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A Model to Estimate the Lifetime of BESS for the Prosumer Community of Manufacturers with OGS

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Abstract

Onsite generation system (OGS) with renewable sources for modern manufacturing plant is considered as a critical alternative energy source for the manufacturers. Prosumer community can be formed by aggregating such manufacturers to achieve a mutual goal of sustainable and resilient power system. As the sustainability of the network depends on the reliable operations of each component in the network, it is required to monitor the performance and lifetime of the components existed in the network. One of the critical as well as costly components used to enhance the reliability and performance of the network is the battery energy storage system (BESS). The paper proposes a lifetime estimation model for the BESS using an integrated approach of cellular automata and system dynamic (SD) to prevent any sudden power outage and build a reliable energy management framework for the community. The major factors such as energy demand of the manufacturing plant, intermittent generation from the OGS, energy sharing capability of the prosumers etc. are considered to simulate the model and determine the amount of battery degradation. Based on the estimated lifetime of the battery, the manufacturers further can control the energy management plan (charging/discharging scheme) to prolong the battery lifetime and ensure a reliable operation for the community. A numerical case study is simulated to illustrate the effectiveness of the model.

Keywords: prosumer community; battery lifetime estimation; onsite generation system; dynamic simulation; cellular automata

1. Introduction

To satisfy the growing demand of electric power through strengthening the resilience and mitigating the disturbances of electricity grid, the onsite generation system (OGS) has been considered a reliable solution [1], [2]. Instead of relying on a centralized scheme, the customer itself can build the OGS to reduce the amount purchased from grid and during period of excess generation, the customer can sell back the excess energy to the grid. This type of customers who not only consume energy but also generate the energy and share with the utility grid or with other energy consumers is known as prosumer [3], [4]. The most promising OGS built by the

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prosumer (especially manufacturer) consists of solar PV, wind turbine, and battery energy storage system (BESS) [5-7]. The BESS is used as the backup resources for the OGS to address the intermittency of the renewable sources [8], [9].

To smooth out the unpredictable fluctuation from the OGS, the BESS usually experiences irregular charge and discharge cycles. As the lifetime of the BESS mainly depends on the depth of discharge and number of charging/discharging cycles, it is required to control the charging/discharging scheme and monitor the battery health for reliable power management of the prosumer. Typically, prosumers determine the remaining life of the BESS based on the standard operating conditions (constant temperature, current, and depth of discharge) provided (quoted) by manufacturers and develop their optimal energy management plan [10-12]. However, the actual operating conditions are quite different from the standard ones. Therefore, in such a scenario where both demand and generation are stochastic, optimally designing the energy management plan using the standard condition can lead to gross errors and may result in a higher system cost due to the early failure. Therefore, to establish a cost-effective and reliable energy management infrastructure for the prosumer, accurate battery life estimation is imperative considering the actual energy dynamics of the system.

A significant number of researches can be reported to estimate and improve the lifetime of BESS for reliable operation in hybrid OGS [13-15]. For example, Drouilhet et al. proposed a battery life prediction method to investigate the effects of varying depths of discharge and rates of discharge in hybrid power applications [14]. Layadi et al. developed a battery aging model using rain flow method to estimate the lifetime of lead–acid batteries for hybrid power sources design [15]. The literatures on estimating the battery life are mostly focused on the residential and commercial sectors where the manufacturing industry is underexplored. As the energy demand is comparatively very high and stochastic in manufacturing industry and reliability is crucial, it is significantly important to monitor the performance and estimate the remaining lifetime of the BESS to schedule the repair and maintenance plan in advance to prevent any sudden failure. However, it is quite challenging to estimate the remaining lifetime for the manufacturers with OGS due to the stochastic nature in model parameters and their structural interdependency. The estimation is even more challenging if such prosumers create a community through sharing their energy. Due to the interdependency and interrelationship, the level of complexity grows substantially with the increase of the number of the neighbors and participants in the community. In such a network, the decision of charging/discharging not only relies on the individual’s demand, generation, and storing capacity but also depends on the energy sharing capability of the neighbors. Therefore, it is required to develop a model to estimate the remaining lifetime of BESS considering all the factors mentioned earlier for reliable power management of the community. To best of our knowledge, no such research exists where all the factors are considered concurrently to estimate the remaining lifetime of BESS for such a prosumer community of manufacturers.

The paper proposes a model to estimate the remaining lifetime of BESS using an integrated approach of cellular automata and system dynamic (SD). The cellular automata model investigates the complex dynamic of energy sharing capability (offer excess energy or demand the shortage of generation) of the neighboring manufacturers while participating as a member in the community. Considering the energy sharing capability of the neighbors along with the generation from OGS, demand of the manufacturer, and the price of grid electricity at any interval, the manufacturer can take the decision of charging/discharging of the battery and corresponding depth of discharge. The degradation due to the decision of charging/discharging is analyzed through a simulation model based on the principles of the system dynamics methodology. Based on the results, the prosumers can optimally plan for the maintenance/replacement schedule as well as control the charging/discharging scheme to prolong the battery lifetime and thus, ensure a reliable energy management infrastructure for the community.

The major contributions of the research can be summarized as follows:

1. The dynamics of the energy sharing capability of the neighbours in such a manufacturer-based prosumer community is investigated through the cellular automata model.
2. The effect of the charging/discharging on battery health under an actual operating condition is investigated through SD model while participating in such a community.

The rest of the paper is organized as follows. Section 2 demonstrates the integrative modeling approach. Section 3 implements the proposed model through a hypothetical case study to illustrate the effectiveness of the model. Section 4 analyzes the results and sensitivity analysis. Section 5 concludes the paper and discusses the future work.

2. Model Description

The model developed to estimate the remaining lifetime of the BESS is discussed into two subsections: (a) Identifying the energy sharing capability of the neighbors using cellular automata model, and (b) Estimating the remaining lifetime of BESS using SD Simulation. The subsections are described below:

2.1. Identifying the energy sharing capability of the neighbors using cellular automata model

To build a self-sufficient, cost-effective, and sustainable community, the prosumers develop a network through sharing their surplus electricity to the neighbors during the period of excess generation. The sharing capability of each prosumer depends on the energy demand of its manufacturing plant, generation from the OGS, charging state of the BESS etc. Besides, the prosumer can also share energy (purchase the shortage of electricity or sell back the excess generation) with the grid based on its energy state, electricity demand of the neighbors, price of electricity etc. Such a community with a representative manufacturer is shown in Fig. 1

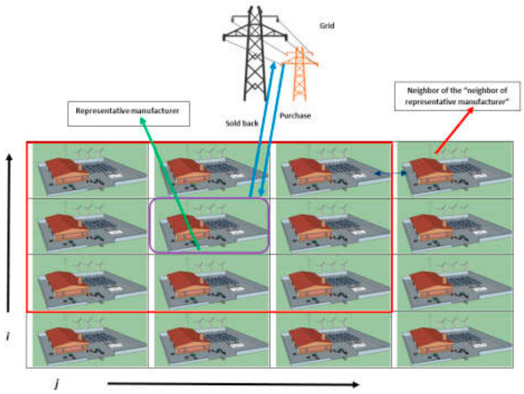


Fig. 1. Grid connected prosumer community of manufacturers with OGS

Like other components in this network, the energy dynamics of the BESS will be influenced by not only the states (excess/shortage of generation, corresponding amount, state of charge of BESS) of the individual but also the states of its immediate neighbors. Therefore, to determine the energy sharing capability of each prosumer through investigating the interaction and temporal dynamics of the neighbors, cellular automata model is implemented.

In cellular automata model, the state of the BESS control scheme for the representative prosumer is a function of the state of energy status of the prosumer and its neighborhood in accordance with a set of transition rules which can be represented by:

$$CB_{ij}^{t} = f(ES_{ij}^{t}, \Omega_{ij}^{t}, C, NP) \tag{1}$$

where CB_{ij}^{t} , ES_{ij}^{t} , and Ω_{ij}^{t} are the control schemes (charging/discharging and depth of discharge) of the battery, energy state, neighborhood evaluation function for the manufacturer at cell *ij* at decision epoch *t*, respectively. *f* is the transition function. *C* and *NP* are constraints for feasible power flow and number of participants in the community, respectively.

2.1.1. Cell and its state definitions

The square-lattice represents the prosumer community while the 2D-regular square grid illustrates each manufacturer in the cellular automata framework. The possible states of each manufacturer (prosumer) can be characterized by:

State 1: the cell representing manufacturer are able to share.

State 2: the cell representing manufacturer are not able to share

State 3: the cell representing manufacturer are not participating.

2.1.2. Transition rules

In this model, the state of each cell (each manufacturer) evolves in discrete time steps based on the transition rules defined as follow:

Rule 1. If the representative manufacturer (RM) has excess generation, RM can share electricity with any of the neighbors if the neighbor has shortage of electricity.

Rule 2. If everyone meets their demand in the community, no sharing will happen among themselves.

Rule 3. If the neighbours have excess generation and RM has less generation than demand, RM will take electricity from the neighbours.

2.2. Estimating the battery lifetime using SD Simulation

The SD simulation model is developed to determine the health state of BESS and corresponding degradation periodically to estimate the remaining lifetime considering the actual operating conditions mentioned earlier.

2.2.1. Model variables

The structure of a SD model contains stock and flow variables. In this model, stock variables represent the energy states within the system. The flow variables represent the flows in the system (i.e. power), which result from the decision-making process. The model variables (stock and flow) and parameters are defined below with their explanation and corresponding units:

current_gen: current generation from the solar and wind (kW)
available_gen: available generation considering both current generation and amount of energy shared by the neighbors (kW)
gen_stat: generation status which defines the excess or shortage of the generation compared to the demand (kW)
grid: available grid power (kW)
sold_back: sold back amount (kW)
battery_state: status of the charge of the BESS (kW)
charging: amount of energy available for charging in BESS (kW)
discharging: amount of energy available for discharging in BESS (kW)
battery_health: status of the battery health (%)
Total_degradation: amount of battery health degraded (%)

The parameters used in the SD simulation are given below:

solar_gen: amount of solar generation (kW)
wind_gen: amount of wind generation (kW)
ca_decision: decisions from cellular automata model whether the neighbors have the capability to share energy or not (binary decision; 0: not capable to share, 1: capable to share)
neigh_share: amount that can be shared by the neighbors (kW)
demand_manf: demand of the manufacturing system (kW)
cost_chack: grid electricity cost ($/kW)
capacity_grid: capacity of the grid (kW)
sold_back_rate: rate of sold back electricity ($/kW)
initial_charge: initial state of charge in BESS at the beginning of the simulation (kW)
battery capacity: capacity of the BESS (kW)
initial_helath: health status of the BESS at the beginning of simulation

2.2.2. System Dynamics (SD) diagram

The first step of building a SD model is to construct a SD diagram based on the interrelationships among the system operations. Fig. 2 illustrates the SD simulation model for the system developed in Anylogic platform. The diagram is constructed using three building blocks: stocks, flows, and parameters. The stock variables (symbolized by rectangles) represent the state over time, flow variables (symbolized by arrow with valves) represent the rates of change in stock variables used to fill in or drain the stock variables.

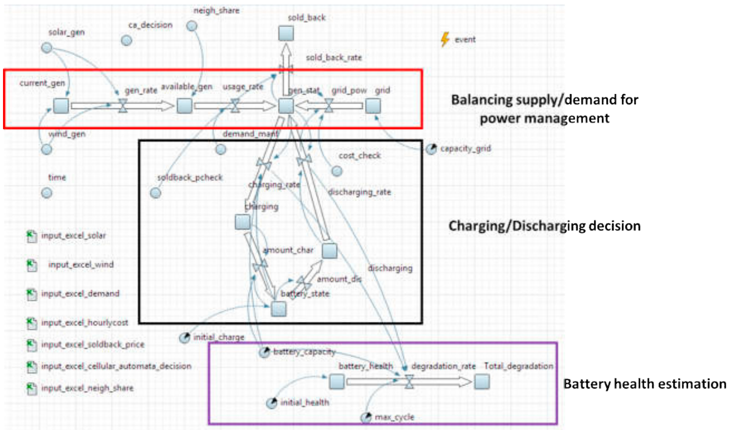


Fig. 2. SD model diagram

2.2.3. Physical constraints for the SD model

The next step of SD methodology includes the physical constraints which are required to develop the feasible model based on the interrelationships existed among the variables. The stock-flow diagram can be easily translated to a system of differential equations. The state of the stock variables can be defined by

$$Stock(t) = [Inflow(t) - Outflow(t)] \cdot dt + Stock(t) \tag{2}$$

$Inflow(t)$ and $Outflow(t)$ represent the value of the inflow and outflow at any time t between the initial time t_0 and current time t. The energy flow constraints in the model are determined as follows:

$$\frac{d(current\_gen)}{dt} = solar\_gen + wind\_gen - gen\_rate \tag{3}$$

$$\frac{d(available\_gen)}{dt} = gen\_rate + neigh\_share \tag{4}$$

$$\frac{d(gen\_stat)}{dt} = grid\_pow + usage\_rate \tag{5}$$

The power generation from different sources, battery degradation estimation, and important model assumptions are presented below:

The power generated by the solar PV, r_{t_m}, can be calculated by

$$r_{t_m} = a \cdot I_{t_m} \cdot \delta / 1000 \tag{6}$$

where I_{t_m} is the solar irradiance at interval t_m (W/m^2) and m represents the month.

The power generated by the wind turbine, w_{t_m}, can be calculated by

$$w_{t_m} = \frac{1}{2} \cdot \rho \cdot \pi \cdot r^2 \cdot v_{t_m}^3 \cdot \theta \cdot \eta_t \cdot \eta_g \cdot h / 1000 \tag{7}$$

where v_{t_m} is the wind speed at interval t_m.

The state of charge in BESS must be bounded within a given range, which can be formulated as

$$SOC_{\min} \le SOC_{t_m} \le SOC_{\max} \tag{8}$$

where SOC_{max} and SOC_{min} are the maximum and minimum states of charge of the BESS (%). SOC_{t_m+1} can be calculated recursively as follows

$$SOC_{t_m+1} \cdot e = SOC_{t_m} \cdot e + \eta_c \cdot bc_{t_m} \cdot \Delta t - \frac{1}{\eta_d} \cdot bd_{t_m} \cdot \Delta t \tag{9}$$

where η_c and η_d are the charging and discharging efficiencies, respectively. e is the battery capacity. bc_{t_m} and bd_{t_m} are the charging and discharging rate at decision epoch t_m.

As the degradation of BESS depends on the charging-discharging cycles, depth of discharge, and corresponding capacity of the BESS, it can be calculated by

$$degradation_{t_m} = \sum_{m} \sum_{t_m=1}^{T_m} \left(\frac{(bc_{t_m} + bd_{t_m}) \cdot \Delta t}{2Ne(SOC_{\max} - SOC_{\min})} \right) \tag{10}$$

where N is the maximum number of recommended charging/discharging cycle for the battery.

3. Implementation of the proposed model:

A hypothetical manufacturing prosumer community is used to build the case study. Total number of prosumers participated in the study is 100. The temporal horizon selected for the study is 50 months based on the cyclic performance of the battery for 50% depth of discharge mentioned in reference [16]. The location used for the weather data is Chicago, Illinois.

The manufacturing plant is assumed to be operated with twenty-four hours per day, seven days per week, and all the weeks per year. The energy-related parameters are shown in Table 1 for illustration.

Table 1. Rated power of the manufacturing machines in RMA

Machine Name	Rated Power (kW)
OP10 Turn-1	105
OP20 Turn-2	105
OP30 Turn-3	105
OP40 Window milling	155
OP50 Turn-4	120

For simplicity, it is assumed that every prosumer has similar size of OGS; area of the solar PV: 2000 m^2, number of wind turbine: 2, and capacity of BESS: 1000 kW. Initially, the BESS is charged by 10%. The maximum number of cycles the battery can go for full depth of discharge is considered as 5000 cycles. The power generation profile from the solar and wind turbine as well as the energy demand of the manufacturing system used for the SD simulation model are shown in Fig. 3.

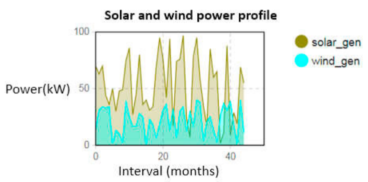


Fig. 3a. Power generation profile from the OGS

Fig. 3b. Power demand profile for manufacturing

Fig. 3. Power generation and demand profile for the simulation

Based on the simulated demand and generation from the OGS, the energy status (excess generation, or shortage of generation, or equal to the demand) of each prosumer is determined and used as the input for the cellular automata model. It is considered that each prosumer has eight neighbors and each of the neighbors has also eight neighbors. Therefore, in cellular automata, while the energy sharing capability of the representative prosumer is determined, not only the energy status of the representative prosumer but also the energy sharing capability of their neighbors are also considered.

4. Result and sensitivity analysis:

Result analysis

As the energy sharing capability of each prosumer changes over time based on the parameters (energy demand of manufacturing, generation from OGS, price of the grid electricity, and state of BESS), the state of the prosumer in square-lattice (energy sharing capability of the capability) will be changed accordingly. Based on the result obtained from the cellular automata model, the state of the representative manufacturer (blue dot: able to share; white cell: not able to share) at two different intervals are shown in Fig. 4.

The dynamics of the energy sharing capability of each prosumer obtained from the cellular automata is used as the input of the SD model. Considering the energy sharing capability of the neighbors of representative manufacturer along with other factors (demand of the representative manufacturer, generation from his OGS, price of the grid electricity, and state of BESS), the SD model is simulated to estimate the degradation over time. The degradation or battery health profile obtained from the model is shown in Fig. 5.

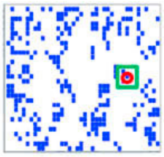


Fig. 4a. Neigboring state of the RM at decision epoch *t*

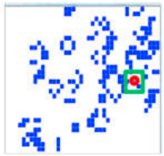


Fig. 4b. Neigboring state of the RM at decision epoch *t*+1

Fig. 4. Sharing capability of the neighbors of representative manufacturer at different decision epoch

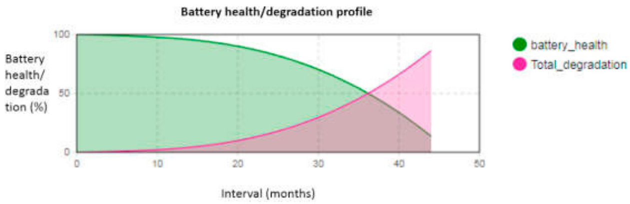


Fig. 5. Battery health and degradation profile

From Fig. 4, it can be seen that the estimated life of BESS is 43 months based on the stopping criteria (10 percent of the battery life) while the expected battery life is 50 months. This is happening due to actual operating condition (irregular charging/discharging cycle and depth of discharge) which is quite different from the standard ones. Again, the actual conditions are influenced by the stochastic parameters such as the generation from the OGS, energy demand of manufacturer, sharing capability of the neighbors etc.

Sensitivity analysis

To determine the impact of the variations of the critical parameters on battery degradation and further, extend the lifetime of the BESS through controlling those parameters, the sensitivity analysis is conducted in this study. The critical parameters considered for the analysis are the available renewable sources and sold back price of the electricity. The results obtained based from the sensitivity analysis are shown in Table 2 and Table 3. The table 2 follows the intuition. Due to high generation from the renewable sources, the number of charging and discharging is increased. Therefore, the degradation rate is higher which leads to a reduced lifetime of the BESS. From Table 3, it is noted that the battery degradation is sensitive with the sold back price. When the sold back price is high, it is more cost-effective to sell the excess energy rather than storing for future. Therefore, the number of charging/discharging cycles is reduced, and the lifetime of the BESS is increased.

Table 2. Comparison of the battery health and degradation profile based on the available renewable sources

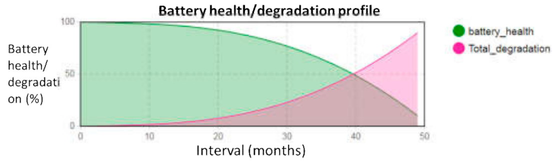
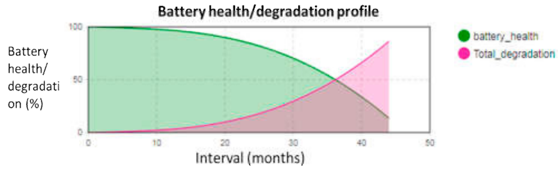
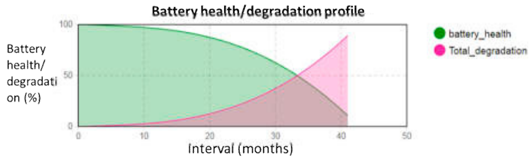
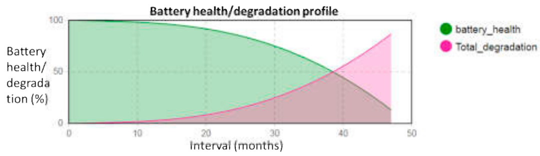
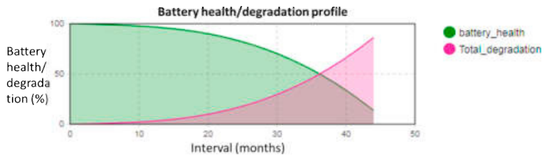
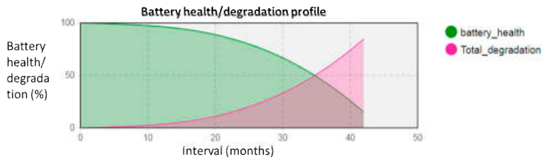
Scenarios	Description of the scenario	Percentage	Lifetime (months)	Battery health and degradation profile
I	High renewable sources	90%	49	
II	Baseline renewable sources	100%	43	
III	low renewable sources	110%	41	

Table 3. Comparison of the battery health and degradation profile based on different sold back price of electricity

Scenarios	Description of the scenario	Percentage	Lifetime (months)	Battery health and degradation profile
I	High sold back cost	110%	48	
II	Baseline sold back cost	100%	43	
III	Low sold back cost	90%	42	

5. Conclusion and Future work

The proposed model will help the prosumers to estimate the battery life more accurately considering the actual operating conditions. The dynamics of the neighboring effect for any prosumer is investigated by the cellular automata model. Considering the effect along with the critical factors of prosumers, the health state of BESS and corresponding degradation can be determined periodically. Therefore, the estimation of remaining battery life will be more accurate and based on the estimation, the prosumer can control the battery management plan (charging/discharging scheme) accordingly to ensure a reliable energy infrastructure for the prosumer community.

The model can be further improved in several aspects. Along with the number of charging/discharging and depth of discharge, the battery operating condition such as temperature, the size of the battery, interval between the two-consecutive charging/discharging cycle can be incorporated into the model to develop better battery life estimation model for the complex network. In addition to the estimation, the control scheme such as demand response program for the prosumers based on the critical parameters is required to develop to prolong the battery life as well as to build a reliable energy management framework for the community.

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