A Smart Power System Operation Using Sympathetic Impact of IGDT and Smart Demand Response With the High Penetration of RES

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ABSTRACT The enhanced penetration of available renewable energy sources (RES) is preferred over-utilizing the maximum cost budget for the conventional power system operation. Severe uncertainty and power generation and load demand balance are the pre and post-challenges of RES penetration respectively. Penetration of RES can be made effective by modeling the RES uncertainty with a computationally efficient technique and controlling the load demand smartly. In this paper for the smooth and stable penetration of RES, the uncertainty of RES is modeled using the sympathetic impact of information gap decision theory (SI-IGDT) to deal with minimum possible uncertainty. Smart demand response (SDR) is modeled using a virtual layer as a smart demand response operator (SDO) between the main grid and consumers for the post-challenge of RES penetration. The SDO categorizes consumers into virtual prosumer (VP), real prosumer seller (RPS), and real prosumer buyer (RPB) using a power flow conditional algorithm (PFCA). The uncertainty of RES is subsequently optimized and implemented using the firefly optimization algorithm (FOA) and the power flow algorithm (PFA). To achieve technical and economic benefits for the main grid and all consumers, a Stackelberg game is formulated using PFCA and multi-objective FOA (MFOA). MATLAB is used for the implementation of the algorithms and the test system. Simulation results show that the maximum available RES power is penetrated up to 300%, and load demand reduction is observed up to 62% which ultimately reduces the power flow loss by 70%.

INDEX TERMS Firefly algorithm, information gap decision theory, renewable energy sources, smart demand response, stackelberg game.

NOMENCLATURE

A. ACRONYMS
RES Renewable energy sources
IGDT Information gap decision theory
SI-IGDT sympathetic impact of IGDT
DR Demand response
SDR Smart demand response
SDO Smart demand response operator
VP Virtual prosumer
RPS Real prosumer seller
RPB Real prosumer buyer

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B. SETS AND INDICES
S Set of RPS buses
B Set of RBP buses
K Set of VP buses
T Set of time in hours
n Index number for buses
e Index either for seller or grid

C. VARIABLES AND PARAMETERS
\( \alpha \) Slope-bound uncertainty limit
\( \tilde{m} \) Forecasted uncertainty parameter
\( m \) Real value Uncertainty parameter
\( \varphi(t) \) Function to control uncertainty limit
\( W_f \) Reward values for RF
\( W_o \) Reward values for OF
\( \alpha_1 \) uncertainty limit for RF
\( \alpha_2 \) uncertainty limit for OF
\( W_{r,r} \) Reward threshold for RF
\( W_{r,o} \) Reward threshold for OF
\( \tilde{x} \) Decision variables
\( \tilde{\alpha}(\tilde{x}, W_{t,r}) \) RF
\( \tilde{\beta}(\tilde{x}, W_{t,o}) \) OF
\( M(\alpha, \tilde{m}) \) Updated uncertainty function of OF
\( \hat{M}(\alpha, \tilde{m}) \) Updated uncertainty function of RF
\( Z(\tilde{x}, m) \) RES objective function
\( Z_0(\tilde{x}, \tilde{m}) \) RES base objective function
\( GD_t \) Generation-to-demand ratio
\( \rho \) Power consumed by the consumer
\( \sigma_n \) Prosumer preference parameter
\( \theta_n \) Predetermined constant or can be a variable with time
\( \rho_{t,b} \) Power bought from RPS
\( \rho_{t,b} \) Power bought from main grid
\( D_{t, b} \) Power demand at buyer bus
\( G_{t, b} \) Power generation at buyer bus
\( r_{t} \) Energy price from RPS
\( s_{t} \) Total demand from the sth RPS
\( u_{t}(...) \) Utility function of RPS
\( u_{t}(...) \) Utility function of RPB
\( u_{t}(...) \) Utility function of VP
\( R_{t, b} \) Energy price offered by the main Grid
\( R_{t, b} \) Incentive for the demand reduction
\( D_{t} \) Power reduced by the VP
\( \omega_k(D_{t}) \) Dissatisfaction cost function
\( D_{t}^{base} \) Base load of VP
\( L_{R,k} \) Load reduction limit
\( \Delta_k \) Dissatisfaction factor
\( D_{t,k} \) Maximum value of \( D_{t} \)
\( \rho_{t, b} \) Maximum power purchased
\( \rho_{t, b} \) Maximum power sold by the RPS
\( R_{t, b} \) Maximum energy price offered by the main grid
\( R_{g}/R_{rg} \) Energy price for main grid power/reserve generation

I. INTRODUCTION

A. BRIEF OVERVIEW
Climate change has a perceptible effect on the forecasting of RES. Because of the COVID-19 pandemic, the global weather showed diverted behavior from its normal data. In such situations, the forecasting of RES has become extremely challenging. The World Meteorological Organization has released a report that the COVID-19 pandemic has negatively affected the quantity and quality of weather forecasts, and climate monitoring [1]. Consequently, the level of uncertainty has increased. In this paper, uncertainty is defined as the actual information gap between forecasted data and real-time data. Thus, the integration of RES with the running stable system demands dealing with the level of uncertainty. In the past, stochastic and probabilistic methods were used to deal with uncertainty. However, this could only be achieved with essential historical data, probability density functions, and a high computational burden. IGDT is an alternative method that is considered to be better equipped to deal with uncertainty. After the integration of RES two possible situations must be considered:
1) Power supplied from the RES is less, or
2) Greater than the demand at the point of common coupling of the RES.

In the first case, an incentive-based SDR is a remedial solution, while an ESS can be used to reserve the surplus power from the MG in the second case. The second case can also be handled through the local energy trade between real prosumers.

B. LITERATURE REVIEW
The motivation of this study is to model the uncertainty, which is essential for power system design as it has uncertain parameters like RES. In such situations, uncertainty can be excessively risky. Therefore, decision-makers determine the parameters of the power system to ensure that the power system does not cross the allowed limits due to uncertainty. Various techniques have been used to model uncertainty, such as possibilistic, Z-number, interval analysis, robust optimization, and information gap decision theory [2]. The probabilistic approach has been used to model the uncertainty effectively [3]. Stochastic programming is the main tool used in designing the parameters and finding their probability and optimal solutions. To deal with the uncertain load values, electricity market price, and daily distance traveled by the electrical vehicles, Monte Carlo simulations

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were used in [4]. This method helped in finding the optimal points for the integration of plugin electrical vehicles. In [5], wind turbine (WT) power, photo-voltaic (PV) power, and consumer load were considered uncertain parameters. A stochastic bi-objective approach based on chance-constrained programming was used to find the maximum probability of minimum cost. The uncertainty modeling of the aforementioned parameters was achieved by the scenario-based multi-objective stochastic framework to find the optimal control of the volt/var of the distribution network [6]. However, the requirement of precise information to determine the probability density function and a heavy computational burden are the main drawbacks of the stochastic and probabilistic methods. This has resulted in alternative methods such as IGDT, which is better at handling uncertainty based only on available information. Different mathematical models of IGDT have been developed in [7] to deal with different scenarios of uncertainty. IGDT has many applications in economics, medical, and engineering. It has also been used to find the optimal solution to many power system problems [8], [9], [10], [11], [12], [13]. Optimal power flow has been found using IGDT considering the uncertainty of wind power [8]. Congestion scenarios have been managed with reactive power and demand response as the decision variables of IGDT against uncertain wind power [9]. Transmission expansion planning goals have been achieved using IGDT considering the investment risk of uncertain wind form output and demand [10]. The economic dispatch problem [11] has used IGDT to model uncertainty. An energy hub at LAMBDA lab MG, Sapienza University Rome, has been developed through optimal scheduling of RES, conventional sources, and nuclear energy sources [12]. They have used the IGDT for the robust uncertainty modeling of RES and real-time load. In [13], to model the uncertainty of load and wind forms fuzzy-IGDT has been utilized considering the decision maker’s preferences. Sometimes economic bidding is required along with the requirement of carbon emission reduction. So the proposed model by [14] has optimized the scheduling of the RES and dispatch able loads of virtual power, maintaining the optimal bidding along with carbon emission reduction. Risk-averse, risk-seeker, and risk-neutral methods have been used for the stable and economic operation of the virtual power plant. Almost the same way, a risk-averse strategy of robust function has been adopted in [15] to model the RES and load uncertainty of industrial MG considering the price variation. The foreign investment industrial park located in East-Azarbaijan, Iran has been used as a real case study to prove the effectiveness of the proposed strategy to achieve techno-economic benefits.

From the literature review of IGDT, we conclude that the demand response (DR) can be considered a supporting tool for the efficient deployment of the uncertainty model [16]. The DR acts as the virtual power source whose output response can be changed as per the requirement. Future smart grids and MGs will have communication and IoT sources for efficient coordination. The DR can also coordinate using the available sources in normal and emergency events [17], [18], [19], [20], [21]. In case of power fluctuations, the requirements of power ramp-up and ramp-down are a bit challenging. Nevertheless, the DR can provide a better and faster ancillary service for a stable economic operation [22]. If flexible demand response and uncertainty of RES are considered together then a stable integration of community energy users to the main power system can be developed. A strong community-integrated energy system considering electric vehicle charging stations using sequence operation theory is developed by [23]. To test the balanced coordination between the community-integrated energy system and electric vehicle charging stations and the effective role of flexible demand response and RES, a real-time case study in North China has been considered. Stackelberg game-based DR models have been a great source of benefits for providing power system stability to both consumers and the main grid [24], [25], [26]. From [8], [9], [10], [11], [12], [13] to [27], [28], [29], it has been observed that the research interest was on the robust solution and lack of focus on the opportunistic solution. Here, the sympathetic impact of IGDT (SI-IGDT) has been exploited to boost the opportunistic solution that would maintain system stability from minimum to maximum RES available. It means that maximum energy is harvested from RES whether it is greater or lower than the forecasted energy. Although DR has been modeled in [24] and [25] to fill the gap between power generation and demand, there is still space to improve the consumer behavior to the main grid. In this work, consumer behavior analysis and control are designed by a novel factor using SDR. In this model, power is exchanged between the prosumers by considering not only their technical and economic benefits but also the selection priority which causes the power system loss reduction.

C. CONTRIBUTION AND STRUCTURE
The main contributions of this paper are summarized as follows:

1) To utilize the maximum RES power, uncertainty is modeled using the SI-IGDT which has made possible the integration of RES whether it is greater or less than the forecasted value.

2) A virtual layer of the smart demand response operator (SDO) is developed by designing a power flow conditional algorithm (PFCA) and developing a multi-objective firefly optimization algorithm (MFOA), where the former is used for sorting consumer types. It means that SDO plays the role of an intelligent and autonomous aggregator.

3) A single leader and multi-follower Stackelberg game is modeled to achieve the optimal power values and the UF values for related consumers. This game formulation reduces the burden of the load on the main grid and power flow losses by increasing the energy exchange.
between local prosumers. At SE, the benefits are optimally distributed among the leader and all followers.
4) To achieve the best results for the SE, PFCA and MFOA are coupled under SDO.
5) An STF is modeled, which is used to study consumer participation behavior and the main grid strategy.

The rest of the paper is organized as follows: the sympathetic behavior of IGDT functions is modeled and discussed in detail in Section II. The incentive-based DR and concept of local trading transformation in SDR are detailed in Section III. The objectives and constraints are listed in Section IV. Simulation and results, which include the sympathetic impact, SE, and STF impact analysis are given in Section V. Finally, conclusive remarks are put forward in Section VI.

II. INFORMATION GAP DECISION THEORY

The discrepancy between known and unknown data is interpreted as uncertainty, which is modeled by the IGDT. This discrepancy is controlled by the uncertainty horizon limit, which depends on the requirements of the uncertain parameters. There are mainly three types of uncertainty models in IGDT,

i. Energy-bound model
ii. Envelope-bound model
iii. Slope-bound model.

Most of the researchers have used the envelope-bound model as given below,

\[ M(\alpha, \tilde{m}) = \{ m(t) : |\tilde{m}(t) - m(t)| \leq \alpha \varphi(t) \}. \] (1)

This model can be used both for RF and OF. The drawback of this model is that uncertainty space is fixed for both RF and OF.

Here, the slope-bound model has been adopted. Related function \( M(\alpha, \tilde{m}) \) is given in (1),

\[ M(\alpha, \tilde{m}) = \{ m(t) : \left| \frac{d(\tilde{m}(t) - m(t))}{dt} \right| \leq \alpha \varphi(t) \}. \] (2)

Here \( m(t) \) and \( \tilde{m}(t) \) are the real and forecasted values of the uncertain parameters respectively while \( \alpha \) and \( \varphi(t) \) denote the slope bound limit and function to control the uncertainty limit. The slope-bound model was chosen to not only control the uncertainty deviation but also the slope of deviation. This model can boost the SI-IGDT by maximizing the horizon of uncertainty. The comparison key points between the two uncertainty models have been given in Table 1 after further detail. In TABLE 1, all 5 points of the proposed slope bound model are advantages over the envelope bound model. The proposed model has been developed first time here.

Before detailing the IGDT model used in this study, it is beneficial to briefly review the uncertainty model used in [27] and [28]. Here, an assumption was made that actual uncertain values would be less than the forecasted values. This robust solution found the optimal allocation of RES and controlled the voltage at the expense of the maximum permissible cost and the minimum available RES in [27] and [28] respectively. In addition to the same assumption made in [27] for a robust solution, another assumption was made in [29], that unknown values of RES would be greater than forecasted values to find the opportunistic solution. In both cases, the operating cost of the smart grid and MG was the objective function. So, the maximum possible cost with the minimum RES power in the robust case, and the minimum cost with the maximum possible RES power in the opportunistic case were determined. All the above cases were more focused on the robust solution with the pre-assumptions, which availed the least power of PV and WT. However, the goal of this study is to utilize the maximum possible available RES power with minimum possible cost without any pre-assumptions which is more close to the real uncertain behavior of RES.

In general, the two main functions of IGDT are;

1) The RF is related to the risk-averse method, and
2) The OF is related to the risk-seeker method.

A deep study of [7] shows that RF shows immunity to failure while OF shows immunity to possible success. With uncertainty limits \( \alpha_1 \) and \( \alpha_2 \), general form of RF and OF are given in (3) and (4) respectively,

\[ \bar{\alpha}(\bar{x}, W_{t,r}) = \max_{\alpha_1} \left\{ \alpha_1 : \min_{\bar{x}} W_r \geq W_{t,r} \right\} \] (3)

\[ \bar{\beta}(\bar{x}, W_{t,o}) = \min_{\alpha_2} \left\{ \alpha_2 : \max_{\bar{x}} W_o \leq W_{t,o} \right\} \] (4)

where \( \bar{x} \) is the decision variable, \( W_r \) and \( W_o \) are the reward values for RF and OF respectively with \( W_{t,r} \) and \( W_{t,o} \) as the threshold values. RF tends to gain the maximum permissible cost (minimum reward) with a wide range of uncertainty resulting in improved immunity to failure. While OF has the immunity to possible success but within a minimum possible range of uncertainty. The immunity expected response is shown in FIGURE 1.

The left side of FIGURE 1 shows a tendency of the robust function, which seeks maximum uncertainty with low reward.
TABLE 1. Comparison between the uncertainty models.

| S. No. | The proposed slope-bound uncertainty Model | Envelope-bound uncertainty Model |
|--------|------------------------------------------|----------------------------------|
| 1      | The proposed model has been described in (5) and (6) with different uncertainty limits $\alpha_1$ and $\alpha_2$ for RF and OF | This model has been described by (1) with the same uncertainty limit $\alpha$ both for RF and OF |
| 2      | Uncertainty is measured concerning the time of the running power system | Uncertainty is measured without considering the time of the running power system |
| 3      | There is no assumption, data is randomly generated and traced using both parts of the uncertainty models simultaneously | Most of the researchers have assumed that future unknown value is greater than or less than the known value |
| 4      | Both functions of IGDT behave sympathetically | It is used for most of the robust goals of the system |
| 5      | Usually, Slope bound limit for $\alpha_1$ is set more than $\alpha_2$ because more uncertainty is found in a robust case | This model lacks in setting flexible uncertainty limit |

but it is immune to failure. Thus, it is considered a risky region. The right side of the graph shows the opportunistic region because it has less uncertainty but more reward. This study applies both functions simultaneously and moves the point of operation from the risky region to the opportunistic region. This collective action is called sympathetic impact, and immunities of both functions are called sympathetic immunities.

The difference between the general response of IGDT and SI-IGDT is that in SI-IGDT RF also tends to the minimum uncertainty with a greater reward which is synched with the behavior of OF. To achieve this target, the uncertainty model in (2) is modified in (5) and (6).

$$
\tilde{M}(\alpha, \tilde{m}) = \left\{ m(t) : \frac{d(m(t) - \tilde{m}(t))}{dt} \leq \alpha_2 \phi(t) \right\}
$$

(5)

$$
\hat{M}(\alpha, \hat{m}) = \left\{ m(t) : \frac{d(\hat{m}(t) - m(t))}{dt} \leq \alpha_1 \phi(t) \right\}
$$

(6)

where (5) deals with the situation when the actual unknown RES profile value is greater than the forecasted value and (6) is applied when the forecasted RES profile value is greater than the actual value. It is found that the data is found more uncertain in the robust case, that’s why it is better to deal with the uncertainty margin for RF and OF separately. Overall, the real RES profile data is estimated without any assumption. It is important to note that both $\alpha_2$ and $\alpha_1$ are minimized which ultimately tends to achieve the maximum target reward. If the condition in (7) is fulfilled, then both immunities will sympathetically support each other,

$$
0 < \frac{\partial \hat{\beta}(\tilde{x}(W_r), W_o)}{\partial W_r}.
$$

(7)

From (7) it is clear that if the rate of change of opportunistic function value concerning robust target reward is positive then it means both functions are sympathetic otherwise antagonistic. Now we can conclude that a new function named here as the sympathetic impact function (SIF) can be developed as in (9):

$$
\alpha = |\alpha_1| + |\alpha_2|
$$

(8)

$$
SIF = M(\tilde{x}, W_i) = \min_{\alpha} \left\{ \alpha : \max_{x} W \geq W_i \right\}
$$

(9)

The SIF combines the features of RF and OF from (3) and (4) in (9) by using (5), (6), and (8). The unique feature of SIF is that it tends to minimize uncertainty and maximize the target reward.

III. MODELING THE SMART DEMAND RESPONSE

Demand response has a strong relationship with RES and smart grids [30], [31]. Balancing the load and power generation, specifically at peak hours of the main grid, is especially challenging. This issue can be resolved either by managing the power generation sources or the loads. The first solution is relatively difficult as it is complex and costly due to the power ramp-up and ramp-down operations of the power generation sources. The second solution balances the power by controlling loads of consumers as per the required power management. Despite the difficulty of this task, emerging algorithm development, advancement in communication technology, and advanced metering infrastructure have made it possible to develop an SDR [32].

There are two types of DR programs: incentive-based DR and price-based DR. For the price-based DR, the consumer manages the load to get the minimum price available at a specific time slot. Despite this, the price-based DR consumer does not get any benefit from the utility except the reduced cost. In contrast, for the incentive-based DR, the load of consumers is controlled either by the utility or the consumer itself under any DR type. The consumer gets the incentives either in the form of a reduction of energy units or cash payment [33]. Consequently, more consumers are encouraged to participate in incentive-based DR. Thus, consumers can play the role of a VP as well. As shown in FIGURE 2, SDR coordinates between the SDO and prosumers. The SDO interprets the real-time prices and incentives of the main grid and subsequently communicates them to the prosumers.

A. MODELING OF RPB, RPS, AND VP

It is assumed here that the consumer either behaves as a VP or RP. Let $k$ denote the number of VPs and $n$ denote RPs. Generation of the RP either consists of PV or WT or both. The RP is further divided into two types RP seller (RPS) and RP buyer (RPB).
Consumers are differentiated by using the following generation-to-demand ratio $GD_n$ (10),

$$GD_n = \begin{cases} \frac{G_s}{D_s}, & GD > 1 \\ \frac{RPS_s}{D_s}, & GD < 1 \end{cases}$$

where subscript $s$ and $b$ shows seller and buyer index number respectively. While $G_n$ and $D_n$ are power generation and demand at the consumer node respectively.

The behavior of the RPS can be modeled using the UF described in [34]. There are two types of UF used in literature: logarithmic and quadratic. In this paper, the quadratic UF has been used. If $\rho$ is the power consumed by the consumer, then the UF is given by (11),

$$u'_{\rho}(\rho_n) = \sigma_n \rho_n - \frac{\theta_n}{2} \rho_n^2$$

where $\sigma_n > 0$ is a prosumer preference parameter, $\theta_n$ is a predetermined constant, and $t$ is the time interval in hours. The UF of RPB and RPS is given by (12) and (14) respectively [35],

$$u'_{\rho}(\rho_{s,b}) = u'_{\rho}(\rho_{s,b} + G'_b) - r'_s \rho_{s,b}$$

where

$$\rho'_{s,b} = D'_b - G'_b$$

$$u'_{s}(r'_s) = u'_{\rho}(\rho'_s) + r'_s S'_s$$

$$r'_{s,min} \leq r'_s \leq r'_{s,max}.$$  

Here in (12) $\rho'_{s,b}$ is the power bought from the seller, $G'_b$ power generation at RPB node, $r'_s$ is the energy price from RPS, in (13) $D'_b$ power demand at RPB node, and in (14) $S'_s$ is the total demand for the $s$th RPS. Maximum limit of the $r'_s$ in (15) is defined by the energy price of the main grid and the minimum limit is chosen by RPS itself.

Let $R'_{d,b}$ be the price offered to the buyer by the main grid at the time $t$ and $R'_b$ be the incentive for the demand reduction at the time $t$ for the VP. If $\rho'_s$ is greater than $S'_s$, then (12) holds, otherwise the RPB will be shifted to the grid, as shown in (16). The UF of the VP is defined using $R'_{b,k}$, as given in (17) [36],

$$u'_{b}(\rho'_{d,b}) = u'_{b}(\rho'_{d,b} + G'_b) - R'_{d,b} \rho'_{d,b}$$

$$u'_{b}(D'_{b,k}) = D'_{b,k} R'_{b,k} - \Lambda_k \omega_k (D'_{b,k})$$

$$0 \leq D'_{b,k} \leq D'_{b,k}^{base} L_{R,k}.$$  

where in (16) $\rho'_{d,b}$ is the power bought from the main grid (subscript 'd' is used because of SDO), in (17) $D'_{b,k}$ is the power reduced by the VP, $\omega_k$ is the dissatisfaction cost, which shows how much the VP has violated the agreement with the main grid through the SDO, in (18) $D'_{b,k}^{base}$ is the base-load of VP, $L_{R,k}$ is load reduction limit. In (17) $\Lambda_k$ is defined as the dissatisfaction factor of the agreed load reduction.

The dissatisfaction cost is given in (19),

$$\omega_k (D'_{b,k}) = \alpha_k D'_{b,k}^2 + \frac{\theta_k}{2} (D'_{b,k})^2$$

where $\alpha_k$ denotes the type of prosumer and $\theta_k$ is the load reduction behavior.

B. SMART DEMAND RESPONSE OPERATOR MODELING

The UF of SDO includes the UF of RPS, RPB, VP, generation cost, and the cost of the reserve power. It is given by (20),

$$u(D'_k, \hat{\rho}_{d,k}, \hat{\rho}_{s,k}, R'_{d,b}) = \sum_{b \in B} u(\rho'_{d,b}) + 0.03 \sum_{s \in S} u(r'_s,b)$$

$$- \sum_{k \in K} u'_{s}(D'_{k}) R'_k P'_s - \Lambda_k R'_k P'_g$$

$$u(D'_k, \hat{\rho}_{d,k}, \hat{\rho}_{s,k}, R'_{d,b}) = \sum_{b \in B} (u'_{b}(\rho'_{d,b} + G'_b) - R'_{d,b} \rho'_{d,b})$$

$$+ 0.03 \sum_{s \in S} (u'_{s}(\rho'_s) + r'_s S'_s) - \sum_{k \in K} (D'_{k} R'_k - \Lambda_k \omega_k (D'_{k}))$$

$$- R'_g P'_g - \Lambda_r R'_g P'_g.$$  

In (20) 0.03 is 3% benefits of seller paid to the main grid through SDO, $\Lambda_g$ is the cost, $P'_g$ is the power generation of the main grid, $\Lambda_rg$ is the reserve power generation factor, $P'_rg$ is the reserve power and $R'_rg$ is the generation cost for the reserve power. Here $\Lambda_rg$ has the same value as that of $\Lambda_k$. This means that the dissatisfaction with agreed demand reduction leads to the generation of the reserve power. The total incentives offered and paid to the VPs must be less than the maximum allowed budget of the main grid, as shown in (22). The price offered $R'_{d,b}$ to sell power to the RPB is also bounded by the minimum $R'_{d,b,min}$ and maximum $R'_{d,b,max}$ values,

$$\sum_{k \in K} R'_{d,k} \leq R'_f$$

$$R'_{d,b,min} \leq R'_{d,b} \leq R'_{d,b,max}.$$  

C. FORMULATION OF STACKELBERG GAME

The purpose of the SDR is to develop efficient coordination between the main grid and consumers to achieve optimal
benefits for all. Formulation of the SDR using the Stackelberg game can be an effective approach as it has been found in [24] and [25]. Thus, SDR is further formulated following the theorem and rules of the Stackelberg game.

**Theorem 1:** An optimal solution for the SDO, VP, RPS, and RPB is found after achieving the SE by the Stackelberg game. The existence is ensured through an algorithm.

**Definition and Rules:** The ultimate goal of this game is to find an optimal beneficial solution for the leader (SDO) and the followers (VP, RPS, and RPB). Each game is played under some specific rules which are listed below [24].

Each player in the game adheres to the following rules,

1. The strategy set of each player is nonempty, convex, and compact.
2. Each player has a unique optimal best-response strategy, provided by the SDO (leader).
3. The SDO adopts a unique optimal strategy by identifying the best strategies of the VP, RPS, and RPB.
4. Steps 2 and 3 are repeated until an optimal solution is targeted at SE.

To find the maximum value of the strategy of the leader, the maximum optimal values of all followers must be found.

**Proof 1:** The objective function of the VP is to maximize the incentives from the SDO by avoiding the dissatisfaction factor, as shown in (24); while (24) is derived from (17) and (19),

$$u_b^t(D_k^t) = D_k^t R_k^t - \Lambda_k \cdot \left( \sigma_s D_k^t + \frac{\theta_k}{2} (D_k^t)^2 \right).$$

By calculating the first derivative of (24) w.r.t. $D_k^t$, we get as,

$$\frac{\partial u_b^t(D_k^t)}{\partial D_k^t} = R_k^t - \Lambda_k \sigma_s - \Lambda_k \theta_k D_k^t.$$

By equating the derivative to zero in (25), the maximum value of $D_k^t$ is $\hat{D}_k$ given in (26),

$$\hat{D}_k = \frac{R_k^t - \Lambda_k \sigma_s}{\Lambda_k \theta_k}.$$ (26)

The second derivative of (24) has a negative value $(-\Lambda_k \theta_k)$; this means that the objective function is concave.

**Proof 2:** The objective function of the RPB maximizes the power purchased either from the main grid or from the RPS through the SDO. Here, it is assumed that in both cases, the cost of the purchasing power would be the same: $R_k^t = \tilde{R}_k^t$. This assumption is for calculation purposes only. Hence, the UF of the RPB can be written as,

$$u_b^t(\rho_{e,b}) = u_b^t(\rho_{e,b} + G_b^t) - R_{e,b} \rho_{e,b}$$ (27)

where $\rho_{e,b}$ is the power purchased either from the RPS or the main grid. By using the values from the UF of the RPB, (27) becomes,

$$\hat{u}_b^t(\rho_{e,b}) = \sigma_b (\rho_{e,b} + G_b^t) - \frac{\theta_b}{2} (\rho_{e,b} + G_b^t)^2 - R_{e,b} \rho_{e,b}.$$ (28)

Now taking the first derivative, (28) becomes,

$$\frac{\partial \hat{u}_b^t(\rho_{e,b})}{\partial \rho_{e,b}} = \sigma_b - \theta_b (\rho_{e,b} + G_b^t) - R_{e,b}.$$ (29)

To find the maximum power purchased $\hat{\rho}_{e,b}$, we equate the derivative to zero and solve by (30),

$$\hat{\rho}_{e,b} = \frac{R_{e,b} - \sigma_b - \theta_b G_b^t}{\theta_b}.$$ (30)

The second derivative of (28) is negative $(-\theta_b)$ and therefore concave, which shows maximization function.

**Proof 3:** The objective function of the RPS maximizes the revenue obtained from selling the power to the RPB. This means that power will be sold in equal proportion to its demand. The UF of the RPS is given in (31),

$$u_s^t(r_s^t) = \sigma_s \rho_s^t - \frac{\theta_s}{2} (\rho_s^t)^2 + r_s^t S_s^t - 0.03 (\sigma_s \rho_s^t) - \frac{\theta_s}{2} (\rho_s^t)^2 + r_s^t S_s^t.$$ (31)

Here, $S_s^t$ is the total power demand from RPS, and it is assumed to be the nominal case, $S_s^t = \rho_s^t$. By taking the derivative of (31) w.r.t. $\rho_s^t$, we get

$$\frac{\partial u_s^t(r_s^t)}{\partial \rho_s^t} = 0.97 (\sigma_s - \theta_s \rho_s^t - r_s^t).$$ (32)

Now to find the maximum possible value of power sold by the RPS, we equate (31) to zero and obtain the maximum power in (33),

$$\hat{\rho}_s^t = \frac{\sigma_s - r_s^t}{\theta_s}.$$ (33)

The second derivative of (31) is also negative $(-\theta_s)$ and concave.

**Proof 4:** After finding the maximum values of $D_k^t$, $\hat{\rho}_{e,b}$, and $\hat{\rho}_s^t$, the maximum possible value of the main grid energy price $\hat{R}_{d,b}$ can be found from (21) by using the aforementioned values. Before we derive the expression for $\hat{R}_{d,b}$, it is important to note the following,

i. $\hat{R}_{e,b}$ is considered as $\hat{R}_{d,b}$.
ii. $\hat{\rho}_{e,b}$ is considered as $\hat{\rho}_{d,b}$.
iii. $S_s^t$ is considered as $\hat{\rho}_s^t$.
iv. $r_s^t$ is considered as $\hat{R}_{d,b}$.
v. $R_k^t$ is used in terms of $\hat{R}_{d,b}$ as $0.2 \hat{R}_{d,b}$ (20% is assumed as the incentive from the main grid at peak hours).

Hence, the UF of the SDO from (20) using the values of $\hat{D}_k$, $\hat{\rho}_{e,b}$, and $\hat{\rho}_s^t$, and considering all the points mentioned above is given as,

$$u(\hat{D}_k, \hat{\rho}_{e,b}, \hat{\rho}_s^t, \hat{R}_{d,b}) = \sum_{b \in B} \left( \frac{1}{\hat{\theta}_b} ((\sigma_b \hat{R}_{d,b} - \sigma_s^t \hat{R}_{d,b}^t) - \frac{\theta_b}{2} (\hat{R}_{d,b}^t - \sigma_s^t \hat{R}_{d,b}^t) - \frac{1}{2} (\hat{R}_{d,b}^t - \sigma_s^t \hat{R}_{d,b}^t)^2) \right) \left( \frac{1}{\hat{\theta}_s} (\sigma_s^t - \hat{R}_{d,b}^t)^2 - \frac{1}{2} (\sigma_s^t - \hat{R}_{d,b}^t)^2 \right)$$
\[
\begin{align*}
&- \sum_{k \in K} \left( \frac{1}{\Lambda_k \theta_k} \left( (0.2R_{d,b}^l)^2 + 0.2 \Lambda_k \sigma_k R_{d,b}^l \right) \right) \\
&- \frac{1}{\theta_k} \left( 0.2 \Lambda_k \sigma_k R_{d,b}^l + \Lambda_k \sigma_k^2 \right) - \frac{1}{2 \Lambda_k} \left( (0.2R_{d,b}^l + \Lambda_k \sigma_k)^2 \right) \\
&- R_s P_s^l - \Lambda_{eq} R_{eq} P_s^l.
\end{align*}
\]

Now, to find the maximum value of \( R_{d,b}^l \), we take the derivative of (34) w.r.t \( R_{d,b}^l \). The result is obtained by equating the derivative to zero, as shown in (35) and (36),

\[
\frac{\partial u}{\partial R_{d,b}^l} = \sum_{b \in B} \frac{1}{\theta_b} \left( 2 \sigma_b - 2R_{d,b}^l + \theta_b G_b^l - \theta_b R_{d,b}^l \right) + \theta_b \sigma_b + 0.03 \sum_{s \in S} \left( -2R_{d,b}^l + \sigma_s - R_{d,b}^l \right)
\]

\[
- \sum_{k \in K} \left( \frac{1}{\Lambda_k \theta_k} \left( (0.08 R_{d,b}^l - 0.04 R_{d,b}^l) \sigma_k \right) \\
- 0.2 \theta_k \Lambda_k \sigma_k \right)
\]

\[
R_{d,b}^l = \left[ \sum_{b \in B} \left( 2 \sigma_b + \theta_b G_b^l + \theta_b \sigma_b \right) + 0.03 \sum_{s \in S} \sigma_s \\
+ \sum_{k \in K} 0.2 \theta_k \right] \cdot \frac{1}{STF}
\]

In (36) STF is termed as the SDR tuning factor for the cost of power from the main grid through SDO which is given as,

\[
STF = \frac{2 \sigma_b \theta_k \Lambda_k + 2 \sigma_b \theta_k \Lambda_k \theta_b + \theta_b \theta_k \Lambda_k + 0.08 \theta_b \theta_s + 0.04 \sigma_k \theta_b \theta_s}{\theta_t \theta_b \theta_k \Lambda_k}.
\]

The unique novel factor STF derived in (37) is the best source to observe the behavior of VP, RPS, and RPB to the main grid. By using STF, the behavior of VP, RPS, and RPB can be tuned and a new respective point can be achieved.

**D. PROPOSED METHODOLOGY ALGORITHMS**

Based on section II and section III, the proposed methodology has been developed as shown in FIGURE 3. It consists of mainly two algorithms i.e algo.1 and algo.2. Algo. 1 deals with the SI-IGDT part while algo. 2 deals with SDR through Stackelberg game. Algo. 1 is discussed in detail regarding simulation data in section V, a) while algo. 2 is discussed in detail in section V, b).

The brief execution procedure has been given below;

**Algo. 1:**

i. When algo. 1 is called, it receives the forecasted RES profiles as the reference known data

ii. FOA of Algo. 1 initializes the variables and generates the random future RES profiles data

iii. OFn of FOA consists of (5) and (6)

iv. Above step iii is also the partial part (\( min_a \)) of the SIF function in (9)

v. To execute OFn of FOA, PFA is called considering the constraints (43)-(45)

vi. OFn of FOA checks the uncertainty slope of RES future expected profiles and PFA is executed to check and follow the constraints

vii. Then final uncertainty slope and RES profiles are sent back to FOA from PFA for further sorting to optimize

viii. The steps v, vi and vii are repeated till the final iteration to get the minimum possible uncertainty slope and related RES profiles

ix. These minimum optimum RES profiles are sent to the algo. 2.

**Algo. 2:**

i. RES profiles are updated based on the optimum RES profiles received

ii. So the power generation of RES is updated as well accordingly

iii. RES power generation and load data are sent to MFOA as reference

iv. MFOA initializes the variables and generates random data

v. OFn of the MFOA are the decision variables in (41) which are the player outputs of the Stackelberg game i.e (26), (30), (33) and (1)

vi. To execute OFn, PFCA is called

vii. In PFCA, prosumers are sorted by (10)

viii. As per TABLE 2, \( \sigma \) and \( \theta \) values are initialized for prosumers

ix. OFn of the MFOA i.e (26), (30), (33) and (1) are executed

x. Final values are sent back to MFOA for further sorting to get optimum values

xi. From vi to x steps are repeated till the final iteration to get optimum values of (26), (30), (33) and (1) at SE

xii. Using the optimum values from MFOA, final UF values ((12), (14), (16) and (21)) and maximum possible output values ((26), (30), (33) and (1)) of Stackelberg players are found.

**IV. OBJECTIVES AND CONSTRAINTS**

For better planning and design of any power system, the objectives must be clearly defined and all sensitive constraints of the system must be considered. The objective of this study is divided into three parts:

1) Uncertainty modeling of RES (PV and WT) to harvest maximum possible RES.

2) To manage the power generation and load (exchange of power) to achieve a supply reserve of up to 10%.

3) To introduce the STF to manage the behavior of the VP, RPS, and RPB.

These three objectives ensure the stability and reliability of the main grid with the integration of the local RES. The concept of reserve power is based on the real-time power supply...
and demand data of the Korea power exchange [37]. It has been observed that the reserve margin remained between 10% and 30% for the last five years, which was not possible without the support of the RES.

The first objective deals with the SIF function of IGDT, which maximizes target reward values and minimizes the uncertainty as given in (8) and (9), and satisfies all constraints in both conditions. Here it is needed to mention that the power of RES penetrated into the power system is considered here as the target reward. So the first objective function can be defined as given in (38) and (39).

$$\max \ SIF$$
$$W(\bar{x}, m) \leq A \cdot W_0 (\bar{x}, \bar{m})$$

The objective function in (8) maximizes the penetration of RES estimating the minimum possible uncertainty. In (39), $\bar{m}$ shows the uncertain profile variables which are minimized by algorithm 1. Now in case of the higher output power of RES available to penetrate, decision variables $\bar{x}$ are set to keep power generation and demand balance by enabling more penetration of RES power within the power system constraints. In (39), $W_0 (\bar{x}, \bar{m})$ shows the base value of RES power penetrated and it can be increased by $A$ factor within the power system constraints.

The decision variables in (39) considered here are the outputs of the (26), (30), (33), and (1) which are the power reduction by VP, power purchased by the RPB, power sold by the RPS and energy cost offered by the main grid respectively. The setting of the $\bar{x}$ is done using the SDR through the Stackelberg game. For this purpose, algorithm 2 i.e MFOA is used to set the values of $\bar{x}$ by taking values in (26), (30), (33), and (1) as objectives of the algorithm. The mutual optimal values are obtained at the Stackelberg equilibrium by algorithm 2. The detail of the algorithms is given in the next section.

So here (39) can be redefined by putting the $\bar{x}$ and the multi-objective target is given in (40) and (41),

$$\max_m \ W \left( \hat{D}_k, \hat{\rho}_e, \hat{\rho}_s, R^d_{d,b}, \hat{R}^d_{d,b} \right)$$
$$W \left( [\hat{D}_k, \hat{\rho}_e, \hat{\rho}_s, R^d_{d,b}], m \right) \leq A \cdot W_0 \left( [\hat{D}_k, \hat{\rho}_e, \hat{\rho}_s, R^d_{d,b}], \bar{m} \right)$$

Here one thing is noted the minimized values of uncertain profiles of RES will come from algorithm 1. As a result of the (40), maximum power can be penetrated by factor $A$ which
would ultimately reduce the operational cost of the main grid. Here $A$ is named as the amplifying factor of the RES power to penetrate.

The total net power $P_{net}^{t}$ should satisfy the power reserve required for a reliable main grid.

$$P_{net}^{t} = P_{g}^{t} + G_{b}^{t} + S_{j}^{t} \geq P_{g0}^{t} + P_{rg}^{t}$$

where $P_{g}^{t}$, $G_{b}^{t}$, $S_{j}^{t}$, $P_{g0}^{t}$, and $P_{rg}^{t}$ are the power generated by the main grid, RPB, RPS, at the required balance and reserve respectively. The reactive power, current, and voltage limits should also be satisfied and are given in (43), (44), and (45) respectively,

$$Q_{n,min}^{t} \leq Q_{n}^{t} \leq Q_{n,max}^{t}$$

$$V_{n,min}^{t} \leq V_{n}^{t} \leq V_{n,max}^{t}$$

$$I_{n,min}^{t} \leq I_{n}^{t} \leq I_{n,max}^{t}$$

where the constraints in (43), (44), and (45) are related to each other. The limit of the current is bounded by 7% of the load of each line in the power system. The voltage limits are assumed as V±5% tolerance, and the minimum and maximum reactive power is managed within the allowed limits of the voltage and current. The economic constraints are related to the price offered by the main grid. It controls the incentives offered to the VP and the price of energy trade between the RPS and the RPB, the grid and the RPB,

$$C_{g,T} = C_{g} + \sum_{k \in K} R_{k}^{t} - \sum_{s \in S} R_{s}^{t} - \sum_{b \in B} R_{b}^{t} \leq C_{g,max}$$

$C_{g,T}$ is the total cost of the main grid limited by the allowed budget $C_{g,max}$, including its generation cost, cost offered to the VP, and the cost obtained from the RPS and the RPB through the SDO. It should be noted that the RPS and VP also have their acceptable limits as given in (15) and (47) respectively, which depends on their comfort and allowed budget.

$$R_{k,min}^{t} \leq R_{k}^{t} \leq R_{k,max}^{t}$$

The minimum limits are based on the tradeoff between the comfort zone and the trading strategy, whereas the maximum limits are bounded by the offered prices for both the VP and RPS.

V. SIMULATION AND RESULTS

This work starts from the application of IGDT, with its sympathetic impact resulting in the additional power from RES into the power system, which requires power and load adjustment. A virtual layer of the SDO serves through the SDR and Stackelberg game using the PFCA and MFOA, which are developed in MATLAB. The algorithm is divided into two layers, the first one is mono-objective (FOA) and the second one is multi-objective (MFOA). The basic idea and structure of FOA are taken from [38]. The method chain is summarized in FIGURE 3. To test the proposed structure, a 37-bus system developed in MATLAB is used as the test system for this study [39]. The detailed data and test system are given in Appendix A. The test system is modified for the best optimal results. Bus 1 is the slack bus and all other 36 buses have residential and industrial loads at different locations. There are some loads at each bus that are continuous and constant. RES consists of PVs and WTs, their locations have been pre-decided in base case using the heat map analysis. The optimal allocation of RES is not the scope of this research. PVs are connected at buses 1, 3, 7, 8, 34, and 35 while WTs are connected at buses 6 and 36. In the base case, each PV and WT has a rating of 100 kW and 200 kW respectively. PVs and WTs follow their relevant forecasted profiles given in Appendix A. Two main grid thermal units each having 1000 kW at buses 26 and 33. Thermal units also follow their specific profiles given in Appendix A. Onward, power is discussed in terms of energy as power is interpreted using time simulation and results.

A. BASE CASE

Before analyzing the impact of the proposed methodology, it is essential to show some aspects in the base which will be considered as reference. The buses where RES are connected are also considered the local MGs. Voltage situation at these buses, energy generation and demand, and energy loss at each bus are shown in FIGURE 4, 5, and 6 respectively. In FIGURE 4, it is observed that at buses 7-8 and 33-35 there is a voltage drop below the -5% threshold. The reason for voltage drop is due to energy supply from main grid sources only at bus 26 and 33 and more energy demand than the generation. It is also worth noting that the generation cost of the main grid is 3264887 KRW (Korean Currency). Cost function coefficients are taken from [40]. From FIGURE 6 it is clear that more energy loss is observed on buses 1-9 due to power flow from buses 26 and 33. The gross energy loss during 24 hours is 78 kWh which can accumulate to a huge amount if it is not reduced.

B. IMPACT OF PROPOSED METHODOLOGY

The impact of the proposed methodology is analyzed in three parts: analysis of SI-IGDT, the role of the SDO to
achieve the SE, and behavioral impacts of the VP, RPS, and RPB; these are analyzed in subsections 1), 2), and 3), respectively:

1) SYMPATHETIC IMPACT OF IGDT
Considering the real possible situation of weather uncertainty, 50 cases of PV and WT output profiles have been generated randomly. FOA is applied to find the minimum uncertainty where maximum RES profile values are found i.e moving from robust region to opportunistic region with a high SIF (min $\alpha$) function value meeting the condition given in (9) and (38). To check the limits of the test system and RES uncertainty limit, each case is processed through PFA using (5) and (6). The variations of $\alpha$ values and diversion from robust to the opportunistic region are shown in FIGURE 7. The opportunistic region limit is 10% more than the forecasted values while the robust region has 12% less than the forecasted values. Their limits are set just to avail RES outputs in any case as per the real uncertainty behavior of RES. In FIGURE 7, five different colors depict $\alpha$ values showing the uncertainty between real and forecasted values of RES (WT+PV) for 5 iterations. Positive $\alpha$ values show that real RES profile values < forecasted profile values. In FIGURE 8 and 9, the future expected values of the PV and WT profiles have been shown which are randomly generated by the algo. 1 for one simulation. Then algo. 1, taking the proposed model in (5) and (6) as the objective function, finds the optimal values of PV and WT profiles with minimum possible uncertainty as required by the SI-IGDT. The final optimized values are highlighted in the relevant figures which will be used in the test system. Here it is needed to mention that these profile values further control the output values of the PV and WT. The profile values of PV and WT as shown in TABLE 7 of appendix are the forecasted values.
### TABLE 2. Load and generation data after applying algorithms as compared to base case.

| Bus | 1   | 3   | 6   | 7   | 8   | 26  | 33  | 34  | 35  | 36  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Base Case | | | | | | | | | | |
| PV Energy Generation (MWh) | 0.883 | 0.883 | 0.883 | 0.883 | 0.883 | 0.883 | 2.802 |
| WT Energy Generation (MWh) | 2.802 | | | | | | | | |
| Thermal Energy Generation (MWh) | | | | | | | | | |
| Load MWh | 3.81 | 4.91 | 3.679 | | 1.576 | | | | |

### At Stackelberg Equilibrium

| PV Energy Generation (MWh) | 2.643 | 2.643 | 2.643 | 2.643 | 2.643 | 2.643 | 7.148 |
| WT Energy Generation (MWh) | | | | | | | |
| Thermal Energy Generation (MWh) | 11.15 | 11.15 | | | | | |
| Load (MWh) | 2.779 | 4.628 | 3.336 | | 0.659 | | |

#### FIGURE 10. Voltage scenario after applying algorithms.

#### FIGURE 11. Energy Loss at each bus after applying the algorithm.

2) ROLE OF THE SDO AND SE

This section describes the performance of the SDO which ultimately supports achieving the SE. Here it is assumed that each consumer at VP bus is subscribed to incentive-based load curtailment with terms and conditions of dissatisfaction deduction and incentive rates given in (16). The value of $\Delta_k$ shows the dissatisfaction level against promised load curtailment. To compensate for this dissatisfaction level $\Delta_{rg}$ must have the same value as $\Delta_k$ to produce power through the reserve. The selection of VPs is done using heat map analysis considering the loading of lines and the selected buses are 1, 3, 7, and 33. PFCA is used to sort consumers into RPS, and RPB via (10). RPB buses are found as 1, 3, 7, 8, 34, and 35 during peak time, it remains above the lower limit present in PFCA. Due to power exchange between RPS and RPB and power reduction by VPs, energy loss is reduced to 25.22 kWh which is only 32% of loss in the base case as shown in FIGURE 11. This happens as the power flow is not required for buses at distances causing more power loss. After meeting all demand, there is still an energy reserve of 2.44 MWh.

This situation of energy generation and demand is shown in FIGURE 12. It is noted from FIGURE 12 that the main generation at buses 26 and 33 is decreased from 22.3 MWh.
TABLE 3. Energy exchange and STF values.

| Bus | 1  | 3  | 6  | 7  | 8  | 26 | 33 | 34 | 35 | 36 |
|-----|----|----|----|----|----|----|----|----|----|----|
| Energy sold to RPB by RPS (MWh) | 0.333 | 0.363 | 0.400 | 0.400 | 0.666 | 0.571 |
| Energy bought from main grid by RPB (MWh) | 0.1971 | 1.621 | 0.292 | 1.297 | 2.239 | 1.304 |
| Energy reduction by VP (MWh) | 1.031 | 0.285 | 0.343 | 0.917 |
| STF | 81.42 | 92.65 | 0.23 | 57.66 | 4.08 | 5.40 | 1.55 | 2.07 | 0.23 |

FIGURE 12. Energy generation and demand after algorithms.

FIGURE 13. Energy generation and amplifying factor $A$.

to 11.15MWh. At PV buses 1, 3, 7, 8, 34, and 35, and WT buses 6 and 36, generation is increased from 0.8836 MWh to 2.673 MWh and, from 2.802 MWh to 7.22 MWh respectively. This is clear evidence that more power from RES is penetrated. Energy demand is reduced from 3.81, 4.913, 3.679, and 1.576 MWh to 2.781, 4.628, 3.34, 0.6593 MWh at buses 1, 3, 7, and 33 respectively by VPs.

It has been observed that after the catalytic effect of the SDR through SE, the RES power penetration has been increased up to 3 times the base case in FIGURE 4. The value of energy generation at each bus along with amplifying factor has been shown in Figure 13. As compared with base case the results after applying algorithms are summarized in TABLE 2. Also the energy exchange and STF values at SE are given in TABLE 3.

3) BEHAVIORAL IMPACTS OF THE VP, RPS, AND RPB

From (10) to (36), $\sigma$ shows the type of prosumer and its worth of participation in SDR while $\theta$ shows the behavior of prosumers to the SDR. Here $\sigma$ is kept constant for each type of prosumer but the value of $\theta$ has a different value at each bus. In the case of optimal SE values of $\sigma$ and $\theta$ are given in Table 4. After finding the optimal values of $\hat{D}^b_t$, $\hat{\rho}_{b,v}$, and $\hat{\rho}_{d,b}$ at SE, optimal energy price ($R^b_t$) (35) for all the consumers is found to be 156 KRW/kW. Optimal power (energy) values for $\hat{D}^b_t$, $\hat{\rho}_{b,v}$, and $\hat{\rho}_{d,b}$ at each bus concerning the STF is shown in FIGURE 14.

It is clear from FIGURE 14 that most of the energy at buyer buses is purchased from the main grid but there is also maximum penetrated power by RES which is sold from RPS to RPB. The optimal value of energy-reduced at relevant buses of VP is shown which is based on the incentives from the main grid. Energy reduction at VP buses 1, 3, 7, and 33 is 1.029, 0.633, 0.3601, and 0.9167 MWh respectively. Energy purchased at RPB buses 3, 7, 8, 34, and 35 from the main grid is 1.79, 0.4817, 1.476, 2.471, and 1.487 MWh respectively. Energy purchased at RPB buses 1, 3, 7, 8, 34 and 35 from RPS is 0.3001, 0.3274, 0.3601, 0.3601, 0.6002 and 0.5145 MWh respectively. It is worth noting that at bus 1 energy is only purchased from RPS. UFs of VP, RPS, and RPB are shown in

TABLE 4. $\sigma$ and $\theta$ values at optimal Stackelberg equilibrium.

| VP  | $\sigma_b = 6$ | RPS | $\sigma_b = 5$ | RPB | $\sigma_b = 4$ |
|-----|----------------|-----|----------------|-----|----------------|
| Bus | $\theta_b$     | Bus | $\theta_b$     | Bus | $\theta_b$     |
| 1   | 5              | 6   | 5              | 1   | 6              |
| 3   | 6              | 36  | 6              | 3   | 5.5            |
| 7   | 5              | 33  | 6              | 7   | 5              |
| 33  | 34             |     | 3              |     | 35             |
|     | 35             |     | 3              |     | 35             |
TABLE 5. Effects of $\theta_k$, $\theta_s$ and $\theta_b$ at optimal power and utility functions of vp, rps, rpb and sdo (main grid).

| $\theta_k$, $\theta_s$ | $\theta_b$ | $\delta_k^L$ | $\rho_{k,b}$ | $\rho_{s,b}$ | $R_{k,b}^L$ | $u^U_k$($\delta_k^L$) | $u^U_s$($\rho_{s,b}^L$) | $u^U_b$($\rho_{b,b}^L$) | $u(SDO)$ |
|------------------------|-----------|--------------|--------------|--------------|------------|-----------------------|----------------------|----------------------|------------|
| Base                   | 2,307     | 2,462        | 6,505        | 156          | 1,570,472  | 91,583                | 927,402              | -437,986             | -483,986   |
| +10%                   | 2,538     | 2,238        | 6,757        | 102          | 2,046,752  | 83,257                | 609,391              | -1,227,461           | -1,307,409 |
| -20%                   | 2,769     | 2,051        | 6,977        | 75           | 2,632,319  | 76,319                | 452,883              | -1,967,307           | -1,997,307 |
| -10%                   | 2,077     | 2,735        | 7,232        | 230          | 1,187,400  | 101,759               | 1,564,495            | 577,508              | 577,508    |
| -20%                   | 1,846     | 3,077        | 6,130        | 323          | 885,829    | 114,479               | 1,870,523            | 1,171,153             | 1,171,153  |

FIGURE 14. Energy of VP, RPS, and RPB at Stackelberg equilibrium.

FIGURE 15. Utility function values for VP, RPS, and RPB.

FIGURE 16. STF values with changing $\theta$ values.

Similarly, a decrease in values for $\theta_k$, $\theta_s$, and $\theta_b$ lowers the $R_{k,b}^L$ and $u(SDO)$, whereas the opposite effect is observed when RPS and its UF are considered.

The variation of the STF values that control $R_{k,b}^L$ for various $\theta$ values is shown in FIGURE 16. The variation of STF has an inverse effect on $R_{k,b}^L$ and $u(SDO)$ as given in (36), which can be easily deduced by analyzing FIGURE 16 and Table 5 simultaneously. Conclusively, it is observed that at SE energy generation or consumption, energy price and UF values for SDO, VP, RPS, and RPB in Table 5 are the best possible values. Either energy reduced by VP or energy trading between local consumers i.e between RPS and RPB, both ways are effective for the economic operation of the main grid which can be realized by comparing base case grid operational cost with any one of the above cases.

To summarize the effect of prosumers behavior on the STF factor that affects the main grid energy price which ultimately affects the participation of VP, RPS, and RPB in the SDR. This is the solid source that helps to achieve the Stackelberg equilibrium for SDR. Participation of VP, RPS, and RPB for the change of $\theta_k$, $\theta_s$, and $\theta_b$±10% has been drawn in FIGURES 17 and 18.

From FIGURE 17, it is clear that 10% rise in $\theta$ values causes an increase in VP and RPB energy values and a decrease in the RPS energy values while a 10% decrease in $\theta$ values cause an increase in the RPS energy values and a decrease in the energy values of VP and RPB. These results also show that the proposed model is more supportive for VP as compared to RPS. But the proposed model can be made flexible and dynamic by the non-uniform variation of $\theta$ values.

FIGURE 17. Utility function values with changing $\theta$ values.
TABLE 6. Comparison of proposed methodology with exiting articles.

| Reference articles                                      | Proposed | [24] | [25] | [26] | [27] | [28] | [29] |
|---------------------------------------------------------|----------|------|------|------|------|------|------|
| IGDT, Robust Solution alone                            | No       | No   | No   | No   | No   | Yes  | No   |
| IGDT, Opportunistnic Solution alone                     | No       | No   | No   | No   | No   | No   | No   |
| IGDT, Robust and Opportunistic Solution (without sympathetic impact) | No       | No   | No   | No   | No   | Yes  | Yes  |
| SI-IGDT                                                 | Yes      | No   | No   | No   | No   | No   | No   |
| DR Stackelberg game                                     | *1xn game| *1xn game | *nxn game | *1xn game | Yes  | Yes  | Yes  |
| Max. RES penetration Focused                           | Yes, *Of=2.8 | No   | Yes | No   | No   | Yes, *Of=0.068 | Yes, *Rf=0.54 |
| Max. Cost focused                                       | No       | No   | Yes | No   | No   | Yes, *Of=0.171 | Yes, *Rf=0.07 |
| Reserve power                                           | 5%       | No   | Yes | No   | No   | Yes, in terms of loading margin (5%) | No |
| Power loss reduction                                    | 68 %     | No   | No | No   | No   | No   | No   |
| Novel factor derivation                                 | STF      | *Dis. function | No | No   | No   | No   | No   |

*1xn= single leader and N players, *nxn=N leaders and N players *Rf= Robust factor, *Of= Opportunistic factor, *Dis. function = Dissatisfaction function

C. OBSERVATION KEY POINTS

The analysis of section V from the base case to the implementation of the proposed methodology is summarized in the following unique points:

1) Maximum possible RES is availed to penetrate into the power system due to the sympathetic impact of IGDT and efficiency of autonomous SDO operation. At PV buses 1, 3, 7, 8, 34, and 35, and WT buses 6 and 36, generation is increased from 0.8836 MWh
TABLE 7. Test system power generation and load profiles.

| HOUR | RES. | IND. | MIS. | PV | THER. | WT |
|------|------|------|------|----|-------|----|
| 1    | 0.4  | 0.2  | 0.35 | 0  | 1     | 0.96 |
| 2    | 0.25 | 0.2  | 0.3  | 0  | 1     | 0.64 |
| 3    | 0.2  | 0.2  | 0.3  | 0  | 1     | 0.27 |
| 4    | 0.25 | 0.2  | 0.35 | 0  | 1     | 0.97 |
| 5    | 0.4  | 0.2  | 0.4  | 0  | 1     | 0.47 |
| 6    | 0.5  | 0.4  | 0.5  | 0  | 1     | 0.31 |
| 7    | 0.65 | 0.6  | 0.6  | 0.4| 1     | 0.7  |
| 8    | 0.7  | 0.9  | 0.7  | 0.7| 1     | 0.31 |
| 9    | 0.65 | 0.9  | 0.8  | 0.88| 1   | 0.62 |
| 10   | 0.65 | 0.9  | 0.78 | 0.95| 1   | 0.81 |
| 11   | 0.6  | 0.9  | 0.76 | 0.988| 1 | 0.49 |
| 12   | 0.6  | 0.9  | 0.74 | 1  | 1     | 0.63 |
| 13   | 0.6  | 0.7  | 0.72 | 0.988| 1 | 0.67 |
| 14   | 0.6  | 0.9  | 0.7  | 0.95| 1   | 0.58 |
| 15   | 0.65 | 0.9  | 0.68 | 0.88| 1   | 0.79 |
| 16   | 0.7  | 0.66 | 0.7 | 1  | 1     | 0.41 |
| 17   | 0.4  | 0.64 | 0.4  | 0.18| 1   |
| 18   | 0.4  | 0.3  | 0.52 | 0  | 1     | 0.14 |
| 19   | 0.4  | 0.4  | 0.45 | 0  | 0.6   | 0.68 |
| 20   | 0.7  | 0.2  | 0.43 | 0  | 0.6   | 0.78 |
| 21   | 0.9  | 0.2  | 0.42 | 0  | 0.6   | 0.47 |
| 22   | 0.8  | 0.2  | 0.4  | 0  | 0.6   | 0.74 |
| 23   | 0.65 | 0.2  | 0.4  | 0  | 0.9   | 0.45 |
| 24   | 0.55 | 0.2  | 0.4  | 0  | 1     | 0.94 |

Table 7: Test system power generation and load profiles.

2) The performance of VP as a virtual power source is proved by showing the reduction in demand from 3.81, 4.913, 3.679, 1.576 MWh to 2.781, 4.628, 3.34, 0.6593 MWh at buses 1, 3, 7, and 33 respectively.

3) After demand reduction and local energy exchange between RPS and RPB, Power flow loss is reduced from 78 MWh to 25.22 MWh, no voltage violation is observed at any bus and overall power reserved is 2.44 MWh for 24 hours.

4) Efficient sorting of PFCA of all consumers into RPS and RPB saves execution time and makes the algorithm 3 times faster. Overall SE is achieved within 5 iterations taking 29s.

5) STF is a unique factor, as compared to the DR strategies presented in [24], [25], [26], [27], [28], and [29], which provides a smart control of consumer behaviors. The proposed SI-IGDT based model effectively integrated with the Stackelberg game is an additional advantage over [24], [25], [26], [27], [28], [29]. A brief comparison is given in TABLE 6.

It can be observed from TABLE 6 that the proposed research has the advantage of a novel application of SI-IGDT over the articles which have applied IGDT. Most of the

**RES= Residential Load **IND= Industrial Load **MIS= Miscellaneous Load **PV= PV rated power**THER= Thermal rated power **WT= Thermal rated power

Note: The test system is 37 bus system. The slack bus is given number 0. The remaining buses are numbered from 1 to 36.

V_{base}=10 \text{ MVA}, \quad I_{limi}= \pm 7%
articles that have presented the DR using the Stackelberg game lack RES penetration focus, reserve power, reduction of power loss and any novel STF can be used to design an autonomous control of consumer loads.

VI. CONCLUSION
In conclusion, our study shows that the SI-IGDT model can deal with the cases where harvesting more RES energy in the opportunistic region is possible. A higher share of the RES energy not only reduces the cost of the main grid but also empowers the RES penetration. Local exchanges of energy between the RPS and RPB reduce the burden on the main grid and the power system losses by 70 %. The concept of the VP being an active supporting tool for the main grid, especially during peak energy hours, is very useful. The performance of the SDO is satisfactory, which provides better coordination between the PFCA and MFOA to achieve the SE with the fast execution of both algorithms. The behavior of the VP, RPS, and RPB consumers is very important and is modeled as a single factor (STF). The variation of the STF can explain the behavior of the VP, RPS, and RPB and the ultimate impact on the energy cost of the main grid.

Furthermore, the SDR can be changed into a smart contract for local energy trade by the dynamic variation control of the \( \theta \) values with improved technical and economic rules. The STF can be used to design an autonomous control of consumer loads.

APPENDIX
See Figure 19 and Tables 7 and 8.

REFERENCES
[1] C. A. Phillips, A. Caldas, R. Cleetus, K. A. Dahl, J. Declé-Barreto, R. Licker, L. D. Merner, J. P. Ortiz-Partida, A. L. Phelan, E. Spanger-Siegfried, S. Talati, C. H. Trisos, and C. J. Carlson, “Compound climate risks in the COVID-19 pandemic,” Nature Climate Change, vol. 10, no. 7, pp. 586–588, 2020.
[2] M. Majidi, B. Mohammadi-Ivatloo, and A. Soroudi, “Application of information gap decision theory in practical energy problems: A comprehensive review,” Appl. Energy, vol. 249, pp. 157–165, Sep. 2019.
[3] G. Infanger, Stochastic Programming, 1st ed. New York, NY, USA: Springer, 2011.
[4] C. Chen and S. Duan, “Optimal integration of plug-in hybrid electric vehicles in microgrids,” IEEE Trans. Ind. Informat., vol. 10, no. 3, pp. 1917–1926, Aug. 2014.
[5] M. Zare, T. Niknam, R. Azizipanah-Abarghoee, and A. Ostadi, “New stochastic bi-objective optimal cost and chance of operation management approach for smart microgrid,” IEEE Trans. Ind. Informat., vol. 12, no. 6, pp. 2031–2040, Dec. 2016.
[6] T. Niknam, M. Zare, and J. Aghaei, “Scenario-based multiobjective Volt/VAR control in distribution networks including renewable energy sources,” IEEE Trans. Power Del., vol. 27, no. 4, pp. 2004–2019, Oct. 2012.
[7] Y. Ben-Haim, Info-Gap Decision Theory: Decisions Under Severe Uncertainty. Amsterdam, The Netherlands: Elsevier, 2006.
[8] A. Rabiee, A. Soroudi, and A. Keane, “Information gap decision theory based OPF with HVDC connected wind farms,” IEEE Trans. Power Syst., vol. 30, no. 6, pp. 3396–3406, Nov. 2015.
[9] C. Murphy, A. Soroudi, and A. Keane, “Information gap decision theory-based congestion and voltage management in the presence of uncertain wind power,” IEEE Trans. Sustain. Energy, vol. 7, no. 2, pp. 841–849, Apr. 2016.
[10] M. Taherkhani and S. H. Hosseini, “IGDT-based multi-stage transmission expansion planning model incorporating optimal wind farm integration,” Int. Trans. Electr. Energy Syst., vol. 25, no. 10, pp. 2340–2358, 2015.
[11] X. Dai, Y. Wang, S. Yang, and K. Zhang, “IGDT-based economic dispatch considering the uncertainty of wind and demand response,” IET Renew. Power Gener., vol. 13, no. 6, pp. 856–866, 2018.
[12] M. Kermani, E. Shirdare, A. Najafi, B. Adelmanesh, D. L. Carin, and L. Martirano, “Optimal self-scheduling of a real energy hub considering local DG units and demand response under uncertainties,” IEEE Trans. Ind. Appl., vol. 57, no. 4, pp. 3396–3405, Jul./Aug. 2021.
[13] M. Eslahi, B. Vahidi, and P. Siano, “A flexible risk-averse strategy considering uncertainties of demand and multiple wind farms in electrical grids,” IEEE Trans. Ind. Informat., vol. 18, no. 4, pp. 2255–2263, Apr. 2021.
[14] M. Shafiekhani, A. Ahmadi, O. Homaeae, M. Shafie-Khah, and J. P. S. Catalão, “Optimal bidding strategy of a renewable-based virtual power plant including wind and solar units and dispatchable loads,” Energy, vol. 239, Jan. 2022, Art. no. 123279.
[15] M. Daneshvar, H. Eskandari, A. B. Sirous, and R. Esmaeilzadeh, “A novel techno-economic risk-overconfidence strategy for optimal scheduling of renewable-based industrial microgrid,” Sustain. Cities Soc., vol. 70, Jul. 2021, Art. no. 102879.
[16] M. Vahid-Ghavidel, M. S. Javadi, S. F. Santos, M. Gough, M. Shafie-Khah, and J. P. S. Catalão, “Demand response based trading framework in the presence of fuel cells using information-gap decision theory,” in Proc. Int. Conf. Smart Energy Syst. Technol. (SEST), 2020, pp. 1–6.
[17] Y. Wang, I. R. Pordonjani, and W. Xu, “An event-driven demand response scheme for power system security enhancement,” IEEE Trans. Smart Grid, vol. 2, no. 1, pp. 23–29, Mar. 2011.
[18] M. S. U. Zaman, R. Haider, S. B. A. Bukhari, H. M. Ashraf, and C.-H. Kim, “Impacts of responsive loads and energy storage system on frequency response of a multi-machine power system,” Machines, vol. 7, no. 2, p. 34, 2019.
[19] M. S. Zaman, S. B. A. Bukhari, R. Haider, K. M. Harazi, C. H. Kim, and H. M. Ashraf, “Demand response augmented control with load restore capabilities for frequency regulation of an RES-integrated power system,” in Proc. Int. Conf. Electr. Eng. (ICEE), 2018, pp. 1–5.
[20] Z. M. Haider, K. K. Mehmood, S. U. Khan, M. O. Khan, A. Wadood, and S.-B. Rhee, “Optimal management of a distribution feeder during contingency and overload conditions by harnessing the flexibility of smart loads,” IEEE Access, vol. 9, pp. 40124–40139, 2021.
[21] T. Cheng, Z. Tan, and H. Zhong, “Exploiting flexibility of integrated demand response to alleviate power flow violation during line tripping contingency,” J. Mod. Power Syst. Clean Energy, early access, Feb. 22, 2022, doi: 10.35833/MPCE.2021.000535.
[22] O. Ma, N. Alkadi, P. Cappers, P. Denholm, J. Dudley, S. Goli, M. Hummon, S. Kiliccote, J. MacDonald, N. Matson, D. Olsen, C. Rose, M. D. Sohn, M. Starke, B. Kirby, and M. O’Malley, “Demand response for ancillary services,” IEEE Trans. Smart Grid, vol. 4, no. 4, pp. 1988–1995, Dec. 2013.
[23] Y. Li, M. Han, Z. Yang, and G. Li, “Coordinating flexible demand response and renewable uncertainties for scheduling of community integrated energy systems with an electric vehicle charging station: A bi-level approach,” IEEE Trans. Sustain. Energy, vol. 12, no. 4, pp. 2321–2331, Oct. 2021.
[24] M. M. Yu and S. H. Hong, “A real-time demand-response algorithm for smart grids: A Stackelberg game approach,” IEEE Trans. Smart Grid, vol. 7, no. 2, pp. 879–888, Mar. 2016.
[25] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, “Dependable demand response management in the smart grid: A Stackelberg game approach,” IEEE Trans. Smart Grid, vol. 4, no. 1, pp. 120–132, Mar. 2013.
[26] M. Yu, X. Zhang, J. Jiang, C. Lee, S. H. Hong, K. Wang, and A. Xu, “Assessing the feasibility of game-theory-based demand response management by practical implementation,” IEEE Access, vol. 9, pp. 8220–8232, 2021.
[27] E. Hooshmand and A. Rabiee, “Robust model for optimal allocation of renewable energy sources, energy storage systems and demand response in distribution systems via information gap decision theory,” IET Gener. Transm. Distrib., vol. 13, no. 4, pp. 511–520, 2018.
[28] A. Khazali, N. Rezaei, A. Ahmadi, and B. Hredzak, “Information gap decision theory based preventive/corrective voltage control for smart power systems with high wind penetration,” IEEE Trans. Ind. Informat., vol. 14, no. 10, pp. 4385–4394, Oct. 2018.

[29] Y. Li, J. Wang, Y. Han, Q. Zhao, X. Fang, and Z. Cao, “Robust and opportunistic scheduling of district integrated natural gas and power system with high wind power penetration considering demand flexibility and compressed air energy storage,” J. Clean. Prod., vol. 256, May 2020, Art. no. 120456.

[30] C. W. Gellings, The Smart Grid: Enabling Energy Efficiency and Demand Response. Boca Raton, FL, USA: CRC Press, 2020.

[31] R. Lu and S. H. Hong, “Incentive-based demand response for smart grid with reinforcement learning and deep neural network,” Appl. Energy, vol. 236, pp. 937–949, Feb. 2019.

[32] M. M. Eissa, “First time real time incentive demand response program in smart grid with ‘i-Energy’ management system with different resources,” Appl. Energy, vol. 212, pp. 607–621, Feb. 2018.

[33] S. Zheng, Y. Sun, B. Li, B. Qi, K. Shi, Y. Li, and X. Tu, “Incentive-based integrated demand response for multiple energy carriers considering behavioral coupling effect of consumers,” IEEE Trans. Smart Grid, vol. 11, no. 4, pp. 3231–3245, Jul. 2020.

[34] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, “Optimal real-time pricing algorithm based on utility maximization for smart grid,” in Proc. 1st IEEE Int. Conf. Smart Grid Commun., 2010, pp. 415–420.

[35] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, “Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model,” IEEE Trans. Ind. Electron., vol. 66, no. 8, pp. 6087–6097, Aug. 2018.

[36] M. M. Yu and S. H. Hong, “Incentive-based demand response considering hierarchical electricity market: A Stackelberg game approach,” Appl. Energy, vol. 203, pp. 267–279, Oct. 2017.

[37] Electric Rates Table | KEPCO. Accessed: Mar. 4, 2021. [Online]. Available: https://home.kepco.co.kr/kepco/EN/F/htmlView/ENFBHP00101.do?menuCd=EN060201

[38] X.-S. Yang, Nature-Inspired Optimization Algorithms. New York, NY, USA: Academic, 2020.

[39] Power System Visual Analysis in MATLAB (Heatmap)—File Exchange—MATLAB Central. Accessed: Mar. 4, 2021. [Online]. Available: https://au.mathworks.com/matlabcentral/fileexchange/64201-power-system-visual-analysis-in-MATLAB-heatmap?s_tid=srchtitle

[40] A. J. Wood, B. F. Wollenberg, and G. B. Sheblé, Power Generation, Operation, and Control. Hoboken, NJ, USA: Wiley, 2013.

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