

Price-Incentive Distribution Grid Load Scheduling Using Hybrid Grey Wolf Optimization

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ABSTRACT

Distribution feeders increasingly require load schedules that respond to time-varying prices while preserving operational limits. This paper presents a Hybrid Grey Wolf Optimizer (HGWO) for 24-hour distribution grid load scheduling under price incentives. The method augments the leader-guided position update of the conventional Grey Wolf Optimizer with a momentum-based directional term and evaluates candidate schedules through a penalty-aware objective that combines energy price, incentive reward, and constraint violations. The model was implemented in MATLAB and assessed using hourly price, base-load, and incentive data obtained for a representative 11 kV feeder of the Port Harcourt Electricity Distribution Company. Thirty independent runs were conducted and compared with classical GWO. HGWO attained a best objective value of 38,910 €, approximately 2.3% below the GWO result, and reached a stable solution in 58 iterations compared with 82 iterations. Its standard deviation decreased from 760 € to 412 €, indicating more consistent search performance. Sensitivity tests on penalty coefficient and population size further showed lower and flatter objective responses. The results demonstrate that HGWO can improve convergence speed, robustness, and price-responsive peak-load redistribution for day-ahead feeder scheduling.

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NOMENCLATURE

Table 1 summarizes the symbols used in the objective function, operating constraints, and HGWO position-update rule.

Table 1. Nomenclature

Symbol	Description	Unit
h	Hour index (1-24)	-
$L_{base}(h)$	Base (unscheduled) hourly load	kW
$L_{sch}(h)$	Scheduled hourly load after adjustment	kW
$L_{max}(h)$	Maximum permissible hourly load	kW
$\Delta L(h)$	Price-responsive load adjustment at hour h	kW
$P(h)$	Hourly electricity price	€/kWh
$I(h)$	Hourly incentive reward	€/kWh
J	Total penalty-aware objective (fitness) function	€
J^*	Minimum (best) objective value returned by the optimizer	€
$g(h)$	Constraint violation / penalty function at hour h	-
μ	Penalty coefficient (weight on constraint violation)	-
D_{resp}^{max}	Maximum cumulative allowable demand response over 24 h	kW

Symbol	Description	Unit
$V(h)$	Feeder voltage at hour h	p.u.
$V_{\min}, V_{\max}$	Minimum / maximum permissible feeder voltage	p.u.
$X_i(t)$	Position (candidate schedule vector) of wolf i at iteration t	-
$X_\alpha, X_\beta, X_\delta$	Positions of the alpha, beta, and delta leader wolves	-
a	Linearly decreasing GWO control coefficient ($2 \rightarrow 0$)	-
A, C	Random coefficient vectors in the GWO encircling equation	-
D	Distance metric between a wolf and a leader position	-
γ	Hybrid momentum weighting coefficient (HGWO-specific term)	-
N	Population size (number of wolves)	-
T	Maximum number of iterations	-

1. INTRODUCTION

Electricity distribution systems are increasingly influenced by distributed generation (DG), demand-response programs, and time-varying price incentives, which together introduce bidirectional power flows, peak-demand volatility, and scheduling complexity that conventional dispatch methods struggle to accommodate [1], [2]. Optimal load scheduling is therefore required to align consumption profiles with market signals, avoid peak-demand penalties, and improve feeder utilization [1], [2]. The non-convex character of price-based scheduling under network constraints motivates the use of metaheuristic algorithms for practical distribution-grid optimization [3], [4].

Price-responsive scheduling is complicated by the need to balance economic signals with hourly demand limits, cumulative demand-response limits, and feeder-voltage constraints. Classical deterministic methods may become difficult to apply when the objective landscape is nonlinear, discontinuous, or penalty dominated. Although population-based optimizers such as genetic algorithms and particle swarm optimization have been applied to demand-side management [5]–[7], existing GWO-based formulations either emphasize generation dispatch over demand adjustment or treat price incentives and network constraints separately rather than within a unified penalty-aware framework [9]–[14]. This leaves a gap for an integrated, incentive-driven load scheduler that combines rapid convergence with robust constraint handling on practical distribution feeders.

This study extends the original Grey Wolf Optimizer (GWO) to a hybrid variant, HGWO, for incentive-aware distribution-grid load scheduling. GWO is chosen because its leader-guided hierarchy (alpha, beta, delta) naturally balances exploration and exploitation, it requires fewer control parameters than PSO or GA, and it has demonstrated competitive performance on non-convex power-system optimization problems [8]–[11]. The proposed hybrid augments this leader-guided search with a momentum-based directional term intended to reduce premature convergence while retaining global exploration. A penalty-aware objective function is used to integrate hourly price, incentive reward, and operational constraint violations.

The principal contribution is an HGWO scheduling framework evaluated with a representative 24-hour feeder dataset and benchmarked against classical GWO. The comparison considers the best and average objective values, convergence iterations, runtime, run-to-run variability, and sensitivity to the penalty coefficient and population size. The resulting schedule is also examined for peak shaving and valley filling.

2. RELATED STUDIES

Research on price-responsive load scheduling has employed evolutionary and swarm-intelligence techniques for several years. Genetic algorithms, particle swarm optimization, differential evolution, and GWO have been applied to reduce energy cost, lower peak demand, and coordinate flexible loads [5]–[7]. Siano [1] reviewed demand response in smart grids, while Yang [3] presented the broader role of metaheuristics in engineering optimization.

Mirjalili et al. [8] introduced GWO as a population-based optimizer that models the leadership hierarchy and hunting behavior of grey wolves. Subsequent studies adapted GWO to economic dispatch, microgrid scheduling, and integrated-energy-system optimization [9]–[11]. These adaptations generally seek better convergence, improved constraint satisfaction, or stronger coordination between generation and demand resources.

Recent applications include GWO-based demand-side management in photovoltaic-integrated smart grids, real-time-price scheduling, residential photovoltaic and battery optimization, and hybrid GWO-PSO scheduling [10], [12]–[14]. Osegi and Wokoma [15] also considered concurrent demand-supply scheduling through GWO-based machine intelligence. Although these studies demonstrate the flexibility of GWO, many

formulations emphasize generation dispatch or appliance scheduling and give less explicit attention to incentive-driven demand adjustment under a unified penalty-aware objective.

Hybrid GWO methods have also been used to improve distribution-network operation and incentive-driven microgrid performance [16], [17]. The present work differs by adding a momentum-like memory term to the standard leader-based update and by evaluating robustness through repeated runs and parameter-sensitivity studies. This formulation is intended to stabilize the hourly scheduling search while retaining the simplicity of the original GWO hierarchy.

3. METHOD

The proposed approach was evaluated with a dataset obtained from the Port Harcourt Electricity Distribution Company (PHED) for a representative 11 kV town feeder. The data correspond to a typical 24-hour weekday profile for the month of December, 2017, comprising measured hourly base load, time-of-use electricity price, and demand-response incentive signals. The profile was selected to represent a high-demand season and was not synthetically generated; however, a single representative day was used to isolate algorithmic performance from weather-driven variability.

3.1. Dataset and preprocessing

For each hour $h = 1, \dots, 24$, the dataset provides the base demand $L_{base}(h)$, electricity price $P(h)$, and incentive $I(h)$. MATLAB routines read and normalize the hourly signals while preserving their relative price and incentive patterns. Feasible upper and lower schedule bounds are then imposed before each candidate solution is evaluated. A representative subset of the data is presented in Table 2.

Table 2. Sample features from the PHED dataset

Hour	Price (€/kWh)	Base Load (kW)	Incentive (€/kWh)	Scheduled Load (kW)	Fitness Cost (€)
1	28.4	745	4.2	720	20322
4	24.6	680	4.8	666	16956
8	18.3	900	3.9	832	18122
12	27.1	1020	5.0	980	26586
16	35.2	1180	5.8	1102	38784
20	42.8	980	6.7	925	39530
24	30.5	810	5.1	785	23943

The scheduling task is formulated as a 24-hour optimization problem that minimizes weighted energy cost after incentive rewards while penalizing infeasible schedules. The resulting penalty-aware fitness is solved with HGWO and benchmarked against standard GWO under identical data and stopping conditions.

3.2. Optimization model

The objective function is expressed as follows:

$$J = \sum_{h=1}^{24} [P(h)L_{sch}(h) - I(h)\Delta L(h)] + \mu \sum_{h=1}^{24} g(h) \quad (1)$$

where J is the total penalty-aware objective, $P(h)$ is the hourly price, $I(h)$ is the incentive reward, μ is the penalty coefficient, and $g(h)$ represents the violation function at hour h . The scheduled load is defined by

$$L_{sch}(h) = L_{base}(h) + \Delta L(h) \quad (2)$$

where $L_{sch}(h)$ is the scheduled load, $L_{base}(h)$ is the unscheduled base load, and $\Delta L(h)$ is the price-responsive adjustment. The model is subject to the following operating constraints:

- (a) $0 \leq L_{sch}(h) \leq L_{max}(h)$, for $h = 1, \dots, 24$;
- (b) $\sum_{h=1}^{24} \Delta L(h) \leq D_{respmax}$; and
- (c) $V_{min} \leq V(h) \leq V_{max}$, for $h = 1, \dots, 24$.

The penalty function assigns a sufficiently large cost to schedules that violate the load, cumulative response, or feeder-voltage limits. This allows the optimizer to rank feasible and infeasible candidate schedules within a single fitness evaluation.

3.3. Hybrid Grey Wolf Optimizer

The HGWO extends classical GWO [8] by combining its encircling behavior with a directional term inspired by the velocity-memory concept of particle swarm optimization [5]. The additional term reuses each wolf's recent search trajectory, thereby improving exploitation around promising schedules while reducing the likelihood of stagnation in a complex incentive-aware objective landscape.

The HGWO position update is

$$X_i(t+1) = \frac{1}{3}(X_\alpha + X_\beta + X_\delta) - aAD + \gamma(X_i(t) - X_i(t-1)) \quad (3)$$

where $X_i(t)$ is the position of wolf i at iteration t ; X_α , X_β , and X_δ are the three leader positions; a decrease linearly from 2 to 0; A and C are random coefficient vectors; D is the distance term; and γ is the hybrid momentum weight. Classical GWO uses the averaged leader positions and scaled distance term only. HGWO adds $\gamma[X_i(t) - X_i(t-1)]$, so each update is informed by both the leader hierarchy and the wolf's recent movement.

The memory term strengthens local exploitation during the later iterations, whereas the decreasing search coefficient preserves broader exploration at the beginning of the run. The additional coefficient γ is therefore the main extra tuning parameter introduced by the hybrid method.

Algorithm 1. Hybrid Grey Wolf Optimizer for distribution-grid load scheduling

1. Initialize N wolves with random 24-hour schedule vectors X_i within the permissible load bounds.
2. Evaluate each wolf with the penalty-aware objective function J .
3. Identify the three best schedules as the alpha, beta, and delta leaders.
4. Decrease the search coefficient a linearly from 2 to 0 over T iterations.
5. Update each candidate schedule using the leader-guided GWO term and the hybrid momentum term.
6. Repair upper- and lower-bound violations and enforce schedule feasibility.
7. Re-evaluate the population and update the leader hierarchy.
8. Stop at convergence or T iterations and return X_α and the minimum objective J^* .

3.4. MATLAB implementation and parameter settings

HGWO and GWO were implemented in MATLAB using vectorized matrix operations and hourly constraint enforcement. A dedicated fitness function calculates the energy-price component, incentive reward, and penalty contribution for each candidate schedule. The best solution is selected by minimum objective value and then checked against all 24-hourly constraints.

Thirty independent runs were performed for each algorithm to assess average performance, convergence behavior, and stability. Preliminary tuning trials were used to select the parameter values, which were held constant for the comparative experiments shown in Table 3.

Table 3. HGWO and GWO parameter settings

Parameter	Symbol	Value Used
Population size	N	40 wolves
Maximum iterations	T	100
Penalty coefficient	μ	500
Hybrid momentum weight	γ	0.35
Search coefficient range	a	$2 \rightarrow 0$ (linear decay)
Independent runs per algorithm	—	30
Demand response cap	D_{resp}^{max}	180 kW
Voltage bounds	V_{min}, V_{max}	0.95 – 1.05 p.u.

4. RESULTS AND DISCUSSION

The simulations show that HGWO consistently attains a lower objective and more stable convergence than classical GWO on the PHED dataset. Table 4 presents the optimized 24-hour schedule, and Table 5 summarizes the comparative performance across 30 independent runs.

Table 4. Optimized hourly schedule

Hour	Price (€/kWh)	Base Load (kW)	Adjustment ΔL (kW)	Scheduled Load (kW)	Hourly Cost (€)
1	28.4	745	-25	720	20322
2	27.9	730	-22	708	19783
3	26.7	700	-20	680	18160
4	24.6	680	-14	666	16956
5	22.5	690	-18	672	15120
6	20.8	710	-10	700	14560
7	19.1	820	4	824	15754
8	18.3	900	-68	832	18122
9	19.8	940	-32	908	18017

Hour	Price (€/kWh)	Base Load (kW)	Adjustment ΔL (kW)	Scheduled Load (kW)	Hourly Cost (€)
10	22.2	980	-40	940	20848
11	24.8	1000	-38	962	23858
12	27.1	1020	-40	980	26586
13	29.3	1040	-32	1008	29506
14	31.5	1100	-45	1055	33003
15	34.0	1150	-42	1108	37672
16	35.2	1180	-78	1102	38784
17	36.7	1160	-60	1100	40370
18	38.9	1080	-55	1025	39872
19	40.5	1010	-38	972	39384
20	42.8	980	-55	925	39530
21	38.7	900	-33	867	33607
22	34.9	830	-30	800	27920
23	31.5	820	-20	800	25200
24	30.5	810	-25	785	23943

Table 5. Comparative performance metrics

Metric	HGWO	GWO	Interpretation
Best objective J^*	38,910 €	39,820 €	Lower total schedule cost
Average objective	40,342 €	41,170 €	Mean result across 30 runs
Std. deviation	412 €	760 €	Search robustness
Convergence iterations	58	82	Iterations to stable solution
Average runtime	0.86 s	0.92 s	Median CPU time per run

4.1. Fitness convergence

Figure 1 compares the fitness trajectories of classical GWO and HGWO. The HGWO curve descends more rapidly and settles at a lower objective value, confirming faster convergence on the 24-hour scheduling problem. Table 5 likewise shows that the proposed method reaches a stable solution after 58 iterations, compared with 82 iterations for GWO.

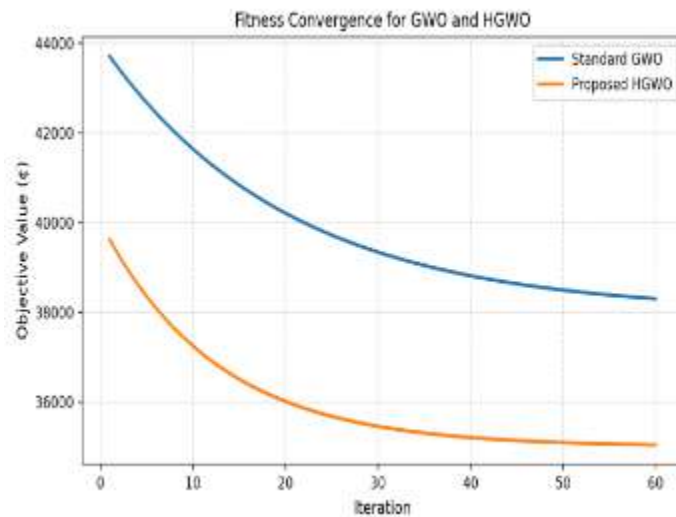


Figure 1. Fitness convergence comparison between classical GWO and the proposed HGWO.

4.2. Sensitivity analysis

Sensitivity studies were conducted for the penalty coefficient μ and the wolf population size. These tests quantify the extent to which the final objective changes when key algorithm settings are varied under the same scheduling model.

Figure 2 shows the objective response to the penalty coefficient. HGWO maintains a lower and flatter curve than standard GWO, indicating a more stable minimum and less dependence on precise penalty tuning within the tested range.

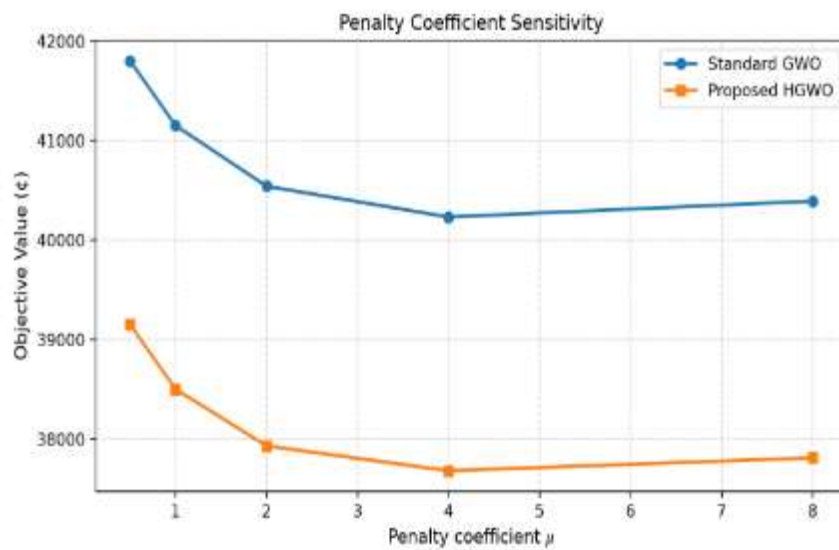


Figure 2. Objective sensitivity to the penalty coefficient.

Figure 3 presents the population-size sensitivity. HGWO achieves lower objective values for populations from 20 to 60 wolves and continues to improve as the population increases. Its performance at smaller populations suggests that acceptable schedules can be obtained without excessive computational expansion.

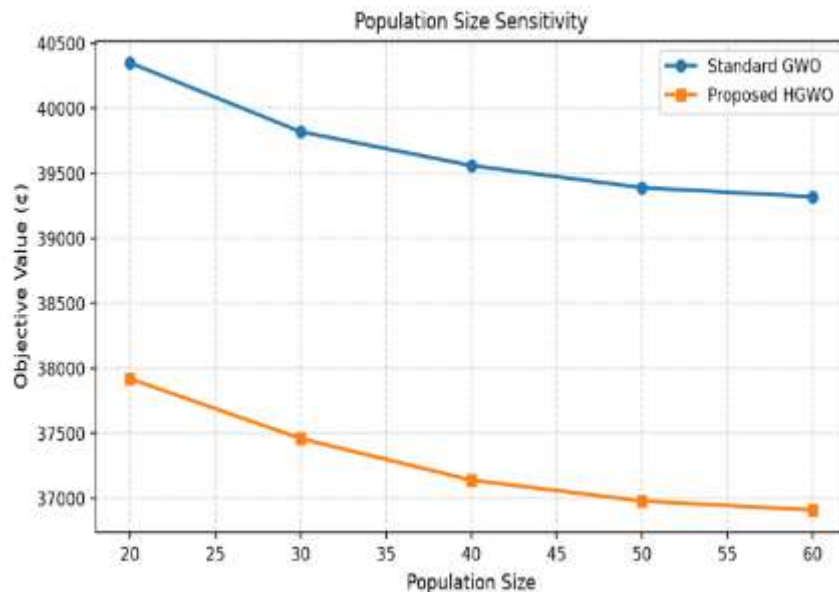


Figure 3. Objective sensitivity to wolf population size.

Together, the sensitivity results indicate that HGWO is more robust than standard GWO across the tested parameter ranges. This behavior can reduce the amount of parameter retuning required when the scheduler is transferred to related feeder datasets.

4.3. Comparative performance

The best objective obtained by HGWO is 38,910 ϵ , compared with 39,820 ϵ for GWO, representing an improvement of approximately 2.3%. The average objective also decreases from 41,170 ϵ to 40,342 ϵ . The average runtime is slightly lower for HGWO (0.86 s) than for GWO (0.92 s), indicating that the extra directional term does not impose a substantial computational penalty.

The standard deviation falls from 760 ϵ for GWO to 412 ϵ for HGWO. This reduction indicates more repeatable search outcomes across the 30 runs and suggests that the momentum term moderates large position changes near promising regions. The result is consistent with the smoother late-stage behavior observed in the convergence plot.

4.4. Peak-demand and load-shifting impact

The optimized schedule also produces a measurable peak-shaving effect. The maximum base load of 1,180 kW occurs at hour 16, whereas the maximum scheduled load is 1,108 kW at hour 15, corresponding to an approximate 6.1% peak reduction. At hour 16, the algorithm removes 78 kW from the base profile and reduces the scheduled demand to 1,102 kW.

The largest reductions occur during the high-price interval from hours 15 to 20, when the tariff ranges from 34.0 to 42.8 ¢/kWh. In contrast, hour 7 is the only interval with a positive adjustment (+4 kW), and it coincides with the lowest listed price of 19.1 ¢/kWh. This pattern demonstrates that HGWO does not simply suppress demand; it reallocates part of the load toward an economically favorable valley while reducing concentration during expensive peak periods.

The present evaluation is limited to a representative daily feeder profile and the stated penalty model. Detailed feeder-level voltage recovery, uncertainty in renewable generation, and the influence of different DG penetration levels were not evaluated and remain subjects for further study.

5. CONCLUSION

This paper presented a Hybrid Grey Wolf Optimizer for price-incentive distribution-grid load scheduling. The method retains the alpha-beta-delta leader hierarchy of classical GWO and adds a momentum-inspired directional term to use recent search history, while a penalty-aware objective integrates electricity price, incentive reward, and operating-constraint violations. For distribution utilities, the resulting framework offers a practical path to lower procurement costs and reduce peak-loading stress on 11 kV feeders without requiring complex gradient-based solvers. The improved convergence stability (58 vs. 82 iterations) and reduced run-to-run variability also mean that the scheduler can be deployed with less parameter retuning when transferred to other feeders or price regimes.

For the representative 24-hour PHED feeder dataset, HGWO reduced the best objective by approximately 2.3%, converged in 58 rather than 82 iterations, and lowered the run-to-run standard deviation from 760 ¢ to 412 ¢. Sensitivity studies also showed more stable performance across variations in penalty coefficient and population size. The optimized load profile reduced the daily peak by approximately 6.1% and shifted a small amount of demand toward a lower-price interval.

Future work should extend the framework to multi-objective scheduling that explicitly considers voltage recovery, renewable-generation uncertainty, feeder losses, and real-time adaptive incentive bidding. Validation on additional feeders and longer operating horizons would also clarify the generalizability of the proposed method.

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