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Forecast Updating and Battery Dispatch in Solar-Assisted Manufacturing: A Fixed-Production Rolling-Horizon Replay Study

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Abstract:
Solar forecast errors can change grid purchases and demand charges after a manufacturing schedule has been released. This paper examines whether updating battery dispatch can improve realised performance while holding production fixed. A reproducible eight-hour computational replay compares a static dispatch plan based on an initially biased photovoltaic forecast with dispatch reoptimised at eight hourly boundaries. Both policies face the same realised solar trajectory, production load, battery constraints, electricity prices and delivery commitments. The updated policy receives perfect information for its next hour, while retaining the original biased forecast beyond that interval. Total reconstructed operating cost falls from ₹169.18 to ₹160.63, a reduction of 5.05%. The grid-demand peak falls from 7.870 to 7.389 kW and purchased energy falls from 31.310 to 30.482 kWh. Battery wear expenditure increases, illustrating the need to evaluate the complete cost boundary. These results demonstrate one information-and-dispatch mechanism under constructed conditions. They do not isolate forecast improvement from update frequency, establish forecast accuracy in practice, or validate production rescheduling during disturbances.

Keywords: rolling horizon; photovoltaic forecasting; battery dispatch; manufacturing; demand charges; computational replay

1 Introduction:

A production schedule commits machines to processing activities, but the associated electricity supply may remain uncertain. Solar output can differ from the trajectory used when the schedule was prepared. An energy manager must then decide whether to accept additional grid imports, alter battery operation or request changes to production. These decisions have different operational consequences. Dispatch can often be revised without changing an operation already promised to a planner, whereas production rescheduling can introduce additional coordination costs.

Dynamic scheduling research has long recognised the importance of reacting to changing system conditions (Ouelhadj & Petrovic, 2009; Vieira et al., 2003). In solar-assisted manufacturing, this issue extends to energy information. Photovoltaic forecasting methods differ in their temporal resolution,

predictors and error characteristics (Antonanzas et al., 2016). A forecast used at the start of a shift should therefore not automatically be treated as equally informative throughout the shift.

Rolling-horizon control solves a sequence of related problems using revised information and the current physical state. Its general logic is well established in predictive control (Mayne et al., 2000). Manufacturing applications additionally require attention to schedule feasibility, stability and computation. Shao et al. (2024), for example, investigate event-triggered hybrid scheduling in an energy-aware setting. The present study makes a narrower contribution: it separates an executable fixed-production dispatch replay from claims about a complete production-rescheduling controller.

2 Related literature and research position:

Forecasting and storage scheduling are closely linked because a battery can respond to both current energy imbalance and expected future conditions. A solar shortfall during a high-load interval may increase imports directly or consume stored energy that would otherwise protect a later demand interval. Cai et al. (2019) examine ageing-aware predictive control for buildings with photovoltaic generation and batteries.

Forecast evaluation should remain separate from control evaluation. A forecast may improve an average error score while contributing little during the particular intervals that determine the electricity bill. Conversely, a modest near-term correction can matter substantially when it changes a binding demand interval. Hyndman and Koehler (2006) discuss limitations of commonly used forecast-accuracy measures. In the present study no forecast model is trained, and forecast-accuracy rankings are not claimed.

Battery dispatch also requires an explicit physical boundary. Charge and discharge efficiencies determine how much external energy is required to restore a terminal reserve. Throughput-based wear is a simplified accounting representation rather than a complete electrochemical ageing model (DiOrio et al., 2015). It nevertheless prevents a controller from treating additional cycling as free.This paper differs from a forecasting-method comparison and from a full dynamic job-shop experiment. Production remains fixed, and all delivery outcomes are therefore inherited from the same feasible schedule. The experiment tests revised energy decisions using improved short-term information. The underlying case is shared with the author's thesis-based formulation, policy-comparison and sensitivity studies (Singh, 2026). It is not an independent industrial sample.

3 Research method and reproducible case:

3.1 Production and energy boundary:

The constructed episode contains sixteen half-hour slots. Three jobs comprise six non-preemptive operations on two machines. A previously computed feasible schedule is held constant throughout both replay policies. The corresponding site-load profile is reported in Table 1. It includes 2.8 kW of continuously energised background and idle demand. Total site consumption is 51.5 kWh, the last operation finishes after 5.5 hours, and all three jobs meet their due dates.

Table 1. Fixed schedule and energy inputs for the replay.

Input	Value
Fixed load by slot (kW)	2.8, 2.8, 2.8, 2.8, 6.4, 11.0, 7.4, 13.0, 13.0, 13.5, 13.5, 2.8, 2.8, 2.8, 2.8, 2.8
Production schedule: operation / machine / start–finish (h)	O0/M0/2–3; O1/M1/3.5–4.5; O2/M1/2.5–3.5; O3/M0/4.5–5.5; O4/M0/3.5–4.5; O5/M1/4.5–5.5
Common production outcomes	51.5 kWh; makespan 5.5 h; utilisation 0.375; 3/3 on time
Nominal / actual PV energy	30.0 / 21.5 kWh
Initial forecast / updated near term	70% of nominal / realised next two slots
Update boundaries	Slots 0, 2, 4, 6, 8, 10, 12, 14

The nominal photovoltaic profile is [0, 0, 1, 2, 4, 6, 8, 9, 9, 8, 6, 4, 2, 1, 0, 0] kW. The initial forecast is 70% of this nominal profile. Realised output equals the nominal profile except in slots 6–9, where it is halved. Actual photovoltaic energy is therefore 21.5 kWh. This deterministic construction creates both initial bias and a concentrated shortfall. It is not estimated from a measured error distribution.

The battery has 4 kWh usable internal capacity and 3 kW AC charge and discharge limits. Both conversion efficiencies are 0.95. Initial and terminal internal energy are fixed at 1 kWh. Grid charging is allowed, export is prohibited and import capacity is 40 kW. These assumptions are common to both policies. They should not be interpreted as permissions verified for a particular utility connection.

Prices are ₹6/kWh in slots 0–3, ₹4/kWh in slots 4–11 and ₹12/kWh in slots 12–15. Demand is averaged over two consecutive slots, representing a one-hour billing interval. A prior peak of 6 kW and an illustrative coefficient of ₹8/kW define incremental demand exposure. Wear is charged at ₹2 per internal kWh discharged. These rates are constructed experimental parameters, not a verified local tariff.

3.2 Dispatch optimisation:

For every remaining slot, the optimisation selects grid import G, utilised solar V, charge C, discharge D and internal stored energy E. Load L is fixed. The essential constraints are:

$$G_t + V_t + D_t = L_t + C_t \quad (1)$$

$$E_{t+1} = E_t + \eta_c C_t \Delta - D_t \Delta / \eta_d \quad (2)$$

Solar use is bounded by the available forecast during planning and by realised output during execution. Import, storage energy and charge/discharge powers satisfy their stated limits. A binary mode prevents simultaneous charging and discharging. The terminal reserve remains attached to the end of the original episode, even when the optimisation starts later.

The objective includes purchased-energy expenditure, incremental demand charges and wear. The retained historical peak is carried into each new optimisation. Demand is reconstructed over utility

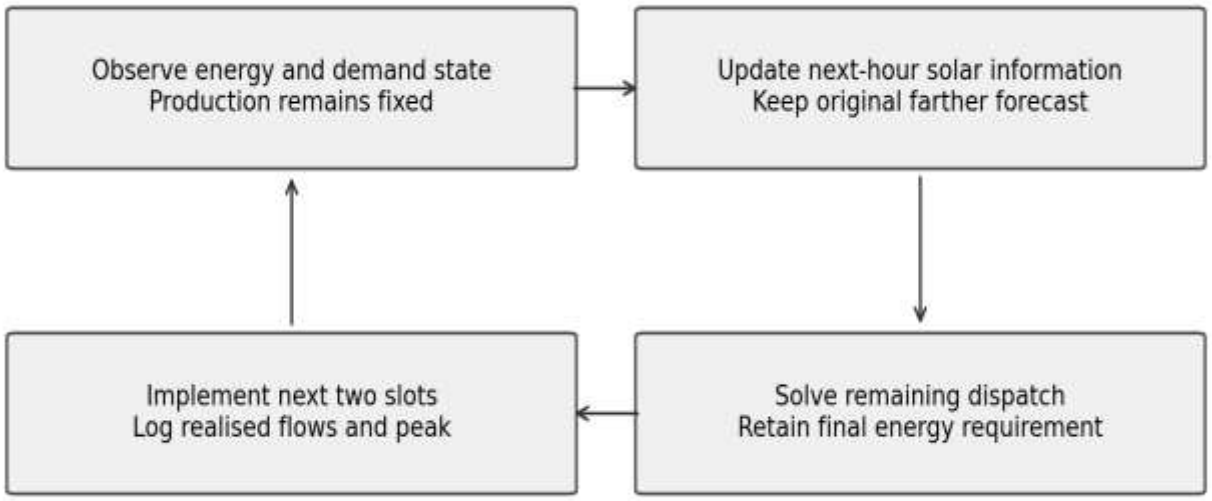
intervals rather than inferred from the largest half-hour reading. Because the updates occur on interval boundaries, no partially completed demand interval needs to be optimised in this particular replay.

3.3 Policy definitions:

The static policy optimises all sixteen slots once using the initial forecast. Its planned charge and discharge powers are then executed unchanged. Realised solar is used up to the amount that can be absorbed after accounting for load and these battery actions. Grid imports close the balance. The relatively high import limit makes this compensation feasible in the constructed episode.

The updated policy reoptimises at slots 0, 2, 4, 6, 8, 10, 12 and 14. At each update, actual output for the next two slots is supplied as the near-term forecast; subsequent slots retain the original 70% forecast. The controller implements the next two dispatch actions, records realised energy and demand, and repeats. Figure 1 shows the replay boundary.

Figure 1. Fixed-production rolling-horizon replay procedure.



This treatment deliberately grants perfect one-hour information. It is an optimistic information experiment. Updating frequency and information quality change together; their separate causal contributions cannot be identified from these two policies. No manufacturing operation is reassigned or shifted during the replay.

3.4 Computation and verification

The implementation uses Python 3.12.14, SciPy 1.17.0 and HiGHS 1.8.0, with presolve, one solver thread, a six-second limit per call and a relative mixed-integer gap target of 0.1%. One static solve and eight updated solves are retained. Runtime does not include industrial communication or operator review.

An independent scorer reconstructs balance, energy dynamics, bounds, charge/discharge exclusivity, the terminal reserve and demand intervals. The production schedule is independently checked for assignment, precedence, releases, non-overlap and due dates. This separation follows the principle that model verification and real-system validation are distinct tasks (Sargent, 2013). The experiment verifies a reduced computational system; it does not establish agreement with measured factory operation.

4 Results:

Table 2 presents realised outcomes rather than the objective predicted using the initial forecast. This distinction matters because both policies encounter solar output different from the trajectory used in their first optimisation.

Table 2. Realised static and updated dispatch performance.

Indicator	Static biased	Updated dispatch
Energy expenditure (₹)	145.8399	140.1277
Demand exposure (₹)	14.9599	11.1136
Wear exposure (₹)	8.3790	9.3912
Complete cost (₹)	169.1788	160.6324
Grid energy (kWh)	31.3100	30.4819
Peak (kW)	7.8700	7.3892
Internal discharge (kWh)	4.1895	4.6956
Battery loss (kWh)	0.4300	0.4819
Direct solar (kWh)	20.6000	20.9000
Solar-origin discharge (kWh)	0.0135	0.4061
Curtailment (kWh)	0.8800	0.0000
Solar-origin terminal energy (internal kWh)	0.0047	0.1425

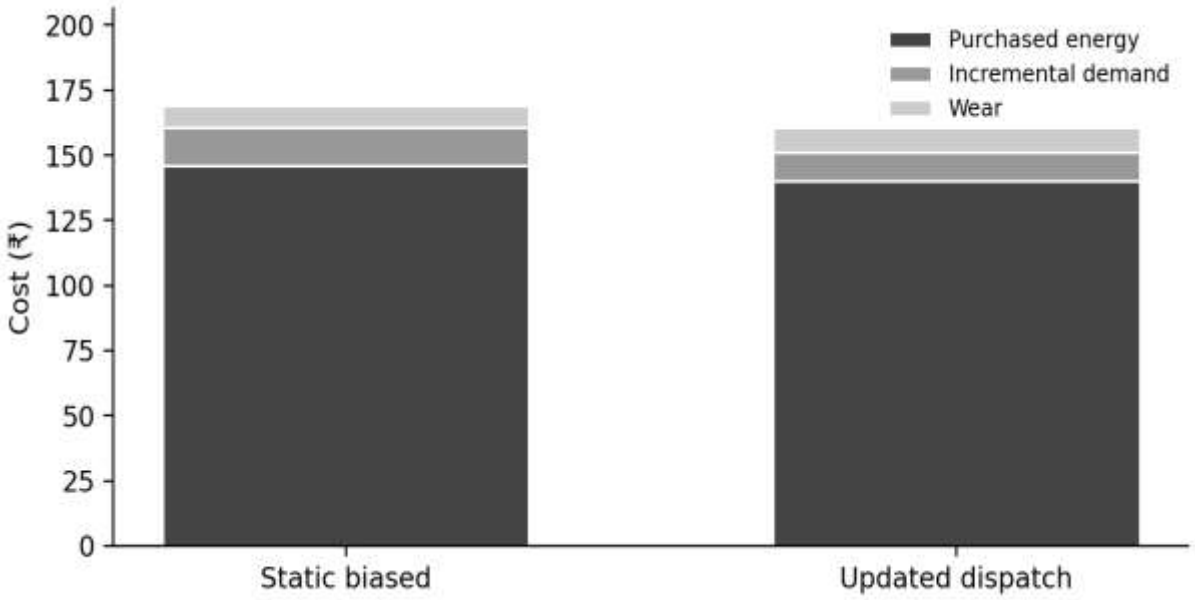
Complete operating cost falls by ₹8.55, from ₹169.18 to ₹160.63. The reduction is 5.05% relative to the static replay. Purchased-energy expenditure falls by ₹5.71 and incremental demand expenditure falls by ₹3.85. Wear expenditure rises by ₹1.01. These components reconcile to the complete-cost improvement, allowing for rounding.

Grid energy falls by approximately 0.828 kWh. The billing-interval peak declines by 0.481 kW. Both peaks remain above the inherited 6 kW level, so the reduction affects the incremental demand charge. The result would have a different economic interpretation if both peaks fell below the inherited level.

Direct solar consumption increases from 20.6 to 20.9 kWh. Solar-origin battery supply increases from approximately 0.014 to 0.406 kWh, while curtailment falls from about 0.880 kWh to zero. The remaining solar-origin energy stored at the end is not counted as energy already supplied to load. Initial battery energy has unknown origin and is not labelled as solar.

All three jobs remain on time under both policies because the production plan is identical. Makespan and machine utilisation also remain unchanged by construction. These observations establish delivery protection within the fixed-production replay; they do not demonstrate that an unconstrained rescheduler would make no production changes.

Figure 2. Realised cost components under static and updated dispatch.



5 Discussion:

The result illustrates how corrected near-term information can influence dispatch without modifying manufacturing commitments. A controller may reconsider whether to retain energy for a later interval or deploy it against the current grid requirement. Because demand charges depend on interval averages and a carried peak, identical energy totals would not necessarily imply identical bills. The outcome also shows why forecast value should be assessed through downstream decisions. A forecast error outside the critical load and tariff intervals may have limited cost consequences. A correction near a demand peak may be more valuable even if it represents only a small fraction of daily solar energy.

The wear increase is economically informative. Excluding wear from the comparison would report the gross energy-and-demand benefit, not the net operating benefit under the stated battery-cost model. Conversely, treating extra throughput as automatically undesirable would overlook the savings it enables. The appropriate comparison depends on a consistent objective and a defensible degradation coefficient. Perfect short-term information establishes a favourable condition for adaptation. It cannot support a claim that an available forecasting service would deliver the same savings. There is also no evidence here about schedule nervousness, machine breakdown recovery or processing-time uncertainty. Those questions require production decisions to remain active, a frozen implementation window, explicit disturbance data and a schedule-change metric. A result obtained with a fixed load should not be relabelled as a complete disturbance-resilient manufacturing controller.

6 Limitations and implementation implications:

The replay contains one constructed trajectory and a small feasible schedule. It provides no sampling-

based confidence interval or hypothesis test. A paired cost difference across two deterministic policies is a descriptive result, not an estimate of average industrial savings.

The battery has constant efficiencies and a linear discharge-throughput penalty. Thermal constraints, calendar ageing, voltage limits and warranty conditions are omitted. Grid charging and no-export operation simplify balancing but must be checked against actual site rules before implementation.

7 Conclusion:

Hourly dispatch revision reduces complete operating cost by 5.05% in a controlled fixed-production replay, despite increased battery wear and conversion losses. The improvement comes from lower energy expenditure and lower incremental demand exposure. The evidence supports the value of evaluating adaptive dispatch under a consistent physical and accounting boundary. It remains a single constructed information experiment, with perfect near-term solar knowledge and no production rescheduling. Broader forecasts, disturbance conditions and industrial measurements are required before drawing adoption or general performance conclusions.

Declarations:

This manuscript uses constructed computational data from the author's thesis research. It shares the same underlying small instance with related thesis-derived manuscripts; its distinct question and shared provenance must be disclosed in any journal submission. No industrial measurements, site permissions, live trials or independent field validation are claimed.

Data and code availability: The accompanying computational supplement contains the source program, input definitions, retained solver results, verification records and environment manifest.

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