Value-stack aggregator optimal planning considering disparate DERs technologies

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Abstract

Federal energy regulatory commission (FERC) Order #2222 prescribes that distributed energy resources (DERs) with 100 kW or more capacity in aggregate should be allowed to participate in organized electricity markets. Most aggregation is via a combination of disparate DER technologies such as solar, wind, storage, electric vehicles, and smart load units. Another stumbling block to enabling participation of DERs in organized electricity markets is the energy limitation. However, there is a lack of aggregator models in the literature that gainfully allow aggregation of disparate DER technologies that are energy limited. To address this shortcoming, we proposed a disparate DER aggregator (DDA) planning model here, that overcomes energy limitation of DERs. The DDA planning model considers multiple revenue streams of (1) capacity credits; (2) energy revenues; and (3) ancillary services revenues. The proposed DDA planning model enables disparate DER technologies to collate and provide a firm power capacity and participate in the market capacity auction and receive capacity credits. This comprehensive DDA planning model considers the dynamic/temporary aggregations with other facilities through peer-to-peer (P2P) trade, and maximization of the net present value (NPV) revenues over the planning horizon. The developed model is tested on sample and practical large-scale case studies. Additional sensitivity analyses are performed, demonstrating the favourable performance and the business potential of the developed DDA planning model.

1 | INTRODUCTION

DISTRIBUTED energy resources (DERs) have extensively penetrated power systems. However, their uncertainty and intermittent nature limit their ability to compete with traditional resources. Aggregation of these DERs could allow them to overcome some of these obstacles and participate proactively in electricity markets. As per FERC Order #2222, the aggregated DERs of 100 kW capacity or more should be allowed to participate in electricity markets [1].

The aggregator concept has received a great deal of attention from power system operators and researchers. Many efforts have been devoted to analyzing its technical and economic benefits and impacts as in [1–3].

1.1 | Literature review of aggregation models

This subsection provides a brief literature survey of the recently published work and state-of-the-art aggregator planning approaches that have been addressed in literature in several models, such as (1) aggregator, (2) virtual power plants (VPP), (3) prosumers, and (4) microgrids.

There are several approaches for addressing the optimization of aggregator’s operation (considering existing aggregated assets) and its interaction with the electricity markets. The first approach when the aggregator serves its own benefits (by maximizing its returns). Further, the aggregator provides the distribution system operator with a good knowledge about loading and generation profiles and trends in its serving area [4].
Second, aggregation may consider a cooperative model that consider the profit-sharing concept between the aggregated DERs and the cooperative/aggregator operator [3]. There is no similar work which considers the planning of the aggregator and optimizes the aggregated assets. The VPP concept refers to the combination of DERs, smart loads, and energy storage units. The components of this combination are not necessarily geographically close to each other [6–8]. In [6], a stochastic planning model for VPP is presented. A strategic framework for planning of emerging VPP based on the automation of the cloud data is presented in [7]. Hess and Schegner presented a planning algorithm for local VPP based on aggregating units of Micro-Combined-Heat-and-Power-Plants (μCHP) in [8].

For prosumer planning, literature shows several multi-level models that consider the planning in one level and the optimal operation of the prosumer in the second level as in [9–11]. In [9], a trilateral stochastic mixed integer bilevel linear programming (MIBLP) mathematical planning approach that includes the interactions between prosumers and the electrical market is presented. The authors considered the problem on two levels; the upper one is a profit maximization optimization for assets considering the interaction with electrical market. On the lower level, the prosumers minimize payments through optimal sizing for PV cells considering the interaction between the prosumers’ community and the electrical market. In [10], a bilevel prosumer planning model is presented. Its upper level is a unit commitment problem that minimizes the total generation cost, while the lower-level problem maximizes prosumers’ aggregate self-consumption. The effects of interaction between the prosumers’ community group and the electrical market have not been addressed. An iterative three-level planning algorithm for a prosumer nano-grid is proposed in [11] without considering the peer-to-peer trans-action mechanism and the capacity revenues of aggregated DERs.

Similar to VPP, a microgrid is a collection of DERs, smart loads, and energy storage units, with the difference being that aggregated entities are geographically concentrated and can operate connected to or isolated from the grid. Numerous studies and models for microgrid planning are reported in the literature, as in [12–15]. In [12], a hybrid optimization model for the sizing and operation of a smart microgrid is presented. A joint optimization model for sizing the DERs and the storage units in an isolated microgrid is developed in [13]. In [14], a capacity investment analysis for mixing renewable energy from solar and wind resources with demand response is presented. A cooperative planning framework based on the Nash bargaining game for multiple interconnected-microgrids is developed in [14]. In [15], a microgrid planning approach that considers the policy impact of renewable energy targets is presented.

Furthermore, there are aggregator models that address the participation into ancillary markets through the aggregation of the same smart load/DER technology as in [16–18].

1.2 | Research gap and motivations

The literature shows an extensive amount of work has been devoted to the optimization of the aggregator operation and much less has been devoted to the planning of assets by an aggregator. Further, in the existing planning models, there is no comprehensive planning business model for an aggregator that considers: (1) The aggregation of disparate technologies of DERs, (2) the aggregator’s participation in power capacity auctions and enabling capacity payments to DERs, and (3) the dynamic aggregation related to the peer-to-peer transactions.

With evolution towards transactive energy distribution system, a new era of financial opportunities and innovative technologies for small and energy limited DERs is ushered in. These small DERs are privately-owned assets connected (or to be connected) to residential and commercial locations and their owners require viable business models for their assets. In this context, it is necessary for them to plan for their aggregated assets using an effective and easy-to-implement model.

1.3 | Major contributions of proposed work

The main contributions of this work can be outlined as follows:

- A value stack DDA planning model that considers disparate technologies of DERs and makes revenues from several revenue streams including: (1) Capacity credits; (2) energy revenues; and (3) ancillary services revenues.
- Accounting for dynamic aggregation through the peer-to-peer trades with other facilities as well as considering the unavailability of aggregated assets.
- An easy-to-implement aggregator planning algorithm that has a business potential to be readily adopted by the private sector to plan for their DER assets investment, based upon mixed integer linear programming optimization.

2 | AGGREGATOR OPTIMAL PLANNING MECHANISM

In this section, the proposed aggregator planning mechanism and its major attributes and features are presented. In Figure 1,
a general overview of the aggregator entity structure and its interaction with the market operator, which may be either the wholesale independent system operator (ISO) or the distribution system operator (DSO), are illustrated. Further, the interactions with other facilities formed outside the aggregation are presented in Figure 1. The developed aggregation model considers the universal (bi-directional) meter type that enables the energy transfer from/to the aggregation entity. In the following subsections the major attributes and characteristics of the DDA are demonstrated.

### 2.1 Disparate DERs technologies

The developed DDA planning model considers disparate technologies of DERs including distributed generators, such as diesel generators and μCHP, renewable resources, such as wind and PV units, ES units, and smart loads. Because of the unique challenges and characteristics of each of these DER technologies, aggregation has a great potential to overcome the uncertainty and non-dispatchability of these DERs and provide them with the economic opportunity to be eligible to participate in electricity markets proactively. The total capital cost, fixed and variable maintenance cost, and the expected revenues of the aggregated DER assets are considered on an annual basis using the net present value (NPV). Further, the lifetime and cycle life of these aggregated DER assets are counted wherever applicable. The full modelling of these DER technologies is provided in the following mathematical formulation section.

### 2.2 Dynamic aggregation- P2P trades

In addition to aggregate disparate DER technologies, the proposed DDA planning model accounts for the bilateral contracts with other facilities that form outside the aggregation entity in the form of P2P contracts. These bilateral/P2P contracts allow the aggregator to meet its market and load commitments even during contingency situations. Furthermore, these P2P trades play an important role in the management of risk associated with the uncertainty and non-dispatchability of aggregated DERs. Nevertheless, although these P2P trades are contracted on an annual basis, they cannot be considered as permanent aggregations. These dynamic aggregations are modelled such that they account for the contracted maximum amount of power capacity as well as the annual number of commitment hours as described later in the following section. It is important to note that P2P trades can benefit the aggregator entity, allowing avoidance of penalty payments in cases where it fails to provide its market commitments. As well, it helps as a deferral for the aggregator’s expected asset upgrades.

### 2.3 Time segment concept

The proposed planning model for aggregator assets can adapt to any planning horizon defined by the operator, as it is formulated as an annually based plan. The proposed DDA planning model considers the multi-segment approach for considering the unique characteristics of the aggregated DER technologies. Also, the developed DDA planning model can adapt to any electricity market regulations and any distribution system specific loading and generation profiles through this multi-segment approach. Each segment will represent a certain time-interval (e.g. a segment of the day or a season in the year) depending on the unique characteristics of each distribution system in which the aggregator participates. It is important to note that an adequate choice for the number of segments to be included within the DDA planning model is key to guaranteeing high performance for the developed model. In this context, the following features should be considered in the selection of these segments:

1. Load consumption profiles: The set of segments should closely fit the consumption profile of the aggregation entities. Furthermore, the types of these loads (e.g. industrial, commercial, or residential) and their growth rates should be considered to pick an appropriate number of segments.
2. Nature of considered renewable resources: in highly penetrated distribution systems, the nature of the DERs (e.g. wind or solar) should be contemplated to determine the segmentation profile, as the nature of the aggregated entities is among the major factors for deciding the optimal aggregation.
3. Jurisdiction regulation: as the aggregator is expected to participate in the electricity market/auction of the local jurisdiction, it is important to select the segmentation approach that matches the regulation and segmentation of the local market. For instance, a morning-daytime-evening approach can be adopted as a basic choice for this DDA model.

### 2.4 Planning horizon – The set NY

The proposed DDA planning model can adapt to any planning horizon defined by the aggregator, as it is formulated on an annual basis. The DDA model optimizes concurrently for all years of the planning horizon NY. The NPV is applied to estimate the considered costs and revenues of the aggregator over the planning horizon NY. While NY is typically viewed as a number of years with steps in terms of one more year, we may also consider steps in fractions of a year, say weeks or months. Accordingly, if NY is five (5) years, the set NY can be defined considering three (3) month steps as equal to $\{0.25, 0.5, 0.75, 1.0, 1.25, \ldots, 4.75, 5.0\}$.

### 2.5 Value-stacked revenue streams

The developed DDA planning model accounts for the aggregator’s revenues based on value stacking. The model considers the potential of the aggregator entity to provide manifold energy and capacity services simultaneously. The proposed planning model anticipates the aggregator revenues as threefold: (1) The energy revenues: The aggregation allows the aggregated assets
to meet the regulations of energy markets in the majority of jurisdictions, meeting a minimum threshold energy production to be eligible to participate in the energy market. The aggregator achieves these revenues by either selling its generated energy into the grid or supplying its own loads during peak hours to avoid some/all of the utility charges; (2) The capacity revenues: Due to the uncertainty and intermittent nature of the DERs, individual DERs cannot provide a firm capacity and gain capacity payments akin to traditional generation units. The aggregation of disparate technologies of DERs can enable them to overcome their individual challenges and be capable of providing a firm/continuous capacity and participating in the capacity auction. Furthermore, the segmentation of the day planning horizon into morning-daytime-evening time segments allows the aggregator to provide a variable capacity during a time segment of the day. This variable capacity can be offered after fulfillment of the firm capacity commitment and should be the minimum available capacity in the time segment that allows the aggregator to make full use of its aggregated assets generation; and (3) The service revenues: The aggregator can provide other services such as demand response (DR) and participate in the DR auction. It is important to note that the DR strategy follows the traditional concept where users are rewarded for reducing their consumption at specified times. The main difference lies in the fact that currently, users participating in DR programs are unable to obtain rewards due to energy injection while the DDA model enable them to obtain it.

As economics provide the opportunity, the value-stacking approach aids the aggregated DER assets in proactively participating in the electricity markets on a competitive basis.

### 2.6 Aggregation – collection of bids by the aggregator

As a pre-process, the proposed DDA planning model considers the bids collected from all the vendors who aim for their assets to be aggregated. These bids comprise the capital investment cost of the assets and the proposed DDA model selects the optimal assets to be aggregated. Furthermore, some exiting facilities outside the aggregation present their bids to transact energy with the aggregator in the form of P2P energy trades, including the limits on the commitment hours.

Finally, the whole proposed DDA aggregator planning process can be briefly described as shown below in the flowchart of Figure 2.

### 3 AGGREGATOR PLANNING MODEL–MATHEMATICAL FORMULATION

In this section, the proposed aggregator planning mathematical model is presented, formulated as a mixed integer linear programming (MILP) challenge. A planning horizon of NY is used and the vendors participating in the DDA planning model are expected to provide bids accordingly.

#### 3.1 Objective function

The objective function as defined in Equation (1) is to maximize the NPV of the aggregator’s profits over the planning horizon.

\[
\text{Max. OF} = \text{TCRC}_{F} + \text{TCRC}_{V} + \text{TDRR} + \text{TER} - \text{TCCE} - \text{TCCP} - \text{TI}_{\text{CDG}} - \text{TI}_{\text{CES}} - \text{TTCP}_{P2P} \quad (1)
\]

The objective function (OF) shown in Equation (1) aims to maximize the aggregator’s estimated revenues from three major revenue streams, all of which are NPVs computed for the horizon NY:

1. capacity payment due to participation in the capacity auction which is the sum of firm capacity payment revenue (\(\text{TCRC}_{F}\)) and variable (non-firm) capacity revenue (\(\text{TCRC}_{V}\));
2. demand response (DR) revenue (\(\text{TDRR}\)); and
3. revenue from participation in the energy market (\(\text{TER}\)).

In addition, the objective function (OF) shown in Equation (1) aims to minimize NPV computed over the planning horizon NY of the three associated costs as shown below:

1. Costs of utility charges for aggregated loads as it relates to energy (\(\text{TCCE}\)) and power capacity (\(\text{TCCP}\));
2. costs of aggregated assets including distributed generator capital cost (\(\text{TI}_{\text{CDG}}\)) and energy storage capital cost (\(\text{TI}_{\text{CES}}\)); and
3. P2P transaction costs (\(\text{TTCP}_{P2P}\)) with other facilities out of the aggregation.

These revenues and costs are systematically presented as follows in Equations (2)–(10). The capacity payment revenues for the aggregator are computed by Equations (2) and (3) when it provides firm (24-h) and variable (applicable to a time segment)
power capacity to the power system, respectively.

\[
TCR_{CF} = \max \left\{ \sum_{j \in NY} \sum_{i \in N} P_{id,j}^{CF} \cdot BF_{h,j} \cdot \left( \frac{1}{1 + r_{i,j}} \right) \right. \\
- \sum_{j \in NY} M \cdot \left( 1 - U_j^{CM} \right), 0 \right\} 
\]

(2)

\[
TCR_{CV} = \sum_{j \in NY} \left[ \left( \sum_{i \in N} P_{id,j}^{CV} \cdot BV_{i,j} \right) \cdot \left( \frac{1}{1 + r_{i,j}} \right) \right] 
\]

(3)

The revenue received by the aggregator by providing DR service is presented in Equation (4). This DR revenue is calculated on annual basis depending on the demand response power \( P_{id,j}^{DR} \) and the demand response credit \( BDR_{i,j} \).

\[
TDRR = \sum_{j \in NY} \sum_{i \in N} \sum_{e \in E} P_{id,j}^{DR} \cdot BDR_{i,j} \cdot \left( \frac{1}{1 + r_{i,j}} \right) 
\]

(4)

In Equation (5), the revenue due to participating in the energy market based on the binary decision \( U_j^{EM} \) is provided.

\[
TEIR^{E} = \max \left\{ \sum_{j \in NY} \sum_{i \in N} \sum_{e \in E} \max \left( P_{id,j}^{Ei}, 0 \right) \cdot \left( KE \cdot S_{i,j} \right) \right. \\
\left. \cdot \left( \frac{1}{1 + r_{i,j}} \right) - M \cdot \left( 1 - U_j^{EM} \right), 0 \right\} 
\]

(5)

It is important to note that participation in energy or capacity markets is jurisdiction based, as there are unique regulations for each jurisdiction. On the other hand, the cost of utility charges is computed in Equations (6)–(10). In (6), the energy consumption cost of aggregated participant loads is obtained.

\[
TCC^{E} = \sum_{j \in NY} \sum_{i \in N} \sum_{e \in E} \sum_{h \in H_{i,j}} \left( P_{id,j}^{Ei} \cdot KE \cdot B_{i,j} \right) \cdot \left( \frac{1}{1 + r_{i,j}} \right) 
\]

(6)

The power capacity charges are computed for DC and UC.

\[
TCC^{P} = \sum_{j \in NY} \sum_{i \in N} \sum_{h \in H} \left( UC_{m,j} \cdot \sum_{i \in H} PDF_{h,i,j} \right) \\
+ DC_{m,j} \cdot \sum_{h \in H} P_{m,j}^{peak} \cdot \left( \frac{1}{1 + r_{i,j}} \right) 
\]

(7)

The total capital cost of aggregated assets is obtained in Equations (8) and (9) for DG units and ES units, respectively. Here, the bids submitted by individual asset owners wishing for aggregation are considered.

\[
TCC^{DG} = \sum_{i \in N} \sum_{j \in NY} \left( U \cdot G_{s,j} \cdot K P_{s,j} \cdot P G_{s,j} \right) \\
\cdot \left[ 1 + K M F_{s,j} \cdot \sum_{j \in NY} \left( 1 + K M V_{s,j} \right) \right] 
\]

(8)

\[
TCC^{ES} = \sum_{i \in N} \sum_{j \in NY} \sum_{s \in S} U \cdot E_{s,j} \cdot \left( K S_{s,j} \cdot E_{S,j} + K P_{s,j} \cdot P S_{s,j} \right) \\
\cdot \left[ 1 + K M F_{s,j} \cdot \sum_{j \in NY} \left( 1 + K M V_{s,j} \right) \right] 
\]

(9)

The costs of P2P trades with other facilities are presented in Equation (10). Here, the bids submitted by individual P2P traders wishing for aggregation are considered.

\[
TCC^{P2P} = \sum_{j \in NY} \sum_{i \in N} \sum_{s \in S} \sum_{t \in T} K_{P2P} \cdot u_{P2P} \cdot \left( \frac{1}{1 + r_{i,t}} \right) 
\]

(10)

The aforementioned objective function is subject to the following set of constraints in Equations (11)–(32).

### 3.2 Power capacity market participation constraints

The aggregator's participation in the capacity auction is modelled in Equations (11)–(13). The aggregated firm capacity should exceed the capacity auction threshold to enable the capacity payments as in Equation (11).

\[
\sum_{j \in NY} P_{id,j}^{CF} \geq U_j^{CM} \cdot P^{CM} ; \forall y 
\]

(11)

Based on morning-daytime-evening time segments, the aggregated variable capacity for each time segment is provided in Equations (12) and (13). The total capacity of a unit in a segment 's' is split optimally between firm and variable capacities, and constrained as below:

\[
\sum_{j \in NY} P_{id,j}^{CV} + \sum_{j \in NY} P_{id,j}^{CF} = \sum_{j \in NY} \sum_{h \in H} P_{m,j}^{peak} ; \forall s, \forall y 
\]

(12)

The minimum value of generated output power for a certain segment 's' by an aggregated entity, which gives the total capacity, is computed as below:

\[
P_{C_{h,s,i,j}} = \max \left\{ \min_{r \in [\alpha]} \left( \frac{P_{id,j}^{O}}{1 + r_{i,j}} \right), 0 \right\} ; \forall i, \forall h, \forall s, \forall y 
\]

(13)
3.3 | Energy capacity market participation constraints

In addition to power capacity constraint in Equation (11), the condition for aggregator’s participation in the energy market is constrained by a minimum amount of energy supply, as presented in Equation (14).

\[
\sum_{i \in N} \sum_{t \in T_i} \left( p_{PO,i,t}^O \right) \geq \sum_{i \in N} p_{CE}^C \cdot \sum_{i \in N} \sum_{t \in T_i} p_{CV}^E - F_{i,j} \quad \forall i, \forall y
\]  

(15)

\[
0 \leq F_{i,j} \leq M \left( 1 - \phi_{m,i,j} \right) \quad \forall i, \forall y
\]  

(16)

\[
\sum_{t \in T_i} \phi_{m,i,j} \geq \phi \cdot T \quad \forall y
\]  

(17)

3.4 | Availability of aggregated assets constraints

The set of Equations (15)–(17) describe constraints on minimum availability of aggregated assets as a percentage (\( \phi \)) of the total hours of availability (\( T \)). A slack value (\( F \)) is introduced to allow the capacity constraint to violate for a maximum number of hours in a year. The value of the hourly binary variable (\( \phi_{m,i,j} \)) turns to 1 whenever the aggregator is available to justify all contracted capacity.

3.5 | Dynamic aggregation - P2P transactions constraints

As the proposed aggregator model considers the P2P trades with other facilities out of aggregation, the limits on the contracted capacity of these facilities and total commitment hours are provided in Equations (18) and (19) respectively.

\[
p_{P2P}^{\text{P2P}} \leq A_{P2P} \cdot \sum_{i \in N} \sum_{t \in T_i} \phi_{m,i,j} \quad \forall i, \forall y
\]  

(18)

\[
N_{P2P} \leq \sum_{i \in N} \sum_{t \in T_i} \phi_{m,i,j} \leq N_{P2P} \quad \forall i, \forall y
\]  

(19)

3.6 | Feeder power balance constraints

The feeder power balance set of equations is presented in Equation (20), accounting for all generated power from all aggregated assets, the transacted power in terms of DR and P2P, and the power demand on each feeder.

\[
\sum_{i \in H_i} p_{PO,i,t}^O = \sum_{j \in D_i} p_j^G \cdot \sum_{i \in E_i} p_{ES,i,t}^E + p_{DR}^D - p_{PO,i,t}^D + \sum_{i \in T_i} p_{P2P}^{\text{P2P}} \quad \forall i, \forall y
\]  

(20)

3.7 | Energy storage assets constraints

The set of constraints on aggregated ES units are given in Equations (21)–(26). The constraints considering the power and energy capacity limits of the ES units are given in Equations (21) and (22).

\[
0 \leq \frac{p_{ES}^O \cdot U_{E_{i,t}}}{E_{i,t}} \leq \frac{p_{ES}^E}{E_{i,t}} \cdot U_{E_{i,t}} \quad \forall i, \forall y
\]  

(21)

\[
0 \leq \frac{p_{ES}^E}{E_{i,t}} \cdot U_{E_{i,t}} \quad \forall i, \forall y
\]  

(22)

The intertemporal energy constraint is provided in Equation (23).

\[
E_{i,t}^E = E_{i,t-1}^E \cdot (1 - \mu_{i,t}) + \left( \frac{p_{ES}^E}{E_{i,t}} \cdot U_{E_{i,t}} \right) \quad \forall i, \forall y
\]  

(23)

The ES power conversion losses are considered in Equations (24)–(26).

\[
\frac{p_{ES}^E}{E_{i,t}} \cdot U_{E_{i,t}} = \frac{p_{ES}^E}{E_{i,t}} \cdot (1 - \eta_{i,t}) \quad \forall i, \forall y
\]  

(24)

\[
\frac{p_{ES}^E}{E_{i,t}} \geq 0 \quad \forall i, \forall y
\]  

(25)

\[
\frac{p_{ES}^E}{E_{i,t}} \leq 0 \quad \forall i, \forall y
\]  

(26)

Further, the number of cycles of each ES unit is modelled in Equation (27) and the limits on the number of cycles are provided in Equation (28).

\[
NC_{i,t} = \frac{1}{E_{i,t}} \sum_{r \in T} \max \left\{ \frac{E_{i,t-1}^E - E_{i,t}^E}{E_{i,t}^E} , 0 \right\} \quad \forall i, \forall y
\]  

(27)

\[
\sum_{r \in N} NC_{i,t} \leq NC_{i} \cdot U_{E_{i,t}} \quad \forall i, \forall y
\]  

(28)

3.8 | Distributed resource assets constraints

The limits on the available generated power of the DG units are provided in Equation (29). It is important to note that the hourly
generated power is based on the typical generation profile for each considered technology of the DGs.
\[
0 \leq \frac{P_G}{p_{i,j}} \leq \frac{P_G}{p_{i,j}} \cdot U G_{i,j} ; \forall i, \forall y
\]  (29)

### 3.9 Feeder capacity limits

The physical capacity limit of the feeders, allotted to an aggregator, is presented in Equation (30).
\[
-P F_i \leq \sum_{i} P^{O}_{\text{h}_i} \leq PF_i ; \forall i, \forall y
\]  (30)

### 3.10 Monthly maximum aggregated demand and annual peak demand factor

Equation (31) calculates the maximum monthly demand power of the aggregator for the purpose of DC estimation.
\[
PO_{\text{peak}} = \min \left\{ \sum_{t \in [u]} P^{O}_{\text{h}_i} ; 0 \right\} ; \forall m, \forall y
\]  (31)

Moreover, the peak demand factor (PDF) is evaluated in Equation (32) to estimate the UC. In Ontario (Canada), the PDF is calculated based on the facility’s share of power consumption of the whole jurisdiction during five identified hours (termed as the coincident peak) and the UC is known as the global adjustment cost. While this factor is unique to Canada, this formula may be adapted to individual jurisdiction as applicable.
\[
PDF_{\text{h}_i} = \frac{\sum_{i=1}^{N_{\text{p}}} \max \left\{ \sum_{t \in [u]} \left( -\min (P^{O}_{\text{h}_i} ; 0) \right) ; 0 \right\}}{\sum_{i=1}^{N_{\text{p}}} \sum_{t \in [u]} OSPD_{\text{p}_t}} \cdot \forall i, \forall h, \forall y
\]  (32)

### 4 ALLOCATING THE PROFITS AMONG THE AGGREGATED DERS

While the proposed planning model of aggregators maximizes the profits obtained from three major revenue streams, a mechanism for distributing these profits among the aggregated DERs is necessary to ensure a successful business model for all aggregated DERs.

It is important to note that DER assets will only aggregate under the premise of economic benefit. Therefore, the profits obtained by a DER owner via aggregated operation must surpass (or at least match) those obtained via disaggregated operation.

In this section, the total aggregator profits \(TAP\) will be equal to the sum of the disaggregated profits for all prosumer \(TDP\) plus an aggregation profit increase \(API\) as shown in Equation (33). Considering a set of aggregated DERs, \(TAP\) must be greater than \(TDP\) (i.e., \(API \geq 0\)). Otherwise, DER owners will be discouraged from aggregating, leading to a prioritization of disaggregated operation schemes.
\[
TAP = TDP + API
\]  (33)

Further, the \(TAP\) obtained is distributed in three main categories:

1. Aggregator’s commission \(AC\): The entity operating the aggregated assets keeps a percentage of the API as profit.
2. Disaggregated payments \(DP\): Are payments issued to DER owners to match their disaggregated operation. The \(DP\) value for each customer is stipulated via contract between the DER owner and the aggregating entity.
3. Performance payments \(PP\): Are payments apportioned to DERs based on the participation of total power capacity and energy dispatched by the aggregator. Similar to \(AC\), \(PP\) will correspond to the remaining percentage of \(API\), that is, \(API = PP + AC\).

The percentage assigned to \(AC\) and \(PP\) depends strictly on the profit distribution policy in place, which is fully disclosed to DER owners prior to entering any aggregation agreement. Once the total values of \(AC\) and \(PP\) are calculated as a percentage of \(API\), they are divided among the aggregated assets using the revenue distribution strategy explained below.

\(PP\) payments for DERs aggregated behind a meter ‘\(x’\) \(PP_{x}^{p}\) is calculated following the expression shown in Equation (34). Here the energy delivered at a meter ‘\(x’\’ is divided by the total energy delivered by the aggregator and multiplied by the total \(PP\) of the aggregator.
\[
PP_{x}^{p} = PP \cdot \frac{\sum_{t \in [u]} (P_{x,t})}{\sum_{t \in [u]} (P_{t})}
\]  (34)

While this is a proposed mechanism, in actual implementation, several variations may be developed and implemented to account for practical aspects and financial interests of participants.

### 5 CASE STUDIES

The mathematical formulation presented in Section 3 has been implemented in MATLAB as a MILP code and solved using the MOSEK solver. In the following subsections, two cases for aggregator planning are presented to demonstrate the effectiveness and flexibility of the proposed DDA model, illustrating the different attributes of the proposed approach and showcasing the strength in aggregating disparate assets.
5.1 Case I – Simple case (single meter)

This simple case study aims to illustrate the attributes and benefits of the proposed DDA planning model by planning for a simple aggregator of one feeder, with several entities aggregated behind one single meter. In Figure 3, all the options of the entities to be aggregated are presented. In addition to DERs being considered, the aggregator includes a 150 kW demand with a flat profile and the main feeder has a maximum capacity of 400 kW. The planning horizon is 15 years (with annual intervals) with a morning-daytime-evening time segmentation approach. In Table 1, the assets available for planning are described. The number of each asset technology as well as the rating of the units are provided. The factors of capital cost for the considered asset technologies are tabulated in Table 2 based on [19, 20]. The generation profiles for PV units and wind units for both summer and winter seasons are provided in Figure 4. The bids for participating in the energy market for energy and service transactions as well as the bids for the power capacity auction are provided in Table 3. It is important to note that the values of utility charges, including hourly energy price, UC, and DC are considered based on the available published data of the independent electricity system operator (IESO) of Ontario, Canada [21]. The hourly buying energy price KEB is assumed to be the hourly Ontario energy price (HOEP), while the hourly selling energy price is assumed to be 110% of HOEP.

The results of the proposed assets planning model are reported in Figure 3, with the optimal selected assets shown inside red rectangles. Figure 5 illustrates the aggregator’s firm capacity and segmented variable capacity for a typical summer day. It is important to note that the computation time for case I is 15 s.

In order to capture the benefits of this aggregation model with disparate technologies, further analysis is performed to compare between the results of optimal aggregation for disparate technologies in terms of revenues and costs with those of the aggregation results of one single DER technology [16–18]. The comparison is reported in Table 4 which shows that with the DDA model, the same aggregated assets can enlarge total revenues by 60.8% and decrease the overall utility charges by 63.1% in comparison to several aggregators each adapting a single technology. This comparison and analysis demonstrates the benefit of aggregating disparate technologies within
TABLE 4  Comparison between aggregation of same technology and aggregation results of disparate technologies

|                             | Aggregation of same technology [16–18] | Aggregation of disparate technologies | Comparison DDA model v/s Individual Aggregator Model |
|-----------------------------|----------------------------------------|---------------------------------------|-----------------------------------------------------|
|                             | PV unit                                | Battery                               | Flexible load                                       |                                                     |
| Rating                      | 200 kW                                 | 50 kW of DR                           | 150 kW/300 kWh                                      |                                                     |
| Firm capacity               | 0                                      | 0                                     | 0                                                   | 140 kW                                             |
| Annual revenues             | Capacity                               | Capacity                              | Capacity                                            |                                                     |
| Energy                      | k$ 91.10                              | k$ 85.41                              | 0                                                  | k$ 176.51                                           |
| DR                          | 0                                      | 0                                     | k$ 13.41                                           | k$ 22.12                                           |
| Annual Utility charges      | Energy                                 | DR                                    | DR                                                 |                                                     |
| DC                          | 0                                      | k$ 45.99                              | k$ 56.94                                           | k$ 89.54                                           |
| UC                          | 0                                      | k$ 17.55                              | k$ 17.55                                           |                                                     |
| Total investment cost       | k$ 889.2                               | k$ 208.4                              | k$ 1,097.6                                         |                                                     |
| Total revenues              | k$ 189.9/year                          | k$ 82.125                             | k$ 13.41                                           | k$ 13.41                                           |
| Total utility charges       | k$ 290.6/year                          | VC                                    | k$ 24.638                                          | k$ 24.638                                          |

FIGURE 6  Signal line diagram of large residential/commercial aggregator case study (P1 and P2 represent P2P traders)

an aggregator and eliciting significant benefits, which is not possible from other methods reported in the literature.

5.2 Case II – Large residential/commercial aggregator

This case study considers the aggregation on a large scale for a set of 100 homes and three Equation (3) commercial smart buildings as shown in Figure 6. The asset planning options are provided in Table 5. In this case study, the market participation thresholds \( P^{EM}, P^{CM} \) are set to be 500 and 1,000 kW for the energy market and the firm capacity auction respectively.

The DDA model is employed to plan for the asset options available to the aggregator, as tabulated in Table 5 based on a planning horizon of 15 years and a morning-daytime-evening segmentation approach for considering the segmented variable capacity. Figure 7 presents the winter and summer typical daily load profiles for both residential and commercial entities.

There are several P2P annual offers available for selection by the DDA model, as shown in Table 6. The availability factor \( \phi \) is assumed to be 100%.

By applying the proposed DDA model, the developed plan of the aggregator is reported in Table 7. It is important to note that the computation time for case II is 4.6 min.
TABLE 5  Summary of available assets options for aggregator

|                      | Residential |                          | Commercial |                          |
|----------------------|-------------|--------------------------|------------|--------------------------|
|                      | Unit        | unit/house               | Unit       | unit/building            |
| DG units             |             |                          |            |                          |
| Roof-top PV          | 7 kW        | 1                        | 50 kW      | 5                        |
| Wind                 | –           | –                        | 100 kW     | 10                       |
| Diesel               | –           | –                        | 100 kW     | 10                       |
| Battery storage      | –           | –                        | 100 kW/200 kWh | 10                       |
| # of participants    | 100 houses  |                          | 3 buildings|                          |

TABLE 6  Summary of P2P annual offers

| Location   | Max. capacity (kW) | Annual Min. commitment hours | Annual Max. commitment hours | Annual contract |
|------------|--------------------|------------------------------|------------------------------|-----------------|
| Feeder# 1 (P2) | 500               | 10                           | 100                          | $ 50k           |
| Feeder# 6 (P1) | 800               | 10                           | 100                          | $ 80k           |

Further, the DDA model contracted P2P trader (P2) for power capacity and an annual number of commitment hours as shown in Figure 8.

The typical daily available generated power profile of the aggregated DGs is illustrated in Figure 9 as well as the total generation of the whole aggregator for a summer day.

In Figure 10, the aggregator firm capacity and segmented variable capacity for a typical summer day of the planning horizon are shown. The resulting percentage representation of each revenue and cost term of the objective function (1) are illustrated in the two pie charts of Figure 11.

The revenue pie chart shows that the limited volatility energy price jurisdiction, such as the used data set, the aggregator makes the majority of its revenues from firm and variable capacity payments which the aggregated assets are not eligible to achieve with the aggregation of one single DER technology. On the other hand, the cost pie chart shows that the bulk of cost are

![Figure 8](image1.png)

**FIGURE 8** Yearly maximum P2P power trades and annual commitment hours

![Figure 9](image2.png)

**FIGURE 9** Typical summer daily total available aggregated generation of DERs

TABLE 7  Summary of optimal aggregator’s assets plan

|                      | DGs |
|----------------------|-----|
|                      | PV   | Wind     | Diesel   | Battery               |
| Each building        | 5 × 50 kW | 4 × 100 kW | 6 × 100 kW | 5 × 100 kW/200 kWh |
| Total commercial     | 750 kW   | 1200 kW  | 1800 kW  | 500 kW/1000 kWh      |
| Each house           | 1 × 8 kW  | –        | –        | –                     |
| Total residential    | 800 kW   | –        | –        | –                     |
FIGURE 10  
Aggregator total firm and variable capacity for a typical summer day

FIGURE 11  
The aggregator’s revenue and cost terms in percentage representation

FIGURE 12  
Changes of the normalized net profit due to change of \( \varphi \)

FIGURE 13  
The energy revenues (%) due to change of KES price bandwidth

5.3 Sensitivity analysis on large aggregator case study

This subsection investigates the attributes and features of the proposed DDA planning model considering several sensitivity analyses. These studies are conducted on the large residential/commercial aggregator of case II, considering changes of three parameters as follows.

1. Sensitivity on the accepted availability factor (\( \varphi \))

In this sensitivity analysis, the effect of changing the value of \( \varphi \) on the aggregator revenues is analyzed. In Figure 12, the results due to changing the value of \( \varphi \) in the range between 90% and 100% on the normalized net profit value are illustrated, where normalized net profit is the ratio of profit Equation (1) for a certain \( \varphi \) value compared to profit Equation (1) considering \( \varphi \) equal to 100%. The results demonstrate that higher the flexibility (\( \varphi \)) given to the aggregator, the higher is the economic opportunity derived by the model.

2. Sensitivity on bidding values to participate in energy market (KES):

In this sensitivity analysis, the effect of changing the hourly energy selling price (KES), used in (5), at which the aggregator is able to sell energy to the distribution system, is analysed. The values of KES are considered with both high and low-price bandwidths. Four price case studies are developed considering −20%, −40%, 20% and 40% electricity price bandwidths, respectively. The prices of case II, which is considered as a base case, are increased and decreased to create these cases. All have the same price variation pattern and same mean price as the base case. In Figure 13, the results show how the total energy revenues (TER) will change due to change of KES price bandwidth. Increasing the KSE bandwidth by 20% leads to a revenue increase of 6% compared to the base case (Case II). However, reduction of the price bandwidth has limited impacts.

3. Sensitivity on bidding values to participate in capacity auction (firm capacity bid – \( BF \)):

In this sensitivity analysis, the impacts of changing the annual firm capacity bid (\( BF \)), used in Equation (2), of the DDA model is investigated. Four bid price case studies are developed considering changes of −10%, −5%, +5% and +10% from the given bid price of case II, which is considered as a base case. In Figure 14, the impacts on the firm capacity revenue and the net profit are illustrated due to change of the \( BF \) bid price and compared with the results of case II. The results show that a 20% decrease or increase in BF could lead to a relatively significant change in the overall net profit with −6.3% reduction and 5.3% increase, respectively.

These sensitivity analyses can be employed by the aggregator as a bidding mechanism that allows it to investigate the impacts of bidding changes on the revenues and profits.
6 CONCLUSION

This paper proposes a comprehensive planning model for aggregators considering multiple revenue streams and disparate distributed energy resource (DER) technologies, the DDA model. The proposed DDA planning model accounts for dynamic/temporal aggregation agreements with other entities, outside the aggregation, through the peer-to-peer (P2P) trades and takes into account the unavailability of aggregated assets. The work contributions can be summarized as follows: first, develop a value stack aggregator’s planning model considering disparate technologies of DERs and target revenues from several revenue streams including (1) capacity credits; (2) energy revenues; and (3) demand services revenues. Second, proposing and accounting for the dynamic aggregation concept through the peer-to-peer trades with other facilities as well as considering the unavailability of aggregated assets. Third, the simplicity and flexibility of the proposed aggregator’s planning model, a mixed integer linear model, increases its business potential to be employed by private sector investors to plan for their investments and use it for their bidding strategies.

The developed DDA planning model is formulated as a mixed integer linear programming problem that optimizes concurrently for all years of the planning horizon. The DDA model was tested on a sample system and a practical large system. The results demonstrate that there is 60% increase in revenue when disparate DER technologies are aggregated, in comparison with traditional aggregation methods proposed in the literature. Sensitivity analysis show that the model behaves as expected when considering parameters that influence the DDA model.

7 FUTURE WORK

From the perspectives of future directions of this work, an optimization model to manage the daily/hourly operation of the aggregated assets in a TEDS framework would be imperative for DER investors. In addition, formulations that explicitly model uncertainty, such as stochastic or robust approaches, can be developed to enhance the accuracy of the proposed results. Furthermore, a comprehensive planning model for the whole transactive distribution system that consider these aggregator models into their planning framework is a must.

**NOMENCLATURE**

- $p_p^{P2P}$: Integer for P2P transaction with prosumer $p$.
- $E_{e}^{ES}$: Available unit energy size of the battery storage.
- $N_{e}$: Maximum number of energy storage operating cycles.
- $N_p^{P2P} / N_p^{P2P}$: Upper and lower commitment hours of P2P transactions.
- $p_{PL}^{EM}$: Minimum firm capacity to participate in LDO’s capacity market.
- $p_{PL}^{EM}$: Minimum capacity to participate in LDO’s energy market.
- $T_{PF}$: Feeder capacity limit.
- $p_{PL}^{P2P}$: Available unit power size of the battery storage.
- $DC_{em}$: Demand charge cost.
- $E_{e}^{ES}$: Energy of the storage unit $e$.
- $G_{AC}^{em}$: Monthly Global Adjust factor costs for Ontario.
- $K_{e}$, $K_{e}$: Capacity cost coefficients for energy storage unit.
- $K_{e}$: Capacity cost coefficient for distributed generator.
- $K_{e}^{P2P}$: P2P transaction contract with prosumer $p$.
- $NC_{e}$: Number of cycles of the energy storage unit $e$.
- $PC_{k, e, g}$, $PC_{k, e, g}$: Segmented variable power capacity.
- $TG_i$: Available unit rating size of distributed generator at feeders $i$.
- $PL_{+, t}^{ES}$, $PL_{-, t}^{ES}$: Energy storage power converter losses.
- $PO_{k, g}$: Monthly peak output power of the aggregator.
- $p_{PL}^{ES}$, $p_{PL}^{ES}$: Power of the energy storage unit $e$.
- $p_{PL}^{ES}$, $p_{PL}^{ES}$: Power of the distributed generator unit $g$.
- $p_{PL}^{P2P}$: Firm capacity at feeder $i$.
- $p_{PL}^{P2P}$: Variable capacity at feeder $i$.
- $p_{PL}^{DR}$: Power of non-dispatchable load at feeder $i$.
- $p_{PL}^{P2P}$: Demand response power at feeder $i$.
- $p_{PL}^{P2P}$: Net output power transferred at feeder $i$.
- $TCC_{e}^{E}$: Utility charges energy components.
- $TCC_{e}^{P}$: Utility charges power capacity components.
- $FIR_{e}^{C}$: Firm capacity revenue ($)$.
- $VCR_{e}^{C}$: Variable capacity revenue ($)$.
- $C_{DG}^{C}$: Capital cost of distributed generators assets ($)$.
- $C_{ES}^{C}$: Capital cost of energy storage assets ($)$.
- $C_{P2P}$: Peer-to-peer transactions cost ($)$.
- $U_{CM}$: Integer for participating as a firm capacity supply.
- $U_{EM}$: Integer for participating into the energy market.
- $U_{e, t}^{EM}$: Planning decision of the energy storage unit $e$. 

**FIGURE 14** Changes of the normalized net profit (%) due to change of BF bids.
Planning decision of the distributed generator unit \( g \).

Power conversion efficiency of the storage unit \( e \).

Self-discharge of the storage unit \( e \).

Demand response credit ($ MW^{-1}$).

Firm capacity credit ($ MW^{-1}$).

Variable capacity credit ($ MW^{-1}$).

Energy storage index.

Slack values to avoid nonlinearity.

Distributed generator index.

Feeder index.

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