



Comparative Reassessment of PSO-Based Optimal Power Flow for the South Sulawesi 150-kV System with Wind Generation

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ABSTRACT

Wind integration changes transmission power flows and increases the need for economical dispatch that remains consistent with network constraints. This paper provides a traceable comparative reassessment of PSO-based Optimal Power Flow (OPF) results for the published 29-bus, 150-kV South Sulawesi system and clarifies the evidence boundary relative to Reference [7]. The assessment uses the same reported 540.165 MW operating snapshot and compares the published existing condition with Standard PSO, PSO with inertia-weight adjustment (PSO-IWA), PSO with constriction-factor adjustment (PSO-CFA), and hybrid inertia-constriction PSO (PSOHIC). The AC-OPF formulation is restated using a quadratic generation-cost objective, active/reactive power balance, generator limits, voltage limits, and branch constraints; numerical consistency is checked using reported generation, demand, losses, dispatch limits, and convergence counts. The reported PSOHIC solution has 558.3199 MW total generation, 18.155 MW active loss, and USD 5,986.6917/h cost, compared with 559.445 MW, 19.2665 MW, and USD 6,428.61/h for the published existing condition. These values correspond to reported reductions of approximately 5.77% in active loss and 6.87% in operating cost, with nine reported iterations. The numerical values in the comparison are reproduced from Reference [7], not generated by new stochastic experiments in this paper. Therefore, the contribution of this reassessment is data provenance, corrected consistency checks, explicit separation of demonstrated results from unreported feasibility metrics, and a transparent statement of the additional experiments required for reproducible algorithm benchmarking.

Keywords: optimal power flow; 150-kV transmission system; wind generation; particle swarm optimization; economic dispatch.

1. Introduction

The South Sulawesi power system has evolved toward a regional grid with significant renewable generation. Wind farms at Sidrap and Tolo Jeneponto contribute to this transition, while variable renewable injections alter conventional-generator dispatch and transmission flows. These conditions motivate constraint-aware economic operation of the 150-kV network [1, 2].

Optimal Power Flow (OPF) determines the economically preferable operating point of a power system while enforcing the nonlinear AC power-flow equations and equipment limits. Since its early formulation, OPF has become a central tool for economic dispatch, voltage control, congestion management, and renewable-energy integration [3, 4]. Modern research also investigates fast data-driven approximations, but feasibility and traceability remain essential when solutions are applied to real networks [5, 6].

Indonesian studies have shown that renewable integration affects power transfer, voltage, and losses in the Sulselrabar and Sulawesi systems [1, 2, 7]. Other work has applied

metaheuristic optimization to economic dispatch of the 150-kV Sulselbar system [8]. However, a generic IEEE test system does not capture the actual generation mix and network conditions of South Sulawesi. A real regional case is therefore more appropriate for evaluating the practical relevance of OPF algorithms.

Reference [7] originally introduced the PSOHIC velocity-update strategy, validated it on the IEEE 26-bus system, and applied it to the 29-bus South Sulawesi wind-integrated case. The present paper does not claim a new PSOHIC algorithm or new simulation outputs. Its contribution is a transparent reassessment of the published South Sulawesi results: the data provenance is made explicit; the active-power balance and generator-limit consistency are rechecked; AC-OPF constraints are stated in a unified notation; and claims are restricted to quantities that are actually available in the published record.

Accordingly, the objectives are to: (i) document the published 29-bus South Sulawesi case and its six participating generator buses; (ii) compare the reported

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Standard PSO, PSO-IWA, PSO-CFA, and PSOHIC solutions using cost, active loss, dispatch, and iteration count; (iii) quantify arithmetic consistency relative to the published existing condition; and (iv) identify the reproducibility and feasibility information that is still required before the results can be treated as an independently validated algorithm benchmark [7, 9, 10].

In transmission systems with a growing share of non-dispatchable generation, the economic dispatch problem cannot be separated from network feasibility. A dispatch that appears economical in a simplified generation-only model may be infeasible once reactive-power balance, voltage limits, and line-loading constraints are considered.[3, 11] This issue is relevant for islanded or weakly interconnected regional systems [12], where generation centers, renewable resources, and load centers are not always located close to one another. In such systems, OPF provides a structured way to identify whether an operating point is not only cheap, but also technically consistent with the physical network[3, 4].

The South Sulawesi 150-kV system is a useful case because it combines conventional generation, wind generation, and regional transmission corridors within a real Indonesian operating environment[1, 7, 2]. Wind farms may reduce the energy supplied by thermal units [13], but their output also changes the location of power injection. As a result, the redispatch of conventional generators must account for the transmission losses and constraints created by the changed power-flow pattern [14]. A method that minimizes cost without respecting the AC network model may underestimate losses or produce dispatch points that cannot be implemented safely[15, 16].

Metaheuristic methods such as particle swarm optimization are frequently used for OPF because the AC OPF problem is nonlinear, nonconvex, and affected by equality and inequality constraints[17]. The attraction of PSO is its relatively simple implementation, small number of control parameters, and ability to search a wide solution space without requiring gradient information. However, basic PSO may suffer from premature convergence [18], excessive oscillation, or slow local refinement. Variants based on inertia-weight adjustment and constriction factors were proposed to improve the balance between exploration and exploitation. Comparing these variants on the same real-system case is therefore important for determining whether additional algorithmic complexity produces measurable benefits[7, 8].

Data provenance is central to this assessment. All numerical values in Tables 2 and 3 are taken from the published South Sulawesi case in Reference [7]. No new PSO executions are presented here. Consequently, the paper distinguishes reproduced benchmark values from new arithmetic checks and interpretation, and it does not introduce unsupported light-, normal-, or peak-load scenarios.

The value of the present paper therefore lies in evidence-traceable interpretation rather than in claiming a new optimization algorithm. This distinction is important because stochastic-optimization results cannot be independently reproduced or compared statistically without algorithm

parameters, random seeds, repeated runs, software details, and the complete feasibility outputs.

2. Methods and modelling

2.1. Methodological framework

The assessment follows five stages: extraction of the published South Sulawesi network and operating data; restatement of the AC-OPF model; provenance-based comparison of the four reported PSO variants; numerical consistency checks; and evidence-bounded interpretation. Figure 1 summarizes this workflow.

The numerical dataset and the reported optimized results are sourced from Reference [7]. The source describes a 29-bus, 35-line South Sulawesi system with 14 generators, of which four thermal plants and two wind plants participate in the reported simulation. The operating case uses peak-load data at 14:00 WITA. The six generator buses listed in the published comparison are 1, 13, 14, 19, 23, and 25, and the reported total demand is 540.165 MW.

The published existing condition reports 559.445 MW of generation, 19.2665 MW of active loss, and USD 6,428.61/h generation cost [7]. These values are retained as source-reported benchmark quantities. A direct arithmetic check gives a 0.0135 MW mismatch between generation and the sum of reported demand and loss, which is small (about 0.0025% of demand) but is explicitly reported here rather than treated as exact balance.

The OPF objective minimizes total quadratic generation cost while satisfying active and reactive power balance, generator active- and reactive-power limits, bus-voltage limits, and branch-flow constraints[3,11]. This formulation retains the physical coupling between generator dispatch, wind integration, network losses, and voltage feasibility.

The four compared cases are Standard PSO, PSO-IWA, PSO-CFA, and PSOHIC, as reported in Reference [19]. PSOHIC combines inertia-weight and constriction-factor velocity updates; the source states an ideal constriction-factor value $K = 0.729$. However, the source record available for this reassessment does not report all numerical settings required for independent stochastic replication, such as swarm size, numerical $c1$ and $c2$ values, inertia endpoints, random seed, software environment, computer specifications, or repeated-run statistics.

Performance is therefore assessed as a comparison of reported-best solutions, not as a new stochastic experiment. The available quantitative indicators are total generation, active loss, hourly generation cost, generator active-power limits, and convergence iteration count. New mean/standard-deviation values, run times, hypothesis tests, or optimality gaps are not fabricated because the underlying repeated runs and deterministic benchmark outputs are not available.

This evidence-bounded design improves transparency but limits reproducibility. Independent reproduction requires the original source code or a complete parameter set, together with current network data and a deterministic AC-OPF benchmark. These requirements are listed explicitly below rather than being implied as already completed.

For every reported method, the same published network snapshot and generator active-power limits are used.

Generator-level feasibility can therefore be checked from the tabulated active-power outputs. Full AC-OPF feasibility, however, also requires bus voltages, generator reactive powers, line loadings, and numerical power-balance residuals; these quantities are not reported in the dataset used for this paper and are not reconstructed [20].

The iteration count is retained only as a source-reported convergence indicator. Because PSO is stochastic, one reported best run cannot establish statistical superiority. A rigorous comparison would require multiple independent runs under identical parameters, mean and standard deviation, execution time, and an appropriate statistical test.

Accordingly, PSOHIC is described as the best reported solution for this specific published case, not as a universally superior OPF solver.

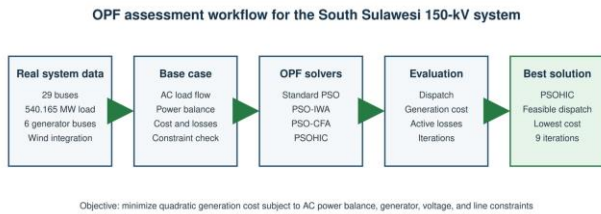


Fig.1. Evidence-traceable OPF reassessment workflow for the published South Sulawesi 150-kV case.

2.2. System description

The study object is the published 29-bus South Sulawesi 150-kV transmission representation with integrated wind generation [7]. Reference [7] reports 35 transmission lines and 14 generators in the wider dataset, while the simulation comparison uses four thermal plants (Tello, Punagaya, Suppa, and Sengkang) and two wind plants (PLTB Sidrap and PLTB Tolo Jeneponto). Figure 2 summarizes only the information explicitly available from the source.

The OPF decision variables include the outputs of generators connected at buses 1, 13, 14, 19, 23, and 25[7]. Their active-power ranges are 19.75-110 MW, 60.85-315 MW, 0-60 MW, 15-62.5 MW, 0-75 MW, and 55-250 MW, respectively. The existing total dispatch of these units is 559.445 MW.

The published operating snapshot uses peak-load data at 14:00 WITA and reports total demand of 540.165 MW [7]. The source identifies PLTB Sidrap and PLTB Tolo Jeneponto as the wind plants, but it does not provide, in the information available for this reassessment, a complete wind-specific parameter set covering installed capacity, separate cost function, reactive-power limits, penetration percentage, or an unambiguous statement of whether each wind output is fixed or optimized. These quantities are therefore not invented in the present paper.

The analysis is limited to the reported steady-state snapshot and the source-reported best solutions. Dynamic frequency response, unit commitment, reserve scheduling, chronological wind uncertainty, N-1 contingencies, and independent deterministic benchmarking are outside the demonstrated result set.

The 29-bus dataset should be treated as a published research representation, not as the current confidential PLN operational model. Practical use requires revalidation with

current topology, generator availability, wind output, load, branch ratings, and state-estimator measurements.

The six optimized generator buses represent the controllable dispatch resources considered in the benchmark. Their different capacity ranges create a nonuniform search space: bus 13 has the largest available upper limit, while buses 14 and 23 can operate at very low output. This asymmetry is important because the least-cost solution is not found by distributing generation evenly among all buses. Instead, the OPF solver must determine how much output should be shifted toward economically attractive and electrically favorable buses while still covering demand and losses.

The inclusion of wind generation in the system model changes the interpretation of conventional generator dispatch. The optimized generators are not simply meeting the entire regional load in isolation; they are operating within a wind-integrated transmission system. Consequently, changes in conventional generation affect both cost and network losses. The OPF solution may reduce the output of one unit while increasing another if the resulting power-flow pattern reduces total cost or supports a lower-loss dispatch. This interaction is one reason that real network models are more informative than generic test systems for regional planning.

The study object is also relevant from a sustainability perspective. A lower-loss dispatch reduces the amount of generation required to serve the same load, which can indirectly reduce fuel consumption and emissions in systems that still include thermal generation[13, 21]. Although the paper does not calculate emission reductions, the reduction in active loss from 19.2665 MW to 18.155 MW indicates that less power is wasted in the network under the best OPF case. This provides a technical link between economic operation and energy-efficiency improvement[22].

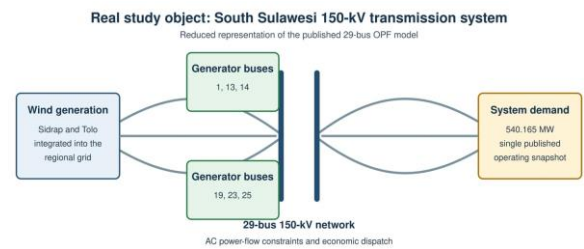


Fig. 2. Source-reported South Sulawesi wind-integrated study object and data boundary.

2.3. Mathematical modelling

The AC OPF seeks a feasible vector of generator outputs, bus voltages, and phase angles that minimizes hourly generation cost [23]. The effects of the documented wind-integrated operating condition are embedded in the system data and power-balance equations.

The total quadratic generation-cost objective is expressed as

$$F = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (1)$$

Where F is total generation cost (USD/h), N_g is the number of participating generators, P_{Gi} is active-power output of generator i (MW), and a_i , b_i , and c_i are the corresponding quadratic cost coefficients.

The active-power balance requires total generation to cover the system demand and active network loss:

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \quad (2)$$

Similarly, the reactive power balance equation is expressed as [23]:

$$Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] \quad (3)$$

Where P_{Di} and Q_{Di} denote active and reactive demand at bus i ; V_i and V_j are bus-voltage magnitudes; θ_i and θ_j are voltage angles; and G_{ij} and B_{ij} are conductance and susceptance elements of the bus-admittance matrix. The same subscript and superscript conventions are used throughout the manuscript.

The operating limits of generating units are represented as:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (4)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad (5)$$

To maintain acceptable power quality and system stability, the voltage magnitude at each bus must satisfy:

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (6)$$

In addition, the apparent power flow through each transmission line must remain below its thermal capacity limit:

$$S_{ij} \leq S_{ij}^{\max} \quad (7)$$

For future chronological studies, a demand multiplier may be applied to the base-case demand:

$$P_D = \sum_{i=1}^{N_B} P_{Di} \quad (8)$$

The load demand factor is then defined as:

$$\lambda = \frac{P_D}{P_{D,base}} \quad (9)$$

Where PD is the total active demand at a selected operating condition, PD_{base} is the documented base demand, and λ is the demand multiplier. In the present comparison, λ is fixed at 1.0 because only the published 540.165-MW snapshot is evaluated.

Equations (1)-(9) define the economic objective, AC power balance, and equipment constraints. The solver changes generator dispatch but must preserve feasibility. No additional load scenarios are introduced without traceable data.

Equations (1)-(7) form the core AC OPF model. The equality constraints enforce active- and reactive-power

balance at the buses, while the inequality constraints define the operating envelope of generators, voltages, and branches. In a radial distribution study, voltage drop may be the dominant concern, but in a 150-kV transmission OPF the interaction among voltage magnitudes, phase angles, generator placement, and transmission corridors is equally important. This interaction explains why the minimum-cost solution and the minimum-loss solution may not always coincide [24].

The quadratic cost model is appropriate for the present benchmark because it provides a smooth representation of generation cost over the permitted output range. The constant term represents fixed cost, the linear term represents the marginal contribution of output, and the quadratic term reflects increasing incremental cost as output rises. When several generators have different coefficients and operating limits, the optimizer searches for a dispatch that shifts production toward units with lower effective cost while respecting network feasibility[8, 19]. The cost function therefore converts the physical dispatch problem into a measurable economic objective [25].

The active-power balance also provides a useful consistency check for the reported results. In the existing condition, generation of 559.445 MW and demand of 540.165 MW imply a difference close to the reported active loss of 19.2665 MW. In the PSOHIC case, generation decreases to 558.3199 MW while the same demand is supplied, and the difference corresponds to the lower reported loss of 18.155 MW. This relationship confirms that the cost reduction is accompanied by a physically meaningful reduction in required generation.

The load-multiplier expressions in Eqs. (8) and (9) are retained only as a formal basis for future chronological or scenario-based studies. They are not used to create additional results in the present paper. This distinction is important because the accuracy of load-scaling scenarios depends on the actual temporal distribution of residential, commercial, industrial, and public loads[17]. A uniform multiplier is useful for sensitivity screening, but it cannot replace measured hourly demand profiles or utility-validated planning cases [26].

In implementation, constraint handling is commonly performed by combining the objective function with penalty terms for violations[9, 10]. Although the present manuscript reports the final feasible results rather than the detailed penalty coefficients, the conceptual role of constraint handling is clear: infeasible particles should be discouraged even if their raw cost is low[27]. A feasible OPF solution must satisfy generator bounds, maintain voltages inside the allowable range, and avoid branch overloads[3, 27]. This preserves the engineering meaning of the optimization result.

2.4. Boundary conditions and model assumptions

The model boundary is the published 29-bus South Sulawesi 150-kV network, including the six optimized generator buses, wind integration, network branches, and the 540.165-MW demand snapshot[7]. The comparison adopts the same network and economic data for all four algorithms.

All cases are steady-state AC OPF calculations. The analysis does not include transient stability, frequency

dynamics, protection operation, N-1 contingencies, generator commitment, or reserve scheduling. These exclusions keep the numerical comparison consistent with the available case-study data.

Generator active- and reactive-power outputs are constrained by their published limits. Bus-voltage magnitudes and transmission flows are treated as feasibility constraints. Detailed bus-voltage and branch-loading tables are not reproduced because the numerical values available for this revision focus on dispatch, total loss, total cost, and convergence.

Only one demand condition is evaluated. The comparison is a secondary reassessment of the source-reported values and does not constitute a new set of stochastic OPF experiments.

The optimized cases in Reference [28] supply approximately the same 540.165 MW demand. For Standard PSO, PSO-IWA, PSO-CFA, and PSOHIC, the generation-minus-demand-minus-loss residuals calculated from the reported table are approximately 0.0000, -0.0005, 0.0000, and 0.0000 MW, respectively. The existing condition has a 0.0135 MW discrepancy, most likely reflecting source-table rounding or transcription; it is retained transparently and not silently corrected.

Table 1 summarizes the case-study boundary, data, and modelling assumptions used in the revised analysis.

Table 1
Case-study boundary and modelling assumptions.

Item	Parameter	Value	Source
Study system	Voltage / buses	150 kV / 29 buses	[1]
Demand snapshot	Active demand	540.165 MW	[1]
Optimized units	Generator buses	1, 13, 14, 19, 23, 25	[1]
Existing state	Generation	559.445 MW	[1]
Existing state	Active loss	19.2665 MW	[1]
Existing state	Cost	USD 6,428.61/h	[1]
Objective	Cost model	Quadratic	[1], [3]
Constraints	Network model	AC balance and limits	[1], [3]
Compared solvers	PSO variants	PSO, IWA, CFA, PSOHIC	[1]
Demand multiplier	Present study	lambda = 1.0	This study

2.4.1. Economic assumptions and cost correlations

The economic assessment minimizes the hourly production cost of the six optimized generator buses[7]. Each generator is represented by a quadratic cost curve, which captures the nonlinear relationship between active-power output and fuel cost within its permitted operating range[3, 9].

The fuel cost function of each generating unit can be expressed as:

$$C_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (10)$$

where F_i is the operating cost of generator i (USD/h), P_{Gi} is its active-power output (MW), and a_i , b_i , and c_i are the corresponding fuel-cost coefficients.

The total generation cost of the power system is obtained by summing the operating costs of all generators participating in the dispatch process:

$$C_{total} = \sum_{i=1}^{N_G} C_i(P_{Gi}) \quad (11)$$

Where N_g denotes the number of generator buses included in the dispatch optimization.

The calculation excludes unit commitment, start-up and shut-down costs, minimum up/down times, maintenance cost, emissions pricing, reserve procurement, and fuel-price uncertainty. Accordingly, the results represent steady-state economic dispatch rather than a complete operational market schedule.

The economic improvement of each algorithm is measured against the existing operating cost. The percentage reduction is calculated as:

$$Cost\ Saving(\%) = \frac{C_{base} - C_{OPF}}{C_{base}} \times 100 \quad (12)$$

where C_{base} is the existing operating cost and C_{OPF} is the optimized cost. Applying Eq. (12) to the PSOHIC result gives a reduction of approximately 6.87% from USD 6,428.61/h to USD 5,986.6917/h.

The cost values are retained in USD/h to remain consistent with the published case data. They should be updated using current fuel prices and PLN operating data before any investment or dispatch decision.

The boundary conditions also define the level of confidence that can be attached to each result. Values directly reported in the published South Sulawesi OPF case, such as total demand, generation, loss, cost, generator buses, and dispatch ranges, are treated as traceable inputs or benchmark outputs. In contrast, any unreported voltage profile, branch loading, contingency margin, or chronological response is not reconstructed in this revision. This prevents the analysis from appearing more detailed than the available dataset supports.

A second assumption is that the wind-integrated operating snapshot is evaluated as a deterministic condition. The study does not model wind-speed uncertainty, forecast errors, curtailment decisions, or reserve requirements[4]. In real operation, these factors would influence how much conventional generation must remain online and how quickly dispatch can be adjusted. Therefore, the reported OPF solution should be understood as an optimized steady-state point for the documented condition rather than a full renewable dispatch schedule.

The same interpretation applies to voltage and branch constraints. The OPF formulation includes them as feasibility requirements, but detailed numerical bus-voltage and line-loading results are not available in the summarized dataset used for this revision. The paper therefore avoids claiming that PSOHIC improves voltage stability or removes congestion unless such values are explicitly reported. This

conservative presentation strengthens the credibility of the comparison because it separates mathematical formulation from demonstrated numerical evidence.

3. Results and discussion

3.1. Case-study performance

The existing South Sulawesi operating condition and four PSO-based solutions are reproduced from Reference [7] for consistency checking and comparative interpretation. They are not new experimental outputs generated by the present authors. Table 2 reports total generation, active loss, hourly cost, and source-reported convergence iterations.

Reference [7] reports 540.165 MW demand, 559.445 MW generation, 19.2665 MW active loss, and USD 6,428.61/h cost for the existing condition. The active-power arithmetic leaves a 0.0135 MW residual. Because the optimized cases close to within approximately 0.0005 MW using the same calculation, the base-case residual is reported as a source-value inconsistency rather than interpreted as a physical imbalance.

All four PSO variants reduce generation cost relative to the existing condition. Standard PSO reaches USD 6,098.5447/h; PSO-IWA reaches USD 6,040.5012/h; PSO-CFA reaches USD 6,047.9272/h; and PSOHIC gives the minimum value of USD 5,986.6917/h. The PSOHIC reduction is USD 441.9183/h, or 6.87%.

Table 2
Comparison of existing and optimized operating results.

Method	Generation (MW)	Loss (MW)	Cost (USD/h)	Iterations
Existing	559.4450	19.2665	6,428.6100	-
Standard PSO	558.3296	18.1650	6,098.5447	41
PSO-IWA	559.2945	19.1300	6,040.5012	29
PSO-CFA	558.7255	18.5600	6,047.9272	20
PSOHIC	558.3199	18.1550	5,986.6917	9

PSOHIC also produces the lowest active loss, 18.155 MW, which is 1.1115 MW or 5.77% below the existing 19.2665-MW value. Standard PSO is close at 18.165 MW, whereas PSO-IWA and PSO-CFA yield 19.130 MW and 18.560 MW, respectively. This indicates that a lower generation cost does not necessarily imply the same ranking in transmission-loss reduction.

The optimized solutions satisfy the same power balance and operating constraints used in the case study. However, the available result set does not support a claim of quantified voltage-profile improvement at individual buses. Voltage is therefore treated as a feasibility constraint, and the discussion is limited to the reported aggregate cost, loss, dispatch, and convergence indicators.

The generator dispatch changes substantially after optimization. In particular, the PSOHIC solution increases output at bus 13 to 293.6061 MW and reduces output at bus 14 to 5.6498 MW, while every reported output remains within its specified range. Table 3 compares the existing and PSOHIC dispatch values.

Table 3
Generator dispatch under the existing and PSOHIC conditions.

Bus	Minimum (MW)	Maximum (MW)	Existing (MW)	PSOHIC (MW)
1	19.75	110.00	34.0000	72.7180

Bus	Minimum (MW)	Maximum (MW)	Existing (MW)	PSOHIC (MW)
13	60.85	315.00	95.9450	293.6061
14	0.00	60.00	60.0000	5.6498
19	15.00	62.50	51.1000	54.8728
23	0.00	75.00	75.0000	14.6648
25	55.00	250.00	243.4000	116.8084

Among the source-reported best solutions, PSOHIC has the lowest cost, the lowest active loss, and the fewest reported iterations. This ranking is descriptive for the published case only; without repeated stochastic runs and a deterministic benchmark, it does not establish statistical superiority or a quantified optimality gap.

The reduction in total generation is modest in absolute terms but meaningful in operational interpretation. Because the demand is fixed at 540.165 MW, reducing total generation from 559.445 MW to 558.3199 MW means that the network requires less generated power to serve the same load. The 1.1251-MW reduction in total generation is consistent with the 1.1115-MW reduction in active loss. Minor differences are attributable to rounding in the tabulated values. This confirms that the OPF result improves efficiency rather than merely shifting reported cost among generators.

The cost reduction is larger in percentage terms than the loss reduction. PSOHIC reduces loss by 5.77% but reduces hourly operating cost by 6.87%. This indicates that the economic benefit is not caused only by the lower loss. It also depends on the redispatch among generators with different quadratic cost characteristics. In other words, the optimizer finds a dispatch that simultaneously reduces the energy wasted in transmission and allocates production more economically among the available units. This dual effect is a key advantage of OPF compared with a simple loss-minimization calculation[3].

The comparison among optimized cases shows that cost and loss are related but not identical objectives [29]. Standard PSO produces almost the same active loss as PSOHIC, with only 0.010 MW difference, yet its cost remains about USD 111.853/h higher. Conversely, PSO-IWA gives a lower cost than Standard PSO but has a higher loss. These results demonstrate that the final ranking depends on the combined influence of generator cost curves and network losses[9]. For practical planning, this means that a method should be evaluated using multiple indicators rather than a single metric[3, 18].

The PSOHIC active-power dispatch remains within the source-reported P_G limits for all six participating generator buses. This verifies one important feasibility dimension. Full AC-OPF feasibility cannot be independently demonstrated from the current result set because bus-voltage profiles, generator Q outputs, branch loadings, and explicit constraint residuals are unavailable.

From the perspective of transmission efficiency, the loss reduction also has cumulative implications[12]. A 1.1115-MW loss reduction during one hour corresponds to 1.1115 MWh of energy not wasted during that hour. If a similar operating condition occurred repeatedly, the avoided energy loss would become significant over time[17]. The paper does not annualize this value because chronological data are not

available, but the hourly interpretation helps explain why even a seemingly small percentage reduction can be operationally relevant in a regional grid[2].

The results also show the value of using an AC OPF formulation rather than economic dispatch alone[3, 11]. A purely economic dispatch would decide generator outputs from cost curves without fully representing network power flows[8]. AC OPF embeds the network equations, so the effect of generation placement on losses and feasibility is included[11, 29]. This is especially important when wind generation and conventional units are geographically distributed across a 150-kV network[2, 7]. The reported improvement therefore reflects both economic and electrical considerations[4].

3.2. Algorithm comparison and convergence

The algorithm comparison shows that convergence behavior is a major practical difference[9, 18]. Standard PSO requires 41 iterations, PSO-IWA requires 29, PSO-CFA requires 20, and PSOHIC converges in nine. Relative to Standard PSO, the hybrid method reduces the reported iteration count by approximately 78%.

The inertia mechanism supports exploration of the search space, whereas the constriction mechanism limits velocity growth and supports stable convergence[9]. Their combination in PSOHIC provides a better balance for this OPF instance, enabling the swarm to reach a lower-cost feasible solution with fewer iterations[18].

PSO-IWA has the second-lowest cost but the highest loss among the optimized cases. Conversely, Standard PSO produces a loss only 0.010 MW above PSOHIC but a cost approximately USD 111.853/h higher. These differences demonstrate why OPF studies should report both economic and technical indicators rather than relying on a single headline metric[3, 4, 17].

At generator level, the hybrid solution shifts dispatch toward bus 13 and away from buses 14 and 23 relative to the existing condition. The solution remains bounded by each unit's minimum and maximum output[3]. This redistribution is consistent with the economic objective and the effect of network losses on marginal generation requirements[11, 29].

No new statistical comparison is claimed. The source reports best-solution iteration counts but does not provide the independent-run dataset needed to calculate means, standard deviations, confidence intervals, execution times, or statistical-test results. These quantities must be generated from reruns of the original algorithms before statistical claims are made.

For utility application, algorithm speed must be evaluated together with data quality and security constraints[17]. A fast solver operating on outdated topology or inaccurate wind and demand inputs can still produce an unsuitable dispatch[24]. The nine-iteration PSOHIC result is promising, but it requires validation against current PLN data and alternative operating conditions[1, 7].

The published comparison identifies PSOHIC as the best reported method for this single case. The present reassessment preserves that observation while explicitly separating it from a statistical claim of algorithm superiority.

The convergence advantage of PSOHIC is practically relevant because OPF studies often need to be repeated for many network conditions[3, 4]. In planning studies, operators may evaluate different demand levels, renewable-output conditions, line outages, generator-availability states, or investment alternatives[2]. A method that reaches a good feasible solution in fewer iterations reduces computational burden when the number of scenarios becomes large[17, 18]. Although this paper evaluates only one documented snapshot, the nine-iteration convergence of PSOHIC indicates promise for expanded scenario analysis.

The improved convergence can be explained by the complementary roles of inertia and constriction. Inertia maintains movement through the search space and helps particles avoid becoming trapped too early near a local solution[9]. The constriction factor limits the magnitude of velocity updates and can improve stability when particles approach promising regions [10]. Combining these mechanisms allows the search to explore sufficiently at the beginning and then refine the solution more rapidly [17]. This behaviour is consistent with the lower iteration count reported for PSOHIC.

Because PSO is stochastic, independent reruns are required for a reproducible performance comparison. A future experiment should report swarm size, acceleration coefficients, inertia schedule, constriction factor, stopping rule, penalty treatment, random seeds, software/hardware, number of runs, mean $\pm$ standard deviation, runtime, and a statistical comparison across algorithms.

For real-time or near-real-time application, OPF performance also depends on data integration[17, 24]. The solver must receive current topology, generator availability, renewable output, demand estimates, transformer tap positions, branch ratings, and contingency definitions[4, 17]. Without reliable input data, even the best optimization algorithm may produce a dispatch that is irrelevant or unsafe. Therefore, the algorithmic result should be viewed as one component of a larger decision-support chain that includes measurement, state estimation, validation, optimization, and operator review[3, 17, 24].

3.3. Limitation and Future Work

The principal limitation is that this paper reassesses published results rather than rerunning the original PSO code. Consequently, several reviewer-requested reproducibility and feasibility quantities are unavailable: complete PSO numerical settings, repeated-run statistics, execution times, bus-voltage profiles, generator reactive-power outputs, branch loadings, and constraint-violation tables. A deterministic AC-OPF benchmark (e.g., MATPOWER/MIPS, IPOPT, or an interior-point solver) is also not available in the source dataset; therefore, no optimality-gap claim is made.

A complete follow-up study should rerun the 29-bus case using documented parameters and current data, publish all AC feasibility outputs, execute each stochastic solver over multiple independent seeds, and compare PSOHIC against a deterministic AC-OPF solver on the same objective and constraints. Chronological demand/wind uncertainty and N-1 security can then be added after the baseline benchmark is reproducible [30].

4. Conclusion

This paper provides a traceable comparative reassessment of the published 29-bus South Sulawesi 150-kV wind-integrated OPF case. Reference [7] reports a 540.165 MW demand snapshot and compares an existing condition with Standard PSO, PSO-IWA, PSO-CFA, and PSOHIC. The source-reported PSOHIC solution has 558.3199 MW generation, 18.155 MW active loss, USD 5,986.6917/h cost, and nine iterations, compared with 559.445 MW, 19.2665 MW, and USD 6,428.61/h for the existing condition. The present reassessment confirms the reported 5.77% loss reduction and approximately 6.87% cost reduction arithmetically and verifies that the PSOHIC active generator outputs remain within the published limits. It also identifies a 0.0135 MW arithmetic discrepancy in the source-reported existing power balance and makes explicit that Tables 2 and 3 reproduce results from Reference [7], rather than new experiments. Because repeated stochastic runs, complete algorithm parameters, bus-voltage/reactive-power/line-loading outputs, and a deterministic AC-OPF benchmark are not available, the paper does not claim statistical superiority, full independent AC-feasibility validation, or an optimality gap. Future work should rerun the complete case with documented parameters, repeated seeds, full constraint reporting, and deterministic benchmarking before operational conclusions are drawn.

CRedit authorship contribution statement

Ahmad Faiz Fauzi: Conceptualization, Methodology, Software, Data curation, Formal analysis, Investigation, Writing – original draft. **Juangky Yusran Tiranda:** Supervision, Validation, Resources, Writing – review and editing.

Declaration of competing interest

No conflict of interest.

Data availability

The numerical case data and benchmark results used in this study are available in the cited publication. Any implementation using the current South Sulawesi network requires authorization and updated data from the relevant system operator.

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