Energy Trading in Local Electricity Market with Renewables- A Contract Theoretic Approach

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***Abstract*—Emerging smart grid technologies and increased penetration of renewable energy sources (RESs) direct the power sector to focus on RESs as an alternative to meet both baseload and peak load demands in a cost-efficient way. A key issue in such schemes is the design and analysis of energy-trading techniques involving complex interactions between an aggregator and multiple electricity suppliers (ESs) with RESs fulfilling a certain demand. This is challenging because ESs can be of various categories such as small/medium/large scale, and they are self-interested and generally have different preferences towards trading based on their types and constraints. This paper introduces a new contract-theoretic framework to tackle this challenge by designing optimal contracts for ESs. To this end, a dynamic pricing scheme is developed that the aggregator can utilize to incentivize the ESs to contribute to both baseload and peak load demands according to their categories. An algorithm is proposed that can be implemented in a distributed manner by trading partners to enable energy trading. It is shown that the trading strategy under a baseload scenario is feasible, and the aggregator only needs to consider the per unit generation cost of ESs to decide on its strategy. The trading strategy for a peak load scenario, however, is complex and requires consideration of different factors such as variations in the wholesale price and its effect on the selling price of ESs, and the uncertainty of energy generation from RESs. Simulation results demonstrate the effectiveness of the proposed scheme for energy trading in the local electricity market.**

***Index Terms--contract theory, electricity suppliers, energy trading, microgrid, renewable energy*.**

I. Introduction

With increasing fossil-fuel prices and climate change, many countries have started to rely on renewable energy sources (RESs) to meet the growing electricity demand [1][2]. For example, Australia sets a target of a 20% share of renewable energy in its electricity supply by 2020 [3]. Such a widespread growth of RESs and advancements in smart-grid technology will open new opportunities for electricity trading between aggregators and electricity suppliers (ESs). However, the effectiveness of the trading largely depends on the willingness of ESs to participate. In reality, ESs are self-centered and want to maximize their benefits regardless of whether a certain demand is met or not [4]. Meanwhile, an aggregator is also a profit-seeking entity interested to maximize its utility. As such, considering the rationality of the different electricity entities, an incentive scheme is required to motivate them to trade energy.

Existing incentive-driven energy trading schemes can be generally classified into three types: 1) price-based, 2) game-theoretic, and 3) contract-theoretic. Pricing is a powerful tool for energy management incorporating an increasing penetration of RESs. It stimulates consumers to behave in an economically optimal way by changing their consumption patterns when electricity prices are high. In [5] and [6], a zero-pricing and a dynamic period partition time of use (TOU) program is proposed respectively, considering current market policies and the surge of renewable-energy development to improve the effectiveness of TOU at the residential level. In [7]-[9], various load-scheduling and energy storage control strategies are proposed using real-time pricing (RTP) mechanisms for residential sites with integrated renewable generation. Although price-based strategies are easy to deploy, their main challenges are to maintain reliability, predictability, and stability of the grid. For instance, it is shown in [10]-[11] that large-scale implementation of price-based programs under the RTP schemes creates power grid stability problems.

Game theory, a well-developed mathematical tool that facilitates the modeling of rational users [4], has been used to analyze the trading decisions of electricity suppliers and consumers in a smart grid [12]-[16]. For instance, in [12], a game-theoretic approach is adopted to fairly allocate and reduce using distributed generators' (DGs) participation in an energy management system. The researchers in [14] present a non-cooperative distributed-coordination control approach to coordinate the individual's benefits in a multi-grid environment, and employs differential game theory to achieve the global objectives. However, most of these game-theoretic models are based on symmetric information models assuming that players have all the necessary information for electricity trading such as the per-unit generation cost of electricity of each supplier and their type.

Given this context, researchers focused on the contract-theory approach to incentivize trading participants in the presence of asymmetric information where actual category, type and the marginal cost of electricity of each supplier is unknown to form a practical scenario [17]. It is based on the principal-agent theory, in which a principal offers the right contract items to the agents to achieve maximum utility, and the agents truthfully select the contract items according to their type, for example, consumption and generation, to maximize their utilities [18]-[19]. Recently, several studies have used contract theory to model the electricity market mechanism. For example, in [20], a contract-based scheme is proposed to coordinate many electric vehicles (EVs) to achieve the charging/discharging request. In [21], a framework is proposed to facilitate electricity trading between aggregators, suppliers, and consumers. In this scheme, a coalition of suppliers will sell excess power and revenue is divided among partners based on the asymptotic shapely values. The work in [22] presents a peer-to-peer energy-trading scheme that consists of energy-contract offers between fuel-based generators and end-users with inflexible and flexible loads. In [23], a contract-theory based direct energy-trading model is used to address the intermittency of RESs.

Indeed, these existing studies have significantly contributed in the area of energy management through energy trading techniques. However, further research work is required to establish the energy trading benefits to the existing power system to implement the energy trading markets in grid-connected systems [24]. Moreover, in real electricity markets, high volatility and high prices are observed with the deregulation of electricity markets due to various reasons [25], therefore, optimal trading strategies that consider price uncertainties are needed. These studies would facilitate the integration of energy trading mechanisms into energy policy. One possible way to show that the energy trading mechanisms can complement the traditional

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Aspect	Previous Scheme [23]	Proposed scheme
Trading mechanism	Direct electricity trading	Hierarchical electricity trading framework
ESs categorization	No categorization	Categorized into three main types and developed trading strategy for each category
Trading scenarios	No classification	Two trading scenarios based on the load demand
Selling price	Constant selling price	Different selling price for different trading scenario
Wholesale price fluctuations impact on the buyer's decision	Not considered	Buyer decides on its strategy taking into account wholesale price fluctuations

power systems is to establish its benefit for an energy retailer (aggregator) considering price variations. The current work is an attempt to establish such a benefit of energy trading strategy by proposing a framework of a dynamic price based trading strategy that can help the aggregator to reduce its cost of energy supply to the consumers and energy purchased from the wholesale market at peak demand periods.

In a developed strategy, the aggregator as a principal strategically sets the purchasing price per unit of electricity for various types of ESs at peak demand periods considering the effect of high wholesale price during peak demand on their selling price and uncertainty in their reliability. With this strategy, the aggregator ensures either the purchase of energy from the wholesale market reduces to zero (thus, reducing the cost of peaking power plants) or ESs pay the penalty charges for not providing the required amount of power. In response to the price offered by the aggregator, ESs, as agents of the scheme, participate in the strategy by accepting the contracts based on their type if it satisfies their constraints. This way the proposed scheme brings a win-win situation for both trading partners.

To this end, this paper aims to design a contract-based incentive scheme for various categories of ESs with different types, assuming a heterogeneous setting where aggregators and ESs have different preferences toward the buying/selling price for different trading scenarios. The contributions of this study are summarized as 1) A new contract-theoretic framework is developed that enables different categories of ESs with various types to individually and strategically trade available surplus power with an aggregator in a hierarchical electricity trading system; 2) A novel dynamic pricing mechanism is proposed which assumes that an electricity supplier (ES) selling price varies depending on the current market state, such as fluctuation in the wholesale price and accomplishing the base and peak load demand; 3) A new contract-based distributed algorithm for electricity trading is presented that guarantees the optimal utility of both parties in various trading scenarios; 4) The aggregator maximization problem is formulated as a principal-agent contract-based approach, and the number of constraints of the optimization problem is simplified to develop an equivalent simpler model for the original problem. Further, optimal contracts are theoretically derived for both baseload and peak load scenarios.

This study is mainly motivated by the work in [21]-[23], but the developed contract-theoretic scheme in this paper is substantially different from these studies. In contrast to [21], the proposed scheme enables ESs to trade their electricity individually and strategically, and the aggregator incentivizes various types of ESs considering their per-unit generation cost. Unlike [22], where a scalable price adjustment process (with fixed increments in buying and selling price) is developed to constitute a network of agreed contracts, a dynamic pricing scheme is proposed in this paper where ESs selling price varies depending on the current market state. Compared to the direct electricity-trading scheme in [23], the proposed method incentivizes various types of ESs considering a hierarchical electricity-trading framework with an aggregator as a profit-seeking entity. Although [23] considers different types of suppliers for electricity trading, it does not categorize them and assume a constant selling price for a certain available power which may deteriorate the ESs utility. It is because ESs unit production cost may increase when RESs are not generating much due to their stochastic nature. Table I summarizes the proposed scheme differences with [23].

TABLE I
DIFFERENCES BETWEEN PROPOSED SCHEME AND EXISTING SCHEME

The rest of the paper is organized as follows. Section II presents the system model with details about the aggregator and ESs modeling. Section III details a theoretical derivation of the contract-based approach for the baseload scenario and an optimal solution of the formulated problem, and Section IV discusses the peak load scenario and the electricity-trading algorithm. Numerical case studies are provided in Section V, followed by the conclusion in Section VI.

II. SYSTEM MODEL

Figure. 1 shows the three-level hierarchical system model considered in this study. The power grid is at the top level, and the aggregator is at the second level. The electricity distribution network is at the third level and consists of various categories of ESs and traditional consumers with no generation sources. The generation sources in a small, medium and large scale building can be solar panels and wind turbine units and this study assumes that the ESs are geographically distributed within a small area. Since the modeling of generators is not a focus of the current research work, therefore, only surplus power available from ESs is considered. Traditionally, the aggregator purchases time-varying electricity from the power grid at the wholesale price and sells it to traditional users, where most of the traditional users still enjoy a fixed flat rate, and ESs inject their surplus power into the power grid at a low feed-in-tariff rate. When the wholesale price is less than (greater than or equal to) the flat rate at a given time, it is referred to as baseload (peak load) demand throughout this paper. In a traditional electricity market, for baseload demand, the aggregator generates a profit but may suffer a loss when the peak demand scenario occurs. The aggregator can maximize its profit by obtaining cheaper electricity through the proposed contract-based incentive mechanism in both scenarios; however, it needs to consider the current market state and uncertainty of RESs. The aggregator has three significant roles in the developed framework: 1) it acts as an intermediary among different categories of ESs and traditional users. It collects surplus electricity from ESs and sells the collected electricity to traditional users; 2) it interacts with several geographically distributed ESs to satisfy a certain demand; 3) it buys electricity from the power grid when the supply from ESs is less than the consumers' demand.

To reflect the diversity of ESs, they are classified into three main categories based on the installed capacity of RESs. 1) small-scale electricity suppliers (ESs^s): suppliers who have installed small-capacity wind turbines or solar panels on their rooftops 2) medium-scale electricity suppliers (ESs^m) with medium-capacity renewable-energy systems 3) large-scale electricity suppliers (ESs^l): suppliers who have installed large-capacity wind-turbine or solar systems. We consider a scenario in which one aggregator as a principal offers the right contract items and S ESs^s, M ESs^m, L ESs^l acting as agents accept the contract according to their type. This study assumes that ESs do not sell at a loss, so their selling price covers all costs including network and net-metering charges.

A. Aggregator Model

Suppose that the aggregator pays d, e, f dollars to obtain s, m, l amount of power from ESs^s, ESs^m and ESs^l respectively. Let W be the total amount of power the aggregator procures from ESs and $R(s)$, $R(m)$, $R(l)$ be its benefit after obtaining s, m and l units of power. The aggregator's benefit reduces if the required power demand is not fulfilled, for example, if $s+m+l<W$. The aggregator gains maximum

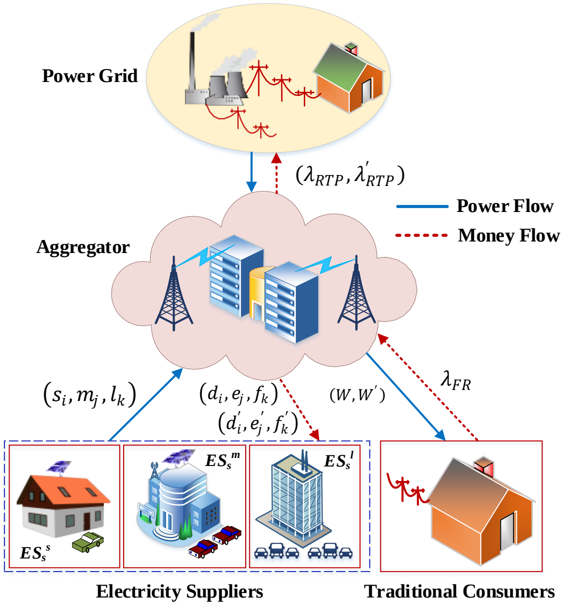

Fig. 1 Proposed three-layer electricity trading model.

benefit when the required power demand is met, i.e., $s+m+l=W$. The equation $s+m+l = W$ suggests that the required power demand is fulfilled from small, medium and large scale electricity suppliers and it's not required to purchase the electricity from the wholesale market. Since the supply from electricity suppliers is cheaper than the wholesale market, therefore, aggregator profit is maximum when all required power is obtained from electricity suppliers.

Thus, with a transaction (d, s), (e, m) and (f, l), the aggregator utility (U_A), which is the benefit minus the cost, is given by

$$U_A = (R(s)+R(m)+R(l)) - (d + e + f) \qquad (1)$$

The first term in (1) is the sum of the benefits gained from the various categories of ESs, and the second term is the payment made to ESs to obtain the desired amount of power. A self-interested aggregator will determine the quantity of power and the cost to obtain that power from various categories of ESs to maximize its utility in a trading process.

B. Seller Modeling

In this paper, we assume that ESs^s, ESs^m and ESs^l can provide (2-20 kW), (21-160 kW) and (161-350 kW) of surplus power respectively, based on the installed capacity of their generation facilities. Any supplier who can provide excess power in the range of (2-20 kW) falls in the category of ESs^s. As renewable energy sources' intermittency has a major impact on a supplier with minimum available surplus power by reducing their reliability, therefore, ESs with at least 2 kW surplus power is considered as a small scale electricity supplier in this study. Moreover, ESs with 0kW cannot participate because they do not have a surplus power available for trading. Similarly, customers who can provide surplus power in the range of (161-350 kW) at a given time are in the category of ESs^l. The heterogeneity of ESs within their category is further characterized based on the per-unit generation cost. ESs' per-unit generation cost varies significantly depending on many factors, i.e. investment on RESs installation, their generation reliability, and maintenance costs. It is assumed that ESs do not sell at a loss; therefore, their selling price should be higher than the generation cost for profit. These cost elements are hidden from the aggregator and are only known to the ESs.

Let the ESs^s, ESs^m and ESs^l selling price be $\dot{a}$, $\ddot{a}$, and $\dddot{a}$ respectively. The aggregator payment should be greater than or equal to the selling price of the various categories of ESs because they will not sell at a loss. Let there be S type ESs^s, M type ESs^m and L type ESs^l according to their selling price. Therefore, ESs whose selling price falls into the i^{th}, j^{th}, and k^{th} cost level $\dot{a}_i$, $i \in \mathrm{S} = \{1,\dots, S\}$, $\ddot{a}_j$, $j \in \mathrm{M} = \{1,\dots, M\}$, $\dddot{a}_k$, $k \in \mathrm{L} = \{1,\dots, L\}$, are called i-type ESs^s, j-type ESs^m and k-type ESs^l. For generalization, the assumptions given in equation (2) is considered.

$$\left.\begin{array}{ll} (a) & \dot{a}_i > \ddot{a}_j > \dddot{a}_k,\ \forall\, i \in S, j \in M, k \in L \\ (b) & \dot{a}_1 > \dot{a}_2 \ldots > \dot{a}_S,\ \ddot{a}_1 > \ddot{a}_2 \ldots > \ddot{a}_M,\ \dddot{a}_1 > \dddot{a}_2 .. > \dddot{a}_L \\ (c) & \dot{a}_i > \lambda_{RTP},\ \forall\, i \in S \\ (d) & \ddot{a}_j,\ \dddot{a}_k < \lambda_{RTP},\ \forall\, j \in M, k \in L \end{array}\right\} \qquad (2)$$

In (2), λ_{RTP} is the wholesale price to obtain electricity from the grid. The assumption (2.a) is based on the installed capacity of the RESs at ESs premises. As the RESs' installed capacity increases, the unit production cost decreases because the RESs have very low maintenance costs, and this ultimately reduces the selling price. (2.b) is based on the type of ESs in a category, to further categorize the ESs in a category; they are arranged in ascending order (lower to higher type) based on the selling price and the surplus power procured by an aggregator. (2.b) suggests that lower-types ESs can provide power at a higher cost; meanwhile, higher-type ESs can provide power at a low rate; thus, the aggregator will obtain more power from higher-type ESs to optimize its profit. (2.c) and (2.d) represent two main two trading scenarios that can happen in the market. (2.c) indicate that the ESs^s selling price is higher than the wholesale price while (2.d) indicate that the ESs^m and ESs^l selling price is lower than the wholesale price. It is because ESs^s lower installed capacity and uncertainty in generation lead to higher per-unit generation cost which may surpass the wholesale price at any given time as mentioned in (2.c). Contrary, ESs^m and ESs^l per-unit generation cost is low due to high installed capacity, therefore, they are capable to sell at a price lower than the wholesale price to attract the aggregator as described in (2.d). However, the medium and large-scale ESs selling price is different because their installed capacity and per-unit generation cost vary.

For trading the selling price of ESs should be $< \lambda_{RTP}$; otherwise, the aggregator has no benefit to trade with ESs. Based on this, following (2.c), the aggregator does not prefer to trade with ESs^s. Hence, a trading strategy is required for ESs^s that is different from the ESs^m and ESs^l trading scheme to take part in a trading process. By considering different scenarios the developed strategy increases the possibility of successful trading by stimulating more ESs.

Traditionally, ESs^s inject surplus power to the power grid at the feed-in-tariff rate (λ_T), which is usually very low. Therefore, ESs^s are willing to sell power at a cost lower than $\dot{a}$ but higher than λ_T to participate in a trading process and further enhance their profit. Let $\varphi\dot{a}$ be the price at which ESs^s are ready to sell their surplus power, where φ is the ratio of the revised selling price and the per-unit production cost of ESs^s. The feasible range of $\varphi\dot{a}$ is $\lambda_T < \varphi\dot{a} < \lambda_{RTP}$ to ensure the rationality of both trading partners.

Suppose that, by selling s, m and l units of power, the ESs^s, ESs^m and ESs^l the benefit is d, e, and f payments respectively from the aggregator. Thus, their utility obtained in the power transaction considering the selling price can be defined as:

$$\left.\begin{array}{l} U(d, s) = d - \varphi\dot{a}s \\ U(e, m) = e - \ddot{a}m \\ U(f, l) = f - \dddot{a}l \end{array}\right\} \qquad (3)$$

As ESs do not want to sell at a loss, it is assumed that $U(d, s), U(e, m), U(f, l) > 0$, when $d, s > 0$, $e, m > 0$, $f, l > 0$. If a supplier does not take part in the trading, it will get nothing. In this condition the utility is $U(0, 0) = 0$.

III. Contract-Based Approach for Baseload Scenario

This section derives the aggregator's optimal contracts, i.e., ð*={$(d_i^*, s_i^*), i \in S$} for the baseload scenario, where the wholesale price is less than the flat rate. In this scenario, the aggregator generates profit through a traditional trading scheme but can further enhance its profit by adopting the proposed contract incentive mechanism.

To model the interactions of the aggregator and the ESs, the framework of a contract-based approach is adopted. In the considered scenario, the aggregator wants to purchase a certain amount of power from ESs^s, ESs^m and ESs^l in the local electricity market. Although the actual selling price of ESs^s, ESs^m and ESs^l is not known to the aggregator, it needs to determine the quantity of power each type of ES can provide and the cost to obtain that power so that its utility is maximized.

Suppose that the aggregator trading scheme for the *i*-type ESs^s is given in the form of (d_i, s_i), where d_i is the agreed payment and s_i is the amount of power the aggregator would obtain from the *i*-type ESs^s. Therefore, the set inclosing the aggregator schemes for all *S* ESs^s constructs a contracts ð ={$(d_i, s_i),\ i \in S$} with (d_i, s_i) being called a contract item. Similarly, (e_j, m_j), (f_k, l_k) are contract items for *j*-type ESs^m and *k*-type ESs^l respectively.

For a contract theoretic approach, the solution must be incentive compatible and individually rational.

Definition 1: A trading strategy (d_i, s_i), (e_j, m_j), (f_k, l_k) is said to be individually rational (IR), if for *i*-type ESs^s, *j*-type ESs^m and *k*-type ESs^l, we have:

$$\left.\begin{aligned} U_i(d_i, s_i) &= d_i - \varphi\dot{a}s_i \geq 0 \\ U_j(e_j, m_j) &= e_j - \ddot{a}m_j \geq 0 \\ U_k(f_k, l_k) &= f_k - \ddot{a}l_k \geq 0 \end{aligned}\right\} \quad (4)$$

Here, $U_i(\cdot)$, $U_j(\cdot)$, $U_k(\cdot)$ is the utility function for *i*-type ESs^s, for *j*-type ESs^m and *k*-type ESs^l. The IR constraint confirms that ESs^s, ESs^m and ESs^l will have a positive utility if they follow this scheme, hence motivating ESs to participate in the trading process actively.

Definition 2: A trading strategy (d_i, s_i), (e_j, m_j), (f_k, l_k) is said to be incentive-compatible (IC) within a category if, for the *i*-type ESs^s, *j*-type ESs^m and *k*-type ESs^l, we have:

$$\left.\begin{aligned} U_i(d_i, s_i) &\geq U_i(d_{i'}, s_{i'}) \quad && i \neq i',\ i, i' \in S \\ U_j(e_j, m_j) &\geq U_i(e_{j'}, m_{j'}) \quad && j \neq j',\ j, j' \in M \\ U_k(f_k, l_k) &\geq U_k(f_{k'}, l_{k'}) \quad && k \neq k',\ k, k' \in L \end{aligned}\right\} \quad (5)$$

Equation (5) ensures that an *i*-type ESs^s selects a contract item designed according to its selling price. If a lower *i*-type ESs^s selects a contract item designed for a higher *i*-type ESs^s then the high demand for power may degrade its utility. Similarly, if a higher *i*-type ESs^s selects a contract item designed for a lower *i*-type ESs^s then, due to the lower power demand, payment cannot compensate for the total production cost. Thus, with IC constraints, *i*-type ESs^s, *j*-type ESs^m and *k*-type ESs^l gain no profit by hiding the true cost and falsely select the contract item of others' type, because only their type of contract within a category brings maximal utility. Likewise, a trading strategy should meet the IC constraint according to the ESs' category.

Definition 3: A trading strategy, i.e., (d_i, s_i) is said to be incentive-compatible (IC) according to its category, if for the *i*-type ESs^s, we have:

$$\left.\begin{aligned} U_i(d_i, s_i) &\geq U_i(e_j, m_j) \quad && \forall\, i \in S, j \in M,\ i \neq j \\ U_i(d_i, s_i) &\geq U_i(f_k, l_k) \quad && \forall\, k \in L, i \in S,\ i \neq k \end{aligned}\right\} \quad (6)$$

Equation (6) confirms that ESs^s choose the contract item designed according to their category of supply capacity. If an *i*-type ESs^s selects the contract item designed for a *j*-type ESs^m or *k*-type ESs^l then its utility is degraded, as the aggregator demands a higher amount of power that is available, and the opposite is true for *j*-type ESs^m or *k*-type ESs^l. Similar equations hold and considered for *j*-type ESs^m and *k*-type ESs^l IC constraints according to their category and are not discussed here due to a limitation on page numbers.

A well-designed contract should also consider the supply capacity of ESs according to their category and type, i.e.,

$$\left.\begin{aligned} & s_{i,min} \leq s_i \leq s_{i,max} && \forall\, i \in S \\ & m_{j,min} \leq m_j \leq m_{j,max} && \forall\, j \in M \\ & l_{k,min} \leq l_k \leq l_{k,max} && \forall\, k \in L \\ s.t.\quad & m_{j,min} > s_{i,max} && j = 1, i = S \\ & l_{k,min} > m_{j,max} && k = 1, j = M \end{aligned}\right\} \quad (7)$$

where $s_{i,min}$, $s_{i,max}$, $m_{j,min}$, $m_{j,max}$, $l_{k,min}$, $l_{k,max}$ are the minimum and maximum supply capacity of ESs^s, ESs^m and ESs^lrespectively. Several ESs of various categories will fulfill the aggregator demand, therefore we can write

$$W = \sum_{i=1}^{S} n_i s_i + \sum_{j=1}^{M} n_j m_j + \sum_{k=1}^{L} n_k r_k \quad (8)$$

where n_i, n_j, n_k is the number of *i*-type ESs^s, *j*-type ESs^m and *k*-type ESs^l respectively, and *W* is the total hourly power demand.

It is assumed that by employing the latest forecasting techniques [26] and other strategies (i.e., using storage devices, and hybrid generation system) [27], [28], the ESs can overcome the generation uncertainty to provide the contracted amount of power. In this way, the aggregator can procure the required quantity of power from ESs. As renewable generation forecasting and hybrid generation systems is not a focus of this paper, therefore, it is not discussed in this study. The power demand is the amount of desired power that aggregators would like to purchase from ESs and the amount of traded electricity is the quantity of power received from all electricity suppliers. The power demand can be equal or higher than the traded electricity. If the electricity suppliers fulfill the power demand then the amount of traded electricity is equal to the power demand. Otherwise, the amount of traded electricity is less than the demand and aggregator purchases the deficit power from the wholesale market.

As it is assumed that aggregator and ESs are contracting under incomplete information; therefore, the aggregator does not know the actual category, type, and the number of each type of ESs. Even though obtaining such asymmetric information of each category and type of ES is a challenging task, in the literature, a multi-armed bandit model is available to build a learning algorithm to explore the asymmetric information. In a multi-armed bandit model, each contract item is regarded as an arm, and the learning algorithm is a procedure of the exploration (type) versus exploitation (profit) trade-off. Interested readers are referred to [20], [29], [30] for more detail about the learning algorithms and the bandit model.

A. Optimal-Contract Calculation

The aggregator's best trading strategies i.e., optimal contracts towards all S-type ESs^s, M-type ESs^m, L-type ESs^l can be obtained by solving the following maximization problem using MATLAB.

$$\max U_A = \sum_{i=1}^{S} n_i (R(s_i) - d_i) + \sum_{j=1}^{M} n_j (R(m_j) - e_j) + \sum_{k=1}^{L} n_k (R(l_k) - f_k) \quad (9)$$

$$s.t.\ (4)\ (5)\ (6)\ (7) \text{ and } (8) \quad (9.a)$$

From equation (9.*a*) it can be deduced that the optimal contract-designing problem is a complex problem with $S^2 + M^2 + L^2$ where IR and IC constraints for small, medium and large scale

ESs respectively, which results in computational complexity. Here, it is required to derive necessary and sufficient conditions for simplifying the problem by reducing the constraints. Likewise, in [23], [31], the optimal solution elements, i.e., the payments $\{d_i, e_j, f_k\}$ and the amount of electricity traded $\{s_i, m_j, l_k\}$, are monotonically increasing in *i*-type, *j*-type, and *k*-type ESs respectively. Hence, following *Lemma 1 & 2* in [31] and *Lemma 1* in [23], the number of IR and IC constraints can be reduced from S^2 to S+1, M^2 to M+1 and L^2 to L+1 to form linear constraints as follows:

$$d_1 \geq \varphi\dot{a}_1 s_1,\ \ e_1 \geq \ddot{a}_1 m_1,\ \ f_1 \geq \ddot{a}_1 l_1 \tag{10}$$

$$\left.\begin{aligned} s_S > s_{S-1} \ldots\ldots > s_1 > 0 \\ m_M > m_{M-1} \ldots\ldots > m_1 > 0 \\ l_L > l_{L-1} \ldots\ldots > l_1 > 0 \end{aligned}\right\} \tag{11}$$

To understand the process of obtaining (10) and (11), the interesting readers can follow the proof of *Lemma 1* provided in the supplementary information in [23] and the proof of *Lemma 1 & 2* provided in *Appendix A* and *B* in [31]. To solve the maximization problem several models and theories are required, all of which cannot be included in the paper due to page limitations. Therefore we have referred existing information and only included a new algorithm and model in the paper.

Equation (10) implies that if the IR constraint holds for the lowest-type ES, whose energy is most expensive in a category, and then the IR constraint for all other types is automatically satisfied. Following the assumption (2.*b*) $\ddot{a}_1 > \ddot{a}_2 \ldots. > \ddot{a}_L$, (11) implies that the aggregator procures more power from the ESs whose energy is cheaper, which means that ESs with a cheaper energy option can gain more profit. With equation (10) and (11) suppositions, the number of IR and IC constraints is reduced and equation (9) can be written as:

$$\max U_A = \sum_{i=1}^{S} n_i (R(s_i) - d_i) + \sum_{j=1}^{M} n_j (R(m_j) - e_j) + \sum_{k=1}^{L} n_k (R(l_k) - f_k) \tag{12}$$

$$s.t. \quad (7)\ (8)\ (10) \text{ and } (11) \tag{12.a}$$

The above maximization problem can be solved using a linear programming technique.

Theorem 1. The proposed energy trading strategy of the aggregator that maximizes its utility is the optimal energy trading strategy.

Proof: To determine the optimal contract items that maximize the aggregator utility, it is assumed that the power demands from ESs^s, ESs^m and ESs^l are known and satisfy equation (11). That is, the optimal price and the given contracted power amount are positively correlated with one another. Therefore, as the amount of contracted power increases, the optimal trading increases as well. Now, considering the linearity of the contract function in equation (12), the optimal contract items $d_i^*(s_i)$, $e_j^*(m_j)$ and $f_k^*(l_k)$ can be derived using *Theorem 1* [22] as follows:

$$d_i^*(s_i) = \left.\begin{cases} \varphi\dot{a}_i s_i & \text{if } i = 1 \\ d_{i-1}^* + \varphi\dot{a}_i (s_i - s_{i-1}) & \text{if } i = [2, \ldots S] \end{cases}\right\} \tag{13}$$

$$e_j^*(m_j) = \left.\begin{cases} \ddot{a}_j m_j & \text{if } j = 1 \\ e_{j-1}^* + \ddot{a}_j (m_j - m_{j-1}) & \text{if } j = [2, \ldots M] \end{cases}\right\} \tag{14}$$

$$f_k^*(l_k) = \left.\begin{cases} \ddot{a}_k l_k & \text{if } k = 1 \\ f_{k-1}^* + \ddot{a}_k (l_k - l_{k-1}) & \text{if } k = [2, \ldots L] \end{cases}\right\} \tag{15}$$

By substituting the values of $d_i^*(s_i)$, $e_j^*(m_j)$ and $f_k^*(l_k)$ in (12), the optimal amount of electricity, i.e., s_i^*, m_j^*, l_k^* that the aggregator buys from different ESs can be obtained as:

$$s_i^* = \left.\begin{cases} d_i / \varphi\dot{a}_i & \text{if } i = 1 \\ n_i d_i + n_{i-1} d_{i-1} / (n_i + n_{i-1})\, \varphi\dot{a}_i + s_{i-1}^* & \text{if } i = [2, \ldots S] \end{cases}\right\} \tag{16}$$

$$m_j^* = \left.\begin{cases} m_j / \ddot{a}_j & \text{if } j = 1 \\ n_j e_j + n_{j-1} e_{j-1} / (n_j + n_{j-1})\, \ddot{a}_j + m_{j-1}^* & \text{If } j = [2, \ldots M] \end{cases}\right\} \tag{17}$$

$$l_k^* = \left.\begin{cases} l_k / \ddot{a}_k & \text{if } k = 1 \\ n_k f_k + n_{k-1} f_{k-1} / (n_k + n_{k-1})\, \ddot{a}_k + l_{k-1}^* & \text{if } k = [2, \ldots L] \end{cases}\right\} \tag{18}$$

Since the optimal solution is derived based on equation (10) and (11), which considered individual rationality and incentive compatibility, the following corollary can be stated: Corollary 1. The proposed energy-trading contract is both individually rational and incentive compatible.

IV. Contract-Based Approach for Peak Load Scenario

This section derives the optimal contracts, i.e., $ð^* = \{(\acute{f_k}^*,\ l_k^*, \mathrm{r}_k), i \,\epsilon L\}$ during the peak demand for time slots when the wholesale price is greater than or equal to the flat rate. To design an optimal contract strategy for this scenario, the aggregator needs to consider various factors such as the intermittency problem of RESs and the wholesale price spikes effect on the ESs' selling price.

A. Seller and Buyer Modeling

Peak load demand refers to a period when the electricity demand peaks at its highest level and it causes wholesale price spikes. At these times, the wholesale price may exceed the fixed flat rate [32], and the aggregator suffers a loss through the traditional trading scheme. It can generate profit by obtaining cheaper electricity from ESs; however, the aggregator benefit of trading with ESs in this scenario depends on the consistency of RESs' generation and the selling price of ESs. Due to the intermittent and uncontrollable characteristics of the output of RESs, potential ESs may not be able to provide the contracted power during the peak demand period, and thus the aggregator utility deteriorates. For that reason, the aggregator introduces the concept of a reliability level to capture the power supply uncertainty of ESs. This reliability level is expressed using a random variable r, and it expresses the probability to meet the contracted energy by ESs within the contracted periods. The ESs' reliability levels are assumed to be within the range of [0, 1] for simplicity, and it is drawn identically and independently. The reliability level r = 0, when the power provided by ESs by the end of the contracted time is zero. Likewise, the reliability level r = 1, when the power provided by ESs by the end of the contracted time becomes equal or more than the contracted quantity. As to the power that ESs cannot provide, there is one way to complement it: the aggregator buys deficit power from the power grid but imposes penalty charges to ESs for the cost of the complement power. Considering the huge penalty charges in the case of power shortages, ESs will set a higher selling price for the same amount of power compared to the baseload scenario.

B. Contract-Based Approach Formulation

Let $\acute{\lambda}_{RTP}$ be the price to obtain electricity from the power grid when peak demand occurs. In this paper, we assume that $\acute{\lambda}_{RTP} > \lambda_{RTP} > \dot{a},\ \ddot{a},\ \ddot{a}$. Let r_i be the reliability level of ESs^s and $\acute{d}$ the payment to obtain *s* amount of power in a peak demand scenario. If ESs^s are unable to provide the contracted amount of electricity at times of wholesale price spikes, then they suffer penalty charges for the supply shortage. Penalty charges are assumed to be equal to $\acute{\lambda}_{RTP}$. As $\acute{\lambda}_{RTP} >> \dot{a}$; therefore, to encourage ESs^s to make contracts for the peak demand scenario with a probability of high penalty charges in case of supply shortages, the aggregator pays more than the baseload scenario to obtain the same amount of power; therefore, we assume $\acute{d} > d$. Moreover, in reality $\acute{\lambda}_{RTP}$ is public information, which is known to both the aggregator and ESs. Thus, ESs are unwilling to sell their electricity at the same rate in both scenarios. Therefore, in this paper, $\acute{d}$ is set to be positively correlated to $\acute{\lambda}_{RTP}$ to maximize the ESs utility.

For the peak demand scenario, the aggregator will design the contract item $(\acute{d}_i, s_i, \mathrm{r}_i)$ for i-type ESs^s, where $\acute{d}_i$ is the payment to obtain the s_i amount of electricity from ESs^s when peak demand occurs. The cost to supply the contracted amount s_i is $s_i\varphi\dot{a}\mathrm{r}_i$ and the power deficit cost is $s_i(1-\mathrm{r}_i)\acute{\lambda}_{RTP}$. The total cost will be $s_i\varphi\dot{a}\mathrm{r}_i + s_i(1-\mathrm{r}_i)\acute{\lambda}_{RTP}$. In this case, the ESs^s utility function, which is benefit minus cost, is given as

$$\acute{U}_s(\acute{d}, s, \mathrm{r}) = \acute{d}_i - \left(\varphi\dot{a}_i s_i \mathrm{r}_i + (1-\mathrm{r}_i)s_i\acute{\lambda}_{RTP}\right) \qquad (19)$$

Similarly, the ESs^m and ESs^l utility function for this case can be obtained by replacing the baseload payments (e_j, f_k) by the peak demand scenario payments ($\acute{e}_j$, $\acute{f}_k$) respectively.

$$\left.\begin{aligned} \acute{U}_m(\acute{e}, m, \mathrm{r}) &= \acute{e}_j - \left(\ddot{a}_j m_j \mathrm{r}_j + (1-\mathrm{r}_j)m_j\acute{\lambda}_{RTP}\right) \\ \acute{U}_l(\acute{f}, l, \mathrm{r}) &= \acute{f}_k - \left(\dddot{a}_k l_k \mathrm{r}_k + (1-\mathrm{r}_k)l_k\acute{\lambda}_{RTP}\right) \end{aligned}\right\} \qquad (20)$$

The first term in equation (19) and (20) is the benefit that ESs obtain by selling s, m, l amounts of electricity. The second term is the cost to produce the s, m, l amounts of power and the third term is the cost to complement the deficit power. The third term is zero when $\mathrm{r} = 1$, which indicates the condition when ESs maximize their utility by providing the contracted amount of power. However, the ESs' utility decreases as r decreases because the cost to complement the power increases. In equation (19) and (20), $\acute{d}_i$, $\acute{e}_j$, $\acute{f}_k$ can be calculated for two conditions.

1) $\acute{\lambda}_{RTP} = \lambda_{FR}$

When the difference between $\acute{\lambda}_{RTP}$ and λ_{FR} is zero, it represents the breakeven condition for the aggregator in a traditional electricity market, as the buying and selling price is the same. In this case, the aggregator trades with ESs to make a profit and ESs are willing to sell their surplus power at a higher rate than for the baseload scenario. Let $\acute{\dot{a}}_i$, $\acute{\ddot{a}}_j$, $\acute{\dddot{a}}_k$ be the payment made by the aggregator to obtain s, m, l amounts of power from ESs^s, ESs^m and ESs^l respectively in this condition. Thus, the ESs' utilities obtained in the transaction can be defined as:

$$\acute{d}_i = \acute{\dot{a}}_i s_i \mathrm{r}_i + (1-\mathrm{r}_i)s_i\acute{\lambda}_{RTP} \qquad \forall\ \{i=1\ldots..S\} \qquad (21)$$
$$\acute{e}_j = \acute{\ddot{a}}_j m_j \mathrm{r}_j + (1-\mathrm{r}_j)m_j\acute{\lambda}_{RTP} \qquad \forall\ \{j=1\ldots..M\} \qquad (22)$$
$$\acute{f}_k = \acute{\dddot{a}}_k l_k \mathrm{r}_k + (1-\mathrm{r}_k)l_k\acute{\lambda}_{RTP} \qquad \forall\ \{k=1\ldots..L\} \qquad (23)$$

where

$$\acute{\dot{a}}_i = \varphi\dot{a}_i + 0.015,\ \acute{\ddot{a}}_j = \ddot{a}_j + 0.015,\ \acute{\dddot{a}}_k = \dddot{a}_k + 0.015 \qquad (24)$$
$$s.t. \quad \varphi\acute{\dot{a}}_i, \acute{\ddot{a}}_j, \acute{\dddot{a}}_k < \lambda_{FR} \qquad (24.a)$$

Equation (24) suggests that in this condition the per-unit payment to ESs is 0.015 \$/kWh higher than the baseload scenario for the same amount of power as that procured by the aggregator. The concept of selling the same amount of electricity at different prices is reasonable and follows the idea of a flexible pricing tariff that energy retailers offer to consumers. Based on this idea, consumers are charged with different rates depending on the time of electricity usage (off-peak, peak) for the same amount of electricity consumed.

2) $\acute{\lambda}_{RTP} > \lambda_{FR}$

This condition represents the case where the aggregator suffers a loss through a traditional trading scheme, as the buying price is higher than the selling price. In this case, the aggregator's objective is to avoid loss through trading with ESs. The aggregator loss is positively correlated to the ($\acute{\lambda}_{RTP}$ - λ_{FR}) price difference that directly depends on $\acute{\lambda}_{RTP}$ because λ_{FR} is constant. This is intuitive since, ESs, being rational, would also correspond their selling price to $\acute{\lambda}_{RTP}$. Let the aggregator payments is $\bar{\dot{a}}_i$, $\bar{\ddot{a}}_j$, $\bar{\dddot{a}}_k$ to procure s, m, l amounts of power from ESs respectively in this scenario. Thus, the ESs' utility functions are given as:

$$\acute{d}_i = \bar{\dot{a}}_i s_i \mathrm{r}_i + (1-\mathrm{r}_i)s_i\acute{\lambda}_{RTP} \qquad \forall\ \{i=1\ldots..S\} \qquad (25)$$
$$\acute{e}_j = \bar{\ddot{a}}_j m_j \mathrm{r}_j + (1-\mathrm{r}_j)m_j\acute{\lambda}_{RTP} \qquad \forall\ \{j=1\ldots..M\} \qquad (26)$$
$$\acute{f}_k = \bar{\dddot{a}}_k l_k \mathrm{r}_k + (1-\mathrm{r}_k)l_k\acute{\lambda}_{RTP} \qquad \forall\ \{k=1\ldots..L\} \qquad (27)$$

where

$$\bar{\dot{a}}_i = \varphi\dot{a}_i + (\acute{\lambda}_{RTP} - \lambda_{FR}) * 0.2,\quad \bar{\ddot{a}}_j = \ddot{a}_j + (\acute{\lambda}_{RTP} - \lambda_{FR}) * 0.2 \qquad (28)$$
$$\bar{\dddot{a}}_k = \dddot{a}_k + (\acute{\lambda}_{RTP} - \lambda_{FR}) * 0.2$$
$$s.t. \quad \varphi\bar{\dot{a}}_i, \bar{\ddot{a}}_j, \bar{\dddot{a}}_k < \lambda_{FR} \qquad (28.a)$$
$$\varphi\bar{\dot{a}}_i, \bar{\ddot{a}}_j, \bar{\dddot{a}}_k > \varphi\acute{\dot{a}}_i, \acute{\ddot{a}}_j, \acute{\dddot{a}}_k \qquad (28.b)$$

The following can be inferred from equation (28); 1) in this condition the 0.1 \$/kWh price difference of $\acute{\lambda}_{RTP}$ and λ_{FR} corresponds to the 0.02 \$/kWh increment in per-unit payment to ESs compared to the baseload scenario for the same amount of power obtained by the aggregator; 2) every time there is an increment of 0.1 \$/kWh in the $\acute{\lambda}_{RTP}$ and λ_{FR} price difference due to an increase in the wholesale price ($\acute{\lambda}_{RTP}$) leads to an increment of 0.02 \$/kWh in the per-unit payment to ESs. This is to ensure that as $\acute{\lambda}_{RTP}$ increases the ESs' benefit also grows. However, the ESs' revenue increases with an increase of $\acute{\lambda}_{RTP}$, until the per-unit payment is less than the flat rate. This is because a per-unit payment equal to the flat rate is the saturation point and beyond that, the aggregator utility becomes negative, thus (24.*a*) and (28.*a*) assure the aggregator utility under different scenarios.

The value 0.015 in (24) and 0.2 in (28) are determined by carefully considering various constraints defined for the peak load scenario.

The value 0.015 satisfy the constraint (24.a) defined for a condition when peak wholesale price is equal to the flat rate and value 0.2 satisfy constraints (28.a) and (28.b) defined for a condition when peak wholesale price is greater than the flat rate. Any value higher or lower than these values does not meet the constraint conditions. Also, (24), (28), (28.b) are designed carefully considering the various cost constraints mentioned in (2) to generate the dynamic pricing mechanism considering the current market state for trading between the aggregator and the ESs.

C. Optimal Contract Calculation

Similar to the baseload scenario to derive the aggregator's optimal trading strategies for the peak load scenario, it is required to define the following constraints: IR, IC, ESs' supply capacity and total power demand. The ESs' supply capacity and the IC constraints are the same as for the baseload scenario as defined in equation (7) and (11) respectively, whereas the aggregator's total peak power demand is given as:

$$W' = \sum_{i=1}^{S} \acute{n}_i s_i + \sum_{j=1}^{M} \acute{n}_j m_j + \sum_{k=1}^{L} \acute{n}_k r_k \qquad (29)$$

where $\acute{W}$ is the total hourly peak power demand of the aggregator and $\acute{n}_i$, $\acute{n}_j$, $\acute{n}_k$ is the number of i-type ESs^s, j-type ESs^m and k-type ESs^l respectively contributing to fulfilling the peak load demand. Since the peak demand ($\acute{W}$) is higher than the baseload demand (W), it is assumed that $\acute{n}_i$, $\acute{n}_j$, $\acute{n}_k > n_i$, n_j, n_k correspondingly.

The IR constraint under conditions *1* and 2, respectively in simplified form is given below following (10).

$$\acute{d}_1 \geq \varphi\acute{\dot{a}}_1 s_1,\quad \acute{e}_1 \geq \acute{\ddot{a}}_1 m_1,\quad \acute{f}_1 \geq \acute{\dddot{a}}_k l_1 \qquad (30)$$
$$\acute{d}_1 \geq \varphi\bar{\dot{a}}_1 s_1,\quad \acute{e}_1 \geq \bar{\ddot{a}}_1 m_1,\quad \acute{f}_1 \geq \bar{\dddot{a}}_1 l_1 \qquad (31)$$

Equation (30) and (31) imply that if the IR constraint of the supplier whose energy is most expensive in a category is satisfied, then the IR constraint for all other ESs will automatically exist since we made the assumption ($\acute{\dot{a}}_1 > \acute{\dot{a}}_2 > \ldots \acute{a}_M$), ($\overline{a_1} > \overline{a_2} \ldots > \overline{a_L}$) by following (2.*b*). The aggregator's optimal contracts for the peak load scenario considering all types of ESs can be obtained by solving the following optimization problem:

$$\max(\acute{U}_A) = \sum_{i=1}^{S} n_i(R(s_i) - (\acute{d}_i)) + \sum_{j=1}^{M} n_j(R(m_j) - (\acute{e}_j)) + \sum_{k=1}^{L} n_k(R(l_k) - (\acute{f}_k))$$

$$s.t.\quad (7)\ (11)\ (29)\ \text{and}\ (30) \qquad \textit{for condition 1} \tag{32}$$
$$s.t.\quad (7)\ (11)\ (29)\ \text{and}\ (31) \qquad \textit{for condition 2}$$

The solution of (32), i.e. $(\acute{d_i}^*, s_i^*, \Gamma_i)$, $(\acute{e_j}^*, m_j^*, \Gamma_j)$, $(\acute{f_k}^*, l_k^*, \Gamma_k)$, $\forall\ i \in S, j \in M, k \in L$, can be easily obtained by following subsection III(A), where $\varphi\dot{a}_i$, $\ddot{a}_j$, $\dddot{a}_k$ are replaced by $\acute{a}_i$, $\acute{\ddot{a}}_j$, $\acute{\dddot{a}}_k$ for condition *1* and replaced by $\bar{a}_i$, $\bar{\ddot{a}}_j$, $\overline{\dddot{a}_k}$ for condition *2*.

D. Electricity Trading Algorithm

This section presents a procedure for the aggregator to procure power from ESs and an algorithm for electricity trading between an aggregator and ESs that can be implemented by both parties in a distributed manner. Following the optimal contracts, i.e., $\{d_i^*, s_i^*\}$, $(\acute{d_i}^*, s_i^*, \Gamma_i)$ etc., from the previous sections, the aggregator achieves a higher utility from higher types of ESs than from lower types in a category, *i.e.* $U_k^L > U_k^{L-1}$, $U_j^M > U_j^{M-1}$, $U_i^S > U_i^{S-1}$. Moreover, the aggregator utility from the lowest type of ESs in a large-scale category is higher than from the highest type of ESs from a medium-scale category. As similar conditions apply to medium and small-scale category ESs, we can write $U_k^1 > U_j^M$ & $U_j^1 > U_i^S$, subject to the difference between the requested amount of power and the surplus power from any ES is within a -2.5% variation.

In a developed electricity-trading scheme, each type of ES provides a certain excess power at a specific rate. If the difference between the surplus power and the requested amount of power is more than -2.5%, then the ES either rejects the contract or will provide that requested power at a higher rate. This is because an ES opportunity cost increases if it may not be able to capitalize on unsold power; therefore, it would like to sell as much as it could have [33]. In this situation, it is more economical for the aggregator to buy power from an ES whose surplus power is within the -2.5% variation of the requested quantity. This way, the proposed scheme enables all types of ESs within a category to take part in a trading process, depending on the demand in an hour.

The basic functionality of the contract-based electricity trading approach is provided in Algorithm 1. Firstly, the trading strategy receives the electricity demand from an aggregator, pricing information including wholesale price and flat rate, number of electricity suppliers and their reliability level and supply capacity.

Then, aggregator based on the supply capacity of each supplier computes the IC constraints using (11). After this, the wholesale electricity price is compared with the flat rate to solve the relevant part of the algorithm. For instance, when the wholesale price is less than the flat rate then step 3 of the algorithm is followed. In step 3, the aggregator calculates the IR constraint using (10). The IR and IC constraints are the basic conditions of the trading process for an aggregator. These are to ensure that ESs receives the non-negative utility and gain maximum benefit by truthfully selecting the contract items of their type. Further, the aggregator derives the optimal contracts by solving the maximization problem as defined in (12) and sends the optimal contracts to each supplier to purchase the electricity from them. Finally, considering that the IR and IC conditions are met, electricity suppliers accept the contracts and provides the requested quantity of power to the aggregator.

Algorithm 1. Contract-Based Electricity Trading Algorithm

1: Initialize: $W, \acute{W}, \lambda_{RTP}, \acute{\lambda_{RTP}}, \lambda_{FR}$, ESs' reliability level $\Gamma_i, \Gamma_j, \Gamma_k$, and ESs' supply capacity, number of ESs, i.e., $n_i, \acute{n}_i$.

2: Aggregator computes the IC constraint using (11) for steps 3, 4 and 5.

3: **if** $\lambda_{RTP} < \lambda_{FR}$
Aggregator computes the IR constraint of the lowest type of ES that satisfies (10). Further, it solves the problem (12) to derive optimal contracts (d_i^*, s_i^*), (e_j^*, m_j^*), (f_k^*, l_k^*) as described in subsection *III. A.*

4: **else** $\acute{\lambda_{RTP}} = \lambda_{FR}$
Aggregator calculates the IR constraint of the lowest type of ES that satisfies (30). Further, it solves the problem (32) for *condition 1* to derive optimal contracts $(\acute{d_i}^*, s_i^*, \Gamma_i)$, $(\acute{e_j}^*, m_j^*, \Gamma_j)$, $(\acute{f_k}^*, l_k^*, \Gamma_k)$ as defined in *IV. C.*

5: **else if** $\acute{\lambda_{RTP}} > \lambda_{FR}$
Aggregator computes the IR constraint of the lowest type of ES that satisfies (31). Further, it solves the maximization problem (32) for *condition 2* to derive optimal contracts as described in subsection *IV. C.*
endif

6: Aggregator sends the contracts, i.e., (d_i^*, s_i^*), $(\acute{d_i}^*, s_i^*, \Gamma_i)$, $i \in S$, to ESs and purchases electricity from them.

7: ESs accept the contracts and the aggregator procures power from ESs following subsection *IV.D.*

V. Numerical Results

In this section, the performance of the proposed contract-based approach is presented and evaluated for both baseload and peak load demand scenarios considering one aggregator and 48 ESs from which there are 10, 16 and 22, *i*-type ESs^s, *j*-type ESs^m and *k*-type ESs^l respectively. ESs^s selling prices $(\varphi\dot{a}_i)$ are chosen randomly from a range of [0.38 to 0.65] \$/kWh from highest to lowest type in a small-scale category, and the value of φ is 0.67. Likewise, ESs^m and ESs^l selling prices $(\ddot{a}_j, \dddot{a}_k)$ vary from [0.34 to 0.64] and [0.11 to 0.32] \$/kWh following highest to lowest type in a medium and large-scale category respectively. The demand of the aggregator is chosen randomly from a range of [500-7000] kWh. The unit price to buy electricity from the wholesale market is 0.67 \$/kWh for the baseload and the peak load scenario, the price varies from 0.68 to 5.4 \$/kWh. Since, in the real-time market, the wholesale electricity price fluctuates at each time interval of the market, the electricity price during peak demand hours can be multiple times the electricity price during baseload demand [34]. Therefore, in this study, the wholesale price variation from 0.67 \$/kWh to 5.4 \$/kWh is considered to show the effectiveness of the proposed strategy under various conditions.

The aggregator sells the electricity to retail customers at a fixed flat rate of 1.1 \$/kWh. The feed-in-tariff rate is \$0.11/kWh and its value is taken from [35]. All cost values are chosen following the assumptions in (2). Since the Australian electricity market operates on a 30-minute time interval [36][37] therefore, simulations are performed for seven different hours from 10 am to 4 pm on a 30-minute basis. It is because the aggregator demands and ESs' surplus powers are updated each hour. Table II lists the various simulation cases to evaluate the performance of the designed contract-based incentive scheme.

TABLE II
SIMULATION CASES TO EVALUATE THE DEVELOPED INCENTIVE SCHEME

Trading Scheme	Reliability Level	Case Type	Wholesale price	Condition	Performance Evaluation
Tr ad	1.0	Base Case	0.67	$\lambda_{RTP}<\lambda_{FR}$	Aggregator profit
Contract-Based		Case I	0.67		Aggregator/ESs profit
		Case II	1.1	$\lambda_{RTP} = \lambda_{FR}$	Aggregator/ESs utility
		Case III	2.0	$\lambda_{RTP} > \lambda_{FR}$	Aggregator profit/loss
		Case IV	1.2 to 4.6		Total payment to ESs
		Case V	1.8		ESs participation
	1.0	Case VI	1.2 to 5.4		ESs optimal revenue
	1.0 to 0.6	Case VII	1.2 to 4.6		Reliability impact on trading partners utility

A. Performance of the Proposed Contract-Based Scheme

1. Aggregator Profit Under Base Case and Case 1

This case study compares the aggregator profit under the traditional and contract-based trading scheme, and the results are shown in Fig. 2. It is observed that given the same power demand at different hours, the contract-based electricity-trading scheme outperforms the traditional scheme in terms of aggregator profit. In the traditional scheme, an aggregator obtains electricity from the power grid at a wholesale price; however, the contract-based scheme allows the aggregator to obtain more profit by purchasing cost-effective electricity from ESs. The reason is that, in the contract approach, each the contract is designed for the corresponding ESs' type, and the maximum profit is generated by following the IR and IC constraints (10) and (11) respectively. Nonetheless, in a traditional scheme, the aggregator purchases the bulk amount of electricity at the wholesale price, sells it to retail consumers at a fixed flat rate, and thus cannot improve its profit.

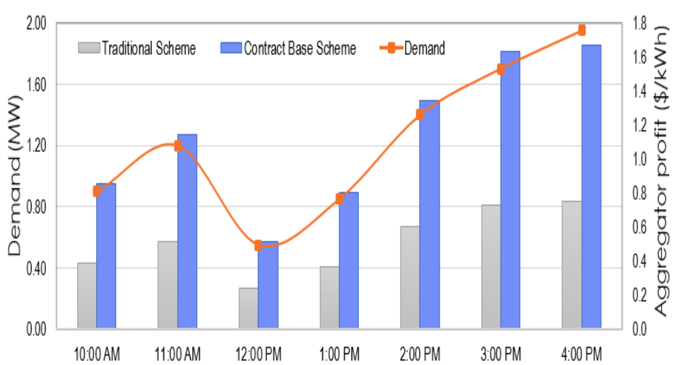

Fig. 2 Profit generated by aggregator with different schemes under Case I.

2. Aggregator Utility for Base Case and Case II

The objective of this study is to compare the performance of two schemes when wholesale price becomes equal to a flat rate. The simulation results are shown in Fig. 3 demonstrates that for the same power demand, as in Case I, the profit with the traditional trading scheme under this case is zero. This is because the retail revenue from customers is equal to the purchasing cost. However, the aggregator generates profit by trading with ESs through the contract-based trading scheme at the breakeven point. For instance, at 4 pm with 1.96 MW demand, the aggregator profit is 1.67 $/kWh and the ESs' revenue is 0.30 $/kWh following the subsection IV.*B*.1 trading strategy. Given the same setting as in Fig. 2, Fig. 3 reveals that the aggregator profit at 4 pm is reduced from 1.67 to 1.62 $/kWh because it is paying more to get the same amount of power in Case II.

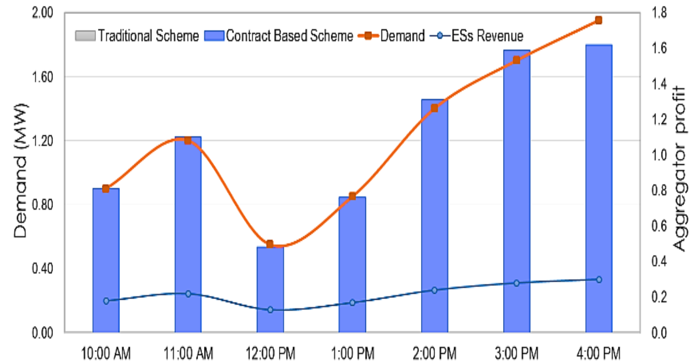

Fig. 3 Aggregator and ESs utility with different schemes for Case II.

3. Comparison of Aggregators' Profit for Base Case and Case III

The simulations, in this case, compare the performance of two schemes when wholesale price surpasses the fixed flat rate. This happens when the power demand increases in extreme weather conditions and wholesale price climbs, which causes a financial loss of aggregator under the traditional trading scheme. However, aggregator gains profit by adopting the contract-based trading scheme as shown in Fig. 4. The result reveals that the aggregator generates revenue by employing the designed strategy mentioned in subsection IV.*B*.2. For example, at 3 pm with 6 MW demand, the aggregator's loss with the traditional scheme is -4.20 and its profit with the contract-based scheme is 4.50 with ESs' revenue of 2.10. It is clear that the ESs' revenue is positively correlated with energy demand and a rise in wholesale price, and is higher than the previous case. This is because ESs correspond their selling price with the wholesale price.

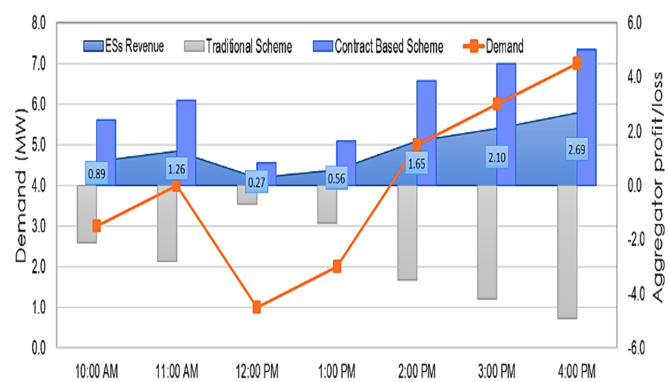

Fig. 4 Aggregator and ESs revenue with different schemes under Case III.

4. ESs' payment versus wholesale price spikes (Case IV)

This case study aims to examine the effect of wholesale price spikes and ESs reliability level on the payment they received. Figure 5 reveals that the payments received by ESs from the aggregator to meet a specific power demand increase as the wholesale price increases. It is intuitive that, as the wholesale price grows, ESs have a strong incentive to increase their selling price. The payments received by ESs, i.e., for 1-2 and 4-7 MW demand are in the scenario where the ESs are paying no penalty charges because they are providing all the contracted amount of electricity with r=1. However, as the reliability level goes down, the ESs' profit significantly reduces, i.e., for 2-4 MW demand because the penalty charges for deficit power is higher than their selling price. Thus, to ensure that ESs benefit in a trading process with a probability of penalty charges, ESs set a higher selling price than in the base case for the same demand as the wholesale price increases following (28). This way, the proposed strategy aligns the ESs' benefit with wholesale price spikes.

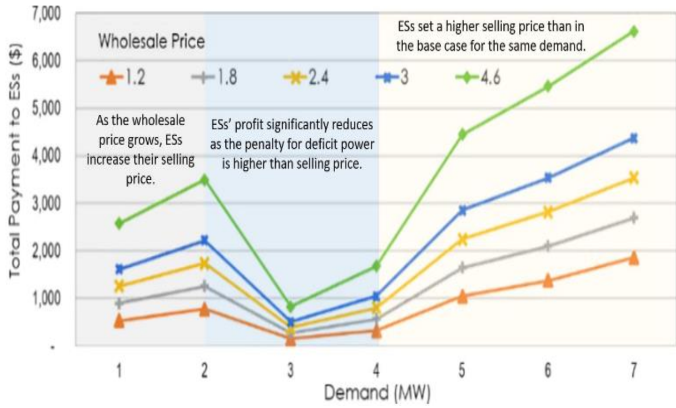

Fig. 5 ESs payment at various wholesale prices.

5. *Power Obtained from Different Categories of ESs (Case V)*

This study aims to illustrate how much electricity the aggregator procures in the optimal contracts from various types of ESs in various categories. It is seen from Fig. 6 that the aggregator obtains most of the required power from ESs^l followed by ESs^m and ESs^s. Further, within a category, the aggregator trades more electricity with higher types of ESs than with lower types following subsection IV.*D*. The main reason is that the aggregator will obtain more power from ESs

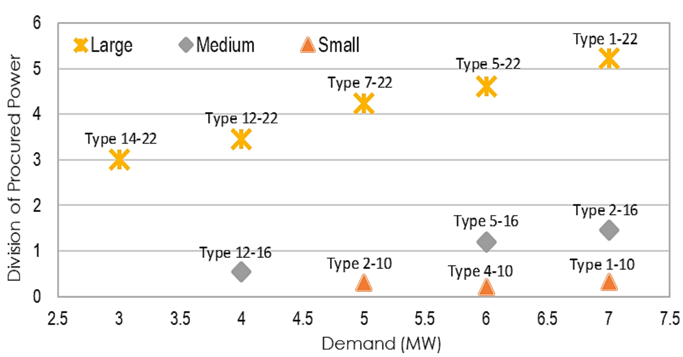

Fig. 6 Power procured from ESs based on their category and types.

whose energy is cheaper to derive more profits. It also reveals that, as electricity demand increases lower types of ESs are included in the contract to meet that demand. Additionally, ESs^s can participate in a trading process despite their high per-unit production cost as discussed in subsection II.*B*. Moreover, the difference between the profits gained by the aggregator through trading at a given demand is affected by the amount of electricity obtained from various types of ESs and the corresponding payments.

6. *Optimal Revenue of ESs (Case VI)*

In this case, we study the existence of optimal revenue for a given demand and how it is affected by the variations in the wholesale price. Figure7 demonstrates that, in each case where a certain demand is given, an optimal revenue does exist at which the ESs utility reaches a maximum and stays constant. The main reason is that the aggregator will pay more to ESs to meet a certain demand as the wholesale price increases until the per-unit payment to ESs is less than the flat rate following the subsection IV.*B* payment constraint (28.*a*). This is because the aggregator's utility becomes negative when the per-unit payment to ESs is more than the flat rate. Figure 7 highlights that ESs' revenue increases as the wholesale price grows from 1.2 to 4.2 \$/kWh; after that, it remains constant with further increases in the wholesale price. This way the designed scheme ensures the benefit of both trading partners and a win-win result arises.

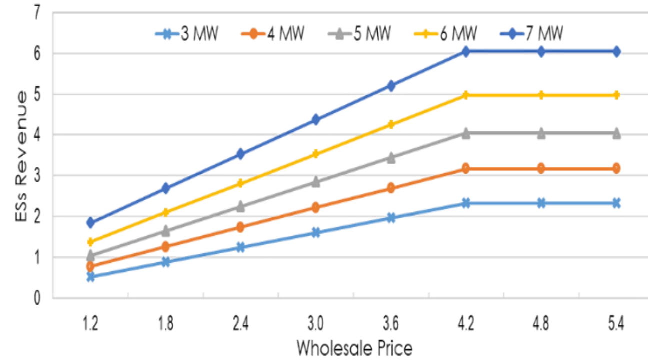

Fig. 7 ESs optimal revenue at various wholesale price spikes.

7. *Trading Partners Utility versus Reliability (Case VII)*

In Case VII, the aggregators and the ESs' utilities are evaluated at three different reliability levels with variations in the wholesale price, as shown in Fig. 8. It can be deduced that two factors reduce the aggregator utility: 1) increments in the wholesale price 2) low-reliability level of ESs. This is because, as the wholesale price increases, the ESs' selling price rises, and the aggregator has to pay more to procure power. Moreover, as a low-reliability level is negatively correlated with the deficit power, the aggregator's total payment to purchase a certain amount of demand grows because it purchases the deficit power from the wholesale market at a high price. Furthermore, from the ESs' perspective, the penalty charges to balance the deficit power at low-reliability levels significantly reduce the ESs' revenue, and this impact is more prevalent at a high wholesale price. For instance, at wholesale price 3, ESs and aggregator utility decrease from 12.9 to 10.1 and 11.7 to 8.37, respectively, with a change in the reliability level from 0.8 to 0.6.

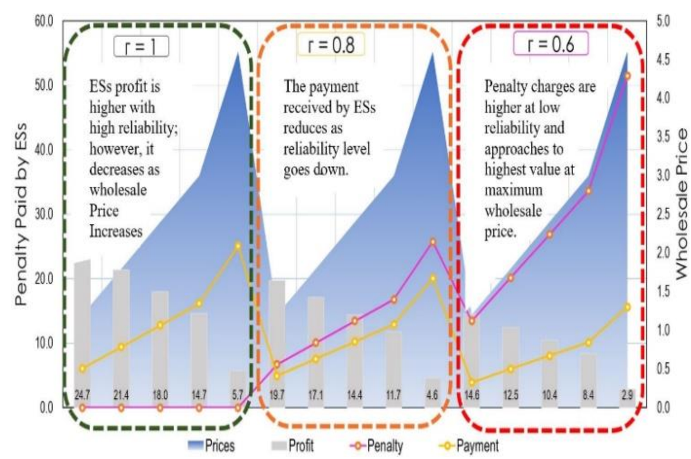

Fig. 8 Aggregator and ESs revenue at different reliability levels.

B. *Comparison with Existing Game-Based Schemes*

In this subsection, the developed noncooperative contract-based scheme with dynamic pricing (CBS-DP) performance in terms of cost incurred by the aggregator at peak times is compared with two existing schemes for electricity trading, i.e., noncooperative

Stackelberg game with flat pricing (NSG-FP) [12] and noncooperative Stackelberg game with TOU pricing (NSG-TP) [16]. The performance of these schemes is evaluated for the peak load scenario where the aggregator total cost to incur a power at peak times for the same demand is considered. For comparison, it is assumed that the ESs' reliability level is 0.7 which implies that due to generation uncertainty the ESs are capable to provide 70% of the required demand at peak time and the results are shown in Fig. 9.

From Fig. 9 it can be seen that among the three schemes, the CBS-DP performs the best and NSG-FP performs the worst. It is because the NSG-FP scheme does not consider ESs reliability level but in reality, the supply deficit appears as ESs reliability goes down. In this case, the aggregator has to procure an insufficient part of the energy from the wholesale market at a higher price, which results in a much higher payment.

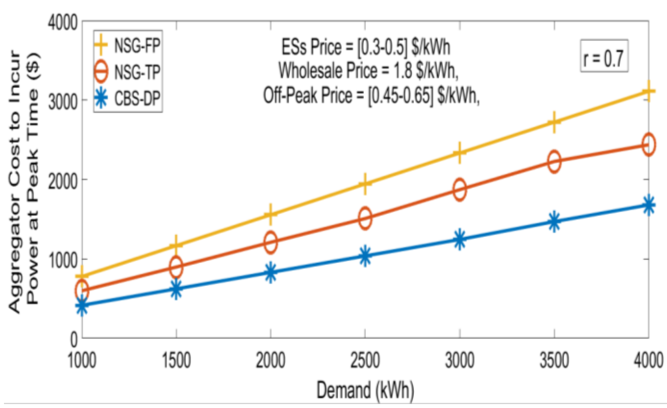

Fig. 9 The proposed scheme comparison with game-based schemes

The NSG-TP scheme, for a given demand, performs better than the NSG-FP because it tackles the ESs reliability issue by taking advantage of TOU pricing with a storage device. It stores energy when the grid price is low and this stored energy provides a certain fraction of the deficit energy to the aggregator at peak times. However, the aggregator has to buy a certain fraction of its requirement at a high price from the wholesale market depending on the storage device characteristics. Moreover, the NSG-TP scheme does not offer an attractive incentive mechanism to ESs providing electricity at peak times which may result in low participation of ESs in the trading process when the demand is high. These factors deteriorate the aggregator utility under the NSG-TP scheme and the aggregator total cost with a proposed scheme is minimum.

In the developed strategy, the ESs' supply shortage is under control by the mechanism of the penalty factor. The aggregator's loss is made up of the compensation from ESs, and thereby on average, the cost saving is 31.38% for the proposed scheme compared to the NSG-TP approach. Likewise, the average cost is 45.34% lower than that of the NSG-FP technique. Additionally, the proposed scheme offers the incentives considering IR and IC constraints and fluctuations in the wholesale price which motivates the ESs to provide the electricity at peak demand time compared to other schemes.

VI. Conclusion

In this paper, a novel framework is developed for studying the complex interactions between an aggregator and different categories of ESs of various types to trade their surplus power to the aggregator strategically in the smart grid. The interaction between aggregator and ESs is formulated as an optimal-contract design problem, and optimal contracts are theoretically derived for both baseload and peak load scenarios. By adopting the proposed scheme, the aggregator can maximize its profits while stimulating ESs to satisfy the load demand with positive utility. Comprehensive simulation results show the effectiveness of the proposed contract-based incentive mechanism over a conventional trading scheme. The results indicate that with the proposed scheme the aggregator can procure the same amount of energy with only 22.55% and 16.41% of the payment in baseload and peak load scenario respectively with the traditional scheme. Meanwhile, the developed strategy brings significant profit increment of 38.14%, 51.37%, and 72.22% for 1.2, 1.8 and 2.4 $/kWh wholesale price respectively compared to a conventional scheme. Moreover, the proposed scheme is more useful with a dynamic pricing mechanism to reduce the total cost at peak time compared to existing noncooperative game based schemes.

The designed incentive mechanism is characterized for regular distributions, as the aggregator only needs to publish an optimal unit price to ESs for implementation. Moreover, it is easily deployable on a large scale in smart-grid operations of the future because of its compatibility with the current electricity-tariff structure. This work can be extended to study the more practical scenario i.e. if multiple sets of small/medium/large scale ESs exist and they compete with each other to sell their electricity. The challenging task is to prioritize the same category and type of ESs to procure energy in the electricity trading market under the circumstances of asymmetric information. Another future aim is to investigate the strategies for ESs when their surplus power is much larger than the demand. For instance, a) feeding the power back to the grid; b) storing the remaining surplus power by charging batteries or electric vehicles; c) individually selling power to the neighbor buildings and/or other aggregators, etc [38]. The final future area of research is to establish a methodology for calculating local network charges and how they can affect the scale of electricity trading in a distribution network [39. 40].

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