A hierarchical, market-based, non-cooperative game-theoretic approach to projecting flexible demand-side resources: Towards more realistic demand response-integrated, long-term energy planning models

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Abstract—This paper presents a non-cooperative, zero-sum, symmetric game approach to projecting the flexible demand-side resources to improve the reliability and robustness of long-term strategic energy planning models. A specifically devised distributed algorithm is put forward to determine the unique, pure-strategy Nash equilibrium of a non-cooperative game formulated for the delivery of aggregator-mediated demand response resources, at which no player can yield a higher payoff by deviating from its best-response strategy. The simulation for the operation of renewable energy systems is run over the course of a year. Furthermore, using a metaheuristic-based solution algorithm proposed for the optimal capacity planning of micro-grids, the model was satisfactorily applied to the energy infrastructure planning of a test-case system conceptualized for the town of Ohakune, in New Zealand. The simulation results suggest that not only does the proposed market-directed, incentive-based, strategic demand-side management planning framework help elicit further contributions from the customers, which, in turn, reduces the reserve capacity requirements to meet the peak demand, it also guarantees the highest possible payoff for all players of the game. According to the simulation results, the test-case system's life-cycle cost can be reduced by up to ~29% compared to the case, where no demand response is considered.

Index Terms—Demand-side management, Distributed algorithms, Load management, Strategic planning, Transactive energy.

I. INTRODUCTION

Exploiting the flexibility offered by demand response (DR) resources could have a significant positive impact on the long-term economic viability of renewable and sustainable energy systems (RSESs) [1]–[3]. The academic literature on energy system optimization has been informed by attitudinal challenges associated with the implementation of aggregator-mediated demand-side management (DSM) programs almost exclusively over short-term planning horizons [4]–[6]. On the other hand, several studies have incorporated DSM plans into their strategic equipment capacity-planning models. For instance, Chauhan and Saini [7], Amrollahi and Bathaee [8], and Zhu et al. [9] have formulated energy investment planning

problems considering direct load control programs. Also, Nojavan et al. [10], Husein and Chung [11], and Zheng et al. [12] have integrated time-of-use strategies into their integrated resources planning models, while Yu et al. [13] and Gazijahani and Salehi [14] have examined the impact of critical peak pricing programs on the financial viability of renewables-based micro-grids (MGs).

As the above review of the literature indicates, current approaches to integrating responsive loads into the design process of RSESs have tended to employ frameworks that were particularly devised for day-ahead energy scheduling targets. Equally important, while the characterization of the underlying interactions between utilities, responsive load aggregators, and end-consumers can play a key role in improving the accuracy of DR-aware strategic energy planning models integrating smaller DR products, it has, as far as can be ascertained, been overlooked in previous studies.

In response, using insights from non-cooperative game theory [15], this paper introduces the first long-term demand-side resources projection model tailored towards the design optimization of RSESs integrating aggregator-activated DR products. The model provides a platform to leverage the full potential of small to medium responsive loads in shaving peak demand, while optimally designing integrated RSESs. Notably, two novel generalizations of standard MG design optimization are established: (1) characterization of the epistemic uncertainty associated with the delivery of DR resources in the long run, and (2) modeling of the competing behaviors between utilities, DR aggregators (DRAs) who parcel up a set of smaller active loads, and end-consumers. To this end, a two-stage DSM market model is proposed for transactions of aggregator-mediated, incentive-responsive loads, which is developed on the basis of endogenous leader-follower relations. In addition, the conceptualized MG structure is novel in that it integrates three key flexible end-use energy consumption categories in the residential sector, namely smart appliances, electric mobility, and electric heating – in the context of efforts to decarbonizing energy systems through electrification.

The remainder of this paper is structured as follows. Section II presents the proposed game-theoretic approach to projecting aggregator-mediated DR resources. Section III integrates the proposed approach into a long-term strategic energy planning model of MGs. Section IV provides the test-case, while Section V presents the simulation results and shows the significance of the model in reducing the whole-life cost of the test-case. Finally, Section VI summarizes the main conclusions.

II. GAME-THEORETIC DR SCHEDULING MODEL

This section mathematically defines the non-cooperative game-theoretic, day-ahead, market-based DR scheduling model developed to characterize the interactions between a distribution system operator (DSO), DRAs, and customers. The proposed model focuses on the strategic decision-making of these rational, self-interested, utility-maximizing economic agents in the delivery of small to medium incentive-responsive DR products in a non-cooperative setting, such as a grid-integrated residential MG that is designed, built, owned, and operated by a third-party company to serve different consumer classes. Fig. 1 depicts a schematic of the general model architecture with the communication sequence overlaid.

Fig. 1. Schematic of the general (hierarchical) model architecture.

A. Distribution System Operator

On a day-ahead basis, the DSO forecasts the critical hours with reference to the wholesale prices, the internal generation capacity of distributed energy resources (DERs), and the full demand on the system. It then notifies the DRAs of an upcoming event and posts its dynamic incentive offers for load reduction to the wholesale DSM market for each critical hour (t) of the coming day based on the optimized value of the objective function in (1), which is subject to (2) and (3).

$$\min OC_{DSO}(t) = \pi_{im}(t)P_{im}(t) + I_{DSO}(t) \sum_{n \in N} D_{DRA}^n(t), \quad (1)$$

$$I_{DSO}^{min} \leq I_{DSO}(t) \leq I_{DSO}^{max}, \quad (2)$$

$$P_{def}(t) = P_{im}(t) + \sum_{n \in N} D_{DRA}^n(t), \quad (3)$$

where OC_{DSO} is the operational cost of the distribution system; π_{im} is the wholesale price; P_{im} is the imported electricity; I_{DSO} is the DSO-offered incentive with superscripts min and max denoting its lower and upper bounds, respectively; P_{def} is the on-site power generation capacity deficit of the system; and D_{DRA}^n is the total load reduction procured by the n -th DRA.

B. Demand Response Aggregators

The DRAs conduct load reduction auctions and form a retail day-ahead incentive-based market to establish forward contracts with end-consumers for each hour of the coming day. Specifically, the DRAs, keep a proportion of the DSO-posted incentive rate and pass along the rest to their end-users (the actual DR suppliers) through market-based mechanisms. Accordingly, the objective function of the DRAs is defined in (4), which is subject to (5) and (6).

$$\min Pr_{DRA}^n(t) = (I_{DSO}(t) - I_{DRA}^n(t)) \sum_{m \in S_n} d^{m,n}, \quad (4)$$

$$I_{DRA}^{n,min} \leq I_{DRA}^n(t) \leq I_{DRA}^{n,max}, \quad (5)$$

$$D_{DRA}^n(t) = \sum_{m \in S_n} d^{m,n}(t), \quad (6)$$

where Pr_{DRA}^n is the n -th DRA's profit, I_{DRA}^n is the incentive signal posted by the n -th DRA to the retail DSM market, $d^{m,n}$ is the load reduction contributed by the m -th customer of the n -th DRA, and S_n represents the set of customers subscribed to DRA n , which is a proper subset of all the end-consumers within the distribution system's territory, S .

C. End-Consumers

The liberal retail DSM market provides the end-consumers, who are willing to participate in load curtailment programs, the opportunity to leverage the full benefits of their flexibility potential without compromising their comfort standards. Equation (7) expresses the objective function of each end-user, which is to be maximized subject to (8) and (9).

$$\max U^{m,n}(t) = (I_{DRA}^n(t) \times d^{m,n}(t)) - dis^{m,n}(t), \quad (7)$$

$$0 \leq d^{m,n}(t) \leq d_{ncr}^{m,n}(t), \quad (8)$$

$$d_{orig}^{m,n}(t) = d_{cr}^{m,n}(t) + d_{ncr}^{m,n}(t), \quad (9)$$

where $U^{m,n}$ is the utility of the m -th customer of the n -th DRA, $d_{cr}^{m,n}$ and $d_{ncr}^{m,n}$ respectively denote the critical and non-critical portions of the original load, $d_{orig}^{m,n}$, while $dis^{m,n}$ represents the discomfort level experienced due to load reduction, which can be calculated from (10), while adhering to the constraint in (11) [16].

$$dis^{m,n}(t) = c_1^{m,n}(d^{m,n}(t))^2 + c_2^{m,n}(1 - \delta_n)d^{m,n}(t), \quad (10)$$

$$dis_{min}^{m,n} \leq dis^{m,n}(t) \leq dis_{max}^{m,n}, \quad (11)$$

where $c_1^{m,n}$ and $c_2^{m,n}$ are customer-specific parameters that characterize the sensitivity of the customers to the curtailment of the non-critical portion of their entire demand, and δ_n denotes the collective elasticity of supply of DR capacity by the customers enrolled with DRA n .

D. Solution Algorithm

To solve the day-ahead DR scheduling market design, which is formulated as a hierarchical (bi-level) decision-making problem, a distributed algorithm is developed. While it can be proved that the developed game has a unique, pure-strategy Nash equilibrium that can be obtained from an analytical treatment, an iterative, distributed algorithm [17] is indispensable to addressing customer privacy concerns. Accordingly, Algorithm 1 in the Appendix ensures a minimal information exchange by numerically computing the near-optimal, unique, pure-strategy Nash equilibrium of the game in light of complete but imperfect information – which assumes the players' common knowledge of each others'

strategy sets and types, but the players may not know the exact form of utility functions the other players are seeking to optimize. The superscript “*” used in the algorithm denotes that a variable lies in the globally-optimum, pure-strategy Nash equilibrium.

III. DR-INTEGRATED MG DESIGN OPTIMIZATION

This section integrates the proposed day-ahead DRA-mediated DR scheduling framework into a standard long-term strategic energy planning problem of MGs.

The objective function is to minimize a grid-tied, DR-integrated MG’s life-cycle cost (LCC) using the net present value (NPV) method, which entails the system components’ capital, replacement, and operation and maintenance (O&M) costs, along with the costs associated with procuring DR resources and trading energy with the main grid, as follows:

$$\min LCC_{MG} = \sum_{c \in C} NPC_c + \frac{NPV(OC_{MG})}{PL} - \frac{NPV(ER)}{PL}, \quad (12)$$

where LCC_{MG} is the MG’s life-cycle cost, NPC_c is the net present cost of the component $c \in C$, the term $\frac{NPV(OC_{MG})}{PL}$ denotes the total operational cost of the MG attributable to the procurement of DR resources and importing electricity over the project lifetime, PL (implemented in (3)), while the term $\frac{NPV(ER)}{PL}$ denotes the total electricity export revenues over the analysis period, which can be calculated from (13) for each t .

$$ER(t) = FiT \times P_{ex}(t), \quad (13)$$

where FiT represents a flat feed-in-tariff, and $P_{ex}(t)$ is the exported power in time t of the MG operation.

For reasons of space, the reader is referred to [18]-[20] for a detailed description and mathematical formulation of the NPV method and its variant, the net present cost (NPC) method, in the context of long-term MG capacity planning.

The objective function in (12) is subject to a set of constraints, including the operational limits of the on-site DERs, state of charge (SoC) of the storage media, the operating points of the power generation technologies, energy exchange with the main grid, and reliability factors, as follows [21], [22]:

$$SOC^s(t_0) = 0.5 SOC^{s,max}, \quad (14)$$

$$SOC^s(T) \geq SOC^s(t_0), \quad (15)$$

$$SOC_{min}^s \leq SOC^s(t) \leq SOC_{max}^s, \quad (16)$$

$$P_{oper,min}^g \leq P_{oper}^g(t) \leq P_{oper,max}^g, \quad (17)$$

$$P_{ch,min}^s \leq P_{ch}^s(t) \leq P_{ch,max}^s, \quad (18)$$

$$P_{dch,min}^s \leq P_{dch}^s(t) \leq P_{dch,max}^s, \quad (19)$$

$$|P_{exch}(t)| \leq P_{exch,max}, \quad (20)$$

$$LOLP \leq LOLP_{max}, \quad (21)$$

where SOC^s denotes the SOC of storage technology $s \in C$, P_{oper}^g is the operation point of generation technology $g \in C$, P_{ch}^s and P_{dch}^s respectively denote the charging and discharging rates of the storage technologies, P_{exch} and $P_{exch,max}$ respectively denote the exchanged power with the utility grid and the maximum allowable power exchange (in accordance with the size of the hybrid inverter that is connected at

the point of common coupling (see Fig. 3 for an example), t_0 and T respectively denote the baseline and final time periods in the (year-long) operation of the MG for a representative year, while $LOLP$ represents the loss of load probability index, which is defined as the ratio between the sum of all the time-steps where the total demand is not met and the specified total number of time-steps for a given year.

The MG design optimization model solves an energy balance problem for each time-step of the system operation in the baseline year, where the total load on the MG is met by some mix of on-site non-dispatchable generation, discharged energy from storage equipment (where available), imported energy, and dispatchable demand. In this light, the reduced load forecasts generated by the proposed DRA-mediated DR scheduling framework serve as an input for the energy balance analysis – and are treated as ‘modified dispatchable demand’. This energy balance analysis is then assumed to repeat for each of the ensuing years in the life-cycle of the project, where the MG’s annual recurring cash flows are discounted back to present value. The output of the MG design optimization model is a cost-optimal combination of the size of the components considered in the candidate pool, and the associated LCC of the project.

The standard MG design optimization problem has been shown to be a non-deterministic polynomial time-hard (NP-hard) problem [23]. This suggests the necessity of a meta-heuristic optimization approach for optimizing a solution to this problem. Accordingly, the moth-flame optimization algorithm [24] was selected because its superior performance over a broad range of both state-of-the-art and well-established meta-heuristics in nearing the globally optimum solution to the long-term energy planning problem is supported in [25]-[28]. Fig. 2 illustrates the meta-heuristic-based MG design optimization solution algorithm that incorporates the game-theoretic, DRA-mediated DR scheduling framework.

Fig. 2. Meta-heuristic-based solution approach for the MG design problem.

IV. TEST-CASE

The suggested model is applied to the case example of an end-use sector-coupled, grid-tied MG, shown schematically in Fig. 3, conceptualized for the town of Ohakune, in New Zealand. According to the national Census, the usual resident

population of the town in 2018 was 1,182, living in 429 dwellings with an average household size of 2.7 people. It is assumed that a third-party (private company) is planning to invest in non-dispatchable renewables – precisely, solar photovoltaic (PV) panels and wind turbines (WTs) – and (Li-ion) battery storage capacity, as well as an electric vehicle (EV) charging station to serve the residential consumers and EV charging loads with the aid of the utility grid. It is also assumed that the government aspirations for electrifying the heat and transport sectors could facilitate large-scale uptake of heat pumps and EVs. Specifically, a 40% penetration level for smart appliances, a 50% penetration level for heat pumps, and a fleet of 100 light-duty EVs were considered.

Fig. 3. Schematic diagram of the conceptualized grid-connected MG.

Figs. 4 and 5 depict the one-year forecasts for time-series global horizontal irradiance and wind speed data, respectively. For reasons of space, the reader is referred to [28] for the flat-panel PV and WT power output calculations. Also, Figs. 6 and 7 show the one-year forecasts for time-series wholesale price and total load demand data. Costs are always cited in \$NZ.

Fig. 4. Forecasted hourly global horizontal irradiance profile.

Fig. 5. Forecasted hourly wind speed profile (at 50 m height).

Fig. 6. Forecasted hourly wholesale electricity price profile.

Fig. 7. Forecasted hourly total load power demand profile.

Table I lists the techno-economic specifications of the technologies in the candidate pool [26]–[30]. Table II provides the economic assumptions underlying the MG planning model, while Table III presents the parameter settings for the DRA-mediated DR scheduling framework integrated into the long-term MG investment planning model [6]. Table III includes two parameters that are not defined in Section II, namely $C_{DR,max}^n$ and N_n^m (with the cardinality of $|S_n|$), which respectively denote the customer class-specific maximum DR capacity and the number of customers enrolled with the DRA n . Note that $C_{DR,max}^n$ is different from δ_n in an essential way: $C_{DR,max}^n$ represents the maximum achievable capacity of DR resources that are used to define the non-critical portion of the customer-specific original loads, whereas δ_n characterizes the fact that the willingness of customers to supply DR capacity differs across different end-use categories considered, namely

smart appliances, electric heating, and electric mobility. Moreover, to decompose the hourly forecasts of energy demand and allocate them down to each customer, n random N_n^m -element vectors of load reduction were generated for each hour of the MG operation.

TABLE I. CANDIDATE COMPONENTS' TECHNO-ECONOMIC SPECIFICATIONS

Component	CC^a	RC^a	$O\&M^a$	LC^a	η^a
PV module	\$0.8/kW	\$0.8/kW	\$1.5/kW/yr	25 yrs	17%
WT	\$1.9/kW	\$1.7/kW	\$13.5/kW/yr	20 yrs	42%
Li-ion battery	\$1k/kWh	\$1k/kWh	\$2.5/kWh/yr	15 yrs	95%
Inverter	\$1.5k/kW	\$1.5k/kW	\$1.3/kW/yr	15 yrs	96%
EV charging station	\$2.6k/kW	\$2.5k/kW	\$2.4/kW/yr	25 yrs	99%

a. CC , RC , and $O\&M$ respectively represent the capital, replacement, and O&M costs of the components, while LC and η respectively denote their life-cycle and (average/round-trip) efficiency.

TABLE II. KEY ECONOMIC ASSUMPTIONS OF THE MODEL

Input	Assumption	Input	Assumption
PL	20 years	$LOLP_{max}$	0.03%
FiT	\$0.08/kWh	Real interest rate	2.6%
Nominal discount rate	4.3%	Expected inflation rate	1.62%

TABLE III. PARAMETER SETTINGS FOR THE DR SCHEDULING GAME

Parameter	Load type		
	Smart app.	E-heat	E-mobility
δ_n	0.3	0.5	0.4
c_1^{m,n_a}	$[1.07 \times 10^{-3}, 1.16 \times 10^{-3}]$	$[0.98 \times 10^{-3}, 1.06 \times 10^{-3}]$	$[0.90 \times 10^{-3}, 0.97 \times 10^{-3}]$
c_2^{m,n_a}	$[11.4 \times 10^{-3}, 11.8 \times 10^{-3}]$	$[11.2 \times 10^{-3}, 11.4 \times 10^{-3}]$	$[11.0 \times 10^{-3}, 11.3 \times 10^{-3}]$
d_{orig}^{m,n_a} [kWh]	[0.3, 44.8]	[0.3, 3.5]	[1.4, 3.5]
d_{ncr}^{m,n_a} [kWh]	[0.1, 12.1]	[0.2, 2.8]	[1.1, 2.8]
$C_{DR,max}^n$ [%]	27	85	80
N_n^m	172	215	100

a. Where a parameter is end-consumer-specific, its value is reported by a continuous range of possible values, rather than a single value.

V. RESULTS AND DISCUSSION

The proposed model was programmed in MATLAB (Version 9.5) and solved for the conceptualized test-case.

A. Typical Day Operation

To evaluate the effectiveness of the DR scheduling model, a typical cold winter day, the hourly total load profile of which is shown in Fig. 8, was selected for energy management analysis. Fig. 9 presents the contribution of each load category to the total load reduction in time periods where the game-theoretic DR program was triggered based on the DSO's event calls. The figure also shows the imported power from the utility grid and the unreleased DR capacities. Fig. 8, furthermore, depicts the modified total daily load curve.

Fig. 8. Original and modified total load curve on a typical winter day.

Fig. 9. Hourly imported power and DR supply by sector.

Notably, the resulting trade-offs between load reduction and imported electricity in Fig. 9, together with the modified total load curve in Fig. 8, indicate that the Nash equilibrium of the devised DSM game, which quantifies the payoff of each player, is able to improve the daily load factor – the average load divided by the peak load – by up to ~21% (to 0.63 from 0.52) and reduce the peak-to-valley difference by ~30% (to 564.0 from 811.2), while treating the dynamic behavior of residential consumers in responding to incentive price signals.

To examine whether the proposed two-stage DSM market mechanism is incentive-compatible – and can be truthfully implemented in real-life settings – in that no economic agent is motivated to deviate from truth-telling, two sets of sensitivity analyses were executed for a representative time-step of the typical day, where the DR program is executed. Specifically, the sensitivity analyses, shown in Fig. 10, assess the robustness of the DRAs' profits with respect to the incentive price signals they post to the retail DSM market, as well as the utility of the largest customer of each class (as a representative) with respect to its contributed load reduction, in time 9 a.m. – at which the most intense peak is observed.

Fig. 10. Incentive-compatibility analysis: (a) DRAs, (b) representative users.

As Fig. 10 shows, the suggested game achieves the maximum possible profit for the DRAs and the maximum possible utility for the representative customers. Hence, the proposed market design provides an incentive for the involved economic agents to truthfully reveal their private information.

B. Long-Term Investment Planning Results

Table IV presents the cost-optimal MG design results, where the total discounted cost is broken down into three different categories – the costs associated with the MG equipment, energy exchange (with the utility grid) costs, and the DR compensations – in three cases, where: (1) the DSM is implemented using the proposed game-theoretic market design, (2) the DSM is implemented in a non-game-theoretic setting using an unreported market model that replicates the main features of the proposed game-theoretic DSM market framework, but the ability for the economic agents to negotiate on optimizing their utility functions and find the lowest operational costs, and (3) no DSM is considered during the planning phase. Also, Table V lists the optimal size obtained for the MG components in the cost-minimal solution in the abovementioned cases.

TABLE IV. BREAKDOWN OF THE MG'S LCC IN DIFFERENT SCENARIOS

C	Total NPC of the MG (LCC_{MG}) [\$]	Total discounted equipment-driven cost [\$]	Total discounted cost of power imports [\$]	Total discounted revenue from power exports [\$]	Total discounted compensation of DRAs in the wholesale market [\$]
1	7.75m	6.04m	0.21m	-0.47m	1.97m
2	10.93m	7.35m	2.63m	-0.54m	1.49m
3	12.44m	8.29m	4.73m	-0.58m	N/A

TABLE V. OPTIMAL SIZE OF THE MG EQUIPMENT IN DIFFERENT SCENARIOS

C	PV [kW]	WT [kW]	Battery [kWh]	Inverter [kW]	Charging station [kW]
1	405	603	581	852	972
2	503	739	811	1,102	1,126
3	579	850	977	1,307	1,180

These comparative modeling results are revealing in two ways. First, the proposed game-theoretic distributed algorithm – which dynamically updates the DSO- and DRA-offered incentive rates – is able to reduce the LCC of the MG by ~29% and ~38% compared to the non-game-theoretic DR-integrated counterpart and the case where no DR program is considered, respectively. The main reason for the outperformance of the proposed model lies in producing the optimal trade-off between imported power and exploited DR potential during time periods when the MG customers' demand peaks at the time of peak demand on the national grid – and wholesale prices are high. Second, the resulting optimal combinations of the equipment size in different cases suggest that much of the savings are attributable to a reduction in the size of capital-intensive storage, WT, and the multi-mode inverter. Crucially, flattening the load curve using DR solutions that are aware of the interactions between the DSO, DRAs, and customers has reduced the storage bank's size by ~28% and ~41% compared to the non-game-theoretic DR-integrated and non-DR-integrated cases, respectively. Notably, the oversized storage capacity in the non-game-theoretic counterpart is used, to some extent, as a resource to hedge against the aggregator monopoly.

VI. CONCLUSIONS

This paper developed a long-term MG equipment-capacity planning model, which leverages the potential of flexible, incentive-responsive demand-side resources to meet peak demand in a cost-efficient way. An important contribution of this model is the introduction of third-party aggregators who activate smaller customers and deliver the twin benefits of helping end-consumers to reap the full benefits of their flexibility potential and avoiding the need for providing overcapacity of renewable supplies and capital-intensive storage devices (or importing electricity when wholesale prices are too high) to meet peaks in demand. Accordingly, this study put forward a bi-level (wholesale and retail) incentive-directed DSM market design that ensures a level-playing field for all participants as well as the strategic allocation of the benefits generated. The optimal decision-making process of the involved independent, rational, competing actors – the DSO, DRAs, and end-consumers – was modeled based on non-cooperative game theory. The numerical results obtained from the application of the model to an end-use sector-coupled MG for the town of Ohakune, in New Zealand, demonstrated the effectiveness of the model in producing an efficient energy dispatch, reducing the cost of integrating renewables, as well as opening up new revenue streams for small-scale customers.

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APPENDIX

Algorithm 1. Proposed distributed algorithm to obtain the Nash equilibrium.

```

1: Initialize:  $I_{DSO}^* = 0$  and  $OC_{DSO}^*(t) = \pi_{im} P_{im}(P_{def})$ 
2: for  $I_{DSO}$  ranging from  $I_{DSO}^{min}$  to  $I_{DSO}^{max}$  at steps of  $i_{DSO}$  do
3:   Send  $I_{DSO}$  to the aggregators
4:   Run the retail DSM market
5:   for each customer  $m \in S_n$  do
6:     Derive the customer's best-response strategy by setting
       the first-order derivative of its utility function in (7) equal to zero
7:   end for
8:   for each DRA  $n \in N$  do
9:     Determine the pure-strategy incentive to be offered to the end-users,
        $I_{DRA}^{n,*}$ , by setting the first-order derivative of the DRA's profit
       function in (4), in which  $d^{m,n}$  is substituted with the best-response
       strategy of the corresponding customers obtained above, equal to zero
10:    Send the signal  $I_{DRA}^{n,*}$  to the corresponding customers
11:    for each customer  $m \in S_n$  do
12:      Calculate the best-response load reduction with respect to the financial
       incentive offered by the DRA it has subscribed to, using the customer-
       specific best-response strategy profile derived above
13:      Send the load curtailment contributed by the customer to its DRA
14:    end for
15:    Aggregate the load reductions supplied by the end-users
16:    Send the total load reduction procured by the DRA to the DSO
17:  end for
18:  Update the hourly operating cost of the DSO as:
     $OC_{DSO} = \pi_{im} P_{im}(P_{def} - \sum_{n \in N} D_{DRA}^n) + I_{DSO} \times \sum_{n \in N} D_{DRA}^n$ 
19:  if ( $OC_{DSO} < OC_{DSO}^*$ ) then
20:    Update the optimal DSO-posted incentive and the DSO's operating
    cost as:  $I_{DSO}^* = I_{DSO}$  and  $OC_{DSO}^* = OC_{DSO}$ 
21:  end if
22: end for
23: Return the set  $(I_{DSO}^*, I_{DRA}^{n,*}, d^{m,n,*})$  as the globally-optimum, pure-strategy
    Nash equilibrium of the DR scheduling game for each hour of the coming day

```