with the set of mixed-integer linear expressions $\mu \geq 0, p \geq 0, \mu \leq \theta M^\mu, p \leq (1 - \theta)M$ where M^μ and M are large positive constants.

3. Small-Scale Case Study

This section presents a simple case study to illustrate the effects of DF in mitigating Inc-Dec gaming, considering the 2-node system illustrated in Figure 2 and a simplified market involving only 2 time periods (a peak period $t = 1$ and an off-peak period $t = 2$) for both DA and RD markets. In this case study, the strategic producer i (which employs the model of Section 2 to optimize its bidding decisions) is connected to the import-constrained node 2. This producer is assumed to have a lower marginal cost than the other competing producer $i-$, connected to node 1.

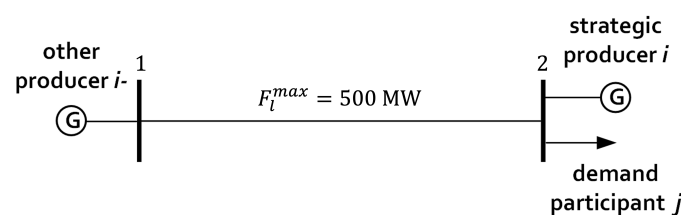


Figure 2. Illustration of the 2-node system.

The parameters of the two producers and the single demand participant j are presented in Tables 2 and 3. For the binary expansion of the linear variables $k_{i,t}^{up}$ and $k_{i,t}^{dn}$ (Section 2.4), we employ $k_{i,t}^{up,min} = k_{i,t}^{dn,min} = -2.5$, $k_{i,t}^{up,max} = k_{i,t}^{dn,max} = 2.5$, and $B = 1024$. In order to comprehensively assess the role of DF in addressing Inc-Dec gaming, we implement and compare three different scenarios:

- *Benchmark*: all producers behave competitively in both DA and RD markets, while the demand does not exhibit any DF. This scenario is implemented by forcing $k_{i,t} = k_{i,t}^{up} = k_{i,t}^{dn} = 1, \forall t$ in the proposed model, as well as setting $\alpha_j = 0$
- *Strategic*: the producer connected to node 2 behaves strategically in the DA and RD markets by employing the proposed model with $k_{i,t}$, $k_{i,t}^{up}$, $k_{i,t}^{dn}$ being decision variables. The demand does not exhibit any DF ($\alpha_j = 0$).
- *Strategic+DF*: the producer connected to node 2 behaves strategically in the DA and RD markets, and the demand exhibits DF characterized by $\alpha_j = 0.2$.

Table 2. Producers' parameters in the 2-node system.

	Producer i	Producer $i-$
Marginal cost [£/MWh]	10	15
Maximum power [MW]	1200	1200

Table 3. Demand parameters in the 2-node system.

	$t = 1$	$t = 2$
Marginal benefit [£/MWh]		10,000
Upward discomfort cost [£/MWh]	0.5	1
Downward discomfort cost [£/MWh]	1	0.5
Maximum baseline power [MW]	1000	400
VoLL [£/MWh]		16,050

In this study, the three modelled scenarios represent different stages in the evolution of the European RD market. The *Benchmark* scenario reflects a design with cost-based, ex-post remuneration mechanisms for RD. The *Strategic* scenario corresponds to the current configuration of early generation-only RD markets. Finally, the *Strategic+DF* scenario illustrates a more advanced market in which flexible demand participates on a level-playing field with generation in RD processes. Strategic behaviour may emerge in the latter two.

3.1. Increase-Decrease (Inc-Dec) Gaming

The effects of Inc-Dec gaming are demonstrated by comparing results from the scenario *Strategic* against those from the scenario *Benchmark*, thus neglecting for now DF. These results are presented in Tables 4 and 5. In the *Benchmark* scenario, where both producers act competitively, producer i supplies the entire demand in each period of the DA market due to its lower marginal cost, while producer $i-$'s offers are not accepted (Table 4). As a result, the network is not subject to any congestion, RD actions are unnecessary, and the daily system cost (£14,000) consists only of the DA market cost (Table 4). The producer connected to node 2 is the marginal producer and does not provide any RD power, therefore achieving a net daily profit of zero (Table 5).

Table 4. System Outcome in 2-Node Case Study.

Scenario	Benchmark		Strategic		Strategic+DF	
Period	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
$g_{i,t}$ [MW]	1000	400	0	400	0	400
$r_{i,t}^{up}$ [MW]	0	0	500	0	420	80
$r_{i,t}^{dn}$ [MW]	0	0	0	0	0	0
$g_{i-,t}$ [MW]	0	0	1000	0	1000	0
$r_{i-,t}^{up}$ [MW]	0	0	0	0	0	0
$r_{i-,t}^{dn}$ [MW]	0	0	500	0	500	0
$d_{j,t}$ [MW]	1000	400	1000	400	1000	400
$d_{j,t}^{up}$ [MW]	–	–	–	–	80	0
$d_{j,t}^{dn}$ [MW]	–	–	–	–	0	80
λ_t^{DA} [£/MW]	10	10	15	15	15	15
System costs [£]						
DA	10,000	4000	15,000	6000	15,000	6000
RD	0	0	5000	0	3040	1240
Total	10,000	4000	20,000	6000	18,040	7240
Daily total	14,000		26,000		25,280	

In the scenario *Strategic*, where producer i bids strategically, an instance of Inc-Dec gaming emerges at the peak period $t = 1$. Specifically, the strategic producer overbids in the DA market (i.e., it offers a price higher than its marginal cost, as indicated by the strategic variable $k_{i,t} = 1.5$, in Table 5), thereby ensuring exclusion from the DA accepted offers (i.e., economic withholding). As a consequence, the whole demand at this period is covered by the competing producer connected to node 1 (Table 4) therefore creating congestion in line l to be resolved through RD actions. The strategic producer then exploits this situation by offering upward RD at the highest possible price (as indicated by the strategic variable $k_{i,1}^{up} = k_i^{up,max} = 2.5$, in Table 5).

Consequently, it earns a profit of £7500 at $t = 1$ (which is entirely achieved in the RD market) while its respective profit in the scenario *Benchmark* was zero. Note that the strategic producer also earns a positive profit at $t = 2$, but this is driven by mere overbidding in the DA market and not Inc-Dec gaming and thus is not discussed further. Overall, the daily system cost in this scenario is increased to £26,000, compared with £14,000 in the *Benchmark* scenario, with the largest part of this negative effect attributable to the Inc-Dec gaming instance at $t = 1$.

Table 5. Strategic Producer's Outcome in 2-Node Case Study.

Scenario	Benchmark		Strategic		Strategic+DF	
Period	$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
$k_{i,t}$	1.00	1.00	1.50	1.50	1.50	1.50
$k_{i,t}^{up}$	–	–	2.50	–	2.50	1.50
$k_{i,t}^{dn}$	–	–	–	–	–	–
Revenues and costs [£]						
Revenue DA	10,000	4000	0	6000	0	6000
Cost DA	10,000	4000	0	4000	0	4000
Revenue RD	0	0	12,500	0	10,500	1200
Cost RD	0	0	5000	0	4200	800
Profit	0	0	7500	2000	6300	2400
Daily profit	0		9500		8700	

3.2. Role of DF in Addressing Inc-Dec Gaming

Similar to the scenario *Strategic* (discussed in Section 3.1), the strategic producer still engages in Inc-Dec gaming during the peak period ($t = 1$) in the scenario *Strategic+DF*. However, the demand participant now contributes to the upward RD during this period by reducing its demand by $d_{j,1}^{up} = 80$ MW (Table 4), which represents its maximum possible alteration from the DA clearing, under the DF constraints (20)–(22). Consequently, the strategic producer's upward RD activation decreases from 500 MW to 420 MW (Table 4), which reduces its profit during this period from £7500 to £6300 (Table 5).

Nevertheless, due to the energy neutrality constraint of DF (20), the demand participant needs to increase its demand by $d_{j,2}^{dn} = 80$ MW at the off-peak period $t = 2$. Therefore, considering the RD balance constraint (12), the strategic producer exploits this situation by offering upward RD of the same amount (Table 4). However, note that this offer is not made at the highest possible price but at a lower one (as indicated by the strategic variable $k_{i,2}^{up} = 1.5$ in Table 5), as a higher offer would render the strategic producer out of the RD merit order and the required upward RD would be provided by the competing producer i — (in the off-peak period the two nodes are not decoupled by network congestion). As a result, its profit at this period is increased from £2000 to £2400.

Considering both time periods, although DF does not affect the overall consumption (the demand reduction at $t = 1$ is equal to the demand increase at $t = 2$), it yields a positive impact in terms of mitigating Inc-Dec gaming, since the overall profit of the strategic producer is reduced from £9500 to £8700 (Table 5) as the profit reduction during the peak period outweighs the profit increase during the off-peak period. This positive impact is also reflected on the overall system cost, which is reduced from £26,000 to £25,280 (Table 4).

4. Large-Scale Case Study

This section aims at demonstrating the applicability of the proposed model and the role of DF in addressing Inc-Dec gaming through a large-scale and more realistic case study. We consider a 24-h market horizon and the modified IEEE RTS 24-node system illustrated in Figure 3. The various parameters of the network (including reactance and capacity of each line), conventional producers (including the marginal cost and maximum power output of each producer), wind producers (including the profile and distribution by node), and the demand units (including the maximum baseline profile and demand distribution by node), are based on [35–37] and provided in Appendix B.

As in the small-scale case study (Section 3), three similar scenarios (*Benchmark*, *Strategic*, *Strategic+DF*) are compared. In the latter two scenarios, we assume that producer $i = 9$ connected to node 18 (highlighted in yellow in Figure 3) acts as a strategic producer. This producer has the highest marginal cost among all producers (Table A4), in contrast to the small-scale case study where the strategic producer had the lowest marginal cost. This choice is made intentionally to demonstrate that Inc-Dec gaming is relevant to producers with different positions in the merit order. In addition, to evaluate how DF affects the economics of the RD market in the presence of Inc-Dec gaming, in the scenario *Strategic+DF*, demand participants connected to node 10, 13, and 15 (indicated in green in Figure 3) exhibit DF characterized by $a_j = 0.2$. The upward and downward discomfort costs for DF range from 0 £/MW to 1 £/MW within the day, and follow the rationale of [31]. Specifically, shifting demand away from a period incurs a discomfort cost proportional to the inverse of that period's baseline demand, whereas shifting demand toward a period incurs a cost proportional to the baseline itself. The wind producers k are assumed to have a marginal cost of zero. The lines connecting node pairs (14, 16) and (15, 21) constitute critical network elements, as they are congested during certain hours even under perfect competition assumptions (i.e., in the *Benchmark* scenario).

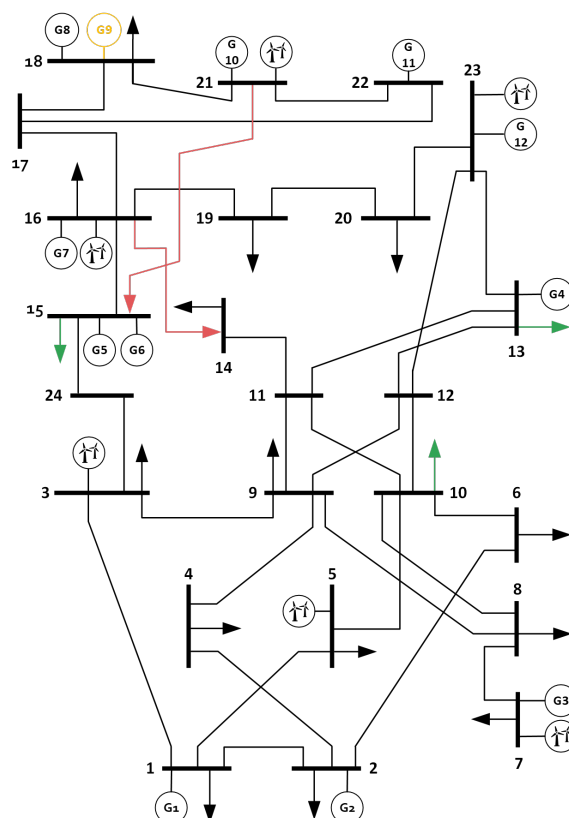


Figure 3. Illustration of the modified IEEE RTS 24-node system.

These lines are shown in red in Figure 3, with arrows indicating the direction of power flow during hours with grid congestion. Specifically, congestion on these lines is caused by power flows from the north-western (nodes 16–18 and 21–22) to the southern part of the system, since 74% of the system demand is located south of the critical network elements (nodes 1–15 and 24), where only 37% of the installed generation capacity is located.

Considering the most generic scenario *Strategic+DF*, the proposed MILP model (Section 2.4) has 11,033 continuous variables, 7968 binary variables, and 18,569 constraints. This model has been implemented using the GUROBI Python Interface [38] and solved through the Gurobi Optimizer solver on a computer with a 28-core 2.6 GHz Intel Xeon processor and 512 GB of RAM. This scenario has been solved in 1931 s with the mixed-integer programming gap set to 1%.

4.1. Increase-Decrease (Inc-Dec) Gaming

As in the small-scale case study presented in Section 3, the effects of Inc-Dec gaming are demonstrated by comparing the scenario *Strategic* against the scenario *Benchmark*. In the latter, the offers of the examined producer 9 are not accepted in either the DA or RD market throughout the day, as it exhibits the highest marginal cost. Consequently, it achieves a daily profit of zero (Table 6).

In the scenario *Strategic*, Inc-Dec gaming emerges during hours 07:00–23:00. Specifically, the strategic producer underbids in the DA market (i.e., it offers a price lower than its marginal cost, as indicated by the strategic variables $k_{i,t} < 1$ in Table 7) in order to ensure its offers are accepted in the DA clearing. Figure 4a shows the DA clearing by producers' category, i.e., wind producers k , strategic producer $i = 9$, and all other conventional producers $i-$. As a consequence, during these hours, the DA dispatch of conventional producers $i-$ at nodes 2, 7, 15, 16, and 23 is replaced by dispatch of strategic producer $i = 9$, and the overall extent of congestion is increased by 107% with respect to the *Benchmark* scenario (Table 6).

Table 6. Results of IEEE 24-Node Case Study.

Scenario	Benchmark	Strategic	Strategic+DF
Producer 9 results			
DA Profit [£]	0	−43,630	−43,630
RD Profit [£]	0	82,738	84,465
Total Profit [£]	0	39,108	40,834
System results			
Congestion [MW]	3399	7049	7049
DA cost [£]	748,058	706,372	706,372
RD cost [£]	39,284	81,228	74,981
Total cost [£]	787,342	787,599	781,353

Specifically, as illustrated in Figure 4b, the strategic action of producer $i = 9$ exacerbates congestion on lines (14, 16) and (15, 21), while also inducing additional congestion on lines (16, 17) and (13, 23). The strategic producer then exploits this situation by offering downward RD at an average price of 7.69 £/MWh (as indicated by the average $k_{i,t}^{dn}$ value of 0.29, Table 7). As a result, producer $i = 9$ is redispatched downwards in hours 07:00–23:00, as illustrated in Table 7 and in the left chart of Figure 5.

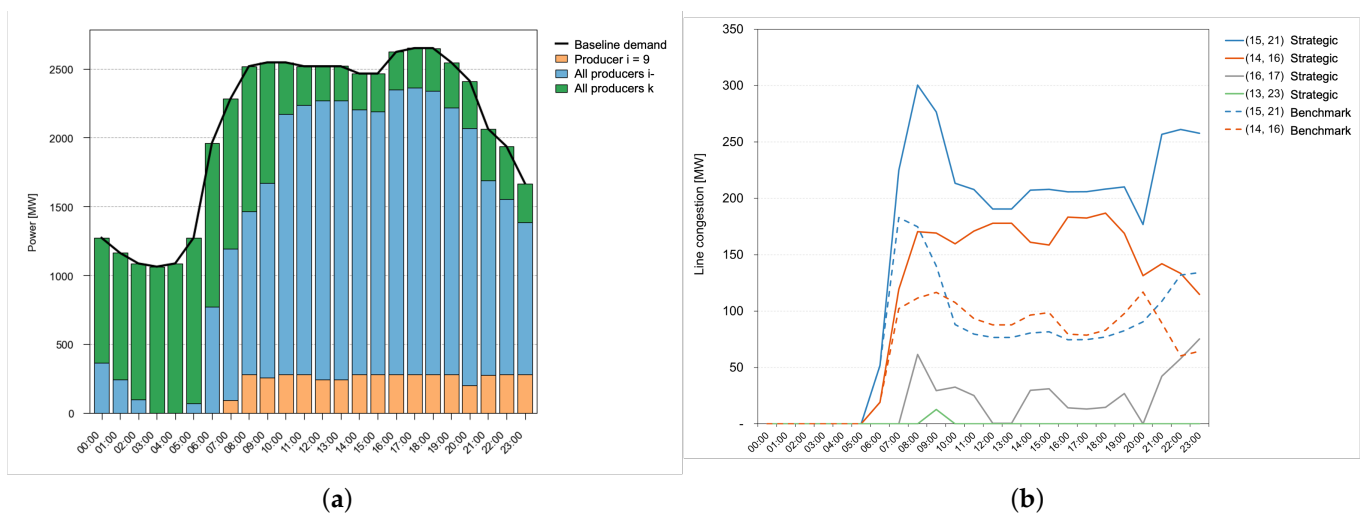


Figure 4. (a) Day-ahead market clearing under the scenario *Strategic* (same in the scenario *Strategic+DF*). (b) Hourly congestion extent for different lines under the scenarios *Benchmark* and *Strategic*.

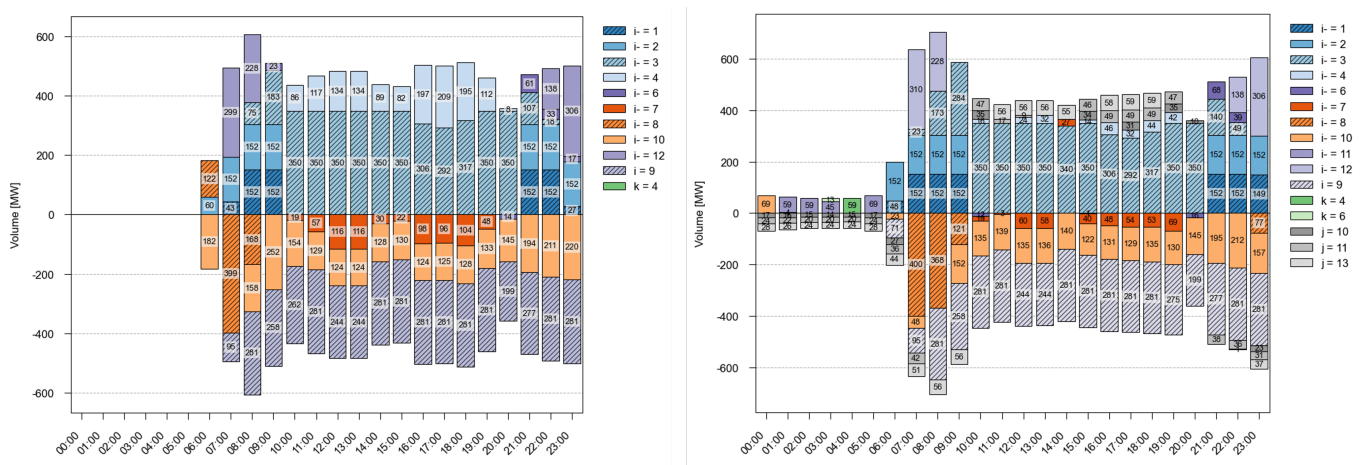


Figure 5. Redispatch market activations under the scenarios *Strategic* (left) and *Strategic+DF* (right).

Although it incurs losses in the DA market (due to underbidding), its total daily profit increases from zero (*Benchmark* scenario) to £39,108. This instance of Inc-Dec gaming increases the daily RD cost from £39,284 to £81,228 (Table 6).

Table 7. Hourly results in the large-scale case study. Left: day-ahead (DA) outcomes ($k_{i,t}$, $g_{i,t}$, λ_t^{DA}), which are identical in *Strategic* (S) and *Strategic+DF* (S+DF). Right: redispatch (RD) outcomes ($k_{i,t}^{\text{dn}}$, $r_{i,t}^{\text{dn}}$, P^{RD}) shown separately for S and S+DF. P^{DA} and P^{RD} denote DA and RD profits, respectively.

t	$k_{i,t}$	$g_{i,t}^S$ [MW]	λ_t^{DA} [£/MW]	P^{DA} [£]	$k_{i,t}^{\text{dn}}$		$r_{i,t}^{\text{dn}}$ [MW]		P^{RD} [£]	
					S	S+DF	S	S+DF	S	S+DF
00:00	–	0	5.47	0	–	–	0	0	0	0
01:00	–	0	0.50	0	–	–	0	0	0	0
02:00	–	0	0.50	0	–	–	0	0	0	0
03:00	–	0	0.00	0	–	–	0	0	0	0
04:00	–	0	0.00	0	–	–	0	0	0	0
05:00	–	0	0.50	0	–	–	0	0	0	0
06:00	–	0	6.02	0	–	–	0	0	0	0
07:00	0.40	95	10.52	–1518	0.23	0.21	95	95	1940	2001
08:00	0.40	281	10.52	–4490	0.23	0.23	281	281	5738	5738
09:00	0.43	258	11.32	–3916	0.25	0.23	258	258	5134	5268
10:00	0.70	281	18.52	–2242	0.25	0.25	262	281	5214	5592
11:00	0.70	281	18.52	–2242	0.32	0.32	281	281	5047	5047
12:00	0.78	244	20.70	–1415	0.32	0.32	244	244	4382	4382
13:00	0.78	244	20.70	–1415	0.32	0.32	244	244	4382	4382
14:00	0.70	281	18.52	–2242	0.32	0.32	281	281	5047	5047
15:00	0.70	281	18.52	–2242	0.32	0.25	281	281	5047	5592
16:00	0.78	281	20.70	–1630	0.32	0.32	281	281	5047	5047
17:00	0.78	281	20.70	–1630	0.32	0.32	281	281	5047	5047
18:00	0.78	281	20.70	–1630	0.32	0.32	281	281	5047	5047
19:00	0.70	281	18.52	–2242	0.32	0.25	281	275	5047	5473
20:00	0.70	199	18.52	–1588	0.25	0.25	199	199	3960	3960
21:00	0.43	277	11.32	–4205	0.25	0.25	277	277	5513	5513
22:00	0.40	281	10.52	–4490	0.25	0.25	281	281	5592	5592
23:00	0.40	281	10.52	–4490	0.25	0.23	281	281	5556	5738

4.2. Role of DF in Addressing Inc-Dec Gaming

In the scenario *Strategic+DF* the DA market clearing does not change with respect to the scenario *Strategic* (Figure 4a and left side of Table 6). However, for what concerns the RD market, results in Tables 6 and 7, together with Figure 5, indicate two important effects of DF.

With respect to system costs, the introduction of DF lowers RD costs by 8% (from £81,228 to £74,981, Table 6) over the 24-h period. The right chart of Figure 5 shows that in peak hours 10:00–20:00 the flexible demand units are activated upwards (i.e., demand is reduced). This yields two economic advantages: (i) it reduces upward RD reliance on peaking producer $i- = 4$ (whose marginal cost is 20.93 £/MWh). This producer is slightly more expensive than the other producer providing upward RD in those hours ($i- = 3$), and considerably more expensive than DF, thereby lowering the effective cost of upward RD. (ii) In most of the hours (e.g., 13:00), it also reduces the total volume of RD required. The latter is due to the higher congestion-relief effectiveness of DF, as part of it is located at node 15, which is directly connected to a congested line and thus associated with a high GSF.

In off-peak and shoulder hours 00:00–06:00 and 21:00–23:00, owing to the energy-neutrality constraint (20), DF is activated downwards (i.e., demand increases). This additional consumption is supplied primarily by low-cost conventional producers ($i- = 1, 2, 10, 11$, with marginal costs between 0.50 £/MWh and 13.32 £/MWh) and wind

producers ($k = 4, 6$) that bid at zero, allowing DF to absorb low-priced energy. Notably, the upward RD of wind producers in hours 04:00–05:00 illustrates DF's ability to reduce day-ahead wind curtailment (Figure 5).

Therefore, as in the small-scale case study, the RD cost reduction driven by DF during peak hours outweighs the RD cost increase during off-peak hours, resulting in an overall positive effect of DF in terms of system costs.

With respect to the profit of the strategic producer, a counter intuitive result emerges: although DF reduces the total RD cost of the system, the profit of the strategic producer in the RD market increases. This is because, thanks to the two system-level economic benefits explained above, the cost per MW of congestion relief decreases in the *Strategic+DF* scenario.

This enables the strategic producer $i = 9$ to slightly adjust its offers in a more convenient way while still remaining selected in the TSO's optimal RD bundle solution. For example, in hours 15:00 and 19:00, the downward strategic variable $k_{i,t}^{dn}$ is reduced from 0.32 to 0.25 (Table 6). By lowering $k_{i,t}^{dn}$, producer $i = 9$ captures a higher profit $r_{i,t}^{dn}(1 - k_{i,t}^{dn})\lambda_i^G$, under pay-as-bid downward RD. In particular, its profit increases by approximately 4%, from £39,108 to £40,834, when DF participates in the RD market in this case study (Table 7).

5. Conclusions and Future Work

Despite increasing attention on the rising costs of redispatch in the European electricity markets and the impact of Inc-Dec gaming, existing literature solely focuses on market models with single time period analyses and is therefore unable to consider demand-side redispatch. As a result, those models fail to fully capture the redispatch markets economics, particularly the role of demand-side integration and the costs associated with Inc-Dec strategies.

This paper introduces a novel optimization model that extends existing Inc-Dec gaming models across multiple time periods and integrates technology-agnostic demand flexibility characteristics into a bi-level market modeling structure. The model features two lower-level problems representing the day-ahead and redispatch markets clearing and employs binary expansion techniques to linearize equations relating to pay-as-bid redispatch decisions. The resulting MILP formulation is tractable using commercial solvers and the proposed approach is demonstrated through two case studies.

These case studies show that Inc-Dec gaming emerges as the optimal strategy for producers located in import-constrained nodes of a small network (Section 3), as well as producers in a larger network with critical network elements (Section 4). In both situations, the activity of the strategic producer worsens grid congestion; a situation that the producer exploits to increase its profit, thereby distorting market outcomes. The large-scale case study also demonstrates that possessing market power in the day-ahead market is not a prerequisite for engaging in Inc-Dec gaming, as profit opportunities can arise purely from the locational and temporal structure of redispatch price signals.

From the system perspective, the introduction of demand flexibility in the redispatch stage, decreases total redispatch costs (around 8% in the case study of Section 4). This goes hand in hand with a reduction of Inc-Dec gaming in the case study of Section 3. Conversely, in the large-scale case (Section 4), a small exploitable bidding slack persists, enabling a marginal increase in strategic profit despite an unchanged congestion pattern.

These model-based findings depend on the specific market design assumptions and parameter settings adopted. Future work aims at enhancing the presented model in two directions. First of all, uncertainty in demand and renewable generation will be incorporated in the developed model and solution. As part of this work, the model will be extended by incorporating demand flexibility also in the day-ahead stage. Secondly, future work should also explore multi-agent strategic behaviour, for example through an

EPEC-based extension of the presented model. Finally, this paper examines one possible measure to mitigate Inc–Dec gaming, namely increasing competition through the inclusion of demand-side flexibility, future research should focus on the evaluation of other market design measures.

Author Contributions: Conceptualization, formal analysis, investigation, data curation, writing—original draft preparation, L.P.; methodology, validation, L.P. and D.P.; software, L.P. and D.Q.; writing—review and editing, L.P., D.P. and V.T.; supervision, D.P. and G.S.; project administration, G.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All data supporting the reported results of this study can be found in the article and its Appendix B.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACER	EU Agency for the Cooperation of Energy Regulators
DA	Day-ahead
DF	Demand flexibility
EPEC	Equilibrium Problem with Equilibrium Constraints
GSF	Generation Shift Factor
KKT	Karush–Kuhn–Tucker
LL	Lower Level
MILP	Mixed-Integer Linear Programming
MPEC	Mathematical Program with Equilibrium Constraints
TSO	Transmission System Operator
RD	Redispatch
UL	Upper Level

Appendix A. Strong Duality Applied to Day-Ahead Revenues

The bi-linear term in (24) representing revenues from the day-ahead market is $(\lambda_t^{DA} - \lambda_t^G)g_{i,t}$. This term can be linearised by adopting linearization techniques exploiting the strong duality theorem [39] of LL1. As a first step, by multiplying both sides of (27) by $g_{i,t}$, summing all terms over t , and applying the constraints in (31) and (32) the following expression is obtained:

$$\sum_t \lambda_t^{DA} g_{i,t} = \sum_t \mu_{i,t}^{G+} g_i^{max} + \sum_t k_{i,t} \lambda_i^G g_{i,t} \quad (A1)$$

Applying the strong duality theorem to LL1 we have that:

$$\begin{aligned} \sum_t k_{i,t} \lambda_i^G g_{i,t} + \sum_{i-,t} \lambda_{i-}^G g_{i-,t} + \sum_{k,t} \lambda_k^G g_{k,t} - \sum_{j,t} \lambda_j^D d_{j,t} = \\ - \sum_t g_i^{max} \mu_{i,t}^{G+} - \sum_{i-,t} g_{i-}^{max} \mu_{i-,t}^{G+} \\ - \sum_{k,t} g_{k,t}^{max} \mu_{k,t}^{G+} - \sum_{j,t} d_{j,t}^{max} \mu_{j,t}^{D+} \end{aligned} \quad (A2)$$

and therefore $\sum_t \lambda_t^{DA} g_{i,t}$ can be expressed in the exact linear form:

$$\sum_t \lambda_t^{DA} g_{i,t} = \sum_{j,t} \lambda_j^D d_{j,t} - \sum_{i-,t} g_{i-}^{max} \mu_{i-,t}^{G+} - \sum_{k,t} g_{k,t}^{max} \mu_{k,t}^{G+}$$

$$-\sum_{j,t} d_{j,t}^{max} \mu_{j,t}^{D+} - \sum_{i,t} \lambda_{i,t}^G g_{i,t} - \sum_{k,t} \lambda_{k,t}^G g_{k,t} \quad (A3)$$

Appendix B. Data Input IEEE 24-Nodes Case Study

The IEEE 24-bus RTS system (Figure 3), widely recognized for evaluating power system reliability and market performance, has been modified to reflect contemporary market conditions and regulatory policies in [36]. The input data includes detailed information on generation units, wind production profile, demand grid distribution and profile, network configurations, and system constraints. This documentation aims to enhance the transparency and reproducibility of the main study, providing a comprehensive resource for researchers analyzing similar market dynamics.

Table A1. Distribution of Installed Wind Capacity by Node.

Node	% of Wind Capacity
3	16.7
5	16.7
7	16.7
16	16.7
21	16.7
23	16.7

Table A2. System wind production profile.

Hour	Wind (MW)	Hour	Wind (MW)
1	907	13	250
2	925	14	250
3	986	15	263
4	1010	16	275
5	1037	17	275
6	1200	18	288
7	1190	19	313
8	1084	20	326
9	1055	21	344
10	876	22	376
11	376	23	382
12	282	24	284

Table A3. Network Parameters.

From Node	To Node	Reactance (p.u.)	Capacity (MW)
1	2	0.0146	175
1	3	0.2253	175
1	5	0.0907	350
2	4	0.1356	175
2	6	0.2050	175
3	9	0.1271	175
3	24	0.0840	400
4	9	0.1110	175
5	10	0.0940	350
6	10	0.0642	175
7	8	0.0652	350
8	9	0.1762	175
8	10	0.1762	175
9	11	0.0840	400

Table A3. *Cont.*

From Node	To Node	Reactance (p.u.)	Capacity (MW)
9	12	0.0840	400
10	11	0.0840	400
10	12	0.0840	400
11	13	0.0488	500
11	14	0.0426	500
12	13	0.0488	500
12	23	0.0985	500
13	23	0.0884	500
14	16	0.0594	500
15	16	0.0172	500
15	21	0.0249	1000
15	24	0.0529	500
16	17	0.0263	500
16	19	0.0234	500
17	18	0.0143	500
17	22	0.1069	500
18	21	0.0132	1000
19	20	0.0203	1000
20	23	0.0112	1000
21	22	0.0692	500

Table A4. Conventional Producers' Parameters.

Producer <i>i</i>	Node	Marginal Cost (£/MWh)	Maximum Output (MW)
1	1	13.32	152
2	2	11.32	152
3	7	20.70	350
4	13	20.93	591
5	15	26.11	60
6	15	12.52	155
7	16	18.52	155
8	18	6.02	400
9	18	26.50	281
10	21	5.47	400
11	22	0.50	300
12	23	10.52	300

Table A5. Distribution of System Demand by Node.

Demand <i>j</i>	Node	% of System Demand
1	1	3.8
2	2	3.4
3	3	6.3
4	4	2.6
5	5	2.5
6	6	4.8
7	7	4.4
8	8	6.0
9	9	6.1
10	10	6.8
11	13	9.3
12	14	6.8
13	15	11.1
14	16	3.5

Table A5. Cont.

Demand j	Node	% of System Demand
15	18	11.7
16	19	6.4
17	20	4.5

Table A6. Profile of Maximum Baseline Demand.

Hour	Demand (MW)	Hour	Demand (MW)
1	1272	13	2518
2	1166	14	2465
3	1087	15	2465
4	1069	16	2518
5	1087	17	2624
6	1272	18	2651
7	1961	19	2651
8	2279	20	2544
9	2518	21	2412
10	2651	22	2067
11	2624	23	1723
12	2597	24	1193

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