



Sustainable Energy Supply Optimization for a Mine in Yazd Province Using Hybrid Renewable Energy Systems

Amirmohammad Dehghani Fakhraabadi¹ – Negar Tajik² – Reza Mirkhovand Chegini³ – Leila Babaei⁴

¹ Department of Physics and Energy Engineering, Amir Kabir University of Technology, Tehran, Iran (amirdehghani@aut.ac.ir)

² Department of Physics and Energy Engineering, Amir Kabir University of Technology, Tehran, Iran (Negartajik@aut.ac.ir)

³ Department of Physics and Energy Engineering, Amir Kabir University of Technology, Tehran, Iran (reza.mirkhovand@aut.ac.ir)

⁴ Department of Environment, University of Tehran, Tehran, Iran (l.babaei@ut.ac.ir)

ABSTRACT

Off-grid and weakly interconnected mining operations are highly energy-intensive and remain heavily dependent on diesel generation, despite the rapidly improving economic viability of renewable energy and battery storage technologies. This paper presents a mixed-integer linear programming (MILP) model, developed in the Pyomo optimization framework, for the simultaneous long-term capacity expansion and hourly operational scheduling of a hybrid photovoltaic-wind-battery-diesel-grid energy system supplying the mine in Yazd Province, Iran. The formulation incorporates discrete equipment sizing, binary investment timing with fixed mobilization costs, diesel generator unit commitment, and battery lifetime modeling through an energy-throughput constraint. Four planning scenarios (business-as-usual, least-cost economic optimum, a 40% decarbonization pathway, and a 95% deep decarbonization pathway) are evaluated over a 20-year horizon. The economic optimum achieves 87% renewable penetration with a net present cost of USD 106.7 million, a 20.6% reduction from the baseline, while cutting cumulative CO₂ emissions by approximately 90%. A key finding is that the 40% decarbonization scenario is identical to the economic scenario, as the cost-optimal solution already achieves this target. Deep decarbonization (95% reduction) is achieved at nearly the same net present cost (USD 106.9 million) as the economic optimum, in this case, near-zero emissions carry essentially no cost penalty. These results demonstrate that renewable integration in mining is economically superior to continued grid and diesel reliance.

Keywords: hybrid renewable energy systems, mixed-integer linear programming, mine electrification, battery energy storage, capacity expansion planning, unit commitment, Pyomo

1. INTRODUCTION

Mining operations are among the most energy-intensive industrial activities, and many mine sites sit far from strong grid infrastructure and rely heavily on diesel generation, exposing them to volatile fuel prices, logistics risk, and significant CO₂ emissions. Yazd Province, where the mine deposit is located, combines high direct-normal solar irradiance with a favorable diurnal wind pattern, making a PV-wind-battery hybrid retrofit a technically attractive complement to the existing diesel and grid supply [1].

Long-term energy-system optimization for such sites is typically formulated as a linear program (LP) minimizing discounted system cost subject to demand, resource and reliability constraints - the approach underlying widely used open-source frameworks such as OSeMOSYS [2]. A pure LP, however, cannot represent several decisions that are intrinsically discrete: equipment is manufactured and procured in standard unit sizes, investment projects are executed in lumpy batches rather than smooth annual increments, diesel generators must be committed on or off with a minimum stable load, and a battery's usable lifetime is bounded by a finite number of charge-discharge cycles rather than by calendar time alone [3]. Recent literature on mining and remote microgrids increasingly formulates at least the operational layer as a mixed-integer linear

program (MILP) to capture unit commitment and reliability behavior more faithfully [4][1], while techno-economic sizing studies for isolated PV-wind-battery-diesel systems continue to explore both metaheuristic and exact optimization routes [5][6].

This paper reformulates the mine's energy-supply optimization problem as a single MILP, implemented end-to-end in the open-source Pyomo algebraic modeling language [7], and solved with an open-source solver so the workflow remains fully reproducible without commercial licensing costs. The specific contribution relative to a standard LP capacity-expansion formulation is fourfold: (i) new PV, wind and battery capacity is sized in discrete standard-size units rather than continuous MW/MWh; (ii) a binary investment-timing variable per technology per year, linked through a big-M constraint, reproduces realistic lumpy investment and lets the model charge a fixed mobilization cost only in years when a project is actually executed; (iii) the diesel generator is modeled with a full unit-commitment layer (on/off status, minimum stable load, start-up cost); and (iv) battery sizing is coupled to operation through a cycle-life throughput constraint that prevents the optimizer from undersizing storage and over-cycling it beyond what the cell chemistry can survive. Four scenarios (baseline, unconstrained economic optimum, a 40% decarbonization pathway, and a 95% deep decarbonization pathway) are compared over a 20-year horizon for the the site.

1.1 Related Work

Howells et al. [2] introduced OSeMOSYS as a transparent, fully open-source long-run energy-planning LP, which is the formulation this work extends into the mixed-integer domain. Bynum et al. [7] describe Pyomo, the Python-embedded algebraic modeling language used here to implement both the LP and MILP variants. Ranjbar et al. [4] propose a bi-level NSGA-II/MILP planning method for an off-grid mining microgrid that jointly considers cost, emissions and frequency stability, illustrating the trend toward mixed-integer operational layers in mine-site studies. Belboul et al. [5] optimize an isolated PV-wind-battery-diesel microgrid with a metaheuristic (improved Salp Swarm Algorithm), representing the alternative, non-exact branch of the literature that this MILP formulation complements by guaranteeing bound-provable optimality (or a certified gap) for a given scenario. Shi et al. [3] formalize a convex cycle-based battery degradation model for storage planning and operation, motivating the simplified linear cycle-life throughput cap adopted in Section 2.4 as a tractable proxy for the same underlying phenomenon.

2. METHODOLOGY

2.1 Model Overview and Time Representation

The planning horizon spans $Y=20$ years. To resolve diurnal and seasonal dynamics of load, solar and wind without a full 8760-hour model, each year is represented by one representative day per season, each with 24 hourly time-steps. This choice of four representative days was made to capture the distinct seasonal characteristics of solar irradiance and wind patterns in Yazd Province, where summer and winter exhibit significantly different renewable generation profiles. Spring and autumn serve as transitional periods with intermediate resource availability. While a full 8760-hour chronological simulation would provide greater temporal fidelity, the representative-day approach reduces the model size from 175,200 hours ($20 \times 8,760$) to 1,920 representative hours ($20 \times 4 \times 24$), making the MILP computationally tractable. This resolution is sufficient for capacity expansion planning and techno-economic assessment, while future work may refine the temporal resolution to capture inter-day and intra-seasonal variability more accurately.

Each representative hour is scaled by the number of calendar days its season spans, so that summed dispatch reproduces annual (MWh) totals correctly. Decision variables fall into three groups: (a) capacity-expansion variables (new units built per technology and year), (b) investment-timing binaries, and (c) hourly dispatch and storage variables for every (y,s,h) .

2.2 Objective Function

The objective minimizes the net present value (NPV) of total system cost over the horizon:

$$NPV = \sum_{y=1}^Y \frac{\text{AnnualCost}(y)}{(1+r)^{(y-1)}} \quad (1)$$



where r is the discount rate. $AnnualCost(y)$ is decomposed into five components so the results can be attributed transparently:

$$AnnualCost(y) = CAPEX(y) + FOM(y) + VOM + Fuel(y) + Grid(y) + Penalty(y) \quad (2)$$

$CAPEX(y)$ includes technology-specific capital cost (with an annual learning-curve decline applied to the unit cost) plus the fixed mobilization cost triggered by the investment-timing binaries described in Section 2.3; $FOM(y)$ is fixed operations and maintenance on installed capacity; $VOM + Fuel(y)$ covers variable O&M, diesel fuel and generator start-up costs; $Grid(y)$ is the time-of-use cost of grid electricity purchases; and $Penalty(y)$ prices unmet demand at the value of lost load, keeping the model feasible under all scenarios while still discouraging reliability shortfalls.

2.3 Discrete Sizing and Lumpy Investment Timing (MILP layer)

New capacity of technology $t = \{PV, WIND, BATT-E, BATT-P\}$ in year y is an integer number of standard-size unit:

$$capNew_{t,y} = nUnit_{t,y} \cdot UnitSize_t \quad \forall nUnit_{t,y} \in \mathbb{Z}^+ \quad (3)$$

A binary $Invest_{t,y}$ gates whether any new capacity of technology t is built in year y , linked through a big-M constraint, and a fixed cost is charged in the objective only when $Invest_{t,y} = 1$:

$$nUnit_{t,y} \leq M_t \cdot Invest_{t,y} \quad (4)$$

This construction reproduces the batching behavior of real capital projects - a handful of large procurement events rather than a smooth trickle of fractional capacity every year-and lets the fixed engineering/interconnection/mobilization cost of a project be charged only in the year it is actually executed.

2.4 Operational Constraints

Energy balance must hold in every representative hour:

$$PV_{y,s,h} + Wind_{y,s,h} + Diesel_{y,s,h} + Grid_{y,s,h} + Dis_{y,s,h} - Chg_{y,s,h} + Unmet_{y,s,h} = Demand_{y,s,h} \quad (5)$$

PV and wind output are capped by installed capacity times the season/hour capacity factor; the diesel generator is modeled with a full unit-commitment layer using a binary on/off status, a minimum stable load fraction, and a start-up indicator (relaxed to a continuous $[0,1]$ variable, which is driven to the correct binary value at the optimum by its strictly positive cost coefficient):

$$Diesel_{y,s,h} \leq cap_{diesel} \cdot On_{y,s,h} \quad (6)$$

$$Diesel_{y,s,h} \geq f_{min} \cdot cap_{diesel} \cdot On_{y,s,h} \quad (7)$$

$$Start_{y,s,h} \geq On_{y,s,h} - On_{y,s,h-1} \quad (8)$$

Battery state of charge follows standard storage dynamics, applied cyclically within each representative day:

$$SOC_{y,s,h} = SOC_{y,s,h-1} + \eta_{ch} \cdot Chg_{y,s,h} - \frac{Dis_{y,s,h}}{\eta_{dis}} \quad (9)$$

Finally, the battery cycle-life throughput cap ties dispatch to sizing: total annual discharge cannot exceed the maximum number of equivalent full cycles the cell chemistry is rated for per year (rated cycle life divided by target calendar life) times the installed energy capacity - preventing the optimizer from sizing a small, cheap battery and cycling it harder than it could physically survive:



$$\sum_{h \in H} (P_{y,h}^{\text{ch}} + P_{y,h}^{\text{dis}}) \cdot \Delta t \leq N^{\text{cycle}} \cdot E_y^{\text{bat}} \quad (10)$$

2.5 Scenario Definition

Four scenarios are solved with the same model, differing only in which capacity-expansion and emissions constraints are active, so results are directly comparable:

Table 1. Scenario definitions

Scenario	New PV/Wind/Battery allowed?	CO2 cap (final year)
Baseline	No (grid + existing diesel only)	None
Economic	Yes	None
Decarbonization (40%)	Yes	-40% vs. baseline
Deep decarbonization (95%)	Yes	-95% vs. baseline

3. CASE STUDY

3.1 Site

The mine (Yazd Province, Iran) is used as the case study. The mine is presently supplied primarily by the Iranian national electricity grid, with on-site diesel generation providing emergency backup during grid outages or supply interruptions. Its electricity demand exhibits a pronounced industrial load profile, increasing sharply from approximately 08:00 and typically reaching its daily maximum between 12:00 and 16:00, while continuous auxiliary processes such as pumping, lighting, and safety systems maintain a substantial base load of approximately 30–50% of peak demand during lower-activity periods.

The renewable resource potential of the site was characterized using typical meteorological year (TMY) data for Yazd Province. Solar capacity factors reach 0.88 in summer and 0.72 in winter, with an annual average solar irradiance of approximately 5.5–5.8 kWh/m²/day [8]. Wind capacity factors range from 0.24 in summer to 0.42 in winter, with a night-time bonus that increases output during evening and early morning hours. This complementary pattern reduces storage requirements and enhances the economic viability of the PV-wind hybrid system.

3.2 Data and Key Assumptions

Table 2 lists the principal technical and economic parameters used in the base case. The 18% discount rate reflects the prevailing cost of capital for industrial investments in Iran under current economic conditions. The diesel price of USD 0.65/L is based on the free-market price of industrial diesel in Iran, as reported by domestic energy agencies. Technology cost trajectories (annual decline rates) follow global trends reported by IRENA [9]. Absolute capital costs are assumed above the 2023 IRENA global weighted averages (USD 758/kW for solar PV, USD 1,154/kW for onshore wind, USD 273/kWh for battery storage) to reflect the import, financing, and currency-risk premiums typical of sanctioned markets; battery costs align closely with the global average given the more globally-fungible nature of cell supply chains.

Table 2. Principal techno-economic parameters

Parameter	Value	Unit
Planning horizon	20	years
Discount rate	18	%
Peak mine demand	28	MW
Demand growth rate	2	%/yr
PV reference CAPEX	1,200,000	USD/MW



PV CAPEX decline rate	3	%/yr
PV fixed O&M rate	1.5	% of CAPEX/yr
PV variable O&M	1	USD/MWh
PV unit size	1	MW
Wind reference CAPEX	1,500,000	USD/MW
Wind CAPEX decline rate	2	%/yr
Wind fixed O&M rate	2.5	% of CAPEX/yr
Wind variable O&M	2	USD/MWh
Wind unit size	2	MW
Battery energy CAPEX	300,000	USD/MWh
Battery power CAPEX	150,000	USD/MW
Battery CAPEX decline rate	6	%/yr
Battery fixed O&M rate	1.5	% of CAPEX/yr
Battery energy unit size	1	MWh
Battery power unit size	0.5	MW
Battery charge efficiency	97.5	%
Battery discharge efficiency	97.5	%
Battery max DoD	90	%
Battery rated cycle life	5,000	cycles
Battery design life	12	years
Existing diesel capacity	15	MW
Diesel FOM	8,000	USD/MW/yr
Diesel fuel price	0.65	USD/L
Diesel efficiency	0.3	L/kWh
Diesel emission factor	0.84	t CO ₂ /MWh
Grid import limit	40	MW
Grid off-peak price	45	USD/MWh
Grid mid-peak price	75	USD/MWh
Grid on-peak price	125	USD/MWh
Grid price escalation	5	%/yr
Grid emission factor	0.575	t CO ₂ /MWh
Value of lost load	3,000	USD/MWh



4. RESULTS AND DISCUSSION

This section presents the optimal capacity expansion and operational dispatch results for the four planning scenarios defined in Section 2.5. We first compare the overall economic and environmental performance of each scenario, then examine capacity expansion timing, followed by detailed operational behavior of the battery and diesel generator, and finally discuss the implications for mine decarbonization. The model is implemented in Pyomo and solved with the HiGHS MILP solver.

4.1 Scenario Comparison

Table 3 summarizes the key performance indicators for all four scenarios at the end of the 20-year planning horizon. The baseline scenario, representing continued reliance on the national grid and existing diesel generators, results in the highest net present cost (NPV) of USD 134.3 million, final-year CO₂ emissions of 148 kt, and cumulative emissions of approximately 2,600 kt.

Table 3. Scenario results summary (final planning year values)

Metric	Baseline	Economic	Decarbonization (40%)	Deep Decarbonization (95%)
PV capacity (MW)	0	45	45	55
Wind capacity (MW)	0	40	40	35
Battery energy capacity (MWh)	0	40	40	65
Battery power capacity (MW)	0	20	20	32.5
Renewable share (%)	0	87	87	94
NPV cost (MUSD)	134.3	106.7	106.7	106.9
Final-year CO ₂ (kt/yr)	148	15	15	6.97
Cumulative CO ₂ (kt)	2,600	270	270	125
Unmet demand (MWh, total horizon)	0	0	0	0

The economic scenario achieves an 87% renewable penetration while reducing the NPV cost by 20.6% (to USD 106.7 million) compared to the baseline. A key finding is that the 40% decarbonization scenario is identical to the economic scenario. The cost-optimal solution already achieves final-year emissions of 15 kt/yr, which represents an 89.9% reduction from the baseline (148 kt) and exceeds the 40% target. This demonstrates that moderate decarbonization targets may be non-binding and provide no additional incentive beyond what economic optimization already delivers.

The deep decarbonization scenario (95% reduction) achieves 94% renewable share and near-zero emissions (6.97 kt CO₂/yr) at an NPV cost of USD 106.9 million, nearly identical to the economic scenario. In other words, once the model is already building PV, wind and batteries for cost reasons, pushing emissions down further from 15 kt/yr to 6.97 kt/yr adds only USD 0.2 million to the 20-year NPV.

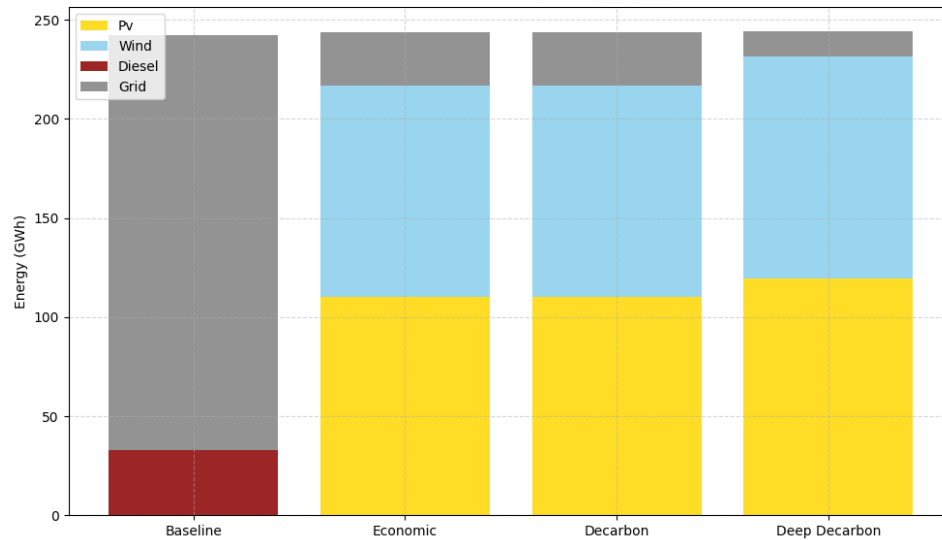


Fig. 1. Final-year electricity generation mix across all scenarios.

Figure 1 illustrates the final-year generation mix. In the economic scenario, PV and wind account for approximately 87% of electricity supply, with grid imports limited to off-peak hours (nights and early mornings) when prices are lowest (\$45/MWh). Diesel generation is nearly eliminated, operating only during a few hundred hours per year when both renewables and grid import are insufficient. As the CO₂ cap tightens, the model progressively displaces grid imports (which have a higher emission factor of 0.575 t/MWh) with additional renewables. This results in an almost fossil-free electricity supply in the deep decarbonization scenario.

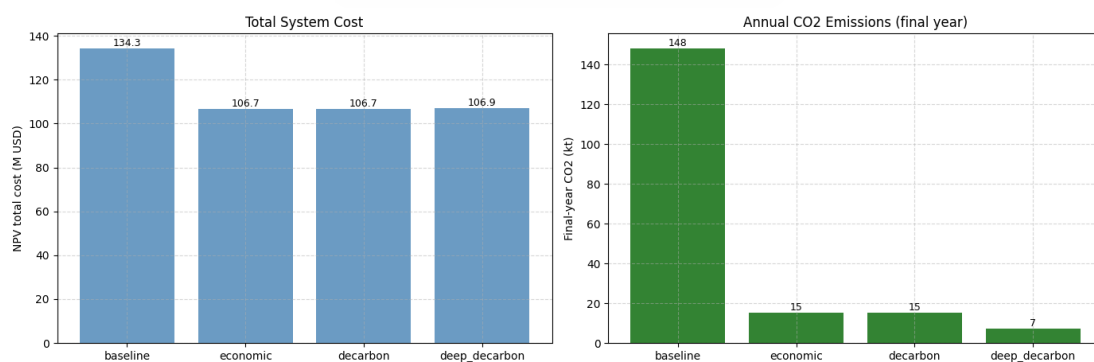


Fig. 2. NPV total cost vs. final-year CO₂ emissions (economic-environmental trade-off).

Figure 2 presents the trade-off between economic and environmental performance. The baseline scenario is the most expensive and the most carbon-intensive. The economic, 40% decarbonization, and deep decarbonization scenarios all have the approximately same NPV cost (USD 106.9 million), but with progressively lower emissions (15 kt/yr, 15 kt/yr, and 6.97 kt/yr, respectively). For this site, the three curves essentially collapse onto a single cost level across a wide range of emissions targets, indicating a flat marginal abatement cost between 15 kt/yr and 6.97 kt/yr.



4.2 Capacity Expansion Timing

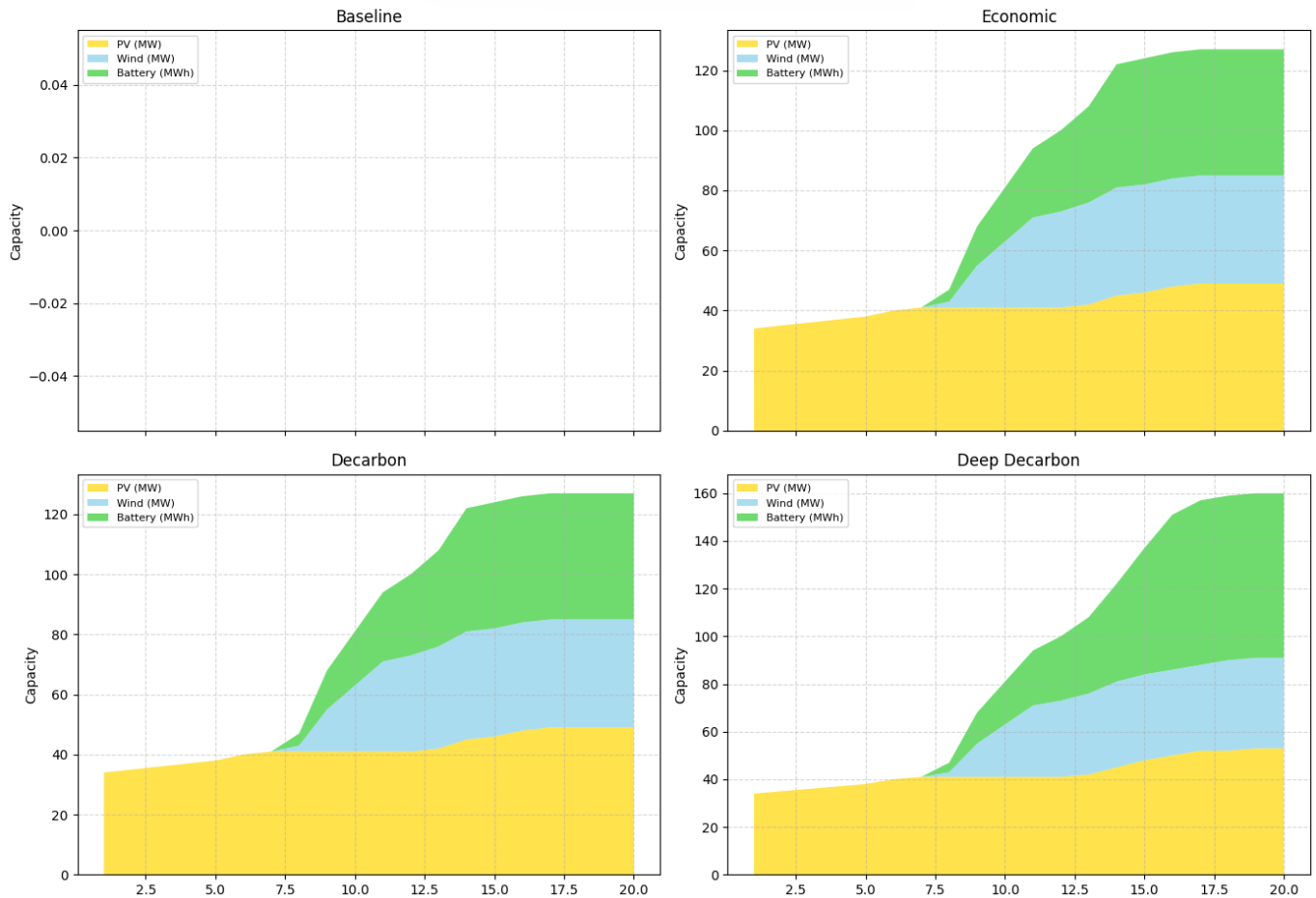


Fig. 3. Cumulative installed capacity over the planning horizon for all scenarios.

Figure 3 shows the cumulative installed capacity for PV, wind, and battery over the 20-year horizon. In the economic scenario, PV capacity reaches approximately 45 MW by year 20, wind reaches 40 MW, and battery energy capacity reaches 40 MWh. In the deep decarbonization scenario, these figures increase to approximately 55 MW, 35 MW, and 65 MWh, respectively. PV is built most aggressively because it has the lowest levelized cost and the fastest learning curve (3% annual decline). The curves exhibit distinct stair-step patterns caused by the discrete unit additions (1 MW PV, 2 MW wind, 1 MWh battery). This confirms that the integer-unit constraints are active and meaningful. PV and battery additions are concentrated in the first 8 years, driven by the high grid on-peak price and the immediate savings from displacing expensive grid imports. Wind additions are more evenly distributed across the horizon.



4.3 Renewable Transition and Emissions

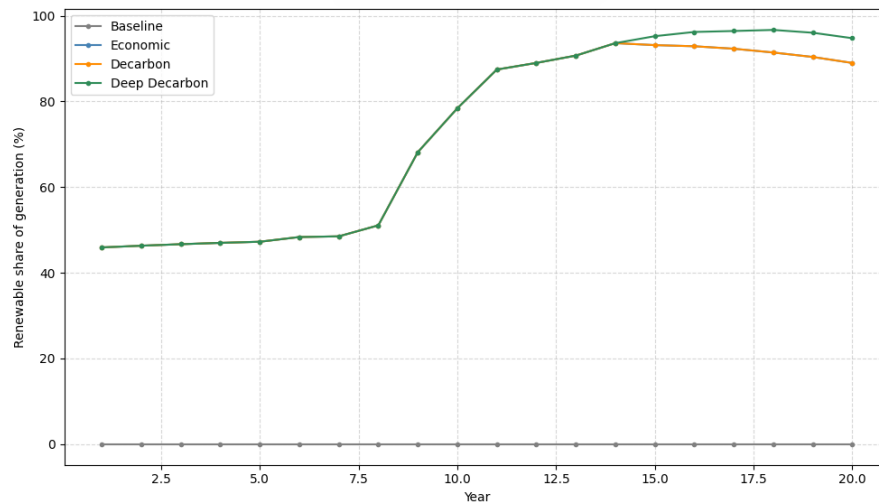


Fig. 4. Renewable share trajectory over the planning horizon.

Figure 4 shows the renewable share of electricity generation over time. The economic and 40% decarbonization scenarios reach 87% renewable by year 20. The deep decarbonization scenario reaches 94%. The front-loaded investment makes economic sense because the benefits, avoiding expensive grid purchases, begin accruing immediately.

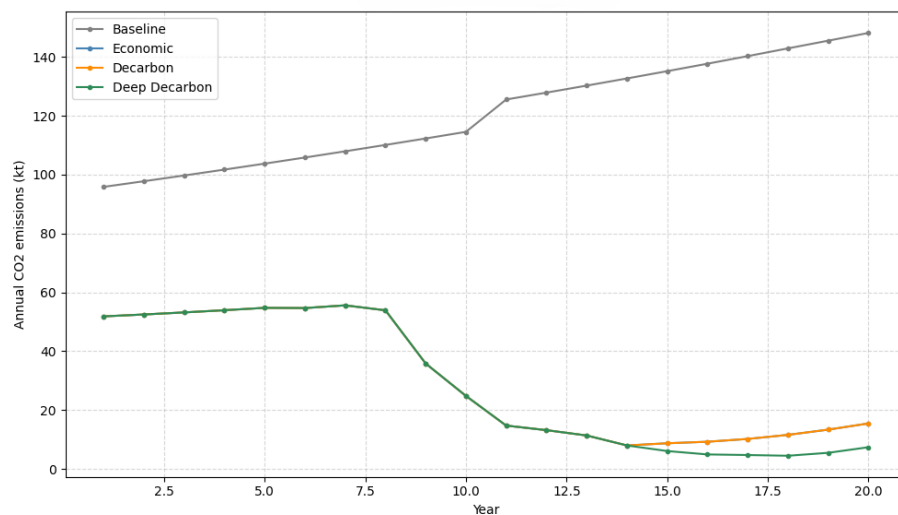


Fig. 5. Annual CO₂ emissions trajectory over the planning horizon.

Figure 5 displays the annual CO₂ emissions trajectory. Baseline emissions are 148 kt/yr. In the economic and 40% decarbonization scenarios, emissions drop sharply in the first 5 years as PV and wind are rapidly deployed, then plateau at approximately 15 kt/yr. The deep decarbonization scenario continues to reduce emissions further, reaching 6.97 kt/yr by year 20.

4.4 Operational Behavior

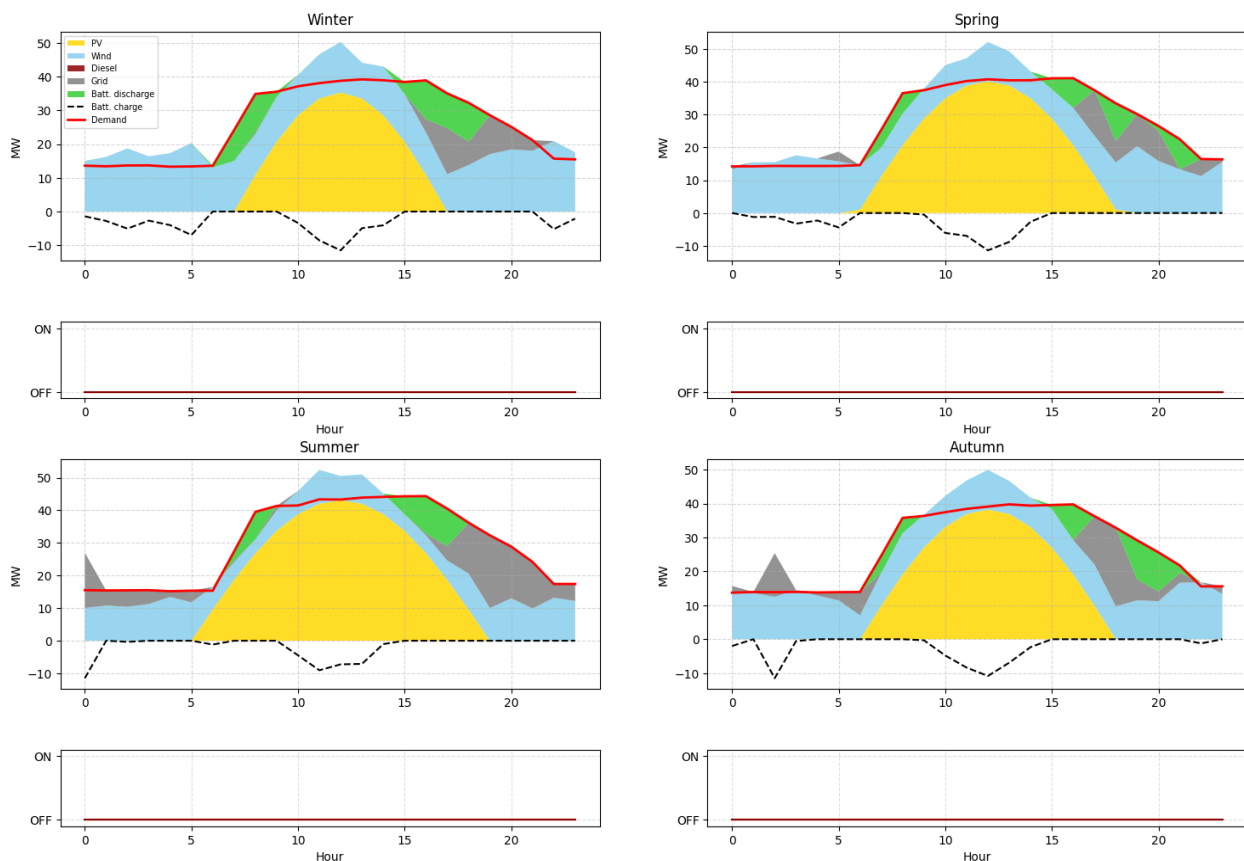


Fig. 6. Seasonal dispatch and diesel commitment (Economic scenario, final year).

Figure 6 displays the representative seasonal dispatch profiles for the economic scenario in the final year. The upper panel shows the generation mix (PV, wind, diesel, grid, battery discharge/charge) and the load demand. The lower panel shows the binary on/off status of the diesel generator. Several observations are noteworthy:

- **Summer:** PV output peaks at approximately 40 MW during midday (12:00-16:00), coinciding with the load peak. The battery charges during the midday solar surplus and discharges during the evening peak (17:00-22:00). Grid imports are minimal, and diesel is off for most hours.
- **Winter:** PV output is lower (peak approximately 25 MW) due to shorter daylight hours and lower solar angles, but wind output is higher, especially during nighttime hours due to the night-time wind bonus. Grid imports increase slightly in the early morning and late evening. Diesel is only dispatched during extreme events or grid outages, which are not captured in the representative-day framework.
- **Spring and Autumn:** These seasons exhibit intermediate behavior, with spring having higher solar output and autumn having moderate wind contribution. The battery follows the same daily charging pattern across all seasons.

The diesel unit commitment logic is clearly visible in the lower panel of each seasonal subplot. The diesel generator is turned on only when grid imports are insufficient and renewable generation plus battery discharge cannot meet the demand. It operates at its minimum stable load fraction (30% of 15 MW = 4.5 MW) and is



started infrequently. This validates the start-up cost penalty and demonstrates that the unit commitment constraints are active and meaningful.

The battery cycle-life constraint is respected, with approximately 380 equivalent full cycles per year, below the 417-cycle cap. This confirms that the battery sizing is realistic and accounts for degradation.

4.5 Discussion

The results in Table 3 point to three findings worth unpacking. First, the model does not need an emissions target to justify renewables at this site: with no CO₂ cap at all, replacing grid and diesel supply with 45 MW of PV, 40 MW of wind, and a 40 MWh/20 MW battery lowers the 20-year NPV by 20.6%, from USD 134.3 million to USD 106.7 million. The saving comes entirely from avoiding on-peak grid purchases at USD 125/MWh and diesel fuel costs, not from any carbon price.

A direct consequence is that the 40% final-year emissions cap turns out to be non-binding. The unconstrained economic optimum already cuts final-year emissions by 89.9% (from 148 to 15 kt/yr), more than double the nominal 40% target. For a site like this mine, a moderate decarbonization mandate would not change investment behavior at all; it would simply certify what the cost-minimizing solution already delivers.

What is less expected is that tightening the final-year cap all the way to a 95% reduction changes the NPV by only USD 0.2 million relative to the unconstrained optimum. Between final-year emissions of 15 kt/yr and 6.97 kt/yr, the model is essentially indifferent on cost grounds (Fig. 2).

Two modeling choices help explain why these numbers look operationally realistic rather than an artifact of over-idealized dispatch. The battery cycles about 380 times per year in the economic scenario, comfortably under the 417-cycle cap implied by the assumed 5,000-cycle rated life and 12-year design life. And the stair-step capacity trajectories in Fig. 3, driven by the integer 1 MW PV / 2 MW wind / 1 MWh battery unit sizes and the binary investment-timing variables, track the lumpy way real procurement and construction happen, rather than the smooth fractional builds a continuous LP would produce.

5. CONCLUSION

This paper has presented a mixed-integer linear programming model for the capacity expansion and operational dispatch of a hybrid renewable energy system supplying the mine. The model extends conventional LP formulations by incorporating discrete sizing, lumpy investment, diesel unit commitment, and battery cycle-life constraints.

Applied to the mine, the model demonstrates four key findings:

1. Renewables are economically superior. The economic scenario achieves 87% renewable penetration with 20.6% cost reduction (USD 134.3M to USD 106.7M NPV) and 90% cumulative CO₂ reduction.
2. The cost-optimal solution already exceeds a 40% CO₂ reduction target, achieving 89.9% reduction in final-year emissions (from 148 kt to 15 kt).
3. Deep decarbonization (95% reduction) is achievable at nearly the same cost as the economic optimum (USD 106.9 million vs. USD 106.7 million). The marginal cost of abatement is negligible (0.2%), demonstrating that near-zero emission electricity supply is economically attainable with almost no additional investment.
4. Discrete modeling produces realistic investment patterns, providing actionable guidance for procurement and construction planning.

The primary barrier to adoption is not lifecycle cost but upfront capital availability. Policy mechanisms such as low-interest green loans, power purchase agreements, or public-private partnerships could unlock substantial savings for the mining sector.



Future work will extend the model along several directions. Resource and demand uncertainty could be incorporated through stochastic or robust optimization, replacing the deterministic TMY-based solar and wind profiles with scenario trees or uncertainty sets that capture year-to-year weather variability and changes in mine production. Hydrogen storage could be added alongside the battery for seasonal energy balancing, particularly to bridge the multi-week gap between the summer solar peak and the wind-favorable winter months. Dynamic load management of mine processing equipment, such as shiftable crushing, grinding, or ventilation loads, could be co-optimized with the supply-side capacity expansion, potentially reducing both peak demand charges and reliance on diesel backup. The representative-day time resolution could also be extended toward a full chronological 8760-hour model, or supplemented with extreme-week analysis, to better capture multi-day low-renewable periods that representative days may under-represent. Finally, extending the model to a fleet-level view, incorporating electrification of mine-site haul trucks and other mobile equipment as an additional flexible load, would connect this site-level energy-supply optimization to the broader decarbonization of mining operations.

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