Bashir, Arslan Ahmad; Lehtonen, Matti

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Day-Ahead Rolling Window Optimization of Islanded Microgrid with Uncertainty

Arslan Ahmad Bashir and Matti Lehtonen
Department of Electrical Engineering & Automation
Aalto University
Espoo, Finland
arslan.bashir@aalto.fi, matti.lehtonen@aalto.fi

***Abstract*—The integral variability of electricity demand and intermittency of renewable energy resources (RERs) pose special challenges in the operation of islanded Microgrid (MG). The uncertainty associated with load and generation data further magnifies the problem resulting in huge energy curtailments in real time thus making MG operation expensive. Hence, this paper proposes a stochastic 24-hour ahead rolling window optimal energy scheduling framework to minimize the amount of lost load and lost generation in islanded MG while considering the demand response (DR) potential of heating, ventilation & air-conditioning (HVAC) loads, end user thermal preferences and storage systems. These thermal characteristics are modeled via two-capacity building model. The proposed methodology is formulated as a stochastic linear programming problem. The effectiveness of the framework is validated by simulation for the entire winter season using realistic data. Ultimately, the results are used to calculate and control loss of load probability (LOLP) and loss of load expectation (LOLE) in islanded MG at minimum cost.**

***Index Terms*— Islanded MG, stochastic optimization, two-capacity building model, LOLP, LOLE**

I. INTRODUCTION

With the onset of clean renewable energy resources, the strategies of operating power system have evolved significantly over the past few years. Microgrid (MG) is seen as an efficient and economic alternative to power system expansion program [1] while it can be viewed as a small scale power system with distributed energy sources, storage facilities and flexible loads capable of operating both in grid connected and islanded mode. On the other hand, providing better reliability and lower cost are the objectives of MG.

Since MGs are able to exchange electricity at market level, optimal strategies should be adopted for generation and load scheduling. At present, a lot of attention is being paid to the power scheduling problem of a MG equipped with both dispatchable and volatile generation. For example, researchers in [2] proposed a multi MG strategy to reduce the operational cost and prepare flexible bids for the aggregator. Reference [3] focused on the optimal battery energy storage system (BESS) sizing concerning long term planning of islanded MGs. This work [3] studied the optimal coordination between BESS and diesel generators to serve critical and non-critical loads in remote MGs. However, the stochastic based day ahead energy scheduling problem in MGs connected to medium voltage network was studied in [4], but this contribution neither exploited the inherent DR potential of the flexible loads nor addressed the investment cost of the medium voltage interconnection. Contrarily, smart management of heating, ventilation & air-conditioning (HVAC) loads under uncertainty was studied in [5] to minimize the MG operational cost and maximize the profit of MG in a market environment where we have variable pricing. A short-coming is that the value and congestion of interconnection were not considered in the optimization problem. In [6], the economic evaluation for the proposed islanded MG model was performed. The work demonstrated that stochasticity needs to be considered in reliability analysis of MG. Moreover, a robust optimization mechanism for MG energy scheduling in an uncertain environment was put forward in [7]. Due to the complexity, the proposed framework is difficult to be embedded in home energy management system (HEMS) or MG aggregator level. The work [8] studied demand supply balance in a small power system with significant wind generation and demonstrated case studies with a 24 hour long horizon, but the hourly imbalances, although small, were not regarded in the long run nor uncertainties were taken into account.

Despite so much work on energy scheduling of MGs, there is still a great need to quantify the amount of lost load and lost generation over a long period under uncertainty to draw a clear picture of islanded MG operating without dispatch-able generation. Lost load and lost generation in real time are a direct measure of the operational cost of islanded network. In the Nordic region and especially Finland, due to long winter season, the space heating load forms a major share in the annual system load profile. The slow thermal dynamics of insulated buildings make thermostatically controlled HVAC loads a major candidate of DR. These loads, in turn alleviate the renewable energy integration problem. The building thermal masses act as storage buffer and can absorb or release heat according to the generation profile of renewable sources, thanks to the building thermal inertia. To implement it, the characteristics of two-capacity building model are obtained from [8] and [9], which describes the connection of indoor air with building mass temperature and outside air. The end user thermal comfort is evaluated by indoor temperature deviation. Users can usually endure some deviation from set point temperature depending entirely on individual preferences. The indoor temperature is allowed to vary within a predefined narrow dead band. In this way, HVAC loads can be scheduled to match the intermittent generation so that thermal comfort of each end user is unscathed.

This paper proposes an optimization framework for scheduling the HVAC loads & BESS amid an uncertain environment in an islanded MG to attain minimum demand supply imbalances. DR is unleashed by exploiting building thermal masses. To model the uncertainty of load and generation, probable scenarios of input variables are generated and the optimization model is solved over all scenarios for 24 hours ahead at a time. Decision variables pertaining to only first hour are implemented and the process is repeated again for each hour of the simulation period using rolling window approach. One novelty of this 24 hour ahead optimization framework is the determination of Loss of Load Probability (LOLP) and loss of load expectation (LOLE) using the optimal load curtailments obtained in various scenarios. Both these parameters reflect the probable cost of power system operation in the long run. LOLP is defined as "the probability that demand will exceed the capacity of the system in a given period". LOLE tells the total number of hours or days in a given period in which it is statistically expected that demand would exceed generation. In this work, the period from September to May is classified as winter season in which heating load is employed by households or district heating plants operate continuously whereas the remaining 3 months period is summer season when no heating load is present. In summer, building thermal masses alone are able to tackle the ambient temperature. Contrarily, in Finnish Winters, temperature profile is well below the set point temperature of HVAC. Hence, the proposed model is simulated for the entire winter season.

The rest of the paper is organized as follows. Section II discusses the models of various components of islanded MG used in this work. The methodology and optimization framework is depicted in section III. Case study and simulation results are presented in section IV. Section V concludes the paper.

II. System Model

A. Two-capacity Building Model

To analyze the indoor air & building mass temperature changes with respect to outdoor temperature variation, two-capacity building model is utilized [8], [9]. As the name suggests, there are two thermal capacitances, C_m allocated to building mass node and C_a for indoor air. There are two unknown temperatures T_a and T_m. The energy balance for the arbitrary indoor node point is given by (1) and (2)

$$C_a \frac{dT_a}{dt} = H_e(T_e - T_a) + H_m(T_m - T_a) + H_g(T_g - T_a) + H_x(T_x - T_a) + Q \tag{1}$$

$$C_m \frac{dT_m}{dt} = H_m(T_a - T_m) + H_y(T_e - T_m) \tag{2}$$

In (1) and (2), H_e is the thermal conductance between indoor T_a and outdoor T_e temperature node points. H_g is the thermal conductance between indoor ambient temperature T_a and ground temperature node point T_g. H_m and H_y model the heat conduction through the solid walls of the building. Due to limited space, interested readers may find more detail about this model in [9].

B. PV Model

A practical model for PV proposed in [10] is employed in this work which uses irradiance and temperature as input. In equations (3) - (5), all the parameters can easily be taken from manufacturer's datasheet.

$$P_{pv} = \frac{PV_{max} G}{G_{ref}} \cdot \frac{ln\ (P_1.G)}{ln\ (P_1 G_{ref})} \cdot \frac{T_{jref}}{T_j} \tag{3}$$

$$P_1 = \frac{I_{sc}}{G} \tag{4}$$

$$T_j = T_{ext} + \frac{NOCT - 20}{80} .S \tag{5}$$

where T_j is photovoltaic cell temperature; T_{jref} is reference cell temperature; T_{ext} is outdoor temperature; S is insolation (mW/cm^2); I_{sc} is short circuit current; V_{oc} is open circuit voltage; PV_{max} is the max. yield under STP conditions; G is irradiance (W/m^2); and G_{ref} is the standard irradiance i.e. 1000W/m^2.

C. Wind Turbine Model

A simple model which explains the characteristics by two straight lines is used as given in (6)-(8), [8].

$$P_w = \begin{cases} \beta \cdot w_w + K, & w_c < w_w \ \& \ w_r > w_w \\ P_r, & w_w \geq w_r \\ 0, & w_w \leq w_c \end{cases} \tag{6}$$

$$\beta = \frac{P_r}{w_r - w_c} \tag{7}$$

$$K = -\beta . w_c \tag{8}$$

Where P_r is the rated power, w_w is the wind speed, w_c is the cut-in speed, w_r is the wind speed at rated power, β is the slope and K is constant.

III. Optimization Framework

Consider a small scale islanded MG equipped with its own PV and wind power production. The consumption portfolio consists of consumers residing in detached houses in Helsinki region with a high degree of HVAC load and some proportion of critical load. Each consumer is also equipped with BESS which may act as a power source or power sink depending on the load condition. MG aggregator is connected to end user via bi-directional communication channel and thus schedules the HVAC loads hour ahead while respecting their thermal comfort levels. In addition, he is able to send charging or discharging signals of BESS to each customer. HEMS provides the platform to implement this information at the consumer level. The dispatchable generation is not considered in the first step of simulation. After utilizing all the MG resources for the optimization horizon, the need for fuel based generator is then assessed based on lost load (Watt hours).

As this MG is relying purely on renewable generation, the uncertainty in the input parameters e.g. external temperature, irradiance and wind speed is of vital significance. All these uncertainties negatively affect the MG operation. Hence, they must be reasonably addressed in the formulation to account for the worst mismatch between supply and demand. The uncertainty is captured by a set of probable scenarios. In this work, just to reduce the model complexity and computational time, uncertainty is assumed in two input parameters namely temperature and solar irradiance. Undoubtedly, the reduction in scenarios reduces the accuracy of the solution but there is always a trade-off between better solution and simulation time. A set of five scenarios each for external temperature and irradiance is considered which makes total 25 scenarios. So, we have uncertainties in both the supply and demand (HVAC load) side. It is assumed that wind speed can be estimated for next 24 hours without significant uncertainties.

The objective function of islanded MG is the minimization of amount of lost load and lost generation in the absence of dispatchable generation. This can be achieved by efficiently managing the system resources. HVAC based DR cost is assumed negligible compared to the value of lost load as long as comfort band is not violated. Further, due to slow thermal dynamics, time resolution in this study is one hour. Mathematically, the objective function is stated as follows:

$$\sum_{s}\rho_s\sum_{h}\left(\left|G_{h,s}-\sum_{n}k^n\left(P^n_{s,h}+X^n_{s,h}-PB^n_{s,h}\right)\right|+\sum_{n}\left(1-k^n\right)\left|Ta^n_{s,h}-Ts^n\right|\right) \quad (9)$$

The subscripts $s \in S$ and $h \in H$ and the superscript $n \in N$ in (9) are the indices belonging to sets of scenarios, time steps and households respectively; ρ_s is probability of a scenario; G is the total production from renewable energy resources (RERs); P is the HVAC demand response for heating load Q; k^n is the coefficient expressing the willingness of DR of each customer n; k^n belongs to interval [0,1] where k^n =1 represents extreme comfort relinquishing customer provided the thermal comfort band is not violated; contrarily, k^n =0 represents a case when customer is not willing for direct load management; X is the fixed or critical load; PB is the BESS charging or discharging power; T_a is the indoor air temperature; and T_s is the set point temperature of HVAC, which is constant in this work.

The objective function in (9) has two components. The first component minimizes the gap between supply and demand using the response of individual households. Net demand as seen from aggregator is the sum of HVAC load (DR), critical load and BESS charging or discharging of individual customer. The second component in (9) entails the maximization of customer's thermal comfort. Indoor temperature should be altered to the smallest possible extent. The function (9) is subject to constraints including (1)-(2) and the rest are declared as follows.

Each household has its own temperature dead band defined by (10)

$$Ts^n_{s,h}-\frac{\vartheta^n}{2}\le Ta^n_{s,h}\le Ts^n_h+\frac{\vartheta^n}{2} \quad ;\forall s\in S,\forall h\in H,\forall n\in N \qquad (10)$$

It is assumed that each house is equipped with a heat pump which can be operated in both heating and cooling mode depending on the season. The electrical input and the HVAC output of heat pump are related by coefficient of performance (CoP) as follows.

$$P^n_{\max}=\frac{Q^n_{\max}}{CoP} \quad ;\forall n\in N \qquad (11)$$

HVAC is able to operate at any power level limited by its maximum rating as follows

$$0\le P^n_{s,h}\le P^n_{\max} \quad ;\forall s\in S,\forall h\in H,\forall n\in N \qquad (12)$$

The charging and discharging of BESS is bounded by following constraints. Charging power is taken as negative and discharging as positive.

$$-PB^n_{\max}\le PB^n_{s,h}\le PB^n_{\max}\,;\forall s\in S,\forall h\in H,\forall n\in N \qquad (13)$$

In order to avoid binary decision variables for BESS charging and discharging, PB is expressed as the difference of two non-negative variables in (14).

$$PB^n_{s,h}=-\left(P^n_{ch,s,h}-P^n_{dh,s,h}\right);\forall s\in S,\forall h\in H,\forall n\in N \qquad (14)$$

For safety and longer life, BESS state of charge (SOC) can range between 10% and 90% of BESS capacity. At any hour h, SOC can be determined by the following constraint.

$$SOC^n_{s,h+1}=SOC^n_{s,h}+\left(\eta_c P^n_{ch,s,h+1}-\frac{P^n_{dh,s,h+1}}{\eta_d}\right).\Delta h-\varepsilon^n_{s,h+1}\,; \quad \forall s\in S,\forall h\in H,\forall n\in N \qquad (15)$$

There will be stand-by / storage losses of BESS which are expressed as linear function of SOC as under.

$$\varepsilon^n_{s,h+1}=\mu^n.SOC^n_{s,h};\forall s\in S,\forall h\in H,\forall n\in N \qquad (16)$$

where μ is loss coefficient. The hourly energy consumption of a household is capped as follows.

$$DR^n_{s,h}+X^n_{s,h}-PB^n_{s,h}\le\psi^n_{s,h} \quad ;\forall s\in S,\forall h\in H,\forall n\in N \qquad (17)$$

where Ψ may be considered as the rating of distribution line or switch board. In order to guarantee the unidirectional power flow in MG, following constraint is imposed.

$$DR^n_{s,h}+X^n_{s,h}-PB^n_{s,h}\ge 0 \quad ;\forall s\in S,\forall h\in H,\forall n\in N \qquad (18)$$

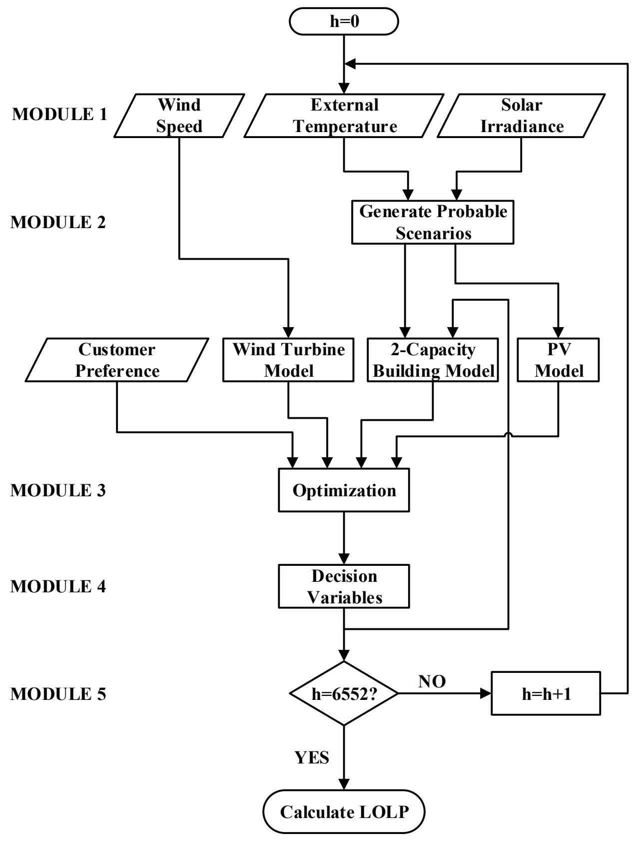

Figure 1. Optimization model flowchart

The above formulated problem is linear and falls under the category of convex optimization that can be solved by any commercial solver. The absolute function in (9) can be reformulated into linear function by introducing auxiliary variables. This approximation [11] increases the feasible region but the optimal solution remains unaffected. The proposed framework is iterative such that problem is solved for each hour separately using rolling window approach as shown in Fig. 1. Length of horizon or window is 24 hours.

The flow chart in Fig. 1 is described as follows:

- Module 1: Input parameters are forecasted using time series methods. Historical input data for Helsinki is utilized for this purpose. Wind speed at 40 m height is simulated using [12].
- Module 2: Five scenarios are generated each for the temperature and irradiance as shown in Fig. 2. The deviation among scenarios grows linearly through the forecast window and is fixed to 10% at hour 24. The probability of each scenario is assigned by discretizing the normal distribution [9]. The generated scenarios are fed into the models discussed in section I to obtain the input parameters for the optimization problem. Customer preferences are also loaded here.
- Module 3: The proposed framework is solved for all scenarios using CPLEX solver for next 24 hours.
- Module 4: The decision variables for next 24 hours are obtained but only the first hour decisions are communicated and implemented. This is how rolling horizon approach works. Generally, the forecast error increases exponentially through the horizon window. The longer the horizon, the higher the error at the end. Rolling window tries to minimize this error. A feedback loop is used to update the input parameters for next hour and estimated input parameters are replaced with the actual measured parameters in that hour. The whole process is repeated for each hour of the study period.
- Module 5: Modules 1 – 4 above detail the methodology of 24-h ahead rolling window optimization. Module 5 controls the simulation over the winter period. After the simulation has completed, LOLP & LOLE are computed.

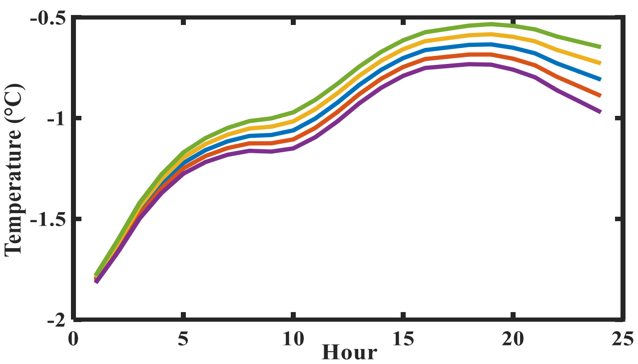

Figure 2. An illustration of temperature scenarios for 24h rolling window horizon

IV. Simulation Results

The proposed framework is implemented on an islanded MG comprising 25 households. Each household is a single family residing in a two – floor detached building with area 180m^2. Building parameters for heating load are adopted from [9] that correspond to medium massive house structures in Finland [13]. The critical load mainly consisting of illumination and domestic appliances, is obtained from actual hourly energy measurements of detached residential houses in Helsinki relying on district heating facility. To capture the diversity among households, it is assumed that P^n_{max} is uniformly distributed in the interval [3, 3.5] kW with CoP=2. We consider medium responsive consumers with k^n ranging between 0.75 and 1. The indoor air temperature of each household can mutate in the interval [20, 22] °C called the comfort zone, with mean temperature 21°C, which is also the HVAC set point. Building occupancy is rendered continuous. It is assumed that both initial indoor and building mass temperature are 21°C. The generation portfolio consists of 3 numbers 25kW wind turbines and various PV strings arranged to produce 75kW$_p$. It is re-iterated that no conventional generation is considered in this part of simulation. Each household is also equipped with BESS, the rating is assumed 45% of the average daily demand, with charging and discharging capability of 3.5kW, efficiency 100% and standby or storage losses 1%. Initial state of charge is 50% of total capacity.

The proposed frame-work in Fig.1 is implemented on a desktop computer with 3.4 GHz Intel Xeon processor and 16 GB RAM. The optimization is performed in GAMS using CPLEX solver while the proposed sliding window methodology is implemented in Matlab. Average simulation time per iteration including CPLEX time is about 15.6 seconds. The simulation results are detailed as follows.

First we estimate the amount of lost load and lost generation for the islanded MG under study without the coordinated operation. To do so, heating load is derived from two-capacity building model using actual outdoor temperature measurements for year 2011-12, illustrated in Fig. 3. The hourly indoor temperature of the building was sustained at 21°C. The photovoltaic (PV) and wind generation (PW) profile alongwith total load simulated for base case are depicted in Fig. 4.

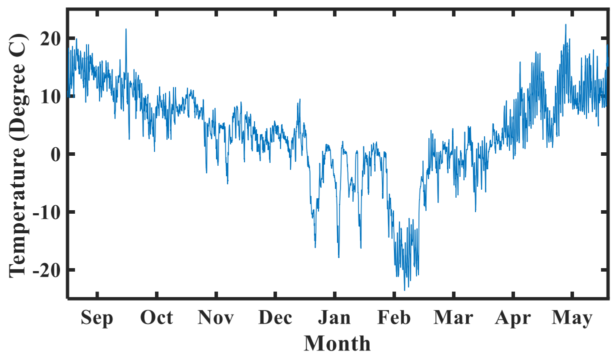

Figure 3. Hourly external temperature of Helsinki for year 2011-12

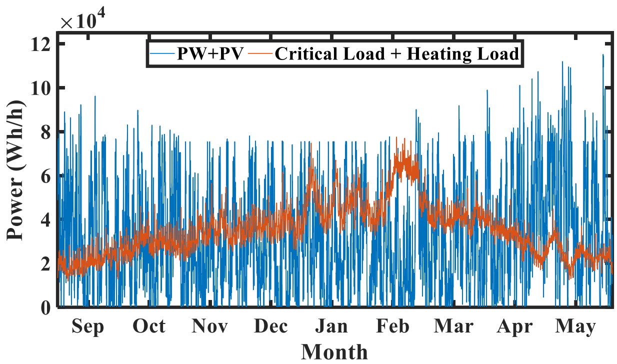

Figure 4. Hourly generation from RERs and total load (base case)

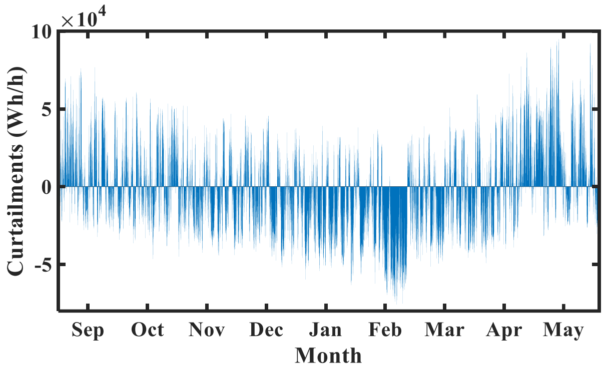

Figure 5. Involuntary load and RERs curtailments (Base Case)

It is noticeable that there is high volatility of RERs. Reason being the geography and variation in length of day (amount of sunlight) in Helsinki. In winter, PV production is almost zero for many weeks. The estimated total load (both heating and critical) for the simulation period is 229.39 MWh. The reported maximum load is 77.56 kWh in the month of February when the outside temperature dropped to -23°C. Figure 5 presents the involuntary energy curtailments obtained for the base case. Please note that negative values in Fig. 5 correspond to lost load while positive values imply curtailed PV and wind generation. The RERs were unable to cope with load especially when both HVAC and critical load are higher and PV production is negligible. The total amount of lost load and lost generation sums up to 85.767 and 67.201 MWh respectively, which makes a significant portion of power profile. The maximum lost load recorded as 75.86 kWh/h in the month of February. Needless to mention that suitable measures are required from aggregator side to mitigate this deviation. The value of this lost energy (€/kWh) portrays the actual cost of MG in islanded mode.

Next, we simulate the proposed stochastic model to probe its performance. Instead of a particular scenario, the optimal expected solution over all scenarios is shown in Fig. 6 while the optimal demand for the two months of January and February are presented in figures 7 and 8 respectively. Here, optimal demand is the net demand seen by the aggregator i.e. after satisfying a portion of demand through BESS discharging or increasing demand through charging. Unlike the base case, this demand tries to follow the RERs closely. In Fig. 7 & 8, the deviation between load and RERs is still significant due to high heating load requirement and less availability of PV generation. Moreover, the storage alone cannot support the load for longer time. The expected optimal lost load and lost generation are depicted in Fig. 9. The magnitude of hourly lost load has been controlled. Most of the load curtailments have very small magnitude now.

For stochastic model, the expected amount of lost load and lost generation sums up to 59.07 and 34.92 MWh respectively. Evidently, lost load and lost generation are decreased significantly implying a reduction in operational cost. Compared to the base case, the reduction is 31.1% and 48% respectively. And the total energy curtailments are reduced by 38.55% at the expense of 2.43% increase in total demand. This increase in total demand is mainly linked to the hourly storage losses. BESS needs continuous charging to maintain the SOC at minimum level. The maximum expected hourly load curtailment gives an insight vision for the rating of a fuel based generation that can be employed in islanded mode. The maximum expected lost load simulated as 71.6 kWh/h while the maximum RERs curtailment is 89.68 kWh/h when there exists high degree of PV output as well.

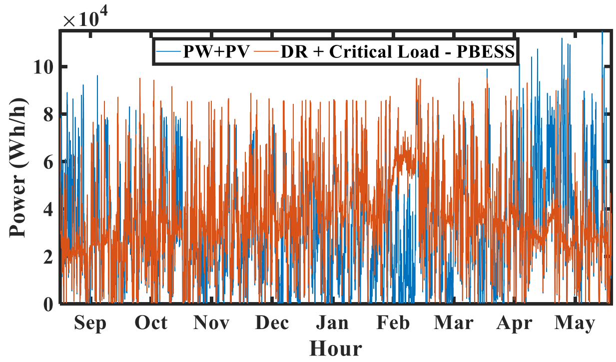

Figure 6. Expected hourly generation and optimal load

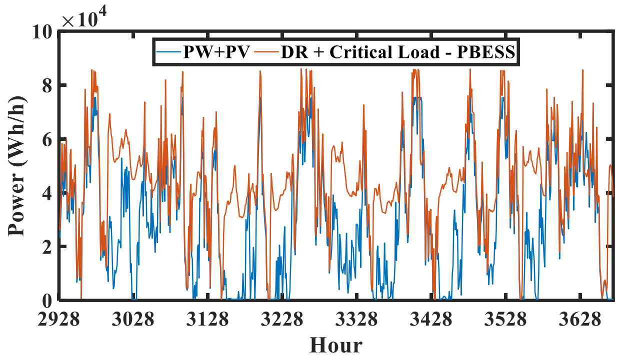

Figure 7. Expected hourly generation and optimal load in January

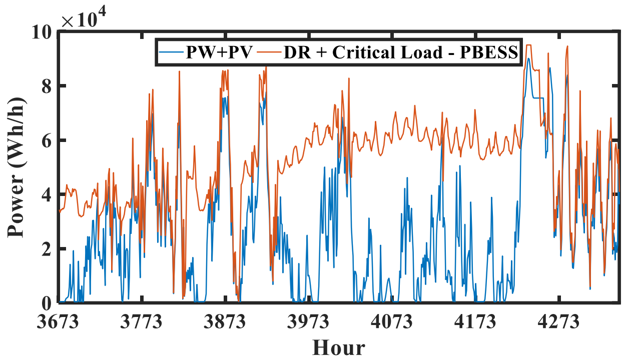

Figure 8. Expected hourly generation and optimal load in February

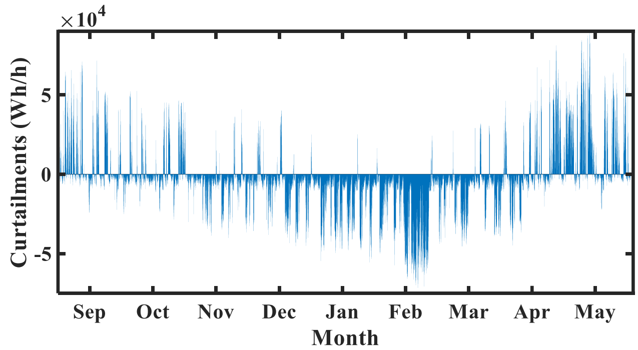

Figure 9. Expected Optimal energy curtailments

Please note that more reduction in lost load could be obtained by considering an integrated thermal storage with HVAC [8], [14]. Although thermal storage behaves similarly as BESS. Charging and discharging capability of BESS considered in this study is based on maximum hourly demand of a household. Another way is to increase the width of temperature dead band that would somehow decrease the thermal comfort. Again, it is incurred at some cost. The best solution being the increased participation in demand response program. If all households become 100% responsive then more reduction in lost load and lost generation could be obtained.

Finally LOLP and LOLE indices are computed using (19) and (20).

$$LOLP = \sum_s \left(\rho_s \cdot T_{LL,s}\right) \quad \forall s \in S \tag{19}$$

$$LOLE = \sum_s \left(\rho_s \cdot t_{LL,s}\right) \quad \forall s \in S \tag{20}$$

where $T_{LL,s}$ is percentage of total time when demand exceeds generation and $t_{LL,s}$ is total number of hours of generation shortage in each scenario. For our study, LOLP = 0.805 and LOLE= 5274.4 hours. Please note that breakdown event of RERs or BESS is not considered in this study. Forced outage rate (FOR) is assumed 0%. In practice, there is non-zero FOR (may be specified by the manufacturer) especially for rotating machines on account for preventive maintenance. Hence, LOLP computed here are the minimum estimation for the given MG parameters. These metrics define the probability of shortage events, not their severity.

Finally, we investigate the impact of fuel based generation on islanded MG after implementing the optimization framework and see how expected load curtailments are scaled down. Table I below lists the outcome. According to the obtained results, there are sheer improvements in LOLP and lost load when the amount of conventional generation is raised. With the introduction of a small diesel generator, LOLP improves greatly. Both LOLP and lost load decline to zero at generator rating 72kW which is the maximum simulated lost load. There will be no expected lost load if generator with this rating is employed in islanded mode provided that reliability of generator is 100%. Alternatively, diesel generator can be replaced by network interconnection. In this case, lost generation can be alleviated by exporting the excess generation to neighboring MGs or participating in electricity markets i.e. behaving as a prosumer. Practically, the value of lost load is higher than the value of lost generation as the former is linked to comfort levels, critical loads and irrational behavior of end users.

TABLE I. EFFECT OF FUEL BASED GENERATION ON MG

Generator Max. Rating (kW)	**LOLP**	**LOLE (hours)**	**Expected Lost Load (MWh)**	**Expected Fuel Based Generation (MWh)**
0	0.805	5274.4	59.07	0
5	0.430	2817.4	38.98	20.08
10	0.224	1467.6	28.94	30.14
20	0.163	1068	16.65	42.42
30	0.104	681.4	7.73	51.34
40	0.045	294.8	3.07	56
50	0.021	137.6	0.98	58.09
60	0.005	32.8	0.14	58.92
70	0.00034	2.2	0.00236	59.071
72	0	0	0	59.072

V. CONCLUSION

This work proposed and validated a probabilistic framework for MG aggregator to reshape the load that follows least energy curtailments in real time and estimate LOLP and LOLE indices of islanded MG. The proposed methodology unleashes DR of HVAC loads using building thermal dynamics while maintaining desired comfort levels. Simulation was carried out for the whole winter season and the results also prompt the load aggregator to estimate the dispatchable generation required for maintaining balance in islanded mode under uncertainty. Moreover, the effect of varying fuel based generation on optimal energy curtailments was also demonstrated. Hence, this simulation tool can also be used to control LOLP of islanded MG. Further, depending on LOLP, an aggregator can perform economic analysis whether to employ diesel generator or import the electricity from neighboring MGs or power system or electricity markets where users are exposed to variable prices. In such a case, the investment cost and congestion of tie lines should be taken into account.

In future, more possibilities of demand response loads shall be investigated in islanded MG so that aggregator may have more interaction with end users and neighboring MGs or power system that would result in operational flexibility as well as maximum utility of both end customers and aggregator. The amount of communication required for such flexibility shall also be investigated with regard to reliability.

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