Distributed Renewable Generation and Storage Systems Sizing in Deregulated Energy Markets

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***Abstract*-- As the needs for distributed renewable generation (DRG) increase driven by the accelerated growth of electric demand in order to deter greenhouse emissions and create a more economic and efficient power supply environment, this papers pays attention to the potential contribution of independent owners (IOs) of DRG operating within the microgrid (MG). In order to assess such role, an optimization scheme is introduced to allocate and size the stochastic DRG with a distributed energy storage system (DESS) based on a novel energy management system (EMS) that accounts for power distribution loss, dynamic pricing environment, demand response, stochastic generation, etc. The proposed EMS utilizes an iterative Newton-Raphson linear programming algorithm that gradually schedule the resources maximizing the objective function and coping with the complicated nonlinear nature of the problem and enabling of efficiently carrying long-term assessments. The EMS is used to evaluate candidate solutions that are generated by a genetic algorithm (GA) working on evolutionary basis to determine the optimal combination of DRG and DESS. A case study for IEEE 34-bus distribution MG in Okinawa, Japan is used for testing the algorithm and analyzing the potential of IO investments and their strategies.**

***Keywords*—Distributed generation, Distributed storage, Energy management system, Demand response, Optimization.**

I. NOMENCLATURE

C_p^t	Energy price at t ($/kWh)
D	Duty cycle, or the period of time that all schedulable appliances have to be committed once within (h).
D_{App}^m	Task commitment duration of an appliance type m (h).
H_m	Shifting time window of appliances type m.
N_B^i	Battery capacity at bus i (kWh).
N_{PV}^i, N_{WT}^i	Installed PV and WT capacities at i (kW).
N_{App}^m	Number of appliances of type m.
n	total number of nodes in the MG.
P_g^t	Power purchased from the grid at t (kW).
$\overline{P_g}$	Maximum power can be purchased from the grid (kW)
P_{re}^t	Renewable generation at t (kW).
P_{ch}^t, P_{dch}^t	Battery charge and discharge power at t (kW).
$\overline{P}_{ch}, \overline{P}_{dch}$	Maximum charge and discharge power per 1 kWh (kW).
P_L^t	Total electric load at t (kW).
P_{NCL}^t, P_{CL}^t	Non-controllable and controllable load at t (kW).
P_{loss}^t	Power loss in the MG at t (kW).
$P_{PV_1}^t, P_{WT_1}^t$	PV and WT generation from equivalent 1 kW scale at t (kW).
P_{App}^m	Average power consumed by online appliance m (kW).
$P_{in}^{t,i}$	Power injected to bus i at t (kW).
$Q_{in}^{t,i}$	Reactive power injected to bus i at t (kvar).
$Q_c^{t,i}$	Reactive power compensation at t (kvar).
$Q_L^{t,i}$	Reactive power of load at t (kvar).
Q_b^t	Energy stored at DESS at t (kWh).
$\underline{SOC}, \overline{SOC}$	Minimum and maximum allowed state of charge.
TH	Optimization time horizon in LP dispatch.
$V_{t,i}$	Voltage of bus i at t (kV).
Y_{ij}	ij branch admittance (mho).
Z_B	Linear degradation factor of the battery.
α_{ij}	Angle of the ij branch admittance.
$\theta_{t,i}$	Voltage angle of bus i at t.
μ_r	Battery roundtrip efficiency.
m, k	Indices of shiftable appliance types.
i, j	Indices of buses.

II. INTRODUCTION

Meeting the accelerated growth of electric demand is one of the biggest economic and environmental challenges facing developing nations. In this term, distributed generation (DG) has been introduced to supply power on the distribution level reducing the dependence on centralized power generation and improving the transmission and distribution efficiency. DG uses fossil fuel like diesel and gas gensets or renewable sources like Photovoltaics (PVs) and wind turbines (WTs). The problem

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of planning DG-integrated power system has attracted significant attentions where a large literature exist [1]–[15]. For example, [13] proposed a model for allocating and sizing DG aiming at minimizing the total investment, operating, and substation and feeder upgrading costs. Ref [3] proposed allocating DG in deregulated energy markets based on the locational marginal price of the network nodes. Ref [5] introduced a novel model for maximizing the utility profits while guarantying the payback of DG owner within a certain period to boost the private sector participation in deregulated electricity market that is more efficient and competitive than regulated market. Although the majority of the aforementioned scopes considered the power supply security constraints, some scope's main objective was to maximize power reliability and supply adequacy as in [11] that was proposed to integrate a mix of DG, reactive resources and DESS into modern power system within MG operation framework. Some scopes discussed the problem in the presence of uncertain consumption due to stochastic control of electric vehicles (EVs) and uncertain DRG due to weather conditions [15]. However, as the smart grid concept rapidly evolves and finds increased acceptance reshaping the conventional power system, profound thoughts should be paid to account for the featured electric consumption flexibility offered by demand response (DR) programs. Regarding the optimization methods, they vary based on the objective and nature of the problem. For fossil fuel based DG a nonlinear programming optimization can be used and it is usually carried for a short time horizon [10], whereas in case of DRG and due to its daily and seasonally variable generation, much longer time horizon has to be considered. Since nonlinear programming method is not computationally efficient in this term, generally, a heuristic optimization method coupled with rule-based strategies for managing the system operation is used. For example in [14], DESS sizing optimization was introduced to mitigate the bid risk of wind generator owners. A good review about this problem is found in [16].

As Japan prepares to deregulate its electricity market and plans to significantly boost renewable generation share, profound studies are required to estimate the potential contribution from small to mid-scale IOs to the green electricity market in order to come up with encouraging pricing strategies. Realizing that IOs seek always to maximize their own profit, this study aims at sizing DRG and DESS from the owner's economic point of view fulfilling the following targets:

1) An Integrated and compressive model that accounts for power distribution loss, dynamic pricing environment, demand response (DR), stochastic generation, performance degradation of DESS, etc.

2) An Intelligent energy management system that coincides with SG operation framework.

3) A Computationally efficient optimization method that can be used practically for long-term planning.

Realizing that energy management in MG can be quite complicated and challenging, several scopes proposed potential methods [17]–[20]. Ref [19] proposed a self-adaptive dynamic programming algorithm for scheduling MG, which proved to be more efficient compared to trust-region and evolutionary algorithms. In [20], a convex optimization algorithm is used for managing a simple MG using two steps: off-line and sliding window online scheduling for real-time control applications. A more realistic typical-structure MG was considered in [17], where a double-layer management scheme was proposed. In [18], a hyper-heuristic method was proposed for optimizing the discharge schedule of an energy storage system. However, none of the introduced methods is proper for long-term assessments. In the light of this, the current work proposes a novel and efficient EMS to tackle the aforementioned challenges simulating optimal control of DG and DESS in real daily operation scenario for long-term basis (one year or more). The proposed EMS utilizes an iterative Newton-Raphson linear programming (NRLP) algorithm that gradually schedule the resources maximizing the objective function while coping with the complicated nonlinear nature of the problem and enabling of efficiently carrying long-term assessments. The proposed iterative procedure eliminates the need for a non-linear programming based method that is highly inefficient in our case. The EMS is used to evaluate candidate solutions that are generated by GA working on evolutionary basis to locate an optimal combination of DRG and DESS. A case study for IEEE 34-bus distribution MG in Okinawa, Japan is used for testing the algorithm and analyzing the potential investments of IOs and their strategies.

III. System structure

In deregulated energy markets, the price of energy unit depends on supply and demand like any other product markets. The wholesale spot market is widely used to trade electricity where a wide variety of competitive generators and retailers bid for selling and buying a certain amount of power at certain prices. Then, the retailers re-price the electricity and sell it to consumers. In this scope, it is assumed that each MG acts as one entity establishing a contract with retailers to buy electricity through the substation at quadratic increasing rates. Such function is widely considered because it reflects the increased cost of power generation under high demand met by fast responsive but less efficient peaking power plant. This pricing model is used also to stimulate DR for shifting controllable load from on-peaks to off-peaks duration. It is assumed also that the MG buys electricity from independent DRG and DESS owners operating within the microgid distribution system at the same real-time rates offered by retailers (or the main grid). The participation of the IOs will reduce the power demanded at the substation and accordingly the energy cost. Usually, in such liberated market, a decentralized EMS is used, i.e. the dynamic pricing is used to stimulate the responses of consumers and IOs rather than being controlled directly by a centralized EMS. Therefore, several levels of coordinated control and scheduling are required. In this scope, and for simplicity, an aggregated EMS is considered to manage and dispatch all available resources (DG, DESS) in aim for maximizing the profit of IOs, and in the same time, it captures the consumer tendency to reduce the energy consumption bill through DR control.

IV. ENERGY MANAGEMENT SYSTEM

In order to avoid using Non-linear programming solvers that are computationally inefficient for long-term evaluation and can result in an intolerable optimization time, an alternative novel EMS that utilize an iterative NRLP dispatch procedure was introduced. The algorithm starts by initiating a dispatch control vector by setting DESS charge/discharge to zero during all durations and randomly distributing the controllable load or scaling it proportionally to the expected non-controllable load. Then, a Newton-Raphson load flow (NRLF) procedure is carried to evaluate associated loss in the MG and the power purchased from the main grid (through the substation). Based on this, the dynamic prices is calculated, and an LP optimization procedure is carried for a several day length to adjust the control vector to a more profitable position. The objective function is then evaluated, where the algorithm terminates the loop if the objective peak is reached. Otherwise, the algorithm goes back to NRLF and so on.

A. Newton-Raphson load flow model

The real and reactive power injected in each bus is written as

$$P_{in}^{t,i} = \sum_{j=1}^{n} V_{t,i} V_{t,j} Y_{ij} cos(\theta_{t,i} - \theta_{t,i} - \alpha_{ij}) \tag{1}$$

$$Q_{in}^{t,i} = \sum_{j=1}^{n} V_{t,i} V_{t,j} Y_{ij} sin(\theta_{t,i} - \theta_{t,i} - \alpha_{ij}) \tag{2}$$

Assuming a flat start, all bus voltage magnitudes are set to 1 p.u and the bus voltage angles are set to 0°. Then, By using Taylor's series expansion, the voltage vector is iteratively updated using the correction vector till the calculated injected real and reactive power convert to the specified corresponding values given as

$$P_s^{t,i} = P_{re}^{t,i} + P_{dch}^{t,i} - P_{ch}^{t,i} - p_L^{t,i} \tag{3}$$

$$Q_s^{t,i} = Q_c^{t,i} - Q_L^{t,i} \tag{4}$$

After the problem is converged, the loss in the MG, power purchased from the main grid, and the energy unit price at each hour t are calculated.

B. LP dispatch model

An LP optimization procedure that manages power dispatch in an aggregated manner (rather than considering the distribution form as in NRLF) starts from the initial solution and adjust the dispatched power (δP_g^t, δP_{re}^t, δP_{dch}^t, δP_{ch}^t, δP_L^t) within limited steps aiming at improving the objective function. The reason for limiting the dispatched power every iteration is that the power prices are dependent on demand and power loss that are calculated from NRLF, and in order to linearize the problem, we consider the prices are negligibly affected with the limited changes that are made to the dispatch strategy at one iteration. LP dispatch is formulated below, where in the following formulation, the considered time step is 1 h, and for ease in presentation, it will be dropped from all formulas. Additionally, all the terms indexed by time and bus number indices (t, i) represent the distributed quantities, while the similar terms indexed by time step (t) only represent the aggregated quantity of the MG.

The total energy balance between generation and consumption at every hour $t \epsilon TH$ is ensured using the following relationship:

$$\begin{aligned} P_g^t + \delta P_g^t + P_{re}^t + \delta P_{re}^t + P_{dch}^t + \delta P_{dch}^t \\ = P_L^t + \delta P_L^t + P_{ch}^t + \delta P_{ch}^t + P_{loss}^t \end{aligned} \tag{5}$$

where the left-hand side represents the energy supply from the main grid, DRGs, and battery discharging, and the right-hand represents the energy consumption by the MG load, DESS charging, and power loss. The variables to be optimized are only the ones preceded by δ, while the other terms are constants calculated from previous iteration or defined by the initial solution.

The DESS energy change over one time step is given as

$$Q_b^{t+1} = Q_b^t + \mu_r(P_{ch}^t + \delta P_{ch}^t) - (P_{dch}^t + \delta P_{dch}^t) \tag{6}$$

The minimum and maximum energy can be stored are restricted by critical values as following

$$\underline{SOC} \cdot \sum_{1}^{n} N_B^i \le Q_b^t \le \overline{SOC} \cdot \sum_{1}^{n} N_B^i \tag{7}$$

The minimum and maximum amount of power can be charged/discharged are also limited as in the following:

$$0 \le P_{ch}^t + \delta P_{ch}^t \le \overline{P_{ch}} \sum_{1}^{n} N_B^i \tag{8}$$

$$0 \le P_{dch}^t + \delta P_{dch}^t \le \overline{P_{dch}} \sum_{1}^{n} N_B^i \tag{9}$$

Maximum grid power is limited by the substation capacity and the minimum grid power is set to zero (no reverse power flow or power selling to the grid is allowed) as following

$$0 \le P_g^t + \delta P_g^t \le \overline{P_g} \tag{10}$$

Dispatched renewable energy is limited by the maximum installed mix of PV and WT as following

$$P_{re}^t + \delta P_{re}^t \le \sum_{i=1}^{n} N_{PV}^i P_{PV_1}^t + N_{WT}^i P_{WT_1}^t \tag{11}$$

The power dispatch adjustment should be limited as following

$$-\overline{\delta P_{ch}} \le \delta P_{ch}^t \le \overline{\delta P_{ch}} \tag{12}$$

$$-\overline{\delta P_{dch}} \le \delta P_{dch}^t \le \overline{\delta P_{dch}} \tag{13}$$

$$-\overline{\delta P_L} \le \delta P_L^t \le \overline{\delta P_L} \tag{14}$$

Residential MGs have several types of high consumption controllable appliances like dishwasher, washing and drying machines, Domestic water heater, and more importantly EV. These appliance can be committed within flexible schedule allowing owners to allocate them to off-peak periods and reduce consumption bill. When planning a high share of renewable generation, and due to their stochastic nature, it is improper to schedule controllable load to a fixed time, and therefore, we integrate the controllable load to the dispatch problem as follow:

For each appliance type $k \in A$, the total electric load during its shifting time window H_k should be larger than the minimum electric consumption, due to the mandatory occurrence of some tasks in addition to the non-controllable load within H_k. This relation is applied every D hr along TH:

$$\sum_{t\in H_k} P_L^t + \delta P_L^t \geq \sum_{m\in A} N_{App}^m\, P_{App}^m\, D_{App}^m\, F_{k,m} + \sum_{t\in H_k} P_{NCL}^t \quad (15)$$

In the above, $F_{k,m}$ represents the ratio of the minimum operation time of appliance type m during H_k to the task duration D_{App}^m, and it can be calculated as:

$$F_{k,m} = 1 - min\left\{\frac{K_{k,m}}{D_{App}^m}, 1\right\} \quad (16)$$

Other constraints are used to limit the minimum consumption at each $t \in TH$ to the non-controllable load required at each step, and to ensure the total daily consumption and task commitment duration. Realizing that IOs seek to maximize their profits when dispatching DESS and DRG, while consumers seek to minimize their power consumption bill when participating in DR programs, we accordingly formulated the objective function of LP procedure as following

$$Max: \sum_{t=1}^{TH} C_p^t(\delta P_{re}^t + \delta P_{dch}^t - \delta P_{ch}^t - \delta P_L^t) - Z_B \delta P_{dch}^t \quad (17)$$

Where the battery value loss for a lead-acid type is assumed linear against cycling [21]. In case of using a more expensive technology like lithium-ion battery, a more accurate battery wear model is needed. A mixed integer LP practical model that was introduced in the authors' previous work [22] is suitable in this case. After LP optimization is carried, the reference power dispatch quantities are updated as following:

$$P_{re}^t = P_{re}^t + \delta P_{re}^t \quad (18)$$

The aggregated values of the power dispatch are then decomposed to the distribution level using the following relation

$$P_{re}^{t,i} = P_{re}^t \frac{N_{PV}^i P_{PV_1}^t + N_{WT}^i P_{WT_1}^t}{\sum_{i=1}^n N_{PV}^i\, P_{PV_1}^t + N_{WT}^i P_{WT_1}^t} \quad (19)$$

Where all the other variables are updated and decomposed in the same manner.

V. Case Study

IEEE 34 node distribution feeder was chosen for the numerical analysis in this study. A time varying electric load in Okinawa, Japan with 31 MWh daily energy consumption and 1750 kWh peak power is assumed. The dynamic energy price was assumed to vary from 0.1 to 0.3$/kWh as a function of the demanded power that is compatible with the current time of use price applied by Tokyo Electric Power Company [23]. For practical considerations, only five locations are taken as candidate spots to install WT and DESS, while PV system is assumed to be installed by residential houses through the MG due to the large area required for installation.

Considering 250 kW WT and 800 kWh DESS integrated to the MG, Fig. 1 shows how the recursive EMS evolve through iterations for maximizing the profit for one day without any DR program. As it was indicated in *Sec IV.B*, the dispatch adjustments made every iteration should be limited to preserve the model accuracy. Accordingly several thresholds for DESS charge/discharge ($\overline{\delta P_{ch}}/\overline{\delta P_{dch}}$), namely 0.5%, 1%, and 2% of the installed DESS capacity, were analyzed. When the step size (threshold) increases the profit peak can be obtained earlier (with a less number of iterations), but this can compromises the solution accuracy. However, all the shown steps led approximately to the same profit peak indicating a good accuracy for all cases. The algorithm should be halted when the peak is reached, whereafter the profit starts to degrade as shown in the case of 2% step size after iteration 12. For a higher conversion rate, big steps can be used in the first iterations and smaller steps later. EMS was carried again for the same day, but this time a 5% controllable load of the daily demand was assumed to be scheduled. It was observed that the net profit of the IOs was reduced from 141$ to 103$ (27% reduction) in this case indicating how significantly DR preprogram can impact the investor profitably, therefor, such consideration should be always highlighted during the system planning.

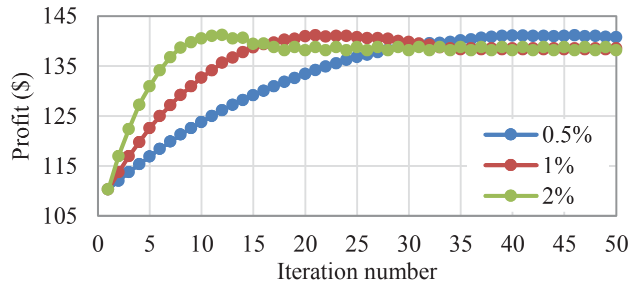

Fig. 1. Profit increase through the iterative NRLP dispatch procedure without a DR program.

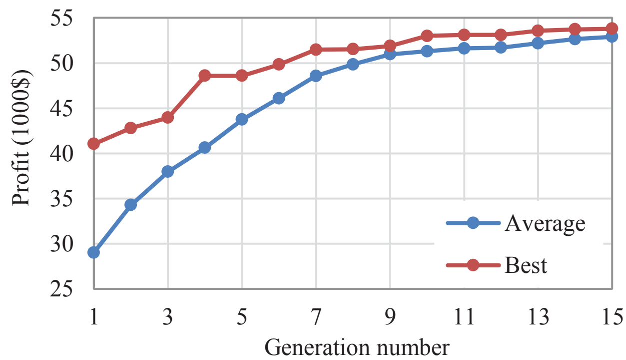

Fig. 2. Profit maximization through GA optimization.

TABLE 1
Optimization results of DRG and DESS sizing

Bus number	820	834	844	848	890
DESS size	60	40	0	100	60
WT size	100	150	225	125	225

The proposed EMS and a GA optimization were used for sizing WT and DESS in the predefined spots. TABLE 1 reports the optimization results. The total DESS and WT sizes were 260 kWh and 825 kW, respectively. A high wind generation system that can return a yearly net profit of $54k was observed, while DESS size was quite small for the assumed MG scale, where its function was mainly to support wind generation by absorbing surplus generation rather than using it for peak shaving application that would compromise the profitability of power selling. Fig. 2 shows how GA evolves through generation, where 60 population was able to converge in 15 generation consuming around 15 h processing time. The algorithm was implemented in Matlab utilizing the parallel processing structure that enabled using a full capacity of CPU and proved high computing efficiency by consuming around 1 min for achieving one year scheduling for a given DRG and DESS combination. CPLEX optimization engine was used for carrying LP dispatch for five days time window at once every time enabling a better long-term planning.

VI. Conclusion

Realizing the increased role of small to mid-scale private investments in DG in deregulated energy markets, this paper introduced an optimization scheme to allocate and size DRG and DESS based on novel EMS that accounts for power distribution loss, dynamic pricing environment, demand response, etc. The proposed EMS utilizes an iterative Newton-Raphson linear programming algorithm that schedule the available resources for maximizing the objective function while dealing with the complicated nonlinear nature of the problem. The EMS is used to evaluate candidate solutions that are generated by GA working on evolutionary basis to locate an optimal combination of DG and DESS. A case study for IEEE 34-node distribution feeder in Okinawa, Japan is used for testing the algorithm and analyzing the potential of IO investments and their strategies. Under the considered dynamic pricing model, it was observed that DR programs can significantly affect the profit achieved by DESS. The optimized system had high WT and low DESS capacities, highlighting a significant profitable role of IO made mainly from WT generation while the DESS was used to support WT stochastic generation rather than profiting from demand peak shaving. Further investigation and optimization scenario will be discussed in future works.

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