

## Intelligent energy management of manufacturing systems integrated with renewable sources

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**Keywords:** Intelligent Energy Management, Smart Manufacturing, Renewable Energy Integration, Machine Scheduling, Energy Optimization

**Abstract.** The growing presence of renewable energy sources into manufacturing systems presents massive challenges in their intermittency and uncertainty, causing inefficiency in energy consumption and production planning. The paper introduces a smart energy management network of manufacturing systems that dynamically balances machine activities with the availability of renewable energy. The suggested solution consists of a predictive model of renewable generation and an optimization-based scheduling system to reduce the cost of energy, delays in production, and grid reliance. There is a multi-objective formulation that is created based on energy use, operating limitations and emission parameters. A smart decision-making policy, founded on machine learning-aided prediction and adaptive scheduling, is applied to guarantee real-time responsiveness when operating in different energy conditions. The framework is tested on a realistic load and renewable profile on a representative manufacturing scenario. Findings show that there are considerable increases in the use of renewable energy, decrease in peak grid demand, and general energy cost savings over traditional scheduling methods. The new methodology provides a scalable and viable approach to sustainable and energy-efficient smart manufacturing systems.

### Introduction

Manufacturing systems constitute one of the highest users of electrical energy which makes up a large part of the operating costs and environmental emissions [1-3]. As more and more people focus on sustainability and reducing carbon footprint, the need to include renewable energy sources in industrial processes like solar and wind power has been given a lot of consideration. The intermittency and unpredictability of these sources of energy however bring new challenges regarding how to keep the production process efficient and the systems reliable. Traditional



manufacturing models are generally tailored to steady grid power, and are not necessarily designed to be responsive to changes in energy supply [4-5]. The idea of smart manufacturing has been developed in recent years, which is aimed at the combination of sophisticated sensing and data analysis with intelligent decision-making in order to optimize the operational efficiency[6-7]. However, there is a significant gap in the coordinated energy and production processes despite these developments and especially when the infiltration of renewable energy is high. Conventional methods of scheduling tend to ignore the variation of energy and energy management systems can ignore production constraints and hence result in suboptimal performance [8-9]. To overcome this difficulty, a smart energy management system is needed which can dynamically match manufacturing processes with the current energy supply. This type of system should include predictive features that would approximate the production of renewables and adaptive measures to maximize the planning of machines and energy consumption. The aim is to reduce both the costs of energy as well as reliance on grid power, and to be able to sustain desired production levels in the face of unpredictable energy situations. This piece of work suggests a technical structure of smart energy control in manufacturing systems coupled with renewable energy. The strategy integrates predictive modeling and optimization based time scheduling to facilitate real-time, energy conscious decision-making. The usefulness of the suggested methodology is illustrated by a typical manufacturing case, where the energy efficiency, cost minimization, and system functionality under fluctuating energy supply are improved.

### System Architecture and Problem Formulation

The system under consideration is a smart manufacturing environment with the combination of renewable energy sources and grid support [10-12]. The manufacturing facility consists of a number of machines that run on predetermined production needs with each machine having time-varying power consumption depending on its working condition [13-15]. The renewable energy subsystem includes renewable sources like solar or wind, which are intermittent and uncertain with regard to generation profiles. The system is also linked to the utility grid, a backup source of energy to provide reliability. It may have an optional energy storage unit to smooth out surplus renewable energy and provide it in shortages. The objective is to intelligently coordinate machine operations with available energy resources in order to achieve optimal performance. This requires simultaneous consideration of production scheduling and energy allocation under system constraints. Let  $P_i(t)$  denote the power consumption of the  $i^{th}$  machine at time  $t$ , and  $P_{renew}(t)$  represent the available renewable energy. The grid power usage is denoted as  $P_g(t)$ , which should be minimized due to associated cost and emissions. The overall objective is formulated as a multi-objective optimization problem that minimizes energy cost, production delay, and environmental impact:

$$\min J = \alpha \sum_t C_g P_g(t) + \beta \sum_i D_i + \gamma \sum_t E(t)$$

where  $C_g$  is the grid energy cost coefficient,  $D_i$  represents the delay in completing job  $i$ , and  $E(t)$  denotes emission associated with grid energy usage. The weighting factors  $\alpha, \beta, \gamma$  are used to balance the objectives.

The system must satisfy the power balance constraint at each time instant:

$$P_{renew}(t) + P_g(t) + P_{storage}(t) = \sum_i P_i(t)$$

Operational constraints ensure that machines follow feasible schedules and respect processing sequences. Renewable generation is subject to uncertainty bounds, which can be modeled using forecasted values with allowable deviations. Additionally, machine scheduling variables  $S_i(t)$  are

defined as binary indicators representing the operational state of machines. The problem formulated is dynamic and nonlinear by nature because the availability of energy and energy production requirements are time-dependent. As such, traditional, non-adaptive optimization methods are inadequate, which inspires the desire to adopt smart and dynamic methods that can make a decision in real-time. The general system architecture that demonstrates how manufacturing units are integrated with renewable energy sources, grid support and the intelligent control module is shown in Figure 1.

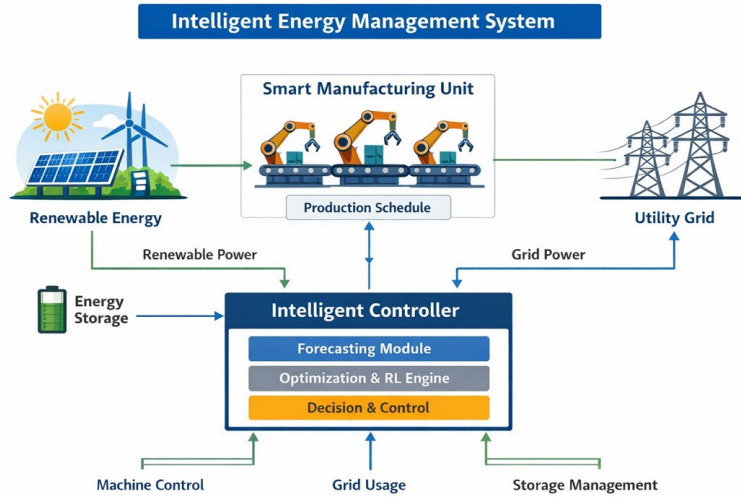


Figure 1: System Architecture Diagram

### Proposed Intelligent Energy Management Strategy

A smart energy management plan is created to dynamically plan manufacturing processes and availability of renewable energy. The suggested solution combines predictive modelling with adaptive decision-making to respond to the variability of energy supply at preserving production efficiency. The framework works in a time-stepped fashion, with energy availability and system conditions constantly monitored, and updated. A machine learning-based forecasting module is employed to estimate short-term renewable energy generation. Let the predicted renewable power at time  $t$  be denoted as  $P_{renew}^*(t)$ , obtained using a trained model based on historical weather and generation data. This prediction enables proactive scheduling decisions rather than reactive adjustments. An intelligent scheduling mechanism based on the forecasted energy availability and the existing situation of the system determines how to operate machines and the power allocated to them. It is possible to formulate the decision process as a sequential optimization problem, where the operational constraints are considered as a cost minimization objective. In order to be more adaptable to uncertainty, a reinforcement learning (RL)-based solution is embraced, and the system learns the best policies by interacting with the environment.

The system state  $S(t)$  includes machine status, job queue, predicted renewable energy, and current energy consumption. The control action  $A(t)$  consists of scheduling decisions and grid power allocation. A reward function is defined to guide the learning process:

$$R(t) = -(\alpha C_g P_g(t) + \beta D(t) + \gamma E(t))$$

in which there are fines on increased grid use, stalling production, and emissions. The learning agent is able to optimize the cumulative reward by updating its policy repeatedly in order to attain

the best trade-offs among competing objectives. The workflow starts with renewable energy prediction, which is then followed by the state observation and decision-making based on the policy learned. Implementation of the scheduling decisions then follows and the performance of the system is assessed to update the learning model. This is a closed loop mechanism which guarantees continuous improvement and resilience in the face of different operating conditions. The suggested plan will make it possible to coordinate the energy supply and manufacturing demand in real-time, based on the data, which will result in a better use of the renewable sources, fewer people will depend on the power produced by the grid, and the efficiency of the entire system will be increased. Figure 2 demonstrates the operational workflow of the proposed intelligent energy management strategy, such as prediction and state observation, decision-making and feedback mechanisms.

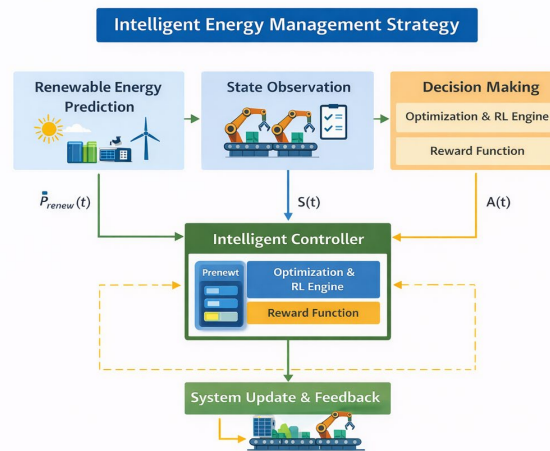


Figure 2: Workflow / Methodology Diagram

## Experimental Setup and Implementation

The intelligent energy management structure proposed is justified with the help of a model of a typical smart manufacturing situation simulated as a job-shop with many machines and time-dependent workloads. Both machines are defined in terms of power consumption as rated, processing time, and operation restrictions. The system is based on a discrete time horizon that is partitioned into non-overlapping intervals and provides time-sensitive analysis of energy use and scheduling actions. Table 1 presents the key parameters and configuration of the system that are used to model the manufacturing and energy system.

Table 1: System Parameters

| Parameter            | Symbol          | Value | Unit  |
|----------------------|-----------------|-------|-------|
| Number of machines   | N               | 6     | —     |
| Machine power rating | $P_i$           | 5     | kW    |
| Time horizon         | T               | 24    | hours |
| Time interval        | $\Delta t$      | 1     | hour  |
| Grid cost            | $C_g$           | 8     | ₹/kWh |
| Max renewable power  | $P_{renew,max}$ | 20    | kW    |

A realistic profile of day-to-day irradiance is utilized to model the renewable energy input which is a solar generation profile. Renewable energy predicted values are created based on the past data and factored in the decision making process. The grid power is taken as a secondary source with a fixed cost coefficient whereas optional energy storage is modelled with charge up

and charge off limits. Table 2 shows the representative renewable energy availability and the load demand profile (load demand) to be used in the simulation.

*Table 2: Sample Energy Profile*

| Time (hr) | Renewable Power P <sub>renew</sub> (t) (kW) | Load Demand (kW) | Grid Power P <sub>g</sub> (t) (kW) |
|-----------|---------------------------------------------|------------------|------------------------------------|
| 6         | 2                                           | 10               | 8                                  |
| 9         | 8                                           | 12               | 4                                  |
| 12        | 15                                          | 14               | 0                                  |
| 15        | 12                                          | 13               | 1                                  |
| 18        | 5                                           | 11               | 6                                  |
| 21        | 1                                           | 9                | 8                                  |

The implementation is done on a computational platform like MATLAB or Python, the intelligent scheduling algorithm is combined with the system model. The reinforcement learning agent is trained on a series of episodes to learn the best scheduling policies, under different energy and demand conditions. Learning rate, discount factor and rewards weights are key parameters that are tuned to have convergence and stability of the solution. In order to test the effectiveness of the offered approach, it is contrasted with the baseline techniques, such as traditional rule-based scheduling and energy-blind production planning. The performance measurements that will be taken into consideration are: total energy cost, the ratio of renewable energy use, peak grid power demand, and production delay. Simulation framework enables the systematic study of system behavior in various conditions such as the renewable penetration in the system and the workload intensity. This gives a full justification of the methodology proposed and its relevance to a real world smart manufacturing environment. The parameters used in the implementation of the intelligent energy management algorithm are shown in Table 3.

*Table 3: Algorithm Parameters*

| Parameter                  | Value |
|----------------------------|-------|
| Learning rate              | 0.01  |
| Discount factor            | 0.9   |
| Episodes                   | 800   |
| $\alpha$ (cost weight)     | 0.5   |
| $\beta$ (delay weight)     | 0.3   |
| $\gamma$ (emission weight) | 0.2   |

## Results and Discussion

The efficiency of the suggested intelligent energy management scheme is compared to traditional rule-based and energy blind scheduling methods. The outcomes obviously show that the combination of predictive intelligence and adaptive scheduling can greatly improve the overall system performance in the variable renewable energy conditions. Table 4 shows the comparison between the performance of the proposed intelligent energy management strategy and the conventional methods.

*Table 4: Performance Comparison*

| Method       | Energy Cost (₹) | Renewable Utilization (%) | Peak Grid Load (kW) | Delay (hrs) |
|--------------|-----------------|---------------------------|---------------------|-------------|
| Conventional | 12500           | 45                        | 18                  | 2.5         |
| Rule-based   | 11000           | 55                        | 15                  | 1.8         |
| Method       | 8500            | 78                        | 10                  | 1.2         |

There is a significant decrease in the amount of grid energy used as a result of proper exploitation of renewable energy available. The suggested approach will be more effective in utilizing renewable energy since machine activities coincide with the times when renewable energy is at its peak. The result is a visible reduction in overall energy expenses and this is mainly due to the lessening reliance on costly grid energy. By contrast, baseline approaches have an ineffective energy consumption behavior, with the common usage of grid energy at peak times. Figure 4 shows that the suggested strategy is successful in minimizing energy expenses, decreasing grid reliance, and enhancing the use of renewable energy sources over the standard practices.

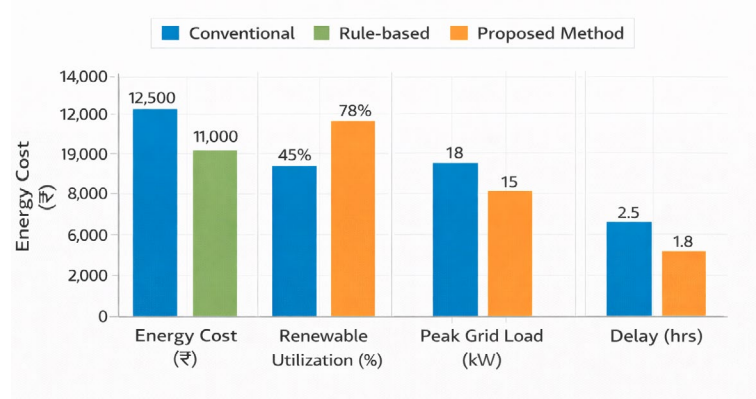


Figure 4: Performance Comparison Chart

It also results in a reduction of the peak grid load, which shows the potential of the intelligent framework to flatten demand profiles and prevent sharp spikes in energy demands. This helps achieve better grid stability and lower stress in infrastructure operation. Further, the suggested model ensures efficiency in production by reducing job delays due to adaptive scheduling. Although there might be minimal delays during severe cases of shortage of renewables, the net effect of the system is a trade-off between energy savings and production objectives. Forecasting and real-time decision-making is an effective way of dealing with the effect of the variability of renewable. The strategy is based on reinforcement learning and can adjust to the changing conditions and constantly enhance the performance of scheduling. Sensitivity analysis also shows that the weighting factors allow prioritizing cost, delay and environmental targets flexibly with proper tuning of these factors. Figure 3 shows the time-varying energy consumption profile as per the proposed strategy, emphasizing the use of renewable resources and grid reliance.

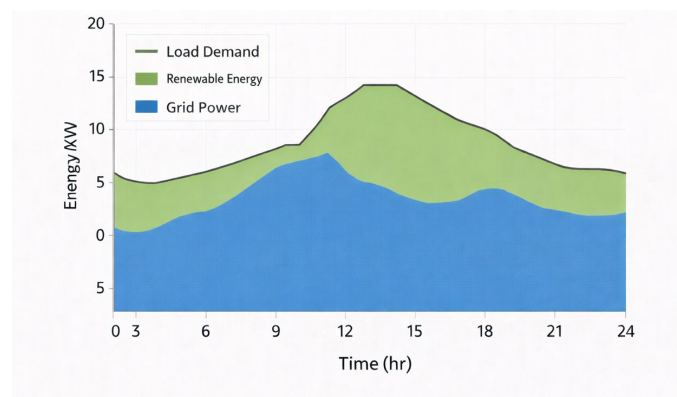


Figure 3: Energy Consumption vs Time Graph

## Conclusion

A smart energy management system of manufacturing systems that is combined with renewable energy sources has been introduced. The suggested solution is a combination of predictive

modeling and adaptive scheduling to deal with the problem of the intermittent availability of energy. To reduce the cost of energy, delay in production and the impact of the environment a multi-objective formulation is created and enabled to meet operational constraints. The implementation shows that smart management of the energy supply and manufacturing demands results in a great enhancement in the use of renewable energy, a decrease in grid reliance, and the general savings of money. The proposed strategy is adaptive, which guarantees its strong performance in dynamic and uncertain scenarios and makes it suitable in real-time industrial use. The framework is practically applicable in the framework of smart manufacturing and sustainable industrial development. Future research could be on adding new sophisticated storage schemes, scaling the model to large scale distributed manufacturing systems and testing the model in real time in industries.

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