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OPTIMAL ENERGY MANAGEMENT STRATEGY FOR A PV-WIND-BATTERY MICROGRID IN NORTHERN NIGERIA USING A HYBRID GGO-MODEL PREDICTIVE CONTROL FRAMEWORK

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ABSTRACT

In an islanded microgrid with limited storage, the energy management system decides which load to curtail when solar and wind output fall short. This paper develops a two-layer strategy for a PV–wind–battery microgrid serving a community of about 1.1 MWh/day in northern Nigeria. An hourly receding-horizon model predictive controller (MPC), formulated as a linear program with critical and non-critical load classes, runs online; offline, the Greylag Goose Optimization (GGO) algorithm tunes five parameters of the MPC cost. Hour-of-day profiles digitised from the author's dissertation drive a stochastic scenario generator, and four independent simulated years are used for testing. Against a rule-based controller with tuned thresholds, MPC with cost-consistent weights cut the lost-load cost by 41% and the total operating cost by 4.8% (Wilcoxon $p < 0.001$, 44 of 48 paired months), and it came within 1.8% of a perfect-foresight MPC. GGO tuning recovered 93% of the cost gap between a naively weighted MPC and the cost-consistent one without being given the true cost weights, but it did not improve on the cost-consistent weights (+0.27%), and GGO, PSO and GWO performed alike. The scenarios are synthetic and one system design is studied, so the results are indicative rather than site-measured.

INDEX TERMS: Energy management, greylag goose optimization, microgrid, model predictive control, battery storage, northern Nigeria.

I. INTRODUCTION

Reliable electricity is still out of reach for a large part of rural sub-Saharan Africa [1]. Where the grid does not extend, mini-grids that combine photovoltaic (PV) generation, wind turbines and battery storage are widely seen as the practical option [2]–[4], and several studies have sized such systems for Nigerian communities [5]–[8]. Sizing, however, fixes only the equipment. Once a microgrid is built, an energy management system (EMS) must decide hour by hour how the battery is used and, when generation falls short, which loads are curtailed [9].

Model predictive control (MPC) is a leading EMS technique because it plans over a forecast horizon, handles constraints explicitly and applies only the first control action before re-planning [10]. MPC has been developed for islanded microgrids with nonlinear storage losses [11], for degradation-aware operation [12], and in combination with evolutionary search [13], [14]. Two practical difficulties remain. First, the weights of the MPC cost (the relative priority of critical and non-critical load, the cost of battery wear, and the value of energy left in the battery at the end of the horizon) are rarely known with confidence, and they interact with forecast errors. Second, most published case studies concern grid-tied or European and Asian systems, and we found few that examine MPC-based load management for a Nigerian off-grid community.

Metaheuristics are a natural tool for calibrating such parameters offline. Particle swarm optimization (PSO) and genetic algorithms have been used to tune controller parameters of islanded microgrids [15]. The Greylag Goose Optimization (GGO) algorithm [16] is a recent optimizer that has been applied to microgrid forecasting and demand management [17], hybrid energy system design [18], and microgrid scheduling or dispatch in improved variants [19], [20]; an evolutionary-game-theory extension has also appeared [21]. In our searches (web search and publisher pages, October 2026) we found no study that uses GGO to tune the cost parameters of an MPC energy manager, nor one for a Nigerian microgrid. Because the metaphor-based metaheuristic literature has been criticized for weak benchmarking [22], this paper treats GGO as one candidate among several and tests it against two established optimizers with the statistical practice recommended in [23].

The contributions are as follows. (i) An MPC energy manager with critical and non-critical load classes is formulated as a linear program for an islanded PV–wind–battery microgrid. (ii) A two-layer GGO-MPC framework is defined, in which GGO tunes five parameters of the MPC cost against a training cost evaluated by closed-loop simulation. (iii) The framework is evaluated on four independent simulated years against rule-based control, MPC with naive

and cost-consistent weights, and a perfect-foresight bound, with paired statistical tests, a forecast-error study and a stressed-design check. (iv) The paper reports, without selection, where tuning helps and where it does not.

II. RELATED WORK AND RESEARCH GAP

Table I lists the studies closest to this work. In [13] and [14] an evolutionary algorithm is used inside the controller to compute set-points, whereas here the optimizer acts outside the controller and the controller itself is a linear program that is solved to optimality in about 2.5 ms. Tuning of controller parameters with PSO, GA and a hybrid is reported in [15], but for the small-signal control of inverters rather than for the EMS cost. Goose-based algorithms have been applied to scheduling and dispatch [19], [20] without an MPC layer. The gap addressed here is the offline calibration of MPC cost parameters with GGO under forecast uncertainty, evaluated against a perfect-foresight bound.

TABLE I: CLOSEST STUDIES AND THE GAP ADDRESSED.

Ref.	Method (as reported)	Difference from this work
[13]	MPC with a genetic algorithm that optimizes diesel and microturbine power over 24 h	Evolutionary search is the inner solver, not an offline tuner
[14]	Genetic algorithm combined with MPC for non-linear, non-convex microgrid control	Hybrid inner solver; no goose-based tuning or perfect-foresight bound
[15]	PSO, GA and a hybrid tune controller and power-sharing parameters of an islanded microgrid	Inverter-level control parameters, not EMS cost weights
[19], [20]	Improved goose-type algorithms for microgrid scheduling and forecasting-based dispatch	No MPC layer; no rolling-horizon evaluation
[12]	Two-layer MPC EMS for microgrids on weak grids, with reduced battery degradation	Grid-tied; weights not tuned by a metaheuristic
This work	GGO tunes five MPC cost parameters; evaluated on four simulated years	Islanded Nigerian microgrid; synthetic scenarios

III. SYSTEM AND SCENARIO MODEL

A. Microgrid and Load

The microgrid is islanded and comprises a PV array, a wind turbine group and a battery energy storage system (BESS); there is no diesel generator and no grid connection. The community load follows the Dirin-Gari daily demand of 1,103.6 kWh reported in the author's dissertation [24], shaped by the hour-of-day curve digitised from its demand figure (peak 60.1 kW). The system parameters are listed in Table II. The design (320 kW PV, 150 kW wind, 650 kWh BESS) is an input to this study, fixed before any controller was run: it was

chosen so that the mean daily renewable energy exceeds the load by about 46% while the storage is too small to ride through the rainy-season weeks without curtailment. It is not an optimum, and a smaller design is examined in Section VI-F.

The PV output and the wind turbine output at hour t are

$$P_{PV}(t) = N_{pv} \eta_{pv} \frac{G(t)}{1000} \quad (1)$$

$$P_{WT}(t) = N_{wt} \pi(v(t)) \quad (2)$$

$$\pi(v) = \begin{cases} 0, & v < v_{in} \text{ or } v > v_{out} \\ \frac{v^3 - v_{in}^3}{v_r^3 - v_{in}^3}, & v_{in} \leq v < v_r \\ 1, & v_r \leq v \leq v_{out} \end{cases} \quad (3)$$

where N_{pv} and N_{wt} are the installed capacities in kW, G is the irradiance in W/m^2 , $\eta_{pv} = 0.86$ is an overall derating factor, v is the wind speed, and $v_{in} = 2.5$, $v_r = 15$ and $v_{out} = 25$ m/s are the cut-in, rated and cut-out speeds. The battery energy E evolves as

$$E(t+1) = E(t) + \eta_c P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}} \quad (4)$$

with $\eta_c = \eta_{dis} = 0.95$. The energy is limited to $E_{min} \leq E(t) \leq E_{max}$ with a depth of discharge of 80% ($E_{min} = 0.2E_{max}$), and $0 \leq P_{ch}, P_{dis} \leq C_r E_{max}$ with $C_r = 0.5$ per hour. The load is split into a critical class, a fixed share $\varphi = 0.6$ of demand, and a non-critical class, the remaining 40%. Either class can be shed, and the power balance at each hour is

$$\begin{aligned} P_{PV} + P_{WT} + P_{dis} - P_{ch} - P_{cur} \\ + S_c + S_n = L \end{aligned} \quad (5)$$

Where P_{cur} is curtailed surplus and S_c and S_n are the critical and non-critical load that is not served, in kW. Performance is measured by the operating cost per day

$$J = \frac{1}{D} \sum_t [\lambda_c S_c + \lambda_n S_n + \omega P_{thr}] \quad (6)$$

With $P_{thr} = P_{ch} + P_{dis}$ the battery throughput, D the number of days, $\lambda_c = 0.80$ and $\lambda_n = 0.20$ USD/kWh the assumed values of lost critical and non-critical load, and $\omega = 0.083$ USD/kWh the battery wear cost per kWh of throughput. The wear cost is the dissertation battery price of 400 USD/kWh divided by an assumed lifetime throughput of $2 \times 3000 \times 0.8$ kWh per kWh of capacity. The two values of lost load and the cycle life are assumptions, not measurements;

Section VI-G shows which conclusions depend on them. The loss of power supply probability (LPSP) is the unserved energy divided by the demand, and the critical LPSP uses the critical demand only.

TABLE II: SYSTEM AND COST PARAMETERS.

Parameter	Value
PV capacity; derating	320 kW; 0.86
Wind capacity; cut-in / rated / cut-out	150 kW; 2.5 / 15 / 25 m/s
BESS capacity; depth of discharge	650 kWh; 80%
BESS efficiency; maximum power	0.95 each way; 0.5C
Daily load; peak	1,103.6 kWh; 60.1 kW
Critical share of load	60%
Value of lost load, critical / non-critical	0.80 / 0.20 USD/kWh
Battery wear cost	0.083 USD/kWh throughput
MPC horizon; time step	24 h; 1 h

B. Scenario Generator and Data Basis

Measured multi-year hourly series for Dirin-Gari were not available to this study. The dissertation provides typical 24-h profiles of load, irradiance and wind speed, which were digitised from its figures with an annual mean irradiance of 5.7 kWh/m²/day and a mean wind speed of 5.1 m/s [24]. A stochastic generator builds a year from these profiles. The irradiance profile is multiplied by a monthly clearness factor, a day-to-day AR(1) term (coefficient 0.6) and an hourly cloud term (coefficient 0.75), capped at 135% of the profile. Wind speed follows the profile multiplied by monthly factors and by day-level and hour-level AR(1) log-normal noise (coefficients 0.7 and 0.9). Load follows its profile with 5% day-level and 4% hour-level noise. The monthly factors, which put the lowest PV yield in the rainy season (July–September) and the highest wind speeds in the dry season, are qualitative assumptions for the Sahel climate and were not fitted to data. The scenarios are therefore synthetic, and absolute figures should be read as illustrations of controller behaviour, not as predictions for the site.

Fig. 1 shows the resulting seasonality. The mean daily yield is about 1,420 kWh for PV and 190 kWh for wind (capacity factor 5.2%), so wind supplies about 12% of the renewable energy. The wind contribution is small because the digitised mean speed of 5.1 m/s lies well below the 15 m/s rated speed of the power curve.

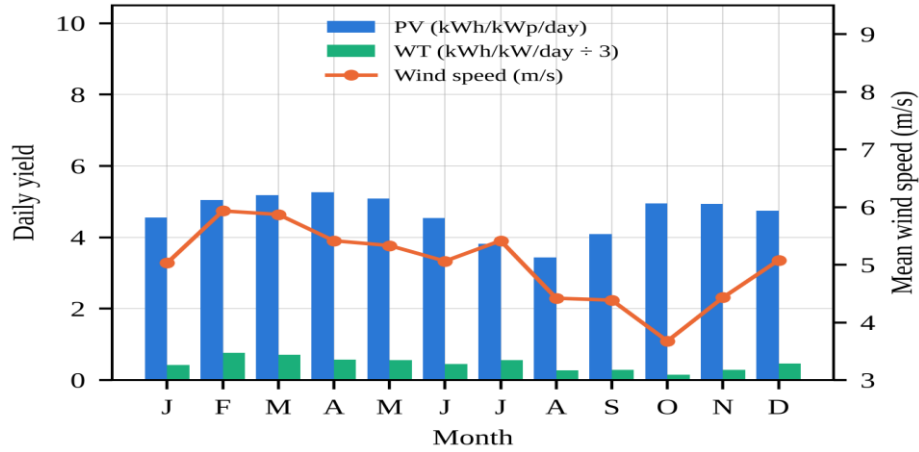


Fig. 1. Monthly mean daily PV yield, wind turbine yield (divided by 3 for display) and wind speed in the four test years.

IV. ENERGY MANAGEMENT FORMULATION

Fig. 2 gives an overview of the framework. An offline layer searches the MPC cost parameters by repeated closed-loop simulation of training windows, and an online layer applies the resulting controller every hour.

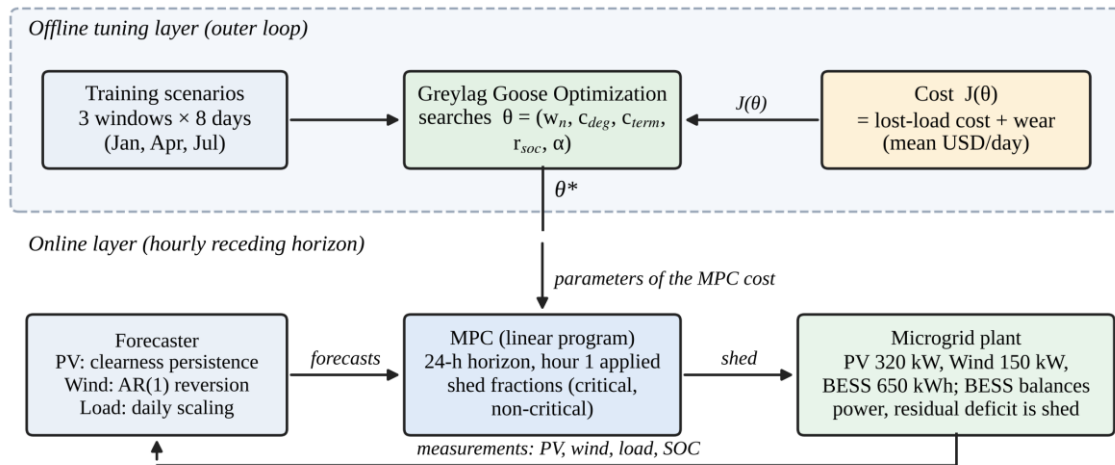


Fig. 2. Two-layer GGO-MPC framework: offline tuning of the MPC parameters by GGO (top) and hourly receding-horizon control of the microgrid (bottom).

A. Model Predictive Controller

At each hour the controller solves a linear program over $H = 24$ steps using forecasts $\hat{P}_{PV,k}$, $\hat{P}_{WT,k}$ and $\hat{L}_k$ and the measured battery energy. Let $\theta = (w_n, c_{deg}, c_{term}, r_{soc}, \alpha)$ be the controller parameters: the cost of non-critical relative to critical shedding, the battery throughput cost, the value of the energy left in the battery at the end of the horizon, a reserve fraction of the

usable battery energy that the plan must keep, and a safety factor on the renewable forecast. The program is

$$\min \sum_{k=0}^{H-1} [S_{c,k} + w_n S_{n,k} + c_{deg}(P_{ch,k} + P_{dis,k}) + \epsilon P_{cur,k}] - c_{term} E_{H-1} \quad (7)$$

subject to the battery dynamics of (4), a forecast power balance

$$\alpha(\hat{P}_{PV,k} + \hat{P}_{WT,k}) + P_{dis,k} - P_{ch,k} - P_{cur,k} + S_{c,k} + S_{n,k} = \hat{L}_k \quad (8)$$

the load limits $0 \leq S_{c,k} \leq \varphi \hat{L}_k$ and $0 \leq S_{n,k} \leq (1 - \varphi) \hat{L}_k$, and a planning floor $E_k \geq E_{min} + r_{soc}(E_{max} - E_{min})$ for $k \geq 1$. The small curtailment weight is $\epsilon = 10^{-4}$. The critical-shedding weight is fixed at 1, so only the ratios in θ matter. Only the first-hour shed fractions are applied. At execution the actual PV, wind and load are known; the shed fractions are applied to the actual load classes and the battery absorbs or supplies the remaining imbalance within its limits. A deficit the battery cannot cover is forced load shedding, non-critical load first, and is counted in the cost. The planning problem therefore never acts directly on the battery, which makes the controller robust to forecast error at the price of less direct control of the state of charge.

B. Forecaster

The forecaster uses only past measurements. PV is forecast as the digitised daily shape scaled by a clearness estimate $\hat{\kappa}_t$ that averages the ratio of measured to profile output over the last 24 h and over the last three daylight hours. Wind speed reverts from the latest measurement to the hourly profile mean, and load is the profile scaled by its ratio over the last 24 h:

$$\begin{aligned} \hat{v}_{t+k} &= \bar{v}_{h(t+k)} + (v_t - \bar{v}_{h(t)})\rho^k \\ \hat{P}_{PV,t+k} &= N_{PV} g_h(t+k) \hat{\kappa}_t \end{aligned} \quad (9)$$

where $\bar{v}_h$ is the profile mean for hour of day h , g_h the PV profile per kW and $\rho = 0.88$. These simple forecasts make errors that are produced by the scenario itself rather than added artificially. Over the 24-h horizon (sampled every 6 h in 60 days of test year 1) the mean absolute error relative to the actual energy was 10% for PV, 5% for load and 90% for wind. The wind forecast is poor, but wind supplies only about 12% of the energy.

C. Controllers Compared

Table III defines the controllers. The rule-based (RB) controller sheds all non-critical load when the state of charge falls below a lower threshold and restores it above an upper

threshold; critical load is shed only when the battery is empty. The default thresholds are 20% and 40% of usable energy, and the tuned thresholds are the best of a 6 by 6 grid on the training windows described below (5% and 15%). MPC-nominal uses cost weights consistent with the performance measure ($w_n = \lambda_n/\lambda_c = 0.25$, $c_{deg} = \omega$) and no terminal value, reserve or forecast margin. MPC-naive is a generic implementation that does not know the costs: it treats both load classes as equally important and ignores battery wear. The oracle uses the nominal parameters with the true future PV, wind and load, and bounds what better forecasting could achieve.

TABLE III: CONTROLLERS COMPARED.

Controller	Definition
RB default	Shed non-critical load below 20% state of charge; restore above 40%
RB tuned	Same rule with thresholds 5% / 15% chosen by grid search on the training windows
MPC naive	$\theta = (1,0,0,1)$: equal class priority, no wear cost, no terminal value
MPC nominal	$\theta = (0.25,0.083,0,0,1)$: cost-consistent weights
GGO / PSO / GWO-MPC	θ found by the named optimizer on the training windows (three independent runs each)
Oracle MPC	Nominal θ with perfect knowledge of the next 24 h

V. GGO-BASED TUNING OF THE MPC

A. Tuning Problem

Let $\mathcal{W}$ be a set of training windows and $J_w(\theta)$ the cost of (6) obtained by running the closed-loop simulation of the MPC with parameters θ on window w . The tuning problem is

$$\theta^* = \arg \min_{\theta \in \Theta} \frac{1}{|\mathcal{W}|} \sum_{w \in \mathcal{W}} J_w(\theta) \quad (10)$$

with $\theta = [0.02,1] \times [0,0.2] \times [0,0.8] \times [0,0.4] \times [0.5,1]$. The training set contains three windows of 8 days (the first day is a warm-up) starting on days 10, 100 and 200 of a training year that is not used for testing (January, April and July). Each evaluation of $J(\theta)$ takes about 1.4 s because it solves 576 linear programs.

B. Greylag Goose Optimization

GGO divides the population into an exploration group and an exploitation group, whose sizes change when the best fitness stagnates [16]. Exploration members move relative to the best solution as

$$\begin{aligned} X_i' &= X_{best} - A |C X_{best} - X_i| \\ A &= 2a r_1 - a, \quad C = 2r_2, \quad a = 2 - \frac{2t}{T} \end{aligned} \quad (11)$$

when $|A| < 1$; otherwise they move relative to three randomly chosen members, or along a spiral path, as described in [16]. Exploitation members move towards the mean of three sentries chosen as the best solutions. The algorithm was implemented by the author from the published description rather than from the original code, so details such as the damping of random-guided moves may differ from the original; the same implementation was used in the author's sizing study of this system. PSO (inertia 0.9 to 0.4, acceleration coefficients 2) and the standard grey wolf optimizer (GWO) were included as comparators. All three used 10 individuals and 15 iterations (160 evaluations), three independent runs each, and the same training windows.

C. Test Protocol

Every controller was evaluated in closed loop on four independent simulated years (generator seeds 1 to 4), each with a one-day warm-up. For the tuned controllers the three runs of each optimizer were evaluated separately and averaged. The monthly cost of each controller, averaged over its runs, was paired by month across the four years (48 pairs), and differences were assessed with the two-sided Wilcoxon signed-rank test [23]. The 48 months come from four years only and are autocorrelated, so the p values overstate the evidence; the number of months in which one controller beats the other is also reported. The effect of tuning is expressed as the share of the cost gap between MPC-naive and MPC-nominal that is closed,

$$\gamma = \frac{J_{naive} - J_x}{J_{naive} - J_{nominal}} \times 100 \quad (12)$$

where J_x is the test cost of the tuned controller.

VI. RESULTS AND DISCUSSION

A. Tuning Outcome

Table IV lists the parameters found. The training cost of MPC-nominal is 62.906 USD/day. The three optimizers reached mean training costs of 62.868 (GGO), 62.763 (PSO) and 62.761 (GWO) USD/day, that is, reductions of at most 0.37% relative to the nominal MPC. The best parameter vectors differ widely between runs and between optimizers (for example w_n from 0.24 to 0.98), which indicates a very flat cost surface: many different cost weights lead to almost the same closed-loop behaviour. Fig. 3 shows that GGO improved more slowly than PSO and GWO on the training windows in this small budget, and its three runs differ more.

TABLE IV: TUNED MPC PARAMETERS AND COSTS. (USD/DAY)

Run	w_n	c_{deg}	c_{term}	r_{soc}	α	Train	Test
Nominal	0.25	0.083	0	0	1	62.906	66.94
GGO #1	0.65	0.145	0.39	0.00	0.98	62.681	67.25
PSO #1	0.29	0.005	0.00	0.00	1.00	62.906	66.94
GWO #1	0.98	0.003	0.65	0.00	0.97	62.681	67.25
GGO #2	0.35	0.036	0.00	0.00	1.00	62.906	66.94
PSO #2	0.70	0.121	0.02	0.00	1.00	62.708	67.29
GWO #2	0.24	0.004	0.02	0.00	1.00	62.922	66.93
GGO #3	0.85	0.075	0.51	0.02	0.85	63.019	67.17
PSO #3	0.84	0.200	0.04	0.00	0.97	62.676	67.25
GWO #3	0.83	0.160	0.11	0.00	0.98	62.679	67.25

Train = mean cost on the three training windows; *Test* = mean cost on four test years.

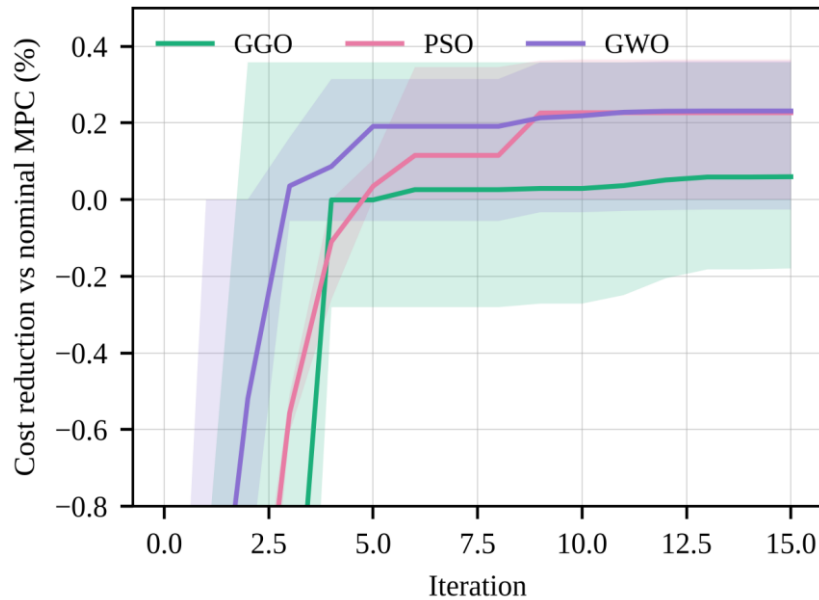


Fig. 3. Reduction of the training cost relative to MPC-nominal during tuning (mean of three runs; shaded band is the minimum to maximum).

B. Test Performance

Table V and Fig. 4 give the results over the four test years. The MPC-nominal controller has an operating cost of 66.94 USD/day against 70.35 for the tuned rule-based controller and 73.97 for the default rule, reductions of 4.8% and 9.5%. Because battery wear is almost the same for every controller (62.3 of the 66.9 USD/day for MPC-nominal), the differences lie in the lost-load cost, which falls from 7.79 to 4.62 USD/day (41%) relative to the tuned rule and from 12.40 (63%) relative to the default rule. The LPSP is about 1.4% for all MPC variants, because the total unserved energy is set by the renewable shortfall; what the controllers change is which load is left unserved. The critical LPSP is 0.36% for MPC-nominal, 1.11%

for MPC-naive and 0.86% for the tuned rule, and 0.05% for the oracle. MPC-nominal is 1.8% above the cost of the oracle, so improved forecasting could recover at most this share in this setting.

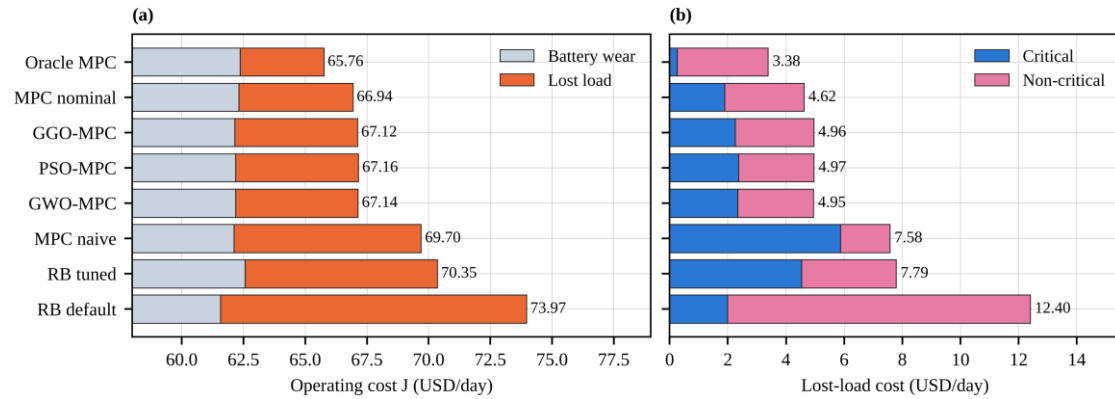


Fig. 4. Operating cost of the controllers over the four test years: (a) total cost split into battery wear and lost load; (b) lost-load cost by load class.

TABLE V: TEST RESULTS, MEAN OF FOUR SIMULATED YEARS.

Controller	J (USD/d)	Lost load (USD/d)	LPSP (%)	Crit. LPSP (%)	Cycles/yr
Oracle MPC	65.76	3.38	1.45	0.05	263.8
MPC nominal	66.94	4.62	1.45	0.36	263.5
GGO-MPC	67.12	4.96	1.48	0.43	262.8
PSO-MPC	67.16	4.97	1.44	0.45	263.0
GWO-MPC	67.14	4.95	1.44	0.44	263.0
MPC naive	69.70	7.58	1.44	1.11	262.7
RB tuned	70.35	7.79	1.98	0.86	264.5
RB default	73.97	12.40	4.94	0.38	260.3

Tuned controllers: mean of three runs. J includes lost-load cost and battery wear.

C. Effect of Tuning

MPC-naive costs 69.70 USD/day, which is 4.1% more than MPC-nominal. The GGO-tuned controllers cost 67.12 USD/day on average (standard deviation over runs 0.13), closing 93% of the gap (y of (12)); PSO and GWO closed 92% and 93%. Tuning therefore recovers nearly all of the loss caused by wrongly weighted costs, and it does so without being told the cost weights: the weights reach the controller only through the training cost. However, the tuned controllers did not beat MPC-nominal on the test years. GGO-MPC cost 0.27% more than MPC-nominal and was better in 6 of 48 months ($p < 0.001$). The gain of at most 0.4% on the training windows did not carry over to other years, a typical sign of fitting a flat surface to three short windows. GGO, PSO and GWO did not differ: GGO-MPC versus PSO-MPC gave

$p = 0.767$ and versus GWO-MPC $p = 0.294$. With three runs per optimizer and 160 evaluations each, no ranking among the optimizers can be claimed, and the result should not be read as evidence for or against GGO in general.

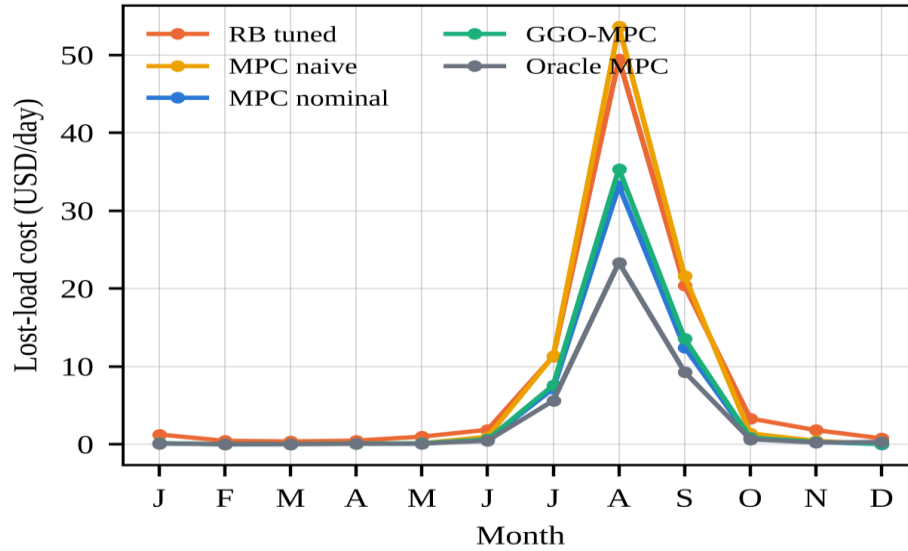


Fig. 5. Monthly lost-load cost of five controllers, mean of the four test years.

D. Seasonal and Hourly Behaviour

Fig. 5 shows that nearly all lost load occurs in the rainy season, with a peak in August: the lost-load cost of the tuned rule is 49 USD/day in August against 33 for MPC-nominal and 23 for the oracle. The training windows did not include August, which is one possible reason why the tuned parameters do not transfer. Fig. 6 shows the worst week for the tuned rule in test year 1 (from day 213). The rule sheds in long night-time blocks when the battery reaches its floor, while the MPC variants shed earlier and at lower power across more hours, keeping the battery higher at dawn on days 3 to 5. The oracle keeps a still higher state of charge ahead of the poor days.

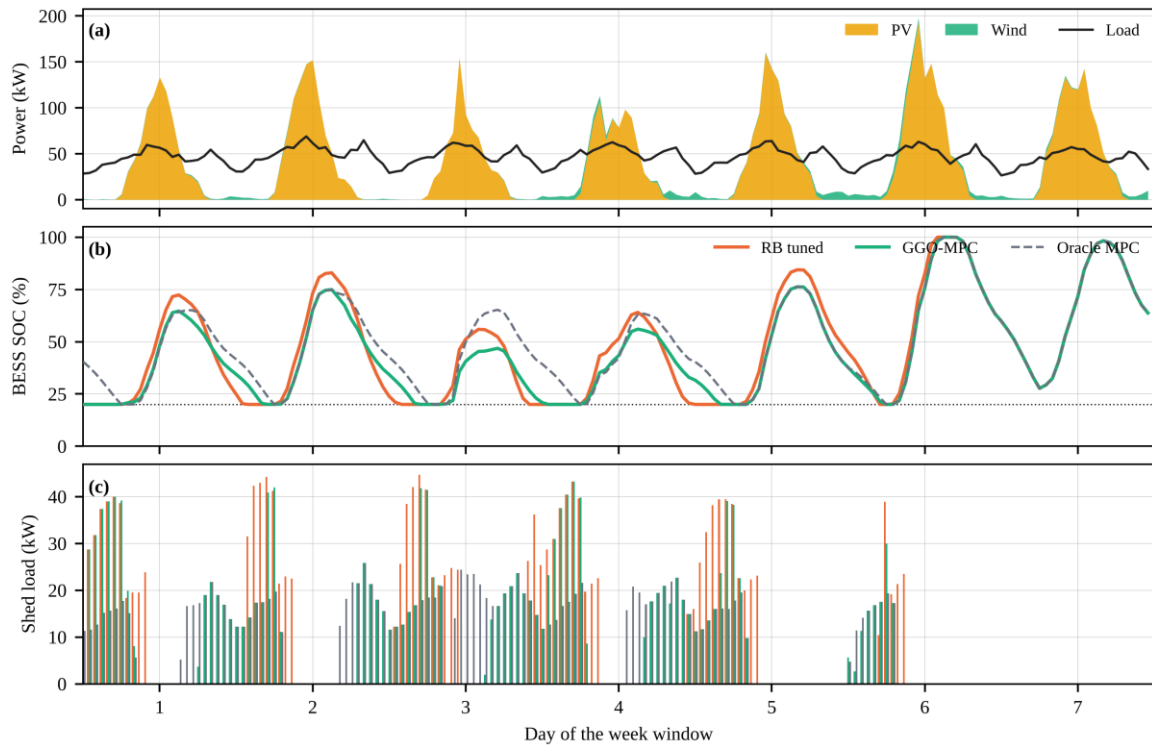


Fig. 6. Dispatch in the worst week for the tuned rule-based controller (test year 1): (a) PV, wind and load; (b) battery state of charge; (c) load shed in each hour. GGO-MPC is the run with the lowest training cost.

E. Statistical Comparison

TABLE VI: PAIRED COMPARISON OF MONTHLY COST (48 MONTHS)

Comparison	Diff. (USD/d)	Diff. (%)	p	Months better
MPC nominal vs. RB tuned	-3.38	-4.8	<0.001	44/48
MPC nominal vs. RB default	-7.01	-9.5	<0.001	48/48
MPC nominal vs. MPC naive	-2.73	-3.9	<0.001	22/48
GGO-MPC vs. MPC naive	-2.55	-3.7	0.003	22/48
GGO-MPC vs. MPC nominal	+0.18	+0.3	<0.001	6/48
GGO-MPC vs. RB tuned	-3.20	-4.6	<0.001	44/48
GGO-MPC vs. PSO-MPC	-0.04	-0.1	0.767	14/48
GGO-MPC vs. GWO-MPC	-0.02	-0.0	0.294	11/48
Oracle MPC vs. MPC nominal	-1.16	-1.7	<0.001	28/48

Negative differences favour the first controller. Wilcoxon signed-rank test, two-sided; months are paired across four years and are autocorrelated.

MPC beat the tuned rule in 44 of 48 months with $p < 0.001$, and the default rule in every month. Even allowing for the autocorrelation among months, the advantage of MPC over rule-based control is large and consistent across the four years (annual costs: 69.17, 66.25, 67.36, 64.98 against 74.18, 69.71, 70.50, 67.03 USD/day for the tuned rule).

F. Forecast Error, Stressed Design and Cost Values

Forecast error. Multiplicative log-normal noise (a component common to the whole horizon plus an hour-specific component) with standard deviation $\sigma = 0.1$, 0.2 and 0.3 was added on top of the forecasts in test years 1 and 2. Table VII shows that the cost of MPC-nominal rises from 67.71 to 68.11 USD/day (0.6%) at $\sigma = 0.3$, and that it stays 5.3% below the tuned rule-based controller. The best GGO-tuned controller (the run with the lowest training cost) cost more than MPC-nominal at every noise level, so the tuned reserve, safety factor and terminal value did not add robustness here. The MPC is robust to forecast error because it only sets shedding and lets the battery absorb the real imbalance.

TABLE VII: OPERATING COST WITH FORECAST NOISE. (USD/DAY, TEST YEARS 1 AND 2)

Controller	$\sigma = 0$	$\sigma = 0.1$	$\sigma = 0.2$	$\sigma = 0.3$
RB tuned (no forecast)	71.94	71.94	71.94	71.94
MPC naive	71.30	71.31	71.34	71.38
MPC nominal	67.71	67.77	67.91	68.11
GGO-MPC (run #1)	68.16	68.25	68.30	68.41

Noise is applied to the PV and wind forecasts only; the plant is unchanged.

Stressed design. The study was repeated with a smaller system (260 kW PV, 120 kW wind, 500 kWh) in test years 1 and 2, using the same controller parameters without re-tuning (Table VIII). The LPSP rises to about 8% and the differences between controllers grow. MPC-nominal costs 80.66 USD/day against 101.91 for the tuned rule (21% lower) and its lost-load cost is 47% lower. Its critical LPSP is 1.55% against 5.54%, and MPC-naive, which does not protect critical load, reaches 6.20%, which is worse than the tuned rule. The oracle is 6.1% cheaper than MPC-nominal, so better forecasts matter more when resources are scarce. The GGO-tuned parameters, found for the larger design, cost 2.1% more than the nominal ones, which shows that tuned parameters do not transfer between designs and would have to be re-tuned.

TABLE VIII: STRESSED DESIGN: 260 kW PV, 120 kW WIND, 500 kWh (TEST YEARS 1 AND 2)

Controller	J (USD/d)	Lost load (USD/d)	LPSP (%)	Crit. LPSP (%)
Oracle MPC	76.04	18.57	7.92	0.28
MPC nominal	80.66	23.71	7.98	1.55
GGO-MPC (run #1)	82.32	26.23	7.93	2.21
MPC naive	98.10	41.96	7.89	6.20
RB tuned	101.91	44.52	10.24	5.54

Parameters of the controllers are those of the main design; no re-tuning.

Cost values. The lost-load values and the wear cost are assumptions, and the controllers were run with their own internal weights, so the stored closed-loop results can be re-scored under other values (Table IX). The order of the controllers, from the oracle to the default rule, is the same under all five scorings, apart from a tie between MPC-nominal and GGO-MPC when the lost-load values are halved. The gap between MPC and the rule-based controller grows when lost load is valued more highly. This re-scoring does not re-run the controllers with different internal weights, so it tests the conclusions about the ranking but not the optimal weights.

TABLE IX: RE-SCORING OF THE TEST RESULTS UNDER OTHER COST VALUES. (USD/DAY)

Scoring	RB tuned	MPC naive	MPC nominal	GGO- MPC	Oracle MPC
Base values	70.35	69.70	66.94	67.12	65.76
Lost-load values halved	66.46	65.91	64.63	64.64	64.07
Lost-load values doubled	78.14	77.28	71.56	72.08	69.15
Wear cost doubled	132.92	131.82	129.26	129.28	128.14
Wear cost excluded	7.79	7.58	4.62	4.96	3.38

Wear cost excluded: the figures are the lost-load cost alone. Same closed-loop runs as in the main test.

G. Computation and Limitations

A forecast and a linear program of 144 variables took 2.5 ms on average (at most 4 ms) on a single core of a general-purpose server, so the controller is far from computationally demanding for hourly operation; it needs no solver licence because the open-source HiGHS solver was used. A tuning run of 160 evaluations took about four minutes. The main limitations are the following. (i) The scenarios are synthetic and were not validated against measured Dirin-Gari series, and the seasonal factors are assumptions. (ii) The value of lost load, the share of critical load and the battery cycle life are assumptions, and the ranking of controllers depends on them; for example, if wear were free, the controllers would not trade throughput against shedding in the same way. (iii) One design was studied in detail, with a second, smaller design as a check. (iv) The training set had three windows, the budget was 160 evaluations and three runs per optimizer were made, which is too small for conclusions about the optimizers. (v) The plant model is hourly and energy-based: converter losses, voltage and frequency control, and battery ageing beyond a throughput cost are not modelled. (vi) The wind forecast is poor and the wind resource is small.

VII. CONCLUSION

A linear MPC energy manager with critical and non-critical load classes was formulated for an islanded PV–wind–battery microgrid, and five of its cost parameters were tuned offline with GGO. On four simulated years built from dissertation profiles, MPC with cost-consistent weights lowered the lost-load cost by 41% and the operating cost by 4.8% relative to a tuned rule-based controller, and stayed within 1.8% of a perfect-foresight MPC. GGO tuning closed 93% of the gap between a naively weighted MPC and the cost-consistent one, which makes it a usable way to calibrate the controller when the cost weights are not known, but it did not improve on cost-consistent weights, and it was statistically indistinguishable from PSO and GWO. The main value of the framework in this study is therefore the MPC itself and an automated route to its parameters, not a superiority of GGO. Future work should use measured hourly data for the site, tune over a larger and seasonally complete set of windows, use a larger evaluation budget with more independent runs, and add converter-level and ageing models.

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