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Prosumer Energy Management Considering Contract With Consumers Under Progressive Pricing Policy

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ABSTRACT The prosumer market allows prosumers to sell their energy surplus to consumers. The prosumer should offer the amount of energy to sell and its unit price to the contracted consumers while economically operating their system. This paper presents optimal operations and business strategies to maximize the prosumer's benefit by utilizing an energy storage system and ensuring a contract with residential consumers under a progressive pricing policy, where electricity unit price increases with the amount of monthly electricity consumption. By the proposed method, a prosumer under time-of-use pricing scheme stores abundant renewable energy or utility energy at a low price and uses it during a high-price period. Moreover, the proposed optimization can determine the amount of energy and the unit price that the prosumer will offer as a contract in a way that gives consumers strong motivation for the contract; the contract can eventually alleviate consumers' electricity rates by avoiding a high-price zone. For optimization, a quadratic objective problem with quadratic constraints is formulated, and the interior-point algorithm with the Hessian function is used. This study investigates the effectiveness of the proposed method not only under the various penetration rates of renewables but in consideration of uncertainties of renewables and loads. Based on actual field data from Jeju Island of South Korea for 30 days, numerical simulations were performed, and the results indicate that the prosumer's operating costs were reduced by about 12%, simultaneously offering a smaller contract price to the consumer. The Hessian function of the Lagrangian reduced the processing time for the optimization by a maximum of 98.3%. Finally, the ensemble forecast method generating multiple statistical scenarios was tested to address the uncertainty of renewables, showing that the uncertainty had no impact on the contract price and energy.

INDEX TERMS Energy management, energy storage, uncertainty, energy efficiency, progressive pricing, prosumer.

NOMENCLATURE

Variables of the Optimization Problems

x	State variables
u	Control variables
t_i	Time index
P_{POC}	Power influx at the point of connection (POC) (kW)

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P_{ESS}	Power output of the energy storage system (ESS) (kW)
P_{PV}	Power output of photovoltaics (PVs) (kW)
P_{WD}	Power output of wind generators (WGs) (kW)
P_D	A prosumer's power loads (kW)
SOC	State of charge (SOC) level of the ESS (%)

Parameters of the Optimization Problems

Δt	Optimization time step
n	Total number of hourly time steps
C	Time-of-use (TOU) unit price (\$/kWh)

E_{ESS}^{max}	Energy capacity of the ESS (kWh)
P_{POC}^{max}	Maximum active power at the POC (kW)
P_{POC}^{min}	Minimum active power at the POC (kW)
SOC^{max}	Maximum SOC level (%)
SOC^{min}	Minimum SOC level (%)
SOC^{init}	Initial SOC level (%)

Variables for Residential Progressive Pricing

F_0	Monthly electricity charge of a consumer to a utility under no prosumer contract (\$)
F	Monthly electricity charge of a consumer to a utility under a prosumer contract (\$)
E_L	Consumers' monthly electricity consumption (kWh)

Parameters for Residential Progressive Pricing

C_{ui}	Electricity rate for Zone i (\$/kWh); $i = 1, 2, 3, 4$
B_i	Basic charge for Zone i (\$/household); $i = 1, 2, 3, 4$
E_i	Maximum energy for Zone i (kWh); $i = 1, 2, 3$

Variables for the Prosumer Contract

C_p	Unit price of a prosumer contract (\$/kWh)
E_p	Monthly amount of energy that a prosumer supplies to consumers (kWh/month)
P_s	Contracted power under a prosumer contract (kW)
R_c	A consumer's revenue earned through the contract (\$)

Parameters for the Prosumer Contract

N_d	Number of days in a month
R_c^{min}	Minimum R_c (\$)

I. INTRODUCTION

The increasing penetration of renewable energy in electric power systems provides a blueprint for a future business model in power industries such as the prosumer market, where a prosumer can provide conventional electricity consumers with surplus energy in peer-to-peer, prosumer-to-grid, or prosumer group forms [1]. Although residential consumers with photovoltaic (PV) panels have the opportunity to gain an economic benefit by taking part in an open market [2], a virtual cluster of prosumers can increase the benefit by reducing the total forecasting inaccuracy [3]. Several prosumers also form a community, which can facilitate the participation of prosumers in the energy market [4]. Moreover, an industrial prosumer with a high capacity of renewable energy can play the role of a prosumer by supplying surplus renewable energy to consumers [5]. The authors also presented the optimal scheduling of an energy storage system (ESS) and real-time operation while taking into account the fulfillment of prosumer contracts.

In the prosumer market, a prosumer contract defines the unit price for the energy transition from a prosumer to a consumer, the period for which energy is supplied, and the

energy capacity. One of the strongest motivations by which a consumer makes a contract with the prosumer is the reduction in the consumer's electricity rate in such a way that the prosumer supplies some portion of the consumer's energy requirement instead of a utility at a unit price that is different from that offered by the utility. In this context, before signing a contract, a prosumer needs to offer the unit price and the total amount of energy provision that can bring economic gain to a consumer.

In South Korea, the progressive pricing policy has been applied to residential electricity customers, while commercial and industrial facilities follow the time-of-use (TOU) pricing scheme [6]. Under the progressive pricing policy, there are four different zones of unit prices based on the monthly electricity usage; if a residential consumer uses electricity beyond a threshold defined by a utility, the unit price for the excessive amount of energy used enters the higher-unit-price zone. However, in the TOU pricing plan, the utility presents the unit price for each hour in advance based on the season, provision capacity, and historical loading conditions. This different pricing policy intends to prevent the excessive use of household electricity and to provide more energy to commercial and industrial consumers, ultimately aiming to promote the national economy [7].

The prosumer contract can be attractive to residential consumers suffering from high electricity rates. If consumers import some portion of their monthly electricity usage from prosumers, then they can avoid entering the high-unit-price zone. In addition, the prosumer can profit from the contract by intelligently operating an ESS and offering the amount of energy provision and the unit price to contracted residential consumers. In the end, prosumer contracts can bring economic benefit to both prosumers and consumers.

Meanwhile, a prosumer with renewable energy resources and ESSs can perform cost-effective energy management. The prosumer operates the ESSs in an optimal way that stores the spare energy of renewables or the energy imported from the utility at a lower price and then releases the stored energy when the electricity rate is high, when the amount of renewable energy is not sufficient, or when the prosumer must supply the energy to contracted consumers.

Previously, many researchers have studied energy management with renewable energy resources and ESSs for operational purposes [8]–[12] or prosumer market participation [13]–[18]. Zhang *et al.* [8] proposed a battery ESS planning method based on the optimization of variable-interval reference signals and fuzzy control over ESS charging/discharging. This method eventually aims at both economic operation and the capability to smooth wind fluctuations. Additionally, the coordinated control of distributed generators (or renewable energy resources) and ESSs can enhance the grid reliability and stability by regulating the voltage [9] or frequency [10] and with three-phase balanced operation [11]. In [12], the authors presented the optimal power flow for the integrated community energy system in consideration of the heat and electricity co-utilization, three

phases, and different scheduling time horizons. From a market standpoint, the ESS enables PV owners to join the energy market efficiently [13]. In [14], the authors used model predictive control for the market participation of PV plants with ESSs. The authors of [15] proposed a stochastic optimization method that balances between prosumers' energy supply and consumer demands. In this work, the authors selected the unit prices of electricity randomly to consider unpredictable market behaviors. Meanwhile, [16] investigated the optimal bidding strategy of prosumers in energy and secondary reserve markets in real-time and day-ahead markets, and [17] studied prosumer's optimal scheduling in the day-ahead, real-time, and wholesale market, aiming profit maximization and imbalance costs minimization. The authors of [18] presented the distributed bidding strategy in the distribution-level energy market, thereby achieving a global optimization from the distribution system operator's perspective.

The main contribution of this work is threefold as follow:

- 1) The paper presents the business strategies under both the progressive pricing policy and the TOU pricing scheme. None of the previous studies [8]–[18] addressed the progressive pricing policy, where the monthly total energy consumption of a consumer is of prime interest since it directly determines the consumer's electricity rate.
- 2) The second contribution of the paper is to present an optimization method that finds the optimal price and capacity that reduce the monthly electricity rate of residential consumers—thus leading to a prosumer contract—and, simultaneously, schedules the ESS operation to reduce the prosumer's operating costs. The previous works [13]–[18] consider neither the prosumer contract nor the optimal price and capacity for the prosumer to offer under the contract.
- 3) Last but not least, the paper performed numerical simulations considering various practical conditions such as minimum customer revenue, optimization performance, renewable penetration rates, and the uncertainty of renewable energy. Among them, the uncertainty is addressed by generating multiple statistical scenarios, using the interdependencies among look-ahead times and forecast bins. In the end, the simulation results prove the effectiveness of the proposed prosumer energy management under the prosumer contract and two different pricing schemes.

Indeed, [19] presented optimal hedge strategies for demand response; however, the target of the work was a combined heat and power consumer aiming at reducing the electric rate by reacting to the real-time pricing. In comparison, this paper focuses on the prosumer who offers the price and the amount of energy to contracted consumers; note that the consumers are under progressive pricing. From the consumers' perspective, the proposed method can be a hedge contract to alleviate their electric rates.

The remainder of this paper is organized as follows. Section II describes two pricing schemes—progressive and

TOU pricing—and the prosumer contract. Then, Section III presents the formulation of the proposed optimization problem, followed by an explanation of the optimization solver in Section IV. Section V presents the numerical simulation and its results, and this paper is concluded in Section VI.

II. PRICING MECHANISM DESCRIPTIONS

This section describes the actual progressive and TOU pricing scheme in South Korea to understand the motivation of the proposed business strategy. Then, the prosumer market architecture and the contract between a prosumer and consumers are explained.

A. PROGRESSIVE PRICING

Table 1 summarizes the monthly progressive pricing scheme in South Korea, expressing four price zones corresponding to low, medium, high, and extremely high unit prices. The unit prices of Zones 3 and 4 are almost 3 and 7.6 times larger than that of Zone 1, respectively. Therefore, for residential consumers under this pricing policy, it is of prime concern to avoid the use of utility electricity beyond Zone 3 or 4.

For example, if the monthly electricity consumption of a residential consumer exceeds 1000 kWh, then the electricity charge for the month can be computed as follows:

$$F_0 = C_{u1}E_1 + C_{u2}E_2 + C_{u3}E_3 + C_{u4}(E_L - E_1 - E_2 - E_3) + B_3, \quad (1)$$

where E_1 , E_2 , and E_3 are 200, 200, and 600 kWh, respectively as computed from Table 1.

TABLE 1. Monthly progressive pricing policy in South Korea [6].

Price zone	Basic charge (\$/household)	Electricity rate (\$/kWh)
Zone 1 (Under 200 kWh)	0.91 (= B_1)	0.0933 (= C_{u1})
Zone 2 (200–400 kWh)	1.6 (= B_2)	0.1879 (= C_{u2})
Zone 3 (400–1000 kWh)	7.3 (= B_3)	0.2806 (= C_{u3})
Zone 4* (Over 1000 kWh)	7.3 (= B_3)	0.7095 (= C_{u4})

For simplification, an exchange rate of \$1 = 1000 KRW is used.

* Zone 4 is available in January, February, July, August, and December.

B. TOU PRICING

Commercial or industrial facilities with renewable energy resources and ESSs can act as prosumers by selling surplus energy to consumers. Aforementioned, commercial or industrial customers pay their electric bills by the TOU pricing. Hence, for the following simulation studies, the actual electricity rate under the TOU pricing in South Korea is applied to prosumers (refer to Table 2). The rates in Table 2 consist of on-, mid-, and off-peak prices in summer for industrial service B (300 kW or more demand), high-voltage A (3300–66000 V), and option II (the average usage time of 200–500h per a month) [6].

TABLE 2. Hourly Electricity Rates (Summer) [6].

Time	\$/kWh	Time	\$/kWh
0:00 to 9:00	0.0561	13:00 to 17:00	0.1911
9:00 to 10:00	0.109	17:00 to 23:00	0.109
10:00 to 12:00	0.1911	23:00 to 24:00	0.0561
12:00 to 13:00	0.109		

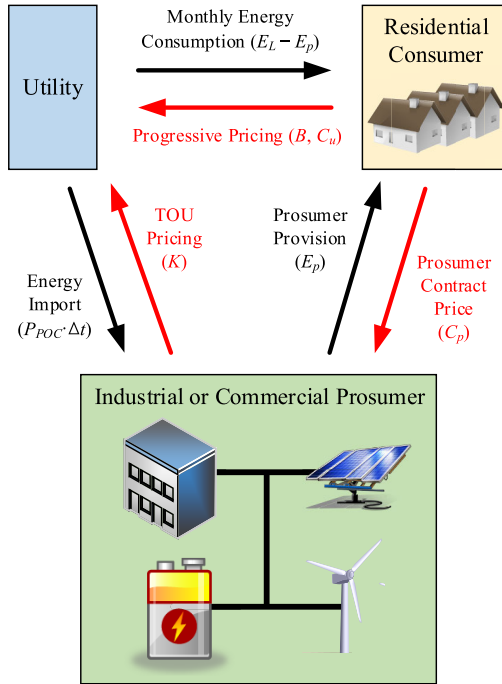


FIGURE 1. Prosumer market and contract.

C. PROSUMER CONTRACT

In general, the electricity usage of residential consumers peaks from 18:00 to 21:00; therefore, a prosumer contract can be made to supply electric energy during that time. Provided that the prosumer provides contracted consumers with a constant amount of power, the contracted power can be calculated as follows:

$$P_s = E_p / (3\mathcal{N}_d). \tag{2}$$

Fig. 1 depicts the prosumer market architecture and contract relationships among the utility, a prosumer, and consumers. The utility provides electricity to both industrial (or commercial) prosumers and residential consumers, who pay their electric bills to the utility under different pricing schemes; while progressive pricing applies to consumers, the TOU pricing to prosumers. A prosumer contract based on E_p , P_s , and C_p (agreed upon by the prosumer and a contracted consumer) may change the monthly electricity charge that the consumer pays to both the utility and prosumer into F . The computation of F depends on how much energy the utility supplies to the consumer after the prosumer’s provision; that is, $E_L - E_p$. As listed in Table 3, there are three computation

TABLE 3. Prosumer provision cases.

Case	Price zone after prosumer contract	Inequality condition
1	Zone 4 → Zone 1	$0 \leq E_L - E_p \leq E_1$
2	Zone 4 → Zone 2	$E_1 < E_L - E_p \leq E_1 + E_2$
3	Zone 4 → Zone 3	$E_1 + E_2 < E_L - E_p \leq E_1 + E_2 + E_3$

cases for an extreme loading condition (that is, E_L is within Zone 4). Note that the case where the consumer’s electricity rate zone still remains at Zone 4 even after the prosumer’s provision is not considered in this paper since this case brings little economic benefit to the consumer, which might give the consumer no motivation for a prosumer contract.

For Case 1, F can be computed as follows:

$$F(E_p, C_p) = C_{u1}(E_L - E_p) + C_p E_p + B_1. \tag{3}$$

The unit price paid by a consumer to a prosumer, C_p , is determined by the prosumer, on the basis of the proposed optimization method described in the following section. Thus, the consumer revenue, $R_c (= F_0 - F)$, is obtained as follows:

$$R_c(E_p, C_p) = C_{u1}(E_1 - E_L) + C_{u2}E_2 + C_{u3}E_3 + C_{u4}(E_L - E_1 - E_2 - E_3) + B_3 - B_1 + C_{u1}E_p - C_p E_p. \tag{4}$$

For Case 2, F and R_c can be calculated as follows:

$$F(E_p, C_p) = C_{u1}E_1 + C_{u2}(E_L - E_1 - E_p) + C_p E_p + B_2, \tag{5}$$

$$R_c(E_p, C_p) = C_{u2}(E_2 - E_L + E_1) + C_{u3}E_3 + C_{u4}(E_L - E_1 - E_2 - E_3) + B_3 - B_2 + C_{u2}E_p - C_p E_p. \tag{6}$$

Finally, for Case 3, F and R_c can be obtained as follows:

$$F(E_p, C_p) = C_{u1}E_1 + C_{u2}E_2 + C_p E_p + C_{u3}(E_L - E_1 - E_2 - E_p) + B_3, \tag{7}$$

$$R_c(E_p, C_p) = C_{u3}(E_3 - E_L + E_1 + E_2) + C_{u3}E_p + C_{u4}(E_L - E_1 - E_2 - E_3) - C_p E_p. \tag{8}$$

III. OPTIMIZATION PROBLEM FORMULATION

The proposed optimization problem is formulated to minimize the operational costs of a prosumer by scheduling a dispatchable ESS and determining the unit price and amount of energy of a prosumer contract. Note that the operating costs are mainly the TOU-based electricity rates paid to a utility for energy import at the point of connection (POC) reduced by the payment from the contracted consumers. Importantly, this optimized scheduling relies on the prediction of monthly profiles for renewables and electricity loads, of which variability may result in different outcomes from the optimized ones during actual operation. However, this variable nature is beyond the scope of this paper and will remain as future research work.

The optimization problem can be formulated as follows:

$$\min_{x,u} \sum_{i=1}^n \{K(t_i)P_{POC}(t_i)\} - C_p E_p, \quad (9)$$

such that

$$\begin{aligned} x &= [P_{POC}(t_1), \dots, P_{POC}(t_n), SOC(t_1), \dots, SOC(t_n)]^T, \\ u &= [P_{ESS}(t_1), \dots, P_{ESS}(t_n), C_p, E_p]^T, \\ n &= 24 \times \mathcal{N}_d, \\ K(t_i) &= \begin{cases} C(t_i) & \text{if } P_{POC}(t_i) \geq 0, \\ 0 & \text{otherwise.} \end{cases} \end{aligned}$$

The sum of the $K(t_i)P_{POC}(t_i)$ indicates the total TOU price that a prosumer pays to a utility, which should be minimized from the economic perspective of the prosumer. The term $C_p E_p$ is the total price that a consumer pays to the prosumer under the prosumer contract, which should be maximized. Note that there is no incentive for energy export at the POC from a prosumer to a utility. As described in (9), the optimization problem is quadratic and subject to several linear and nonlinear constraints in the following subsections.

This work focuses on the optimization of industrial or commercial prosumers, who have relatively small electric power systems. Although energy usage beyond the system limit may affect the optimality of the proposed approach, prosumers' network constraints, such as the operational limits of voltages and currents, are not considered here to focus on the prosumer contract. Nevertheless, it is worthwhile to formulate the empirical constraints, including the grid-side congestion and the nonfulfillment of contracts. These factors will be reflected in future works.

A. POWER BALANCE CONSTRAINTS

At the POC, the power balance between the renewable energy resources, the ESS, and the power exchange with the utility, and the demands of the prosumer and contracted consumers must be satisfied. The ESS can be a supplier in the discharging mode or a consumer in the charging mode. Hence, for $i = 1, \dots, n$,

$$\begin{aligned} P_{POC}(t_i) + P_{PV}(t_i) + P_{WD}(t_i) + P_{ESS}(t_i) \\ = P_D(t_i) + P_s(t_i), \quad (10) \end{aligned}$$

where the system capacity or the transformer rating limits the POC power as follows:

$$P_{POC}^{min} \leq P_{POC}(t_i) \leq P_{POC}^{max} \quad \text{for } i = 1, \dots, n. \quad (11)$$

B. REAL POWER CONSTRAINTS OF THE ESS

In the ESS, the amount of energy to be discharged or charged depends on the state of charge (SOC) level as follows:

$$\left\{ \frac{SOC(t_{i-1}) - SOC^{max}}{100} \right\} E_{ESS}^{max} \leq P_{ESS}(t_i) \Delta t, \quad (12)$$

$$P_{ESS}(t_i) \Delta t \leq \left\{ \frac{SOC(t_{i-1}) - SOC^{min}}{100} \right\} E_{ESS}^{max}, \quad (13)$$

where $i = 1, \dots, n$ and $SOC(t_0) = SOC^{init}$. Note that converter ratings limit the real power output of the ESS as follows:

$$P_{ESS}^{min} \leq P_{ESS}(t_i) \leq P_{ESS}^{max}. \quad (14)$$

It should be noted out that practical ESSs have device-specific charging/discharging efficiencies as models presented in [20] and [21]. However, for simplification, this work does not take into account those efficiencies; instead, the more realistic modeling of an ESS is left as our future work.

C. SOC CONSTRAINTS

The ESS charging/discharging operation changes the SOC level within boundaries. For $i = 1, \dots, n$,

$$SOC(t_i) = SOC(t_{i-1}) - \frac{P_{ESS}(t_i) \Delta t}{E_{ESS}^{max}} \times 100, \quad (15)$$

$$SOC^{min} \leq SOC(t_i) \leq SOC^{max}. \quad (16)$$

D. CONSUMER SATISFACTION CONSTRAINT

A prosumer must ensure that a contracted consumer gains at least the minimum revenue, R_c^{min} , to have motivation for the prosumer contract. Hence,

$$R_c(E_p, C_p) > R_c^{min}. \quad (17)$$

This constraint is quadratic as expressed in (4), (6), and (8).

IV. NONLINEAR OPTIMIZATION

The proposed optimization problem has a quadratic objective function with linear and quadratic constraints and is generally expressed as follows:

$$\min_y \frac{1}{2} y^T Q y + f^T y + c, \quad (18)$$

subject to

$$\begin{aligned} \frac{1}{2} y^T H_i y + k_i^T y + d_i \leq 0, \\ p_j^T y + q_j = 0, \end{aligned}$$

where $y = [x^T, u^T]^T$ that has a components. When there are m inequality constraints and n equality ones, $i = 1, \dots, m$, and $j = 1, \dots, n$. Further, $Q \in \mathbb{R}^{a \times a}$ and $H_i \in \mathbb{R}^{m \times m}$ are symmetric matrices. Note that f , k_i , and p_j are vectors with dimensions of a , m , and n , respectively, and that c , d_i , and q_j are scalars.

To solve this nonlinear optimization problem efficiently, the interior-point algorithm with the gradient and Hessian of the objective and constraint functions is employed [22]. The interior-point method has widely been used for large-scale problems because it can transform an original constrained optimization problem into an unconstrained one, thereby having apparent advantages in convergence and computation time. The interior-point algorithm with the gradient and Hessian presents good convergence, accurate results, and high computational performance because of the simplicity and

convenience of its unconstrained optimization techniques. However, the algorithm is sensitive to the initial value. The Hessian of the Lagrangian is expressed as follows:

$$\nabla_{yy}^2 L(y, \lambda) = \nabla^2 f(y) + \sum \lambda_i \nabla^2 (y^T H_i y + k_i^T y + d_i) + \sum \lambda_j \nabla^2 (p_j^T y + q_j), \quad (19)$$

where λ_i and λ_j are Lagrange multipliers.

In the numerical simulation presented in the following section, the *fmincon* function of the MATLAB optimization toolbox is used as a solver for the proposed optimization. The computing hardware is a PC equipped with an Intel Core i7-4980HQ 2.80-GHz CPU and 16-GB RAM running the 64-bit Windows 10 operating system.

V. NUMERICAL SIMULATION

To validate the proposed optimization method, numerical simulation is performed with the test-bed parameters listed in Table 4. The simulation uses the PV, wind generator (WG), and load profiles of an industrial prosumer based on actual field data from Jeju Island of South Korea for the summer of 2017 (see Fig. 7 in Appendix). For a residential consumer’s load profile, a general daily load curve based on actual field measurement data [23] (see Fig. 2) is used with a variation of 10%. The consumer’s monthly total electricity consumption, E_L , is 1372.3 kWh as listed in Table 4; therefore, the consumer’s monthly electricity rate is originally \$496.06 ($= F_0$).

TABLE 4. Simulation base conditions.

Parameter	Value	Parameter	Value
P_{POC}^{max}	2 MW	P_{ESS}^{max}	100 kW
P_{POC}^{min}	-2 MW	P_{ESS}^{min}	-100 kW
SOC^{max}	90%	N_d	30 days
SOC^{min}	10%	E_{ESS}^{max}	200 kWh
SOC^{init}	50%	E_L	1372.3 kWh

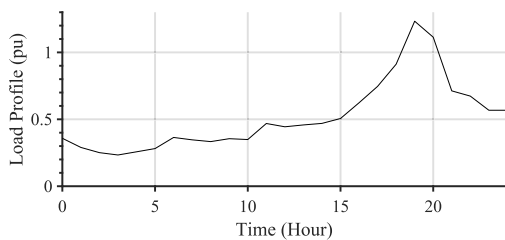


FIGURE 2. Base load profile of a residential consumer.

As a base case with no prosumer contract, only ESS operational schedules are optimized. Thus, the optimization problem for this base case can be formulated as follows:

$$\min_{x,u} \sum_{i=1}^n \{K(t_i)P_{POC}(t_i)\} \quad (20)$$

with the same constraints as the optimization problem defined in Section III except for the consumer satisfaction constraint in (17). To solve this problem, a linear programming method is used, and the solver is the *linprog* function of the MATLAB optimization toolbox. According to the base-case simulation, the operating cost of the prosumer is \$2170.20.

For the numerical simulation in this study, the three prosumer provision cases listed in Table 3 are tested. The following subsections describe the simulation results performed under various practical conditions such as three prosumer provision cases, different minimum customer revenues, different optimization functions, different renewable penetration rates, and the uncertainties of renewables and loads.

A. OBSERVATIONS FROM THE PROSUMER PROVISION CASES

Since a consumer’s monthly electricity consumption (i.e., 1372.3 kWh) is in Zone 4 of the progressive pricing scheme, the consumer has strong motivation for the prosumer contract to avoid payment at the unit price of Zone 4. The proposed optimization with a minimum consumer revenue (R_c^{min}) of \$100 is performed for all cases in Table 3, and the results are displayed in Table 5. The results indicate that Case 1 maximizes the prosumer’s economic benefit (i.e., \$261), but the prosumer contract price (C_p) for Case 2 is the smallest at 0.3206 \$/kWh, which is a more attractive price to the consumer than those for other cases. Hence, Case 2 is desirable for promoting the contract with the consumer.

TABLE 5. Simulation results for different cases ($R_c^{min} = \$100$).

	Case 1	Case 2	Case 3
Prosumer’s operating cost, \$	1909.2	1909.9	1932.9
Prosumer benefit from contract, \$	261	260.3	237.3
Prosumer contract price (C_p), \$/kWh	0.3211	0.3206	0.342
Prosumer contract energy (E_p), kWh	1172.3	1172.3	972.3
Consumer benefit from contract, \$	100	100	100

Fig. 3 depicts that the active power output of the ESS and POC for Case 2 with $R_c^{min} = \$100$, indicating that the power influx from the utility increases since Day 21. This increase is because renewable energy production is deficient in comparison to the prosumer load since Day 21 as shown in Fig. 2.

B. OBSERVATIONS RELATED TO THE MINIMUM CUSTOMER REVENUE

In this section, the influence of the minimum customer revenue, R_c^{min} , on the prosumer revenue from the prosumer contract is investigated by simulating Case 2 with various values of R_c^{min} . The simulation results indicate that the proposed optimization method produces the same customer revenue as R_c^{min} and that the prosumer revenue linearly decreases with the consumer revenue, as shown in Fig. 4. Therefore, the prosumer can set up a business plan based on the revenue

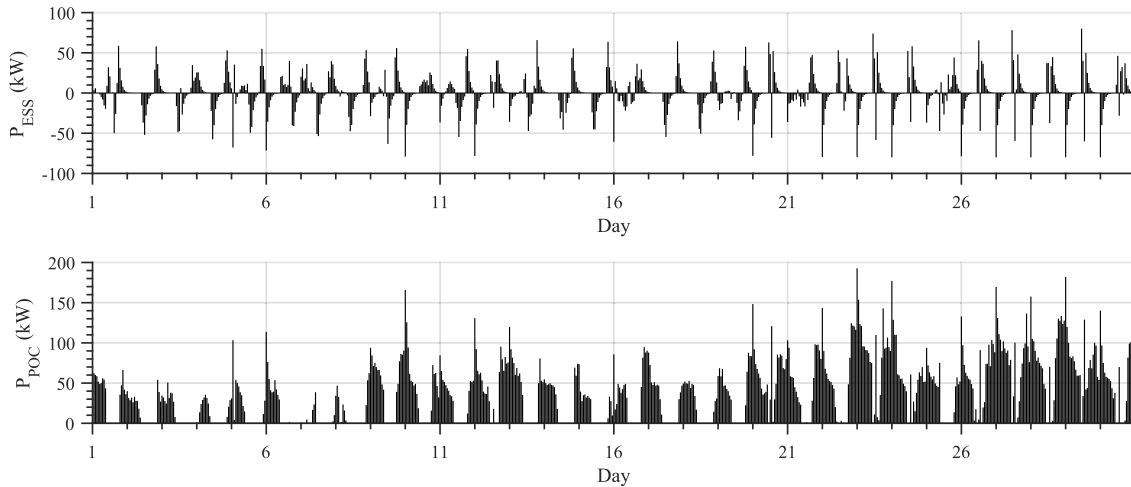


FIGURE 3. Active power output of the ESS and POC.

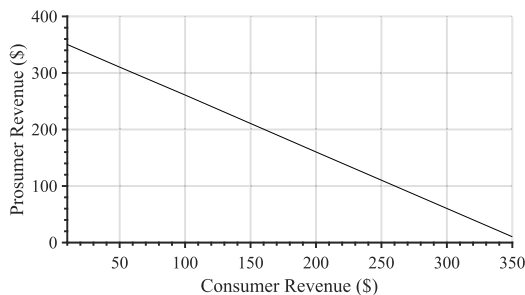


FIGURE 4. Relationship between the consumer and prosumer revenues as the minimum consumer revenue, R_c^{min} , varies. Note that the proposed method yields the same consumer revenue as R_c^{min} .

relationship in Fig. 4, suggesting a unit price and revenue to the consumer before a contract is signed.

C. OBSERVATIONS RELATED TO THE OPTIMIZATION PERFORMANCE

As simulation conditions, the first-order optimality tolerance, step tolerance, and constraint violation tolerance are 10^{-6} , 10^{-10} , and 10^{-6} , respectively. The average processing time for solving the experiments of Case 2 with $R_c^{min} = \$10, 50, 100, 200, 250, 300,$ and 350 is 70.2s.

Table 6 lists the processing times to obtain solutions for Cases 1-3 with $R_c^{min} = \$100$, indicating that, without using the Hessian function of the Lagrangian in (19), the processing time is, at maximum, 59.4 times those of the cases when using the Hessian function; note that optimization results are identical, regardless of the use of the Hessian function. Accordingly, solving the proposed optimization problem requires the Hessian function to obtain efficient computing performance.

D. OBSERVATIONS RELATED TO RENEWABLE PENETRATION RATE

In the test cases presented the previous sections, a total penetration rate of renewables, including the PV and wind energy,

TABLE 6. Processing times for optimization ($R_c^{min} = \$100$).

	Case 1	Case 2	Case 3
With the Hessian function (s)	78.7	64.03	51.6
Without the Hessian function (s)	1019.7	2628.4	3065.9

is 61.7% from the perspective of energy production. In order to investigate the impact of the renewable penetration rate on the prosumer and consumer benefits, several simulations with various renewable penetration rates are performed, with Case 2 and $R_c^{min} = \$100$. The penetration rate is adjusted by scaling up or down the PV and wind generations.

From Table 7 that compares the results, it can be observed that the prosumer benefit due to the prosumer contract increases with the penetration rate while the consumer benefit sustains at \$100 (i.e., R_c^{min}) for any cases. It is noteworthy that the prosumer benefit is maintained at \$248 below the 40% penetration rate, which indicates that even when available renewable energy is rare, the prosumer can earn at least \$248 by the prosumer contract, using the ESS operation without compromising the consumer's benefit. It can be stated that the proposed optimal scheduling method is effective for prosumer energy management regardless of the amount of renewable energy.

E. CONSIDERATION OF UNCERTAINTIES

The previous numerical experiments are based on perfect foresight on the future renewable generation and prosumer load. However, in practical applications, all those parameters are, by nature, uncertain, and therefore the proposed method cannot achieve a truly optimal solution. As an effective measure dealing with the uncertainty, the ensemble forecast, which generates alternative future trajectories based on probabilistic forecast information, has been studied [24]. A strong advantage of the ensemble forecasts is to

TABLE 7. Simulation results for different penetration Rate of renewables (Case 2, $R_c^{min} = \$100$).

Renewable Energy Penetration Rate, %	0	20	40	61.7	80	100	120	140	160
Prosumer’s operating cost without contract, \$	6404.1	4652.5	3151.7	2170.2	1686.3	1360.5	1155.1	1015.3	908.36
Prosumer’s operating cost with contract, \$	6156.1	4404.5	2902.4	1909.9	1413.2	1080.1	866.89	718.92	605.6
Prosumer benefit from contract, \$	248	248	249.3	260.3	273.1	280.4	288.21	296.38	302.76
Prosumer contract price (C_p), \$/kWh	0.3206	0.3206	0.3206	0.3206	0.3206	0.3206	0.3206	0.3206	0.3206
Prosumer contract energy (E_p), kWh	1172.3	1172.3	1172.3	1172.3	1172.3	1172.3	1172.3	1172.3	1172.3
Consumer benefit from contract, \$	100	100	100	100	100	100	100	100	100

generate multiple statistical scenarios (i.e., trajectories) in such a way that the forecast interdependencies among look-ahead times are considered. Each trajectory becomes an input to the deterministic framework, and for a j th scenario generation, all state and control variables in (9) should be updated as follows:

$$x^{(j)} = [P_{POC}^{(j)}(t_1), \dots, P_{POC}^{(j)}(t_n), SOC^{(j)}(t_1), \dots, SOC^{(j)}(t_n)]^T,$$

$$u^{(j)} = [P_{ESS}^{(j)}(t_1), \dots, P_{ESS}^{(j)}(t_n), C_p^{(j)}, E_p^{(j)}]^T.$$

Finally, the outputs of each generated scenario eventually form a final decision as follows:

$$\hat{u}_k = \sum_{j=1}^{\mathcal{N}_s} f^{(j)} u_k^{(j)}, \tag{21}$$

where \hat{u}_k is the final decision of the k th control variable considering all uncertainties, \mathcal{N}_s is the number of scenarios generated, $f^{(j)}$ is the probability of the j th scenario realization, and $u_k^{(j)}$ is the k th control variable under the j th scenario realization. Note that this final decision may not be the most optimal solution for actual practice but feasible for all the possible scenarios.

Before scenario generation, the statistical model of forecast errors should be developed based on the historical forecast and observation data. Many parametric [25] or nonparametric models [26] can be used, but this study employs the normal distribution with zero means for simplification. Furthermore, the statistical model is divided into five forecast bins according to the measured value, each of which describes the probability distribution of the forecast errors. Since this section mainly focuses on the effectiveness of the proposed prosumer energy management scheme under the uncertainties, the forecast errors that follow the normal distribution with zero mean and a standard deviation of 0.01 are generated. For instance, the statistical model of each forecast bin for wind power is described in Fig. 5.

For scenario generation, this study adopts the inverse transform method [24], [26]. The cumulative distribution function (CDF) of power prediction for the lead-time t , denoted by $F(\hat{p}_t)$, can be transformed into a CDF $\Phi(X_t)$ because both CDFs are uniform distributed within $[0, 1]$. Note that Φ^{-1}

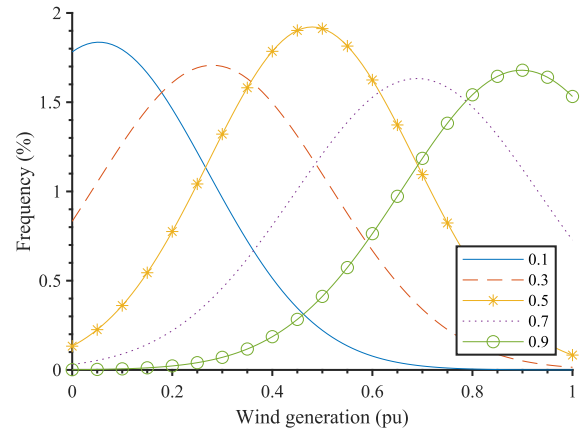


FIGURE 5. The forecast error distributions of wind power for five forecast bins.

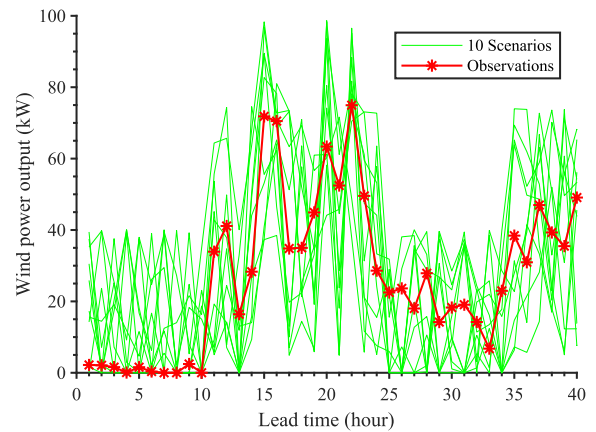


FIGURE 6. Wind power forecast under 10 alternative scenarios.

is the probit function, expressed as follows:

$$\Phi^{-1} : p \rightarrow \sqrt{2} \operatorname{erf}^{-1}(2p - 1), \tag{22}$$

where erf is the error function. Note that X_t is normally distributed with zero mean and unit standard deviation and that the random vector $X = [X_1, X_2, \dots, X_k]^T$ follows the multivariate normal distribution, where k is the maximum lead time; in other words, $X \sim N(\mu, \Sigma)$, where μ is the mean values and Σ is the covariance matrix including the cross-correlation among X_t , which can be computed

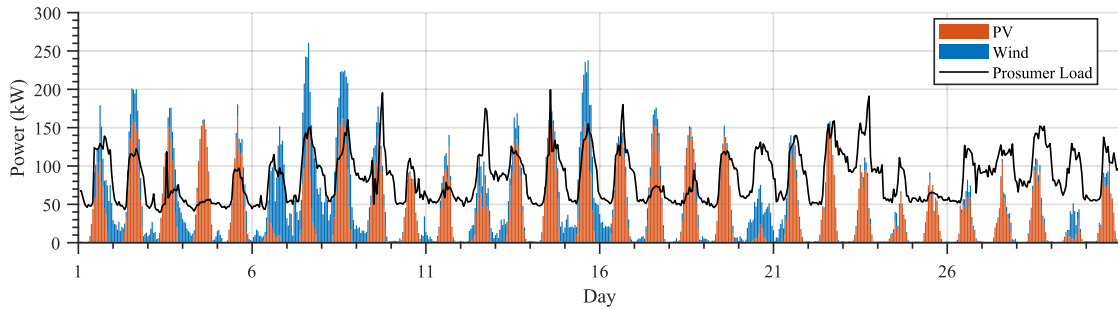


FIGURE 7. The PV, WG, and load profiles of the industrial facility for 30 days.

TABLE 8. Simulation results in consideration of uncertainties (Case 2, $R_c^{min} = \$100$).

Scenarios generated	10	20	30
Prosumer's operating cost without contract, \$	2384.2	2371.6	2375.6
Prosumer's operating cost with contract, \$	2117.9	2107.1	2110.3
Prosumer benefit from contract, \$	266.3	264.5	265.3
Prosumer contract price (C_p), \$/kWh	0.3206	0.3206	0.3206
Prosumer contract energy (E_p), kWh	1172.3	1172.3	1172.3
Consumer benefit from contract, \$	100	100	100

by the recursive estimation [24]. That is, when there are m observations,

$$\Sigma = \frac{1}{m-1} \sum_{i=1}^m X^{(i)} X^{(i)T}, \quad (23)$$

where $X^{(i)}$ is the i th observation. At last, the scenarios can be generated by producing the multivariate normal random variables, which are then transformed into power forecast \hat{p}_t . This generation is performed about PV and wind generation outputs and prosumer loads. As an example, Fig. 6 illustrates ten forecast scenarios of wind generation.

For the final decision making, the proposed optimization is repeatedly executed under 10, 20, and 30 scenarios, with maintaining Case 2 and $R_c^{min} = \$100$. After testing all the scenarios, the final decision \hat{u} is determined according to (21). Table 8 shows the simulation results when applying \hat{u} to the ESS operation and prosumer contract. It can be noticed from the table that when 20 scenarios are generated, the operating costs are minimum; nevertheless, the prosumer contract price and energy in \hat{u} are the same as the case under perfect foresight, which is presented in Table 5. Hence, we can see that the decision on the prosumer contract is irrelevant to the uncertainties. From Table 8, we can also observe that the prosumer's operating costs for Case 2 and $R_c^{min} = \$100$ are around \$2111.8 regardless of the number of scenarios, which is much higher than the case under perfect foresight (i.e., \$1909.9 as shown in Table 5). This increase is inevitable because of the uncertain nature of the renewables and loads. We can, rather, highlight the fact that the prosumer benefit from the prosumer contract is around \$265 regardless of the

number of scenarios. In the end, it is verified that the proposed prosumer optimization can bring benefits to both prosumers and consumers even in consideration of uncertainties.

VI. CONCLUSION

In this paper, an optimization method that simultaneously schedules a prosumer's ESS economically and obtains the optimal unit price and energy capacity that the prosumer offers to residential consumers suffering from high electricity rates due to the progressive pricing scheme was proposed. The primary purpose of computing the prosumer price and energy capacity is to encourage the consumers to sign the prosumer contract by guaranteeing their revenue. In this context, the contribution of this paper is that a prosumer can take into account revenue from the prosumer contract and the consumer's motivation for the contract while optimally scheduling the prosumer's energy resources such as ESSs.

On the basis of actual field data from Jeju Island of South Korea for 30 days, numerical experiments were performed with an optimization problem formulated using a quadratic objective function and quadratic constraints. Finally, it is concluded that the proposed optimization method ensures economic benefit to both prosumers and consumers through optimal ESS operations and the prosumer contract; the prosumer's operating costs are reduced by about 12% in Case 2. Moreover, the case that aims to move the consumer's pricing from Zone 4 to Zone 2 yields the optimal solution for minimizing the prosumer contract price (i.e., 0.3206 \$/kWh) in Case 2, which is, therefore, more attractive to the consumer. The simulation results also indicate that the proposed method can give the consumer the same revenue as the predefined minimum consumer revenue and that the use of the Hessian function of the Lagrangian for the optimization can considerably enhance the computing performance by reducing the processing time by maximum 98.3% in Case 3. In the end, this study proves that the proposed method can bring those benefits not only under the various penetration rates of renewables but in consideration of uncertainties of renewables and loads. The uncertainty is addressed through the generation of multiple statistical scenarios based on forecast interdependencies among look-ahead times. As a result, it is found that the operating costs slightly differ by the number of

scenarios generated, but the uncertainty has no impact on the prosumer contract price and energy.

In future works, the risk due to uncertainties can be addressed by a risk criterion such as value-at-risk or conditional value-at-risk, which measures the risk of loss from the investment viewpoints. The different risk adoption levels can be influential constraints in prosumer energy management, and therefore it is meaningful to observe the impact on optimization results. Besides, consumers can choose multiple energy sources and contracts not only with prosumers but with utilities to hedge their electric bills in the real-time pricing scheme.

APPENDIX FIELD DATA FOR THE PV, WG, AND LOAD PROFILES

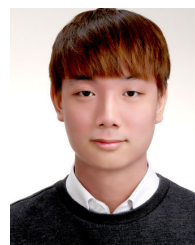
Fig. 7 shows the PV, WG, and load profiles of an industrial facility on Jeju Island of South Korea for 30 days during the summer of 2017.

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