Optimizing Appliance Scheduling for Solar Energy Management Using Metaheuristic Algorithms

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Abstract

Solar energy generation is often misaligned with when households use power, creating a scheduling challenge. We optimize appliance start times in an island microgrid setting to minimize user dissatisfaction while promoting solar use and respecting system constraints. A sequential multi-day scheduling framework using Iterated Local Search (ILS) and Simulated Annealing (SA) considers power consumption, active duration, inverter size, battery limits, and solar forecasts, opening potential to explore trade-offs between cost, system size, and satisfaction.

Keywords

Optimization, Scheduling, Metaheuristics, Renewable Energy, User Satisfaction

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1 Introduction

Residential solar adoption is increasing, but generation often does not match household demand [2]. Efficient appliance scheduling is essential for effective use of solar energy, reducing grid reliance, and maintaining user comfort. This is especially critical in island microgrid settings, where a reliable external grid connection may not be available, as occurs in many rural locations across the world [5]. We propose a multi-day scheduling framework for an island microgrid that handles spillover across days and maintains battery state of charge continuity, overcoming limitations of existing island microgrid models that focus on single day scheduling. Our approach incorporates realistic system constraints, including inverter limits, battery dynamics, and appliance operation windows, and employs metaheuristics to find feasible, near-optimal schedules. Simulations show that appliance demand aligns better with solar availability while minimizing user inconvenience, demonstrating practical relevance for smart home energy management.

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2 Related Work

Efficient renewable energy management in smart homes relies on Home Energy Management Systems (HEMS) that optimize appliance scheduling to encourage greater adoption of renewable energy while satisfying user preferences and operational constraints. In most practical settings, renewable energy is typically integrated with grid electricity; however, there is increasing interest in promoting renewable-only or islanded operation to achieve fully sustainable energy usage. Heuristic, metaheuristic, and machine learning approaches have been demonstrated [8, 9] for minimizing costs, peak demand, and carbon emissions, highlighting challenges such as scalability and real-time implementation. Metaheuristics, including Genetic Algorithms, Particle Swarm Optimization, and SA, have been applied to appliance scheduling with renewable integration [1, 3, 4, 10]. ILS is a robust alternative, though its use in renewable integrated scheduling is limited [6]. Machine learning methods such as Recurrent Trend Predictive Neural Network-based Forecast Embedded Scheduling (rTPNN-FES) [7], have been applied to improve prediction of renewable energy and scheduling efficiency. In particular, rTPNN-FES focuses on renewable only energy systems, where electricity is supplied exclusively from renewable sources without grid dependency. However, these methods often neglect continuous appliance durations, multi-day spillover effects, and dynamic battery constraints. While these existing methods demonstrate strong potential, few explicitly address islanded microgrid scenarios relying solely on solar generation, where challenges include continuous appliance operation, battery dynamics, user comfort, and multi-day scheduling. This motivates the development of approaches that are computationally efficient and practically deployable for realistic rural residential renewable-only energy management.

3 Problem Description

Appliance scheduling is a discrete, combinatorial problem where start times are chosen from hourly slots while respecting operating durations, inverter limits, battery state-of-charge (SoC), and time-varying renewable generation as illustrated in Figure. 2. The search space grows exponentially with the number of appliances ($\approx 24^N$), making exhaustive search impractical. This problem is NP-hard, similar to flexible job-shop and resource-constrained project scheduling, and requires balancing feasibility, user preferences, and cross-day operation. We formulate it as a constrained optimization problem and solve it using metaheuristics SA and ILS to identify near-optimal schedules.

4 Methodology

Appliances are scheduled sequentially over multiple days, accounting for spillover and battery storage (Algorithm 1). Each appliance is assigned a start time while satisfying operational and system constraints, using SA and ILS to explore the feasible search space.

4.1 Objective Function

Minimize user dissatisfaction subject to constraints in (2)-(5):

$$\min \sum_{n=1}^{N} \sum_{s=0}^{S} x(n,s)\, c(n,s) + \sum_{n=1}^{N} p\left(1 - \sum_{s=0}^{S} x(n,s)\right), \tag{1}$$

where:

- $x(n,s) \in \{0,1\}$: appliance n starts at time slot s,
- $c(n,s)$: dissatisfaction cost (Equation (6)),
- $p = 1000$: penalty if appliance is unscheduled.

4.2 Constraints

1. Operational: Each appliance runs full duration once started:

$$\sum_{s \in \{t \le 2S-(a_n-1)\}} x(n,s) = 1, \quad \forall n \tag{2}$$

2. Power: Total consumption not to exceed inverter capacity:

$$\sum_{n=1}^{N} P_n(s)\, x(n,s) \le \Theta, \quad \forall s \tag{3}$$

3. Battery: State updated hourly within limits:

$$B(t) = B(t-1) + G(t) - \sum_{n=1}^{N} P_n(t)\, x(n,t) \tag{4}$$

$$\begin{aligned} Z_{\min} \le B(t) &\le Z_{\max} \quad \text{(SoC limits)} \\ Q_{\min} \le B(t-1) + G(t) &\le Q_{\max} \quad \text{(charging limits)} \end{aligned} \tag{5}$$

4.3 User Dissatisfaction Cost

Dissatisfaction depends on the distance from the preferred start time, modeled as a Gaussian [7]:

$$c(n,s) = 1 - \frac{1}{\sigma_n \sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{s-\mu_n}{\sigma_n}\right)^2\right) \tag{6}$$

where μ_n is the desired start time and σ_n reflects scheduling flexibility. Times outside the allowed range are assigned a cost of 100.

4.4 Framework and Algorithms

We propose a multi-day framework (Algorithm 1) to schedule appliances. A metaheuristic allocates applicances to times within a 48-hour window, allowing spillover into the next day. Once a day's schedule is set, the algorithm rolls forward to allocations for the following day. Within this framework, we work with SA and ILS.

5 Experiment and Results

The case study uses solar forecasts from the rTPNN-FE model [7] and appliance data (Table 1). SA and ILS were each run 30 times using the hyperparameters configurations in Table 2. System constraints are a 7.5 kW inverter size and the battery capacity [0, 100], with allowable charge rates of 0–50 kWh per hour, as defined in Eqs. (4) and (5).

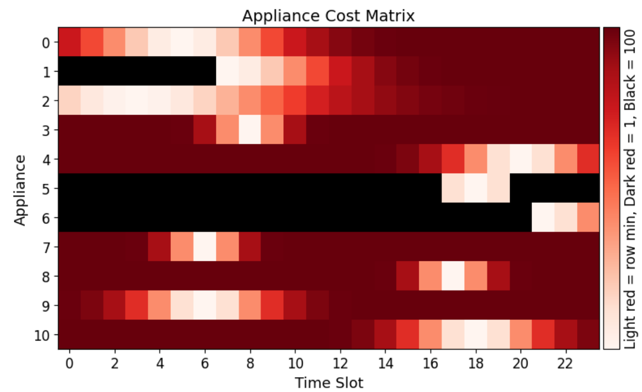


Figure 1: Appliance Cost.

Figure 3 shows user dissatisfaction over 30 runs. SA achieves lower and more consistent fitness than ILS, a difference confirmed as statistically significant by the Wilcoxon signed-rank test ($W = 0$, $p < 0.001$); normality test results are summarized in Table 4. Figures 4 and 5 present the optimized schedules, demonstrating the spillover of the washing task from Day 1 to Day 2. The impact of this scheduling on system operation is further illustrated in Figure 6, which depicts the hourly energy consumption, PV generation, and battery SoC across the two days, and shows how the battery SoC is carried over from one day to the next. As shown in Figs. 6a and

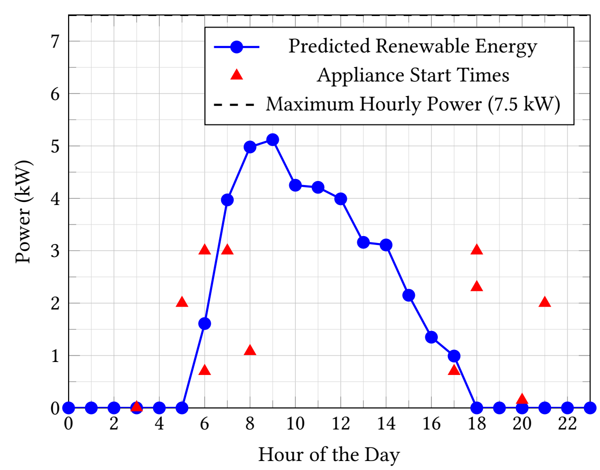


Figure 2: Predicted renewable energy and desired start times under power constraints for Day 1.

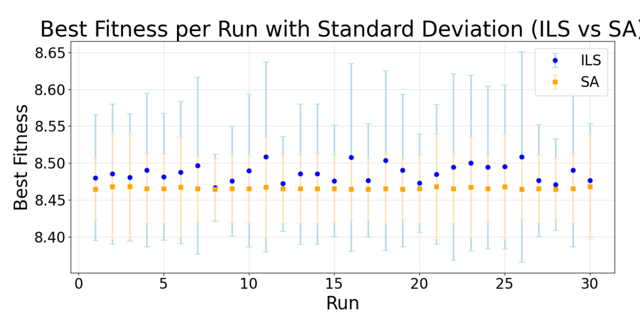


Figure 3: User dissatisfaction for SA and ILS over 30 runs.

Table 1: Appliance Information [7]

Appliance	Pwr. Consump. (kW)	Duration	Desired Start	Variance	Low Bound	Upp Bound
Washing Machine (warm wash)	2.000	2	5	3	0	0
Dryer (avg. load)	3.000	2	7	3	7	0
Robot Vacuum Cleaner (charge)	0.007	2	3	5	0	0
Iron	1.080	1	8	1	0	0
TV	0.150	3	20	2	0	0
Oven	2.300	1	18	2	17	20
Dishwasher	2.000	2	21	2	21	0
Electric Water Heater 1	0.700	1	6	1	0	0
Electric Water Heater 2	0.700	1	17	1	0	0
Central AC 1	3.000	2	6	2	0	0
Central AC 2	3.000	2	18	2	0	0

Table 2: Tuned hyperparameters used in experiments.

Algorithm	Parameter	Value
SA	Initial temperature	1000
SA	Cooling rate	0.993
SA	Shift range	6
ILS	Perturbation max	2
ILS	Perturb shifts	[8, -5, -8, 5]
ILS	Local max iterations	10
ILS	Local shifts	[3, -3, 1, -1]

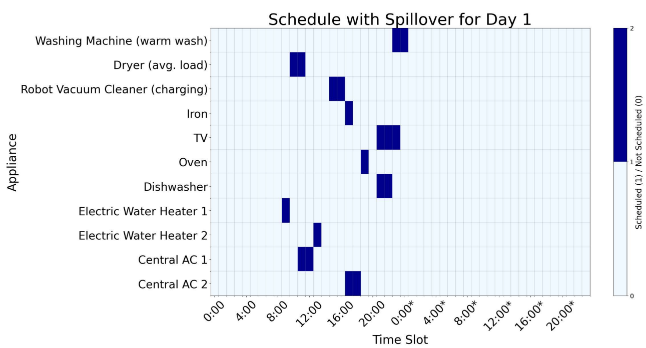


Figure 4: Day 1 schedule (SA) showing washing task spillover into Day 2.

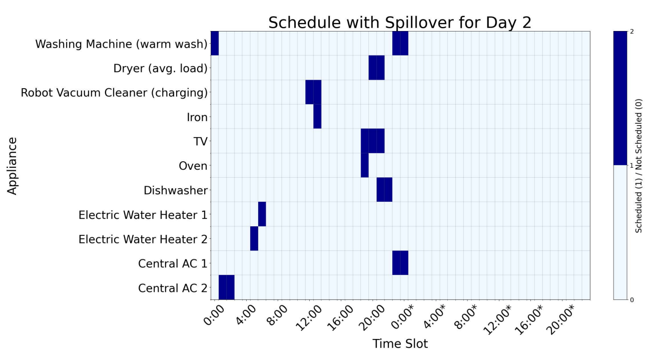


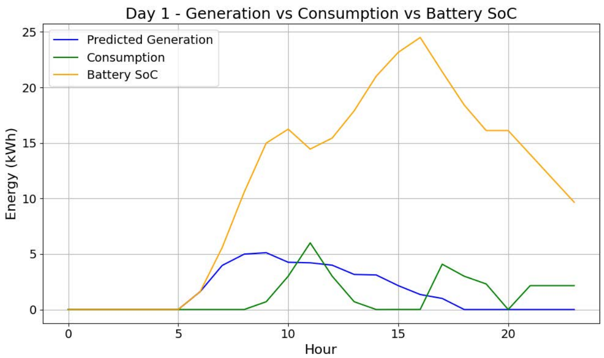
Figure 5: Day 2 schedule (SA) continuing from previous day.

Algorithm 1 Daily Simulation Framework for ILS and SA

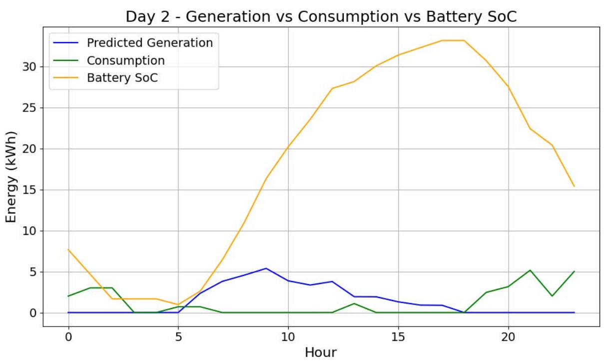
```
SoC ← 0                                        ▷ Initial battery state-of-charge
Spillover ← 0_{N×2S}                           ▷ Cross-day spillover matrix
for d = 1 to D do                              ▷ Loop over all days
    G_48h ← [G_d, G_{d+1}]                     ▷ 48-hour PV forecast
    Cost ← GenerateCostMatrix(N, S)
    (X*, f_best, f_init, StartTimes, Spillover_next) ←
        Optimizer(Spillover, SoC, G_48h, Cost, constraints)
    Record f_init and f_best for day d
    for n = 1 to N do                          ▷ User-deviation metrics
        Deviation[d][n] ← StartTimes[n] − DesiredStart[n]
    end for
    SoC_tmp[0] ← SoC
    for t = 1 to 48 do                         ▷ Simulate battery state for 48 hours
        G ← G_48h[t]
        C ← Σ_{n=1}^{N} X*[n, t] · P_n         ▷ Total appliance load
        SoC_tmp[t] ← min(Z_max, max(Z_min, SoC_tmp[t−1]+G−C))
        if C > SoC_tmp[t − 1] + G then
            X*[:, t] ← 0                       ▷ Force feasibility-corrected schedule
        end if
    end for
    SoC_profile[d] ← SoC_tmp[1 : 24]           ▷ Store first 24 hours
    Spillover ← X*                             ▷ Last 24 hours become next-day spillover
    SoC ← SoC_tmp[24]                          ▷ Carry end-of-day battery state
end for
Return: Recorded metrics (fitness, deviations, SoC profiles)
```

Table 3: Best median fitness over 86-day schedules for different inverter sizes (SA).

Inverter	Run	Best Fitness			
		mean	std	min	max
0.0	6.0	11000.000	0.000	11000.000	11000.000
1.0	6.0	7002.925	0.019	7002.923	7003.102
2.0	7.0	4006.455	10.686	4005.247	4104.400
3.0	7.0	8.860	0.157	8.597	9.393
4.0	6.0	8.662	0.151	8.517	9.293
5.0	1.0	8.565	0.086	8.498	8.944
7.5	3.0	8.465	0.047	8.460	8.897
10.0	4.0	8.465	0.047	8.460	8.897



(a) Day 1



(b) Day 2

Figure 6: Hourly energy consumption, PV generation, and battery SoC for Day 1 and Day 2.

Table 4: Shapiro–Wilk test for fitness distribution normality

Algorithm	Statistic	p-value	Interpretation
ILS	0.9605	0.319	Normal ($p > 0.05$)
SA	0.7065	1.9×10^{-6}	Non-normal ($p < 0.05$)

6b, the battery state at 23:00 on Day 1 is 9.66, and at the start of Day 2 it decreases to 7.66 to maintain continuity, due to spillover consumption from the washing machine of 2 kW per hour.

Inverter capacity limits total appliance power. Median daily fitness for different inverter sizes are shown in Table 3, with best performance at 7.5 kW, highlighting the importance of choosing an appropriate inverter size (not too small to limit concurrent scheduling, but not larger than needed to avoid unnecessary cost).

6 Conclusion

We presented a metaheuristic-based multi-day appliance scheduling framework for solar-powered smart homes, integrating solar forecasts, battery and inverter constraints. Experimental evaluation over 86 days shows SA outperforms ILS, achieving lower user dissatisfaction and more stable performance. Inverter sizing is critical for feasible scheduling and hence user satisfaction. Future work will extend to multi-user environments and adaptive preference modeling to further improve fairness and renewables use.

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