A multiphase AI approach for carbon emission reduction: optimizing solar integration and industrial operations

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Abstract

Addressing the urgent need for carbon emission reduction, this project presents an AI-driven system designed to optimize solar energy adoption in both businesses and households. The system offers a dual approach: a sophisticated multi-phase optimization framework to obtain the best settings for an industry or a private house, and personalized renewable energy planning for machines and utilities. By leveraging real-world datasets, our software determines optimal solar panel and battery configurations based on geographical location and energy consumption patterns, providing clear projections for investment payback. In particular, focusing on an industrial application, a four-phase methodology is introduced. This methodology first establishes a 100% sustainability baseline, then analyzes the economic horizon of this investment, subsequently optimizes a mixed-energy strategy (solar, battery, and grid), and finally develops an optimal operational schedule for machinery to minimize reliance on external energy sources. This approach aims to deliver feasible, actionable insights that drastically reduce carbon emissions while considering economic viability, thereby empowering users to make impactful decisions towards a sustainable future.

1 Introduction

The escalating climate crisis underscores the critical need for innovative solutions to reduce global carbon emissions. Transitioning to cleaner energy sources is paramount, yet the practical implementation of such transitions presents significant challenges for both individuals and industries. Our work is motivated by the principle of ”AI for Social Good,” aiming to leverage artificial intelligence to address these pressing societal issues. We focus on developing practical, data-driven tools that move beyond theoretical exercises to offer feasible and actionable strategies for carbon reduction.

While personalized renewable energy planning for general users is a component of our broader system, this paper specifically details the multi-phase optimization framework designed for industrial settings, where energy consumption is complex and operational efficiency is crucial. This framework systematically guides a company through evaluating full sustainability, understanding the economic implications, optimizing a hybrid solar-grid energy mix, and finally, fine-tuning machine scheduling to maximize self-consumption of produced solar energy and minimize reliance on purchased grid energy. We elaborate on the mathematical models underpinning each phase, the data sources utilized, and the promising results from a case study that demonstrate significant potential for carbon emission reduction in real-world scenarios.

2 Data foundation for intelligent optimization

Our AI system's efficacy relies on comprehensive, realistic data. We utilize two primary categories of data: solar power production and machines' energy consumption profiles.

2.1 Solar power output modeling

To accurately model the energy generated by solar panels, we consider both meteorological conditions and specific panel characteristics.

- **Weather data:** Historical and forecasted weather conditions for specific locations (in our example: Padua, Italy) are obtained via the Open-Meteo weather API (Zippenfenig 2024). This includes parameters like solar irradiance, temperature, wind speed and precipitation probability.
- **Photovoltaic Modeling:** The power output of a specific solar panel model (in our example: Canadian Solar Inc. CS6X-300M) is calculated using the ‘pvlib‘ Python library. This library implements established physical models to estimate the panels' energy generation.
- **Machine Learning model:** To enable rapid calculations within our optimization framework, we trained a Machine Learning model to mimic the weather-to-power conversion functions of ‘pvlib‘. A Support Vector Machine was trained on 2024 weather history, obtaining a mean accuracy of 99.8% in predicting hourly solar power output compared to pvlib calculations over different weather tests (of the year 2025), demonstrating its ability to accurately predict power output based on weather inputs.

2.2 Factory machines' load profile

Understanding the energy demand is critical for optimization. For industrial use cases, we utilize detailed consumption data. The primary dataset employed is the "Industrial Machines Dataset for Electrical Load Disaggregation" (de Mello Martins et al. 2018). This dataset provides hourly power consumption data for various industrial machines within an animal food production company. The specific machines analyzed include two Pelletizers, two Milling machines, and two exhaust fans. This granular data allows our AI to understand the factory's operational patterns, peak load times, and the energy requirements of individual processes.

3 Phased optimization framework for industrial applications

For industrial clients, we propose a comprehensive four-phase optimization process. This structured approach breaks down a complex problem into manageable stages.

3.1 Core scheduling model elements

The optimization models used in the following phases share a common structure, including sets, parameters, and decision variables related to machine scheduling and energy management. Below, we provide an overview of the key parameters that define our models. A full specification can be found in our code repository[1].

To begin with, we discretize the scheduling horizon into time steps. At each time step, we track the predicted energy output of a single solar panel, the maximum available energy (from both solar panels and the grid), and the cost of imported energy, in Watt.

Each machine is assigned a number of jobs, along with the energy required to start the machine at any given time and the energy needed for operation. Jobs also have a specified duration and a cooldown period following execution.

The number of solar panels (N_P) and batteries (N_B), each associated with a specific cost and storage capacity, is determined during Phases 1 and 3.

The resulting decision variables indicate when machines should be powered on and the amount of energy stored in batteries at each time step. Additionally, for imported energy, the model determines how much should be drawn from the grid during each time step.

3.2 Phase 1: baseline 100% sustainability assessment

Objective and constraints. The objective of the first phase is to determine the minimum number of solar panels (N_P) and battery units (N_B) needed for 100% self-sufficiency.

The complete set of constraints includes:

1. **Energy Balance:** At every time step, no energy should be imported from the grid.
2. **Battery Charge Level:** The battery starts fully discharged and can be charged up to its maximum capacity, defined by the number of batteries multiplied by their individual capacity.
3. **Job Completion:** Each job assigned to a machine must be executed for its entire specified duration.
4. **Machine Exclusivity:** At any time step, each machine can process at most one job.
5. **Start-Run Consistency:** A job can only run if it has just started at that time step or was already running in the previous time step.
6. **Maximum Power Draw:** There is a limit on the total energy consumption allowed at each time step.
7. **Mutual Exclusion (Shared Resources):** For groups of machines that share resources, only one machine from the group can operate at a time.
8. **Restricted Operation Windows:** Certain machines are prohibited from running during specific time intervals due to maintenance or workforce scheduling.
9. **Job Dependencies and Deadlines:** Some machines must complete their i-th job before the i-th job of other machines, and every job must be finished by its deadline.
10. **Cooldown Period:** When a machine starts one job, it must have been idle for a certain number of time steps beforehand if it was previously active.

Solutions and use case results This model can be solved using SCIP (Bestuzheva et al. 2021).

Due to its complexity, a heuristic involving binary search on N_P, N_B combined with CSP feasibility checks for the scheduling subproblem was also explored, but it didn't give the expected results.

3.3 Phase 2: temporal horizon analysis

Objective. In the second phase, our goal is to calculate the equivalent operational duration of grid energy covered by the investment made in Phase 1. Let C_{total}^{P1} represent the total cost of batteries and panels from Phase 1, and C_{annual}^{grid} denote the annual cost of grid energy without any solar or battery system. The relationship is given by:

$$\text{Temporal Horizon (years)} = \frac{C_{total}^{P1}}{C_{annual}^{grid}} \tag{1}$$

3.4 Phase 3: optimized hybrid energy configuration

Objective and constraints. Over the time horizon established in Phase 2, determine the optimal number of panels and batteries, N_P^* and N_B^*, that minimize the total energy cost, including both capital and operational expenses. The constraints build upon those from Phase 1, but are adapted to account for grid power usage.

Solutions and use case results. This larger model can be solved using SCIP (Bestuzheva et al. 2021). Due to the complexity of this expanded model, it is solved by first identifying a feasible solution with SCIP, followed by local optimization using a local search algorithm to improve the results.

[1] https://github.com/endlessDoomsayer/AI_for_social_good

3.5 Phase 4: smart operational scheduling

Objective and constraints. With fixed number of panels and batteries (derived from Phase 1 or Phase 3, depending on whether external energy use is allowed), the goal is to determine a daily or weekly schedule that minimizes grid energy costs - or eliminates grid usage entirely. This problem is formulated as a constraint satisfaction problem (CSP). The constraints are those from Phase 1 or Phase 3, respectively, but applied with fixed numbers of panels and batteries.

Solution. The problem is solved using OR-Tools (Perron and Furnon 2024) with the following approaches:

- **Standard Backtracking Search.**
- **Advanced Backtracking Search:** Incorporates heuristics such as Most Constrained Variable and Least Constraining Value, along with advanced methods like Backjumping, No-Good Learning, and Constraint Propagation techniques (e.g., Arc Consistency).

Local Search for Adaptability. If certain constraints evolve over time, techniques such as Simulated Annealing and Tabu Search are used to efficiently adapt and refine the schedules without the need to solve the model from scratch. The results demonstrate the effectiveness of Tabu Search in solving this type of problem.

4 Results and evaluation

Implementation of the four-phase optimization framework generated quantifiable results for the industrial application.

Phase 1 & 2 results determined the infrastructure requirements for 100% energy self-sufficiency: 2491 solar panels and 169 battery units, representing an investment equivalent to 11 years of conventional grid energy expenditure. This configuration demonstrates strong economic feasibility within the 25-year operational lifetime of solar technology.

Phase 3 results optimization yielded a hybrid energy solution requiring 1339 panels and 12 batteries, achieving substantial capital cost reduction while maintaining maximum renewable energy integration over a 4-year payback period.

Phase 4 results are demonstrated through optimized machine schedules. Figure 1 shows an example of an optimal schedule for a 2-day period, illustrating how machine operations are aligned with predicted solar energy production to minimize grid reliance. Furthermore, Figure 2 demonstrates the system's adaptability, showing an adjusted schedule that respects newly introduced "silent periods" where certain machines cannot operate.

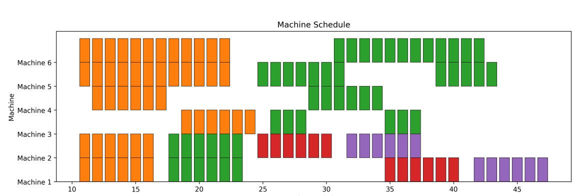

Figure 1: Example of an optimal machine schedule for 2 days, reducing to zero imported energy.

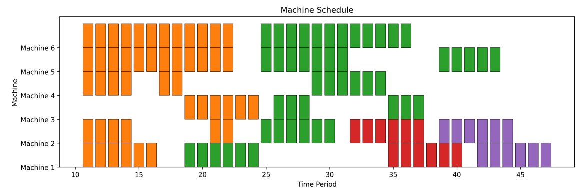

Figure 2: Optimal machine schedule obtained from the one of 1, accommodating different silent periods.

The quantitative outcomes from each phase, particularly the reduction in necessary panel/battery capacity in Phase 3 compared to Phase 1, and the subsequent optimized scheduling in Phase 4, highlight the system's ability to drastically reduce potential carbon emissions by maximizing solar energy self-consumption and minimizing energy purchased from potentially non-renewable grid sources. The economic feasibility is also clearly addressed through payback period estimations and phased investment strategies.

5 Conclusion and future Work

This paper introduced an AI-driven system aimed at reducing carbon emissions through intelligent renewable energy adoption and optimized industrial operations. Our approach, grounded in the "AI for Social Good" paradigm, emphasizes real-world feasibility by providing a detailed four-phase optimization framework for industrial applications.

The system successfully leverages real-world datasets for solar production modeling and factory load profiling. The phased methodology for industrial settings demonstrates a robust pathway to significant carbon reductions and cost-effective green investments. The use of MIP and CSP techniques, coupled with heuristics for adaptability, ensures that the solutions are both effective and computationally tractable for practical deployment.

Future work could involve expanding the range of renewable energy sources considered (e.g., wind), incorporating more dynamic electricity pricing models, and further enhancing the ML models for predictive accuracy of both energy generation and consumption. Introducing additional soft constraints that reflect the preferences of industries and private users could also enable more tailored optimizations.

Ultimately, our work contributes a practical and impactful AI tool to support the transition towards a more sustainable energy future.

References

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