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Recovery Mechanisms in Day-Ahead Electricity Markets With Non-Convexities—Part II: Implementation and Numerical Evaluation

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***Abstract*—In centralized day-ahead electricity markets with marginal pricing, unit commitment costs and capacity constraints give rise to non-convexities which may result in losses to some of the participating generating units. To compensate them for these losses, a recovery mechanism is required. In Part I of this two-part paper, we present certain recovery mechanisms that result in recovery payments after the market is cleared. We also propose a methodology for evaluating the bidding strategy behavior of the participating units for each mechanism. In this paper (Part II), we apply this methodology to evaluate the performance and incentive compatibility properties of each recovery mechanism on a test case model representing the Greek joint energy/reserve day-ahead electricity market. Lastly, we perform sensitivity analysis with respect to key parameters and assumptions and we provide directions for further research.**

***Index Terms*—Day-ahead market, electricity market modeling and simulation, non-convexities, recovery mechanism, unit commitment.**

Nomenclature

Due to space considerations, the nomenclature is listed in Part I of this two-part paper [1].

I. Introduction

THIS is the second part of a two-part paper on the design and evaluation of recovery mechanisms in joint energy/reserve day-ahead electricity markets with non-convexities; a preliminary version of this work is presented in [2], [3].

In Part I [1], we discuss the need for a recovery mechanism in the presence of non-convexities, and we propose certain mechanism design options that result in recovery payments after the market is cleared under marginal cost pricing. The mechanisms differ in the type and amount of payments with which they reimburse each generating unit that exhibits losses. The main features of the mechanisms are summarized in Table I. In Part I we also propose a methodology aimed at evaluating the bidding strategy behavior of the participating units for each recovery mechanism. This methodology employs an iterative numerical algorithm aimed at finding the joint optimal bidding strategies of the profit-maximizing units.

In this paper (Part II), we use the methodology developed in Part I to evaluate the performance and incentive compatibility properties of the proposed mechanisms, by applying it on a test case that represents the Greek energy zonal electricity market. To make the optimization problem computationally tractable, we make certain simplifying assumptions, without loss of generality of the most important features of a realistic zonal market design. This analysis leads to results that allow us to gain insights and draw useful conclusions on the performance and incentive compatibility properties of the recovery mechanisms. Apart from their theoretical interest, these conclusions have significant practical implications, as various system operators often revisit the recovery mechanisms that they employ to attain a reasonable market outcome (e.g., see [4], [5] for recent proposals to modify the parameters or the rules of the recovery mechanisms used in California and Greece).

The remainder of this paper is organized as follows. In Section II, we present the test case market model and we state the main assumptions used in the implementation of the methodology. We also list the performance measures used for evaluating the mechanisms and discuss relevant computational issues. In Section III, we present the most important numerical results and discuss their implications regarding the performance and incentive compatibility properties of the mechanisms. We also take a closer look at the most promising mechanisms. In Section IV, we perform sensitivity analysis to explore the accuracy and extendability of our results. Lastly, in Section V, we summarize the most important findings, and provide directions for further research.

II. Implementation

In this section, we present: 1) the input data of the test case (Subsection A); 2) the assumptions of the implementation of the evaluation methodology (Subsection B); 3) the performance measures that are deployed to evaluate the different recovery mechanisms (Subsection C), and 4) computational issues that are related to the implementation of the evaluation methodology (Subsection D).

A. Test Case Data

The test case that we used to evaluate the recovery mechanisms represents a realistic model of the Greek energy zonal market [6]. Tables II and III contain generation unit data and the hourly energy and reserve requirements that are used as

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TABLE I
RECOVERY MECHANISMS

Mechanism	Conditions for RP ≥ 0	RP if conditions met	NPROF with RP	Regulating Parameter
A.1	REV – VC – CC < 0	$(1+\alpha_1)$VC + CC – REV	α_1·VC	α_1
A.2	REV – VC – CC < 0	$(1+\alpha_2)$(VC + CC – REV)	α_2 (VC + CC – REV)	α_2
B.1	REV – BID – CC < 0	BID + CC – REV	BID – VC	N/A
B.2	REV – BID – CC < 0 and $P^G_{u,h} \in [C^G_u, C^G_u + \beta]$	BID + CC – REV	BID – VC	β

NPROF: Net Profits; REV: Revenues; CC: Commitment Costs; VC: Variable Costs; RP: Recovery Payments; BID: Bids; N/A: Not Applicable.

TABLE II
UNITS' DATA (DAS INPUT)

Unit	$\bar{Q}^G_u$	$\underline{Q}^G_u$	$\bar{Q}^R_u$	C^G_u	MT^{UP}_u	C^{SU}_u	C^{NL}_u
U1	3800	2400	250	35	24	1 500 000	20 000
U2	377	240	137	49	3	13 000	500
U3	476	144	180	52	5	10 000	300
U4	550	155	180	55	5	25 000	350
U5	384	240	144	57	3	15 000	500
U6	151	65	45	64	16	18 000	150
U7	188	105	45	65	16	27 000	250
U8	287	120	10	70	8	50 000	600
U9	144	60	20	72	12	24 000	300
U10	141	0	141	150	0	5 000	200

TABLE III
ENERGY DEMAND AND RESERVE REQUIREMENTS

h	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
D^G_h	4200	3900	3800	3700	3700	3600	4000	4300	4800	5200	5550	5500
D^R_h	450	400	400	400	400	400	450	500	550	600	600	600
h	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
D^G_h	5450	5450	5300	5000	4950	4900	5000	5200	5100	5000	4800	4500
D^R_h	600	600	600	550	550	550	550	600	600	550	500	500

input to the *day-ahead scheduling* (DAS) market clearing problem. Quantities are given in MW, energy generation costs in €/MWh, and commitment costs in €. Minimum uptimes are given in hours and are considered equal to the minimum downtimes. In the Greek market model, the objective function does not include the startup cost; it only includes the shutdown cost with a value equal to the warm startup cost, to discourage DAS solutions from easily shutting down units [5], [7].

The number of thermal units in Greece is about 30. The lignite units serve as base units, and actual competition is mainly limited to the gas units. With this in mind, unit U1 in Table II is an aggregate representation of the available lignite units. Units U2, U3, U4 and U5 are combined cycle units, U6 and U7 are gas units, U8 and U9 are oil units, and U10 is a "peaker", i.e., a gas unit that can provide all its capacity to the tertiary reserve market. All units are classified into three types depending on their variable cost, as follows: 1) Type-L (low cost): U1; 2) Type-M (moderate cost): U2-U9, and 3) Type-H (high cost): U10.

Recovery mechanisms A.1, A.2 and B.2, shown in Table I, depend on a mechanism-specific regulating parameter (for details, see companion paper [1]). The values of these parameters for which we evaluated these mechanisms are:

Mechanism A.1: $\alpha_1 = 0\%$, 5%, and 10%.

Mechanism A.2: $\alpha_2 = 5\%$, 10%, and 100%. We did not try out $\alpha_2 = 0\%$, because mechanism A.2 with $\alpha_2 = 0\%$ is equivalent to A.1 with $\alpha_1 = 0\%$, as is mentioned in [1].

Mechanism B.2: $\beta = 3$, 6, and 9 $(€/\mathrm{MWh})$.

B. Assumptions

The main assumptions concerning the implementation of the evaluation methodology are stated below. These assumptions are mild and do not influence the general applicability of the methodology. They are designed to make the computations tractable and are tailored towards the specifics of the test case market model.

1) Assumption 1 (Initial Status of the Units): Initially:

a. All units, except U1, are offline; unit U1 is online to ensure a feasible solution.
b. All units that are initially online (offline) are assumed to be in this status long enough so that they can be shut down (started up) immediately.

Assumption 1.a is related to the aforementioned Greek market model feature that the shutdown cost is included in the objective function, whereas the startup cost is not. Given this feature, Assumption 1.a allows DAS to commit a unit right from the first hour. Assumption 1.b ensures that the initial values of the time counters (for the hours that the unit has been online/offline) will not affect the dispatching.

2) Assumption 2 (Bid Format): Each unit places:

a. a single price-quantity energy offer, which is the same for all periods; this offer must be between the unit's cost of energy generation and a price cap equal to 150 €/MWh, which is the current cap value in the Greek market;
b. a zero-priced reserve offer;
c. truthful commitment costs.

The behavior of offering the entire capacity at the same price for all periods is observed in the Greek energy market. Assumption 2.b eases the computational burden of the problem, and Assumption 2.c holds true if the commitment costs are auditable, which is true in most markets. Assumption 2, as a whole, significantly reduces the size of the problem.

3) Assumption 3 (Tie-Breaking Rule): If units submit equal bids, a tie-breaking rule favors the unit with the lower variable cost.

4) Assumption 4 (Bidding Strategies): The bidding strategy of each unit depends on its type as follows:

a. Type-L units (U1) always bid at their variable cost.

b. Type-M units (U2-U9) participate in the "repetitive game" described in Section IV of [1] with a profit-maximizing bidding strategy. More specifically, each type-M unit:
   (1) in the initial round, submits truthful price offers;
   (2) in each subsequent round, uses "brute-force" optimization to determine its optimal price offer, as follows:
      (a) it evaluates its net profit for each permissible price offer value between its variable cost and the cap, using an incremental step size of 1 €/MWh, assuming the other units remain at their optimal price offers from the previous round;
      (b) it selects as the optimal price offer the one that generates the highest net profit;
      (c) among all possible multiple price offers that generate equal profits, it selects the lowest.
c. Type-H units (U10) always bid at the price cap.

Assumptions 4.a and 4.c reflect current practice in the Greek market. Unit U1 always has profits, as it has the lowest cost, so it has little interest to bid over its variable cost and risk being shut down. Unit U10 is the last unit to be dispatched for energy, due to its high cost, so it risks bidding at the price cap; its revenues come mainly from the reserve market.

Assumption 4.b states that type-M units try different price offers, starting from their true variable cost, as they set out to find the offer which maximizes their profits. This process is consistent with our overall aim to evaluate the incentive compatibility properties of each mechanism, i.e., the extent to which the participants fare best when they behave truthfully.

C. Performance Measures

In each round of the numerical methodology, besides the optimal bid and the DAS solution (i.e., the energy/reserve clearing prices, scheduled energy/reserve quantities), we also compute the following important performance measures:

Net profits of each generation unit: NPROF_u
Total payments for energy: $\sum_h \lambda_h^G \cdot D_h^G$
Total payments for reserve: $\sum_h \lambda_h^R \cdot D_h^R$
Total recovery payments: $\sum_u \mathrm{RP}_u$
Total uplift on the energy clearing price, due to the reserve and recovery payments: $(\sum_h \lambda_h^R \cdot D_h^R + \sum_u \mathrm{RP}_u)/\sum_h D_h^G$
Producers' cost: $\sum_u(\mathrm{VC}_u + \mathrm{CC}_u)$
Producers' surplus: $\sum_u \mathrm{NPROF}_u$

The aforementioned measures are useful for comparing different mechanisms. Specifying the "best" values of these measures, however, is not obvious. The following criteria are associated with a "good" mechanism: 1) The units that submit truthful bids should not exhibit revenue losses; 2) the uplifts associated with the recovery payments should not be high; and 3) the solution of the DAS problem should not be inefficient in terms of total cost (the benchmark is the DAS solution with truthful bids). In addition, a recovery mechanism should mainly address the needs of the "marginal" and "extra-marginal" units, because these units are more likely to need to recover their costs; the units with low variable costs, which are mostly infra-marginal, will in any case recover their costs and have profits from the day-ahead market.

D. Computational Issues

For each design in Table I, we ran the repetitive game described in Section IV of [1] for a predetermined number of 50 rounds. In some cases, we observed "cycling" in the bidding behavior, which means that from a certain round onwards the bids of future rounds are exactly equal to the bids of previous rounds, so there is no need to run more rounds. In case a cycle was observed, the runs were terminated. This truncation procedure resulted in substantial computational savings.

The brute-force optimization procedure that the profit-maximizing type-M units perform in each round requires the solution of 724 DAS problems, as each of the type-M units searches sequentially over a set of price offers from its cost level up to the price cap; in the best case, the unit with the highest cost (U9) searches over 79 price offers, and in the worst case, the unit with the lowest cost (U2) searches over 102 price offers. During the brute-force optimization of any particular unit, if for a given price offer the DAS solution sets the unit offline for all 24 hours, then, clearly for any higher price offer it will do the same, so there is no need to examine any higher price offers. In this case the optimization can be terminated. This resulted in further computational savings.

Without accounting for the aforementioned computational savings, we had to solve $50(724 + 1) + 1 = 36\ 251$ DAS problem instances per design; namely, 50 rounds per design, with 724 DAS problem instances per round for determining the best price offers, plus 1 instance per round for clearing the market using the best price offers, plus the initial problem instance in which type-M units submit truthful price offers.

Before setting out to solve all these instances, however, we first solved an instance, which we refer to as the *nominal case*, to be used as a reference point for all other instances. In the *nominal case*, each unit submits bids equal to its true variable costs, and if it incurs losses, then it is compensated so as to end up with zero profits. The nominal case is in fact equivalent to the initial round (with truthful bids) of mechanisms A.1 and A.2, with $\alpha_1 = 0$ and $\alpha_2 = 0$, respectively. By exploiting the opportunities for computational savings described above, the number of DAS problem instances was reduced by 38%.

We programmed the DAS problem and the methodology for evaluating the recovery mechanism design options using the mathematical programming language AMPL [8]. We ran the program on a Pentium IV 1.8-GHz dual core processor PC with 1 GB of system memory where we used the ILOG CPLEX 10.2 optimization commercial solver [9] to solve the DAS problem instances. Each DAS problem instance consists of 480 continuous variables, 1000 general integer and 730 binary variables, and 6158 constraints. The average time to solve a single problem instance was approximately 3.9 s and the average time for a single round was 30.5 min.

Finally, it is noteworthy that the evaluation methodology is amenable to significant parallelization, as all the market design options can be evaluated in parallel. The 724 DAS problem instances in each round can also be solved in parallel.

TABLE IV
RECOVERY MECHANISMS AVERAGE AGGREGATE RESULTS

Mechanism	Regulating Parameter	Energy Payments (in €/MWh) (1)	Reserve Payments (in €/MWh) (2)	Recovery Payments (in €/MWh) (3)	Total Uplift (in €/MWh) (4) = (2) + (3)	Total Payments (in €/MWh) (5) = (1) + (4)	Cost Increase (% of Nominal Case Cost) (6)	Producers' Surplus (% of Nominal Case Cost) (7)
A.1	**$\alpha_1 = 0\%$**	57.270	0.522	0.215	0.737	58.007	0.638%	31.707%
	$\alpha_1 = 5\%$	57.523	0.518	0.324	0.842	58.365	0.720%	32.442%
	$\alpha_1 = 10\%$	56.449	0.529	0.530	1.059	57.508	0.550%	30.656%
A.2	**$\alpha_2 = 5\%$**	57.396	0.532	0.164	0.696	58.092	0.631%	31.907%
	$\alpha_2 = 10\%$	57.396	0.532	0.171	0.703	58.099	0.631%	31.925%
	$\alpha_2 = 100\%$	57.937	0.572	0.382	0.954	58.891	0.759%	33.602%
B.1	**N/A**	77.976	1.100	0.893	1.993	79.969	1.477%	80.974%
B.2	**$\beta = 3$**	57.433	0.517	0.244	0.761	58.194	0.590%	32.184%
	$\beta = 6$	59.011	0.528	0.244	0.772	59.783	0.773%	35.625%
	$\beta = 9$	58.837	0.504	0.301	0.805	59.642	0.540%	35.534%
Nominal Case	-	52.276	0.505	0.353	0.858	53.134	0%	21.226%

III. NUMERICAL RESULTS

In this section, we present the most important numerical results. In Subsection A, we present the average aggregate results for all recovery mechanisms, while in Subsection B, we offer a closer look at the prevailing mechanisms.

A. Average Aggregate Results for All Mechanisms

Initially, we evaluated the performance of all four recovery mechanism designs shown in Table I as well as of two other simple designs: one that explicitly compensates the commitment costs and provides no further payments, and one that provides no recovery payments at all. Due to space considerations and the fact that the latter two designs performed poorly as they resulted in negative profits for some units, we do not present results for them. It should also be noted that the first design additionally resulted in elevated uplifts and energy payments.

Table IV shows the average aggregate results for the mechanisms shown in Table I. To facilitate the interpretation of these results, we expressed them in relative rather than in absolute quantities. Specifically, the energy, reserve, and recovery payments are normalized with the daily load; the two latter components form the total uplift, whereas the sum of all three components constitutes the total payments. The average percentage of cost increase reveals the degree of inefficiency in dispatching when compared to the nominal case. The average percentage of the producers' surplus over the cost of the nominal case provides a more comprehensive view for the aggregate profits. All averages are calculated for the total number of rounds, unless a cycle was observed, in which case, they are calculated for the cycle period.

From the results of Table IV, we can see that the total payments under B.1 are much higher than under the other three mechanisms. Given the comparatively poor performance of mechanism B.1, we will henceforth restrict our attention to the three more attractive mechanisms, A.1 (variable cost based RP), A.2 (loss based RP), and B.2 (regulated bid based RP).

B. Closer Look at the Prevailing Mechanisms

The analysis of the results in Table IV for the prevailing mechanisms, A.1, A.2, and B.2, leads to the following remarks.

Remark 1: The aggregate results for the mechanisms A.1, A.2, B.2, for all the tested values of the regulating parameters shown in Table IV, are comparable to each other. Therefore, they are considered equivalent in terms of performance, at least based on the average aggregate results.

Also, the tested values of the regulating parameters do not seem to have a significant or identifiable influence on the average aggregate performance.

Remark 2: The total uplifts produced by mechanisms A.1, A.2, B.2 are quite low, namely, less than 2% of the energy price for all the tested values of the regulating parameter shown in Table IV.

We observe that the uplift component which is related to the provision of reserve is practically the same and close to 1% of the energy price, for all three mechanisms and all tested regulating parameter values. The uplift component due to the recovery payments seems to be slightly increasing with the regulating parameter for all three mechanisms and is less than 1%. In most cases, the total uplifts in absolute numbers are smaller even than the total uplift of the nominal case.

Thus far, we have focused our attention on the average aggregate results over all units. Next, we will take a closer look at the average performance and bidding behavior for each individual generating unit.

Although not shown here for space considerations, the results indicate that the type-L lignite units (U1) have very high profits, due to their low variable cost. In fact, approximately 90% of the producers' surplus belongs to the lignite units. The results also indicate that the profits of the type-H "peaker" (U10) are also quite significant and stable; they are mostly due to the provision of reserve.

Tables V and VI show the average profits and bids for each type-M generating unit for the prevailing mechanisms A.1, A.2, and B.2. Table VI also shows in parentheses the difference of the average bids from the variable cost as a measure of the units' tendency to overbid. The lower this difference, the higher the level of incentive compatibility of the corresponding mechanism.

Comparisons among different units are somewhat delicate because the unit capacities are different. Nonetheless, we can distinguish between two large subgroups of type-M units with

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TABLE V
TYPE-M UNITS' PROFITS UNDER DIFFERENT RECOVERY MECHANISMS

Mechanism	Regulating Parameter	U2	U3	U4	U5	U6	U7	U8	U9
A.1	**$\alpha_1 = 5\%$**	52,578	51,142	27,822	19,320	4,056	5,483	3,551	2,146
	$\alpha_1 = 10\%$	46,282	47,860	33,865	19,737	5,407	10,541	4,458	4,833
A.2	**$\alpha_2 = 10\%$**	48,484	56,279	26,357	20,834	2,736	667	437	784
	$\alpha_2 = 100\%$	56,681	51,660	30,201	23,935	3,840	6,589	7,423	6,989
B.2	**$\beta = 3$**	50,712	48,489	34,280	20,460	3,886	2,762	0	848
	$\beta = 6$	57,421	66,173	29,022	29,876	6,994	7,841	519	193
	$\beta = 9$	56,056	64,624	40,383	32,948	9,073	6,829	1,485	515
Nominal Case	-	39,912	20,948	5,205	0	0	0	0	0

TABLE VI
TYPE-M UNITS' BIDS UNDER DIFFERENT RECOVERY MECHANISMS

Mechanism	Regulating Parameter	U2	U3	U4	U5	U6	U7	U8	U9
A.1	**$\alpha_1 = 5\%$**	**58.04** (9.04)	**63.78** (11.78)	**70.86** (15.86)	**61.28** (4.28)	**66.90** (2.9)	**66.10** (1.10)	**70.04** (0.04)	**72.00** (0.00)
	$\alpha_1 = 10\%$	**56.71** (7.71)	**61.00** (9.00)	**68.98** (13.98)	**61.10** (4.10)	**66.73** (2.73)	**65.78** (0.78)	**70.02** (0.02)	**72.00** (0.00)
A.2	**$\alpha_2 = 10\%$**	**58.57** (9.57)	**62.43** (10.43)	**72.86** (17.86)	**59.43** (2.43)	**69.43** (5.43)	**65.86** (0.86)	**70.00** (0.00)	**72.00** (0.00)
	$\alpha_2 = 100\%$	**57.69** (8.69)	**64.96** (12.96)	**70.96** (15.96)	**62.61** (5.61)	**67.80** (3.80)	**66.69** (1.69)	**70.16** (0.16)	**72.20** (0.20)
B.2	**$\beta = 3$**	**58.24** (9.24)	**64.14** (12.14)	**67.08** (12.08)	**61.14** (4.14)	**66.69** (2.69)	**67.43** (2.43)	**70.18** (0.18)	**73.98** (1.98)
	$\beta = 6$	**59.35** (10.35)	**63.86** (11.86)	**75.86** (20.86)	**63.16** (6.16)	**69.55** (5.55)	**70.08** (5.08)	**72.45** (2.45)	**74.77** (2.77)
	$\beta = 9$	**60.78** (11.78)	**62.22** (10.22)	**72.84** (17.84)	**63.51** (6.51)	**71.39** (7.39)	**71.29** (6.29)	**73.47** (3.47)	**76.16** (4.16)
Nominal Case		**49.00**	**52.00**	**55.00**	**57.00**	**64.00**	**65.00**	**70.00**	**72.00**

similar characteristics and behavior: Group A (U2-U5) and group B (U6-U9). Group-A units have lower variable costs and larger capacities than group-B units. The analysis of the results contained in Tables V and VI leads to the following remarks.

Remark 3: Under mechanisms A.1, A.2, and B.2, the group-A units tend to overbid and have higher profits than group-B units. This bidding behavior of group-A units is somewhat expected since low-cost units take advantage of their higher profit margins and try to set higher energy prices, which would result in higher profits.

Remark 4: Under the cost based mechanisms A.1 and A.2, the units with higher variable costs tend to bid close to (or even at) their cost, which implies a very high level of incentive compatibility for these units.

Remark 5: Under the regulated bid based mechanism, B.2, the units with higher variable costs bid close to their cost for low values of the cap, again implying a high level of incentive compatibility, but tend to bid higher as the cap increases.

Recall that as the bid cap β increases, the behavior of mechanism B.2 approaches that of mechanism B.1, which, as we saw earlier, is unattractive. A question that arises naturally is how often units bid over the cap. Fig. 1 shows the frequency with which units bid over the cap. Units U8 and U9 always bid within the margin and are not shown.

Remark 6: Under mechanism B.2, group-A units tend to bid over the cap more frequently than units with higher variable cost. The frequency of bidding over the cap, in general, decreases as the margin increases. We look next into the units' bidding behavior within the rounds. Fig. 2 depicts the bidding behavior of the type-M units under mechanism B.2, which is also indicative of the other two mechanisms, and leads to the following remark.

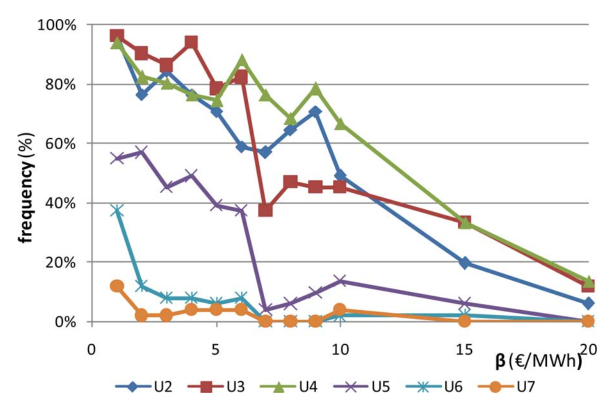

Fig. 1. Frequency of bidding over the cap for mechanism B.2.

Remark 7: Under mechanisms A.1, A.2, and B.2, the group-A units exhibit a rather "volatile" bidding behavior, whereas the group-B units bid more uniformly. Units with lower variable costs exhibit a more speculative bidding behavior, because of their high profit margins, whereas units with higher variable costs bid more conservatively, because they have low profit margins. For mechanism B.2, in particular, the benefits of bidding more aggressively (i.e., outside the margin) diminish as the margin widens.

Fig. 2 also shows the "cumulative" average energy payments and total payments (in €/MWh) over the first n rounds, for $n = 0, \ldots, 50$ (upper figure). It can be seen that the cumulative average "converges" in only a few rounds, which implies that the sample size of 50 rounds that we considered yields confident enough results. In the specific example, the cumulative averages over the last 10 rounds differ less than 0.1 €/MWh. The difference between the total payments and the energy payments yields the total uplift.

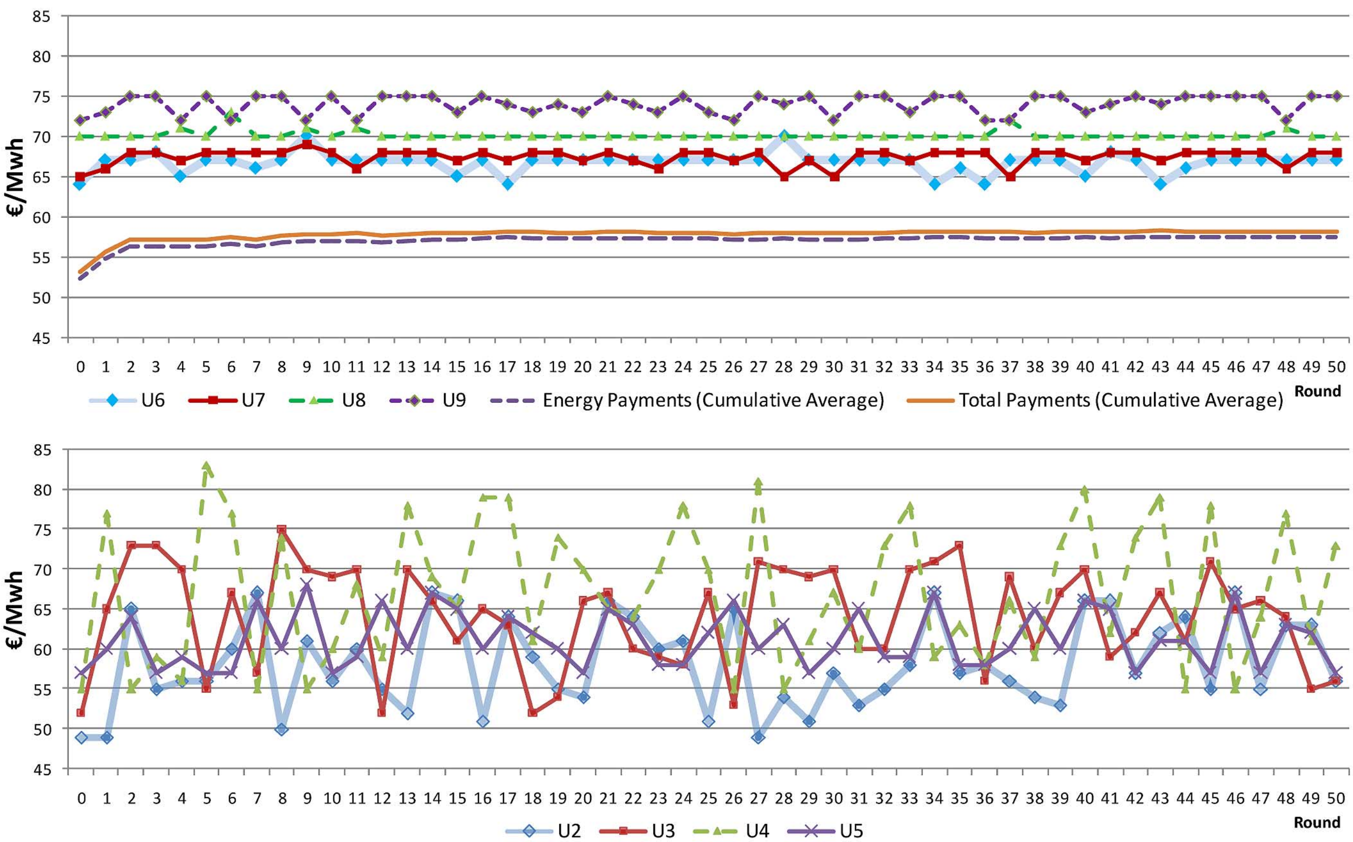

Fig. 2. Bidding pattern for mechanism B.2, with $\beta = 3$.

IV. Sensitivity Analysis

To explore the accuracy and extendability of our results, we perform sensitivity analysis with respect to certain key parameters and assumptions.

In Tables IV–VI, we presented results for some indicative values of the regulating parameters. In this section we select the values $\alpha_1 = 10\%$, $\alpha_2 = 10\%$, and $\beta = 3(\text{€/MWh})$, for the three prevailing designs, and we perform sensitivity analysis with respect to the load (Subsection A), and the profit maximizing bidding strategy assumptions of Type-M units (U2–U9) (Subsection B). Lastly, in Subsection C we examine the impact of allowing the units to bid under their cost.

A. Load Sensitivity Analysis (Low-Demand Scenario)

The demand data that we used to evaluate the recovery mechanisms correspond to a scenario where the demand is rather high, because, as is evident from the results, for the most part, 9 out of 10 generation units are committed to providing energy and/or reserve. In this subsection, we consider a low-demand scenario shown in Table VII, where the hourly demand and reserve requirements are approximately 20% and 30% lower, respectively, than the corresponding values in the high-demand scenario, shown in Table III.

The aggregate results for the low-demand scenario are shown in Table VIII. From these results, it can be seen that the energy payments drop by approximately 27% with respect to the high-demand scenario for all mechanisms. The uplifts, on the other hand, increase by 11%–22% but still remain low. This increase is quite expected, since the revenues for the extra-marginal units are lower in the low demand case (higher competition, lower prices).

Lastly, note that the reserve payments are very low, as there is enough capacity committed to cover the need for reserves, without producing a significant marginal cost for reserve provision (in most hours).

TABLE VII
Energy Demand and Reserve Requirements (Low Demand Scenario)

h	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
D_h^G	3500	3200	3100	3000	3000	2900	3200	3500	3800	4200	4550	4500
D_h^R	300	250	250	250	250	250	300	350	400	450	450	450
h	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
D_h^G	4450	4450	4300	4000	3950	3900	4000	4200	4100	4000	3800	3500
D_h^R	450	450	450	400	400	400	400	450	450	400	350	350

TABLE VIII
Average Aggregate Results (Low Demand Scenario)

Mechanism	**Regulating Parameter**	**Energy Payments (in €/MWh)**	**Reserve Payments (in €/MWh)**	**Recovery Payments (in €/MWh)**
A.1	$\alpha_1 = 10\%$	41.192	0.015	1.168
A.2	$\alpha_2 = 10\%$	41.485	0.015	0.840
B.2	$\beta = 3$	42.336	0.015	0.864

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TABLE IX
SENSITIVITY ANALYSIS ON BIDDING STRATEGY ASSUMPTIONS

Line	Mechanism	Case	Energy Payments (in €/MWh)	Total Uplifts (in €/MWh)
1	A.1	Original	56.449	1.059
2	$\alpha_1 = 10\%$	4.b(2)(a) [Step 0.5]	57.168 (+1.3%)	1.061
3		4.b(2)(c) [Highest offer]	58.153 (+3.0%)	0.891
4		Random offer	56.828 (+0.7%)	1.069
5		Average offer	56.557 (+0.2%)	0.843
6	A.2	Original	57.396	0.703
7	$\alpha_2 = 10\%$	4.b(2)(a) [Step 0.5]	58.385 (+1.7%)	0.814
8		4.b(2)(c) [Highest offer]	58.165 (+1.3%)	0.794
9		Random offer	57.649 (+0.4%)	0.770
10		Average offer	57.590 (+0.3%)	0.652
11	B.2	Original	57.433	0.762
12	$\beta = 3$	4.b(2)(a) [Step 0.5]	57.928 (+0.9%)	0.727
13		4.b(2)(c) [Highest offer]	57.608 (+0.3%)	0.733
14		Random offer	57.793 (+0.6%)	0.803
15		Average offer	56.932 (-0.9%)	0.642

B. Bidding Strategy Assumptions Sensitivity Analysis

Thus far, we have focused our attention on the performance measures of different recovery mechanisms. These measures were estimated using the evaluation methodology developed in Section IV of [1], under the assumptions stated in Section II of this paper. Two of these assumptions, which are related to the profit optimization procedure of each unit in each round, namely Assumptions 4.b(2)(a) and 4.b(2)(c), may appear to be somewhat arbitrary or restrictive; for this reason, we investigate next their impact on the results.

1) Step Size: The purpose of Assumption 4.b(2)(a) is to facilitate the numerical solution of the profit maximization problem of each unit in each round, given by expression (19) in [1], by *discretizing* the theoretically continuous decision space of permissible price offers of the unit, i.e., the interval between the unit's cost of energy production and the price cap, into a number of discrete points, equally spaced by 1 €/MWh apart, then evaluating the net profit at each discrete point (brute-force). To investigate the impact of the discretization step size, we divided it by two, at the cost of having to evaluate twice as many points, and we ran the experiments again. The results show that the difference in total payments is very small, indicating that the original step size yields sufficiently accurate results. Indicatively, lines 2, 7, and 12 in Table IX show the average aggregate energy payments and total uplifts for each mechanism (for an indicative regulating parameter value) for a step size of 0.5 €/MWh. These payments are only 0.9%–1.7% higher (as shown in the parenthesis) than the respective payments in the original runs with a step size of 1 €/MWh, shown in lines 1, 6, and 10, respectively.

2) Bid Selection: The purpose of Assumption 4.b(2)(c) is to resolve the situation where the brute-force optimization, which determines the optimal price offer of each unit and yields the maximum profit, results in multiple price offers. Assumption 4.b(2)(c) resolves this situation by dictating that the unit chooses the lowest offer. To investigate the impact of this assumption on the results, we modified it so that it now dictates that among multiple price offers that yield the same optimum profit, a unit chooses the highest offer. With this modification, we executed the experiments again for the three mechanisms. The results show that the difference in total payments under the modified Assumption 4.b(2)(c) and the original Assumption 4.b(2)(c) is quite limited. Indicatively, lines 3, 8, and 13 in Table IX show the average aggregate energy payments and total uplifts under the modified Assumption 4.b(2)(c). These energy payments are only 0.3%–3.0% higher (as shown in the parenthesis) than the respective payments in the runs under the original Assumption 4.b(2)(c), shown in lines 1, 6, and 11.

Assumption 4.b, as a whole, is at the heart of the evaluation methodology. It states that type-M units set out to find the offers which jointly maximize their profits. In each round, each unit chooses the offer which maximizes its profits, assuming that the other units will use their offers from the previous round. The usefulness of the evaluation methodology is that it reveals patterns of bidding behavior of the individual units, the ranges and averages of different quantities of interest, such as offers, recovery payments, net profits, clearing prices, total payments, etc.

Fig. 2 is typical of the bidding behavior of the units during the execution of the evaluation methodology. Clearly, the bids oscillate from one round to the next and no pure equilibrium solution is attained. Given the apparent lack of an equilibrium solution, the natural question arises as to how a unit can use the results of the evaluation methodology to decide on its bidding strategy. We elaborate on this issue next.

A simple approach is to assume that each unit, not knowing how the other units will bid, will randomly choose one of the offers that it submitted over all rounds of the evaluation methodology with a probability that is equal to the frequency with which that offer was placed during the rounds. Essentially, under this "random offer" approach, each unit uses the *marginal frequency* of its *deterministic optimal* offers, which it extracts from the *joint frequency* of the offers of all units during the course of the evaluation methodology, as the *probability distribution* of its *random* offers. For clarity, we note that this probability distribution does not represent a mixed strategy Nash equilibrium. To evaluate the performance of each mechanism under the random offer approach, we solved the DAS problem for 20 000 instances, where in each instance the offers of each type-M unit were randomly generated using this approach. The results show that the difference in average aggregate total payments under the random offer approach and the original Assumption 4.b is very small. Indicatively, lines 4, 9, and 14 in Table IX show the average aggregate energy payments and total uplifts under the random offer selection approach. The energy payments are only 0.4%–0.7% higher than the respective payments in the runs under the original Assumption 4.b, shown in lines 1, 6, and 11.

An alternative approach is to assume that each unit chooses a particular deterministic offer that is representative of the optimal offers that the unit submitted over all rounds of the evaluation methodology. A natural candidate for the value of that particular offer is the average value of the optimal offers. The results show again that the difference in total payments under the average offer selection approach and the original Assumption 4.b is quite small. Indicatively, lines 5, 10, and 15 in Table IX show the average aggregate energy payments and total uplifts under the average offer selection approach.

TABLE X
AVERAGE AGGREGATE RESULTS (BIDDING UP TO 30% UNDER COST)

Mechanism	Regulating Parameter	Energy Payments (in €/MWh)	Reserve Payments (in €/MWh)	Recovery Payments (in €/MWh)
A.1	**$\alpha_1 = 10\%$**	37.812	0.187	9.976
A.2	**$\alpha_2 = 10\%$**	59.366	0.907	1.079
B.2	**$\beta = 3$**	57.263	0.697	0.220

The energy payments are very close in either direction with the respective payments in the runs under the original Assumption 4.b, shown in lines 1, 6, and 11, and the total uplifts are lower for all mechanisms.

C. Bidding Under the Cost

An interesting inquiry with respect to Assumption 4.b(2)(a) is to check if any benefit can arise from allowing the generation units to bid under their variable cost. To this end, we consider the case in which the units are allowed to bid up to 30% *under* their variable cost. The results are shown in Table X and reveal some interesting outcomes (compared to the results in Table IV).

We observe that mechanism A.1 produces a particularly high uplift combined with low energy payments. As a matter of fact, this particular outcome was an equilibrium point, given the assumptions. At this point, the units bid as low as possible, under their cost, in order to maximize their quantities and benefit from the recovery payments. Due to their low bids, the energy prices are low and it is not profitable to try and bid higher in order to benefit from a higher price. The outcome is characterized as a particularly bad one, as the energy price does not reflect the cost and the uplifts are high.

Mechanism A.2 exhibits some higher energy payments. A closer look at the results shows that the units tend to cycle between high and low bids, as a result of the possibility that they are given for gaming.

Mechanism B.2 seems to have the most stable performance. However, some units may exhibit negative profits, which is also not a good outcome.

In addition, we examined the above option for the low-demand scenario, described in Subsection A, which we did not show in Table X. Mechanism A.1 produced the same equilibrium point, and hence the same remarks apply. Mechanism A.2 reached the same equilibrium point with Mechanism A.1, and produced lower uplifts than A.1 (7.4 as opposed to 10.4 €/MWh) but still particularly high. Mechanism B.2 gave low uplifts (similar to the high demand case) but still resulted in negative profits for some units.

In general, we can conclude that allowing the units to bid under the cost increases their possibility for gaming and seems to have undesired properties with respect to the performance of the recovery mechanisms.

V. CONCLUSIONS AND ISSUES FOR FURTHER RESEARCH

The results presented above can be summarized as follows.

Recovery mechanisms A.1 (variable cost based RP), A.2 (revenue loss based RP), and B.2 (regulated bid based RP) prevail over mechanism B.1 (unregulated bid based RP) which leads to elevated uplifts and total payments. Under either of these three prevailing mechanisms, the total uplifts are quite reasonable. Group-A units (those with lower variable costs) tend to bid higher, exhibit a more "volatile" bidding behavior and have higher profits than group-B units (with higher variable costs). In fact, under mechanisms A.1 and A.2, the units with higher variable costs tend to bid close to or even at their cost. Under mechanism B.2, units with higher variable costs bid close to their cost only for low values of the cap and tend to bid higher as the cap increases. Group-A units tend to bid over the cap more frequently than units with higher variable cost. Further, the frequency of overbidding decreases with the cap.

Despite these minor variations in bidding behavior among different units, the aggregate results for the three prevailing mechanisms are comparable. A multi-criteria approach that evaluates the overall performance of each mechanism on the basis of multiple indicators described herein would be worth pursuing in future research.

Although the three prevailing mechanisms perform similarly, they differ qualitatively. The main disadvantage of the variable cost based mechanism, A.1, is that it sets the net profits proportional to the variable costs, irrespectively of the magnitude of the market losses. This favors units with higher variable costs, i.e., inefficient units. The loss based mechanism, A.2, favors higher losses over lower losses, which may appear as counter intuitive to some participants. The regulated bid based recovery mechanism, B.2, seems to "naturally" align with the participants' perspective.

The results of our further numerical sensitivity analysis showed that the demand (load) level does not significantly affect the performance and still produces comparable outcomes between the three prevailing mechanisms. In addition, the assumptions of the evaluation methodology on the step size have an insignificant impact on the performance. We also saw that the average aggregate performance of the three mechanisms remains practically the same even when each unit randomly chooses its offers from a probability distribution which is equal to the marginal frequency of its deterministic optimal offers during the course of the evaluation methodology. Given that the existence of pure strategy equilibrium solutions is highly improbable, a direction for further research might be to look for mixed strategy equilibrium solutions. One should keep in mind, however, that in real markets one may prefer to settle for reasonable deterministic profits than try to maximize expected average profits.

Our results showed that that the performance of the three mechanisms remains practically unchanged even when each unit chooses a deterministic offer whose value is equal to the average optimal offers during the course of the evaluation methodology. Similarly, placing offers above the regulated bid cap, though mathematically justifiable, carries an uncertainty that many participants may not be willing to tolerate. As such, market participants may be placing offers below the cap more often that our model predicts.

Furthermore, it was seen that allowing the units to bid under their cost does not produce desirable outcomes.

We realize that the sensitivity analysis in a paper can never include all aspects of such a complicated problem. It is rather used to enhance the confidence in the results and perhaps reveal some interesting findings or verify suspected outcomes. Additional sensitivity analysis might be worth performing and might be of interest to regulators and ISOs who may wish to examine the performance of some of the proposed mechanisms. For instance, one could experiment with the technical characteristics and costs of the units which can be affected by fuel prices. Also, the proposed numerical procedure could be straightforwardly extended to accommodate more decision variables for each market participant, but the computational requirements would rise dramatically. Parallel computation could be very helpful in this respect. Another way would be to make further assumptions on the players' bidding options (e.g., Cournot bidding), or simplifying the profit maximizing units' optimization problem by assuming a competitors' response function (e.g., supply function competition), which would make the optimization problem of each profit maximizing unit easier.

Finally, a direction for further research would be to see how the results extend to other market paradigms than the ones based on integrated co-optimized energy and ancillary services without transmission constraints.

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