Predictive Control of Rural Microgrids with Temperature-dependent Battery Degradation Cost

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Abstract—Off-grid systems have emerged as a sustainable and cost-effective solution for rural electrification. In sub-Saharan Africa (SSA), a large number of solar-hybrid microgrids have been installed or planned, operating stand-alone or grid-tied to a weak grid. Presence of intermittent energy sources necessitates the provision of energy storage for system balancing. Reliability and economic performance of those rural microgrids strongly depend on specific control strategies. This work develops a predictive control framework dedicated to rural microgrids incorporating a temperature-dependent battery degradation model. Based on a scalable DC PV-battery microgrid, the realistic simulation shows its superior performance in the reliability improvement and cost reduction. Compared with the day-ahead control without the temperature-dependent battery degradation model, this control strategy can improve the reliability by 5.5% and extend the lead-acid battery life time by 26%, equivalent to lowering the levelised cost of electricity (LCOE) by 13%.

Index Terms—Predictive control, battery degradation, willingness to pay, microgrids

I. NOMENCLATURE

A. Set and indices
   t  Set of control timestep
   a  Set of electrical appliances

B. Constants
   PR  Performance ratio of solar PV panels (%)  
   G_{stc}  Solar irradiance in the standard test (W/m^2)  
   T_{ref}  Ambient temperature in the standard test (°C)  
   \alpha  Peak power temperature coefficient (%/°C)  
   r  Discount rate of the project (%)  
   n_pv  Nominal lifetime of PV panels (year)  
   n_bat  Nominal lifetime of lead-acid batteries (year)  
   m_pv  Cost of PV panel ($/kWp)  
   m_cc  Cost of charger controllers ($/kWp)  
   m_bat  Cost of lead-acid batteries ($/kWh)  
   m_inv  Cost of the inverter ($/kVA)  
   \epsilon_e  Import electricity tariff ($/Wh)  
   \epsilon_b  Battery degradation cost ($/cycle)  
   \epsilon_p  Penalty index for the unmet load  
   P_{grid}  Interconnection capacity (W)  

C. Variables
   G  Battery cycle life versus ambient temperature  
   \lambda  Battery cycle life versus depth of discharge (DoD)  
   \rho_{temp}  Nominal capacity of PV panels (W)  
   T_{amb}  Instantaneous solar irradiance (W/m^2)  
   T_{cell}  Instantaneous ambient temperature (°C)  
   P_{pv}  PV modules cell temperature (°C)  
   P_{bat}  Predicted (actual) solar power (W)  
   P_t  Scheduled (actual) discharging power (W)  
   P_{ch}  Scheduled (actual) charging power (W)  
   P_{ex}  Imported power from utility (W)  
   P_{ar}  Curtained solar power (W)  
   c_t  Stored energy in batteries (Wh)  
   S_{bat}  Battery charge/discharge state  
   U_t  Willingness to pay for electricity on each appliance ($/Wh)  
   c_a  Energy consumed by different appliances (Wh)  
   D_t  Total system demand (W)  
   L_t  Total load met (W)

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II. INTRODUCTION

Off-grid systems are an alternative approach for costly and long-term grid extensions to achieve universal electricity access. To supply customers in a remote area, microgrids flexibly utilize local renewable energy resources and aggregate loads, relying on energy storage for the supply-demand balance. However, the power scheduling and battery control under stochastic generations and loads are challenging. Control actions aiming for delivering the high-quality and reliable electricity stress the battery operations. In addition to lack of battery maintenance and protection in an under-resourced environment, all aforementioned factors lead to
rapid battery degradation and thus significantly increases the energy provision cost of rural microgrids.

In light of rural micro-grids which are both reliable and economically sustainable, the present paper simulates predictive control schemes on rural microgrids and incorporates temperature-dependent battery degradation cost models into the optimization. This work investigates on a scalable grid-tied microgrid design in SSA. It utilizes the multi-year meteorological data and fieldwork survey for load profiles construction and system simulation to be a real-world demonstrator.

A. Related Works

The control scheme is of paramount importance for the operation of off-grid systems. Control theories implemented in modern energy systems such as the predictive control [2], [3] has been gradually applied to rural off-grid applications [4], [5], while the feasibility of advanced intelligent control is yet to be tested [6]. Ref. [4] evaluates the impact of forecast errors in the predictive optimization for a rural microgrid and claims 2%-7% cost savings depending on the forecast quality. Ref. [5] develops a regional rural electrification planning tool considering the existing utility, and evaluates the yearly performance of stand-alone and grid-connected microgrids by a realistic rolling horizon simulation. However, those works use fixed battery wear costs and do not examine the effect of battery degradation under control schemes.

Battery degradation cost constitutes the most expensive part of rural microgrid systems and changes dynamically with operational patterns and conditions [7]. Techno-economic models using static technical parameters such as [1], [8] can effectively aid the system design and battery technology selection, but is restricted to demonstrate the detailed system performance under certain control strategy. Implementing a strategy that optimises operations based on battery degradation is pivotal for less battery replacement and cost reduction of rural microgrids. Current battery degradation models are broadly categorized into empirical and non-empirical models. In light of limited available data from rural communities, empirical models have been adopted practically in the system design [9], battery control [7] and cost estimation [10], [11] of rural microgrids.

III. CONTROL AND OPTIMIZATION FRAMEWORK

As shown in Fig. 1, the microgrid design is a DC PV-battery power generation hub connecting to multiple households radially. The hub consists of a PV array, VRLA or LFP battery bank and maximum power point tracker (MPPT). A capacity-constrained interconnection allows the imported power from the utility/back-up generation unit. Households at each end point have a bidirectional multi-port DC-DC converter allowing five 12V DC appliances to be plugged in. To address the uncertainty of solar power generation, the predictive control scheme is adopted for the power scheduling and battery control at the energy hub.

A. Temperature-dependent battery degradation model

The DoD stress function $I_{bat}^{dod}$ is approximated by a reciprocal function of DoD as (III-A), where parameter $\tau$ is equal to 554.08 via the regression of the experiment data [7]. To quantify the temperature effect, we define a stress index $I_{bat}^{temp}$ to present the relative cycle life under variable ambient temperature relative to the nominal value under the standard test temperature ($20^\circ C$). We derive the stress index function (III-A) for the lead-acid battery, based on the experiment data [12]. The value of $\alpha$, $\beta$ and $\gamma$ are 3.528, 0.272 and 0.023 via the regression. Given its capital cost $m_{bat} E_{bat}$, the cyclic cost function versus two stress factors $\Phi(T_t, DoD)$ can be calculated as (III-A), plotted as Figure 2.

$$I_{bat}^{dod}(DoD) = \frac{1}{\tau DoD}$$ (1)

$$I_{bat}^{temp}(T_t) = \alpha \beta \frac{T_t}{T_{ref}} + \gamma$$ (2)

$$\Phi(T_t, DoD) = \frac{m_{bat} E_{bat}}{I_{bat}^{dod} I_{bat}^{temp}} - \frac{m_{bat} E_{bat}}{\tau (\alpha \beta \frac{T_t}{T_{ref}} + \gamma)} DoD$$ (3)

B. Power flow of the microgrid

The predictive control scheme has a prediction horizon of one day with hourly time steps, based on solar irradiance and ambient temperature forecasts. A mixed integer linear...
programming model (MILP) model for the optimal power scheduling is formulated as follow.

The cost function (3.3.3) describes daily system operation cost (i.e. the sum of battery degradation cost, the import electricity tariff and the penalty for the unmet load). This work quantifies the battery degradation as the multiplication of DoD in a day and temperature-dependent battery cyclic cost. The cumulative DoD is calculated as (3.3.3). It assumes that the (dis)charging process in a cycle is additive as in the rainflow algorithm [13], and the charging and discharging process contribute equally to the cost per cycle by assigning the weight of 0.5. The counting DoD is restricted to be less than one which does not count the micro-cycles. The last term is the soft constraint to make the schedule follows the load curve by assigning $c_p \gg c_e$.

$$J = \sum_{t=0}^{T}[\Phi(T_t, D_t) + c_p p_t^2 + c_b(D_t - L_t)^2]$$

$$DoD_t = \min\left\{\frac{0.5(e^{0.01 t} + e^{-0.01 t})}{\bar{E}_{bat}}, 1\right\}$$

The supply-demand balance is described as (3.3.3). At the certain solar irradiance, the solar power output of PV panels under the MPPT control is modeled as (3.3.3) where the cell temperature $T_{cell}$ is calculated as (3.3.3) given the ambient temperature $T_{amb}$ [14]. The performance ratio (PR) in (3.3.3) is the ratio of the actual energy production to the theoretical maximum energy production assuming PV modules are always performed at the nominal efficiency and there were zero losses in the other components of the system (such as inverters) [15].

The performance ratio (PR) in (3.3.3) is a function of location (longitude, latitude) and the hour of a year, and the clearness index is an instantaneous ratio between actual and theoretical clear-sky irradiance (eq. 4.1). The clear sky irradiance is normalized with the clear-sky model to form a more stationary time series and then be fed to a non-linear smoothing model with a seven-day sliding window. The model are demonstrated in [16]. The clear sky irradiance is calculated as (3.3.3) given the ambient temperature $T_{amb}$.

$$
\begin{align*}
  e &= \frac{3}{2}c_2\left(\frac{1 + a(T_{cell} - T_{amb})}{0.4}\right) \cdot PR \\
  T_{cell} &= T_{amb} + \frac{\Delta T_{NOCT} - 20}{\Delta T_{NOCT}}G_t \\
  \sum_{t=0}^{T} L_t &\geq \sum_{t=0}^{T} D_t \\
  L_t &\leq D_t \\
  p_t^e &\leq P_{grid}
\end{align*}
$$

The initial battery energy is pre-defined ($E_{bat}^{init}$). Battery constraints are as follows: power constraint (3.3.3), energy constraint (3.3.3) and energy balance with the round-trip efficiency (3.3.3).

$$
\begin{align*}
  0 &\leq p_t^{ch} \leq P_{bat}(1 - \eta_{bat}) \\
  0 &\leq p_t^{dis} \leq P_{bat}\eta_{bat}
\end{align*}
$$

IV. PREDICTION
A. Solar irradiation

This work adopts a two-stage approach in which the solar irradiance is normalized with the clear-sky model to form a more stationary time series and then be fed to a non-linear time series prediction model. The advantages of this kind of model are demonstrated in [17]. The clear sky irradiance is a function of location (longitude, latitude) and the hour of a year, and the clearness index is an instantaneous ratio between actual and theoretical clear-sky irradiance (eq. 4.1). The model is demonstrated in [16]. The clear sky irradiance is calculated as (3.3.3) given the ambient temperature $T_{amb}$.

$$
\begin{align*}
  \lambda_t &= \frac{I_{stest}}{I_{stestNOCT}} \\
  \lambda_t &\in [0, 1]
\end{align*}
$$

Hourly clearness index is predicted by the exponential smoothing model with a seven-day sliding window. The model is demonstrated in [17].
predicts the future value as a weighted sum of past observations and the weight assigned is exponentially decreasing for past values. The prediction result within a week is shown in Figure 3. The root mean square error (RMSE) is 23%.

B. Load profile construction

We use the willingness to pay (WtP) for electricity consumed by different appliances and real fieldwork data to construct users’ load profiles. Given the fixed amount of daily electricity consumption and physical constraints of appliances, the household chooses how to spend the electricity on each of them according to their willingness, as the objective function (eq. IV-B). Three basic electrical appliances are considered including light, fan and phone charger. The power, energy, use patterns and utility function of each appliance are listed as below.

\[
U = \sum_{a=0}^{A} \sum_{t=0}^{T} u_t^a
\]  

- Light: The household can have three light bulbs rating at \( P = 3 \text{W} \), and can be switched on during \( T = [4:00, 24:00] \). Its WtP is related to the solar irradiance and formulated as \( u_{light}^t = \frac{2}{G_{stc}} (G_{stc} - G_t) p_{light}^t (p_{light}^t - 400) \).
- Fans: The fan rating at \( P = 5 \text{W} \) can be turned on when ambient temperature exceeds the threshold \( T_{th} = 23 \). Its WtP is related to the ambient temperature and formulated as \( u_{fan}^t = -\frac{T_t}{T_{th}} (p_{fan}^t - 400) \).
- Phone charger: The phone can be charged anytime. Its WtP is formulated as \( u_{phone}^t = 0.5 p_{phone}^t (p_{phone}^t - 400) \).

According to the data of 51 households using off-grid energy systems [17], we sample numbers from it to obtain daily electricity consumptions of dwellings, and then conduct the simulation. Therefore, we can obtain the appliance-level load profiles for one or multiple households with different daily energy consumption in a community (Fig. 4).

V. RESULTS

The micro-grid is assumed to supply 15 dwellings. The PV panel is sized to 0.3 kWp and the lead-acid battery is 1.1 kWh. It is tied to the main grid supplying 10% of the peak load. Two-year solar irradiance data of Gitaru dam in Kenya are used for the full-year simulation. The microgrid is required to meet the 90% daily demand defined as the reliability standard.

| Parameter for sizing PV-Battery system |
|----------------------------------------|
| \( m_{bat} \) | $167/kWh |
| \( \eta_{ch/dis} \) | 90% |
| \( r \) | 5% |
| \( m_{pv} \) | $970/kWp |
| \( \text{SoC}_{\text{min}} \) | 20% |
| \( \tau_{pv} \) | 20 yrs |
| \( m_{cc} \) | $548/kWp |
| \( PR \) | 70% |
| \( n_{bat} \) | 3 yrs |
| \( m_{inv} \) | $503/kWp |
| \( P_{bat} \) | 150 W |
| \( \alpha \) | \(-0.37\%/{ }^\circ\) |
| \( c_e \) | $0.2/kWh |

The day-ahead control scheme makes the only one solar power projection for the entire day and schedules once at the first timestep. In the MPC case, for every timestep, the system forecasts the future solar power according to real PV yields, then schedules based on the updated projection.

Fig. 5 shows the hourly result in a week of June. The daily reliability outcomes of the DA and MPC case are 82.9% and 89.3% on average respectively. The undersupplied load often occurs during the evening peak. As the day-ahead case could not update the solar irradiance forecast, the system fails to import the sufficient electricity in advance.

Fig. 6. SoC in cases with/without temperature-dependent degradation model.
Under the MPC scheme, we simulate battery operations with and without the temperature control (Fig. 6). The system without the temperature control assumes a constant battery temperature at 20°C, while the system with the temperature control discharges or charges batteries considering ambient temperature forecasts.

We develop four cases for full-year simulations listed in Table II.

### TABLE II
#### THE DESCRIPTION OF FOUR CASE STUDIES

| Case Studies      | Case 1 | Case 2 | Case 3 | Case 4 |
|-------------------|--------|--------|--------|--------|
| Predictive Control| DA     | DA     | MPC    | MPC    |
| Temperature Control| Yes   | No     | Yes   | No     |
| Battery lifetime (years) | 2.86  | 2.47   | 2.66  | 1.96   |
| LCOE ($/kWh)     | 0.488  | 0.516  | 0.478  | 0.540  |

Fig. 7 shows the battery aging over a year under four cases. The battery life is significantly extended after incorporating the temperature-dependent degradation cost model, especially in MPC cases.

Fig. 8 summarizes the annual results for four cases. The MPC cases achieve the higher reliability than DA cases, by 5.5% on average. The temperature-dependent battery degradation model can save the cost by extending battery lifetime. We calculate the LCOE for four cases based on the method in [11]. The LCOE is reduced by 13% for MPC (C3 versus C4) and even lower than the DA case.

### VI. CONCLUSION
The paper develops a MPC scheme for rural microgrids incorporating the temperature-dependent battery degradation cost model. We simulate full-year case studies with dedicated load profiles constructed from the real field work data. Results show that MPC can increase the reliability (i.e. 5.5% on average) compared with the day-ahead case but leads to the higher battery degradation cost. The temperature-dependent degradation model can mitigate this situation - For the lead-acid battery, it can extend the life time by 26% under the MPC scheme, resulting in a reduction on LCOE by 13%. To improve further on the cost reduction and smart energy management, operators could conduct demand side management considering users’ willingness to pay, and research on this new topic could bring great economic benefits in the rural microgrid design.

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