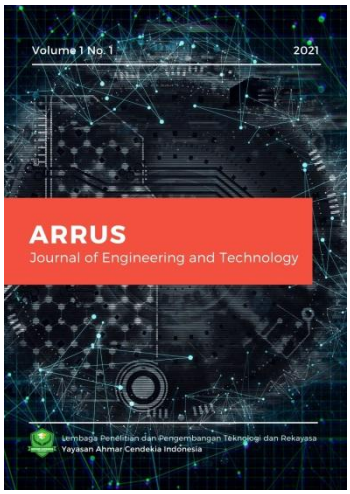
https://doi.org/10.35877/jetech5578

OPEN ACCESS

ISSN : 2776-7914 (Print) / 2807-3045 (Online)



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RESEARCH ARTICLE

Metaheuristic-Optimized Support Vector Regression for Daily Solar Radiation Forecasting in Eastern Indonesia

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Abstract: This study examines whether metaheuristic hyperparameter optimization improves support vector regression (SVR) for one-day-ahead forecasting of daily global horizontal irradiance in Makassar, Kupang, Ambon, and Jayapura, Eastern Indonesia. The study employs daily NASA POWER time series data for 2015–2024, using 2015–2022 for training and expanding-window temporal cross-validation and 2023–2024 for testing. SVR hyperparameters were tuned by particle swarm optimization (PSO), grey wolf optimizer (GWO), and whale optimization algorithm (WOA), each run ten times under an evaluation budget matched to grid search, and compared with a default SVR and a persistence forecast using the Diebold–Mariano test. The results show that all SVR variants significantly outperformed persistence (skill scores 0.13–0.28; test RMSE 0.74–1.30 kWh/m²/day). PSO, GWO, and WOA converged to nearly identical hyperparameters and accuracy, with no significant difference in stability. They reduced validation error by 0.2–0.7% relative to grid search, yet on the test set they were significantly better only in Jayapura, equivalent in Kupang, and significantly worse in Makassar and Ambon. The findings of this study suggest that the choice of metaheuristic matters less than the representativeness of the validation period, which here spanned a La Niña-to-El Niño transition.

Keywords: Support vector regression, Metaheuristic optimization, Solar radiation forecasting, NASA POWER, Eastern Indonesia

1. Introduction

Accurate forecasts of daily solar radiation are a prerequisite for planning and operating solar photovoltaic (PV) power plants, particularly in the archipelagic eastern part of Indonesia, where many electricity systems remain isolated and depend on diesel generation. The region receives high insolation; a RETScreen-based assessment reported solar energy potentials of 5.43 kWh/m²/day in Maluku, 4.97 kWh/m²/day in Papua, and 5.66 kWh/m²/day in West Sulawesi (Amin, n.d.). This potential is not matched by adequate surface radiation measurements: pyranometer networks in Eastern Indonesia are sparse and their records are often discontinuous.

The scarcity of observations has encouraged the use of open satellite- and reanalysis-derived radiation databases such as NASA POWER (Prediction of Worldwide Energy Resources).

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

Harsarapama et al. (2020) compared four satellite radiation databases for Indonesia and found that POWER carries a positive bias of about 3–7% against WRDC ground measurements, while its correlation remains acceptable for describing inter-monthly and inter-annual variability. Because such data cover the whole archipelago uniformly and over long periods, they allow daily forecasting models to be developed for locations without measuring stations.

Among machine learning methods, support vector regression (SVR) is widely used to model solar radiation because it captures nonlinear relationships through kernel functions, resists overfitting through the structural risk minimization principle, and remains stable on medium-sized samples (Mohammadi et al., 2015; Voyant et al., 2017). Its main weakness is the sensitivity of its performance to the choice of hyperparameters, namely the penalty parameter C, the tube width ε, and the kernel parameter γ. Trial-and-error or default settings tend to produce sub-optimal combinations (Ghazvinian et al., 2019), whereas grid search becomes computationally expensive in a continuous three-dimensional search space. In Indonesia, RBF-kernel SVR has been applied to forecast inflation (Isnaeni et al., 2022; Ruliana et al., 2024), gold prices (Annas et al., 2023), coal prices (Ahmar et al., 2025), and the air quality index of Makassar (Rahmat et al., 2023), and all four of these studies selected the hyperparameters by grid search. SVR is not always the most accurate option, however: for Indonesian coal prices, SutteARIMA outperformed the best radial-kernel SVR (Ahmar et al., 2025), which underlines the need for explicit benchmarks.

Metaheuristic algorithms offer an efficient alternative for tuning these hyperparameters. Ghazvinian et al. (2019) coupled SVR with an improved particle swarm optimization (IPSO) to predict solar radiation in Turkey and outperformed M5 tree and MARS models. Fan et al. (2020) reported that SVM optimized by PSO, the bat algorithm, and the whale optimization algorithm (WOA) reduced the RMSD of daily diffuse radiation predictions by 1.1–5.6% compared with an untuned SVM. At the hourly scale, Yasin et al. (2020) showed that the grey wolf optimizer (GWO) paired with LSSVM was more accurate than PSO-LSSVM. In Indonesia, Oktaviani et al. (2025) applied SVR with Bayesian optimization to forecast daily GHI in Jakarta and obtained a test MAPE of 0.182. Rais and Yuniar (2025) used a genetic algorithm to tune SVM hyperparameters for hypertension classification and reported higher accuracy than an SVM without optimization.

Three gaps nonetheless remain. First, studies of optimized SVR for solar radiation in Indonesia concentrate on Java, whereas Eastern Indonesia, with its diverse monsoonal, semi-arid, anti-monsoonal, and equatorial regimes, has not been examined. Second, metaheuristics are usually compared under unequal evaluation budgets and from a single run, so the advantage of one algorithm is hard to separate from chance initialization. Third, many studies use random data splits that ignore temporal structure and do not benchmark against a persistence forecast. As the no free lunch theorem states (Wolpert & Macready, 1997), no optimization algorithm is superior for every problem, so empirical comparisons on specific cases remain necessary.

This study therefore builds and compares SVR models whose hyperparameters are optimized by PSO, GWO, and WOA for one-day-ahead forecasting of daily GHI in four Eastern Indonesian cities. Its contributions are (1) a hyperparameter optimization framework in which every method, including grid search, receives an equivalent budget of 300–343 function evaluations; (2) an assessment of algorithm stability over ten independent runs; (3) temporally ordered cross-validation with Diebold–Mariano significance tests against default SVR and persistence; and (4) forecasting evidence useful for PV planning in data-scarce regions.

2. Literature Review

2.1. *Support Vector Regression*

SVR extends the support vector machine to regression problems (Drucker et al., 1997; Smola & Schölkopf, 2004). Given training data $\{(\mathbf{x}_i, y_i)\}$, $i = 1, \ldots, n$, SVR seeks a function $f(\mathbf{x}) =$

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https://doi.org/10.35877/jetech5578

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ISSN : 2776-7914 (Print) / 2807-3045 (Online)

$\mathbf{w}^{\mathrm{T}}\varphi(\mathbf{x})$ + b that deviates from the targets by at most ε while remaining as flat as possible. The primal problem is:

$$\min_{\mathbf{w},b,\xi,\xi^*} \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad \text{s.t.} \quad \begin{cases} y_i - \mathbf{w}^{\mathrm{T}} \phi(\mathbf{x}_i) - b \le \varepsilon + \xi_i \\ \mathbf{w}^{\mathrm{T}} \phi(\mathbf{x}_i) + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{1}$$

Solving the dual problem gives a prediction function that depends only on the support vectors, here with a radial basis function (RBF) kernel:

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\, K(\mathbf{x}_i, \mathbf{x}) + b, \qquad K(\mathbf{x}_i, \mathbf{x}) = \exp(-\gamma \| \mathbf{x}_i - \mathbf{x} \|^2) \tag{2}$$

Three hyperparameters govern performance: C controls the trade-off between flatness and tolerance of errors outside the tube, ε sets the width of the penalty-free tube and indirectly the number of support vectors, and γ controls the reach of a single data point. Values of C and γ that are too large lead to overfitting, whereas values that are too small lead to underfitting.

2.2. *Particle Swarm Optimization*

PSO imitates the collective behavior of bird flocks (Kennedy & Eberhart, 1995). Each particle i has a position $\mathbf{x}_i$ and a velocity $\mathbf{v}_i$ that are updated using its personal best position $\mathbf{p}_i$ and the global best position $\mathbf{g}$, with an inertia weight w (Shi & Eberhart, 1998):

$$\mathbf{v}_i^{t+1} = w\,\mathbf{v}_i^t + c_1 r_1 (\mathbf{p}_i - \mathbf{x}_i^t) + c_2 r_2 (\mathbf{g} - \mathbf{x}_i^t), \qquad \mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \tag{3}$$

where c_1 and c_2 are the cognitive and social coefficients and r_1 and r_2 are uniform random numbers on (0, 1).

2.3. *Grey Wolf Optimizer*

GWO mimics the leadership hierarchy and hunting mechanism of grey wolves (Mirjalili et al., 2014). The three best solutions are labelled α, β, and δ, and every member of the pack encircles the prey based on them:

$$\mathbf{D}_k = |\mathbf{C}_k \cdot \mathbf{X}_k - \mathbf{X}|, \quad \mathbf{X'}_k = \mathbf{X}_k - \mathbf{A}_k \cdot \mathbf{D}_k, \quad k \in \{\alpha, \beta, \delta\}, \qquad \mathbf{X}^{t+1} = \frac{\mathbf{X'}_\alpha + \mathbf{X'}_\beta + \mathbf{X'}_\delta}{3} \tag{4}$$

with $\mathbf{A} = 2a \cdot \mathbf{r}_1 - a$ and $\mathbf{C} = 2 \cdot \mathbf{r}_2$, where a decreases linearly from 2 to 0. When $|A| > 1$ the wolves explore, and when $|A| < 1$ they attack (exploitation).

2.4. *Whale Optimization Algorithm*

WOA imitates the bubble-net feeding strategy of humpback whales (Mirjalili & Lewis, 2016). With probability 0.5 each whale either encircles the prey or moves along a spiral toward the best solution $\mathbf{X}^*$:

$$\mathbf{X}^{t+1} = \begin{cases} \mathbf{X}^* - \mathbf{A} \cdot |\mathbf{C} \cdot \mathbf{X}^* - \mathbf{X}^t|, & p < 0.5 \\ |\mathbf{X}^* - \mathbf{X}^t|\, e^{bl} \cos(2\pi l) + \mathbf{X}^*, & p \ge 0.5 \end{cases} \tag{5}$$

where l is uniform on $(-1, 1)$ and b defines the spiral shape. When $|A| \ge 1$, the reference $\mathbf{X}^*$ is replaced by a randomly chosen whale, which drives global exploration.

2.5. *Previous Studies*

Studies that tune SVR-type models for solar radiation report consistent but variable gains. Antonanzas-Torres et al. (2015) combined SVR with genetic-algorithm variable selection for

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

daily global irradiation in Spain and reduced the MAE by 19.9–41.4% relative to parametric models. Ghazvinian et al. (2019) found SVR-IPSO superior to SVR-PSO, SVR-GA, SVR-FFA, M5 tree, and MARS in Turkey. Fan et al. (2020) obtained RMSD reductions of 1.1–5.6% from PSO, bat, and WOA tuning of SVM for daily diffuse radiation in China, and Yasin et al. (2020) favored GWO-LSSVM over PSO-LSSVM for hourly irradiance in Malaysia. Oktaviani et al. (2025) reported that Bayesian-optimized SVR outperformed XGBoost for daily GHI in Jakarta. A review by Voyant et al. (2017) concluded that hybrid and ensemble approaches tend to improve accuracy, but that rankings between methods depend strongly on the data set and evaluation protocol. Together, these studies show that hyperparameter optimization usually improves SVR, while the size of the improvement and the best algorithm differ between studies; this motivates comparisons under equal budgets and repeated runs, as performed here. Machine learning has also been applied to the climate of the study region: Hafid et al. (2025) classified rainfall in Makassar with a gradient boosting machine whose hyperparameters were tuned, using BMKG wind speed, humidity, and temperature data, and Rais, Hafid, et al. (2026) combined principal component analysis with classification and regression trees in a model output statistics framework to classify Makassar's monsoonal rainfall.

3. Research Method and Materials

3.1. Study Area and Data

The study uses daily data from the NASA POWER Renewable Energy community (NASA Langley Research Center, 2026) for 1 January 2015 to 31 December 2024 (3,653 days) at four cities representing different climate regimes in Eastern Indonesia (Table 1). Makassar and Kupang lie in the monsoonal rainfall region, Ambon in the anti-monsoonal region with peak rainfall in June–August (Aldrian & Susanto, 2003), and Jayapura has an equatorial character with rainfall spread fairly evenly through the year. This diversity was chosen to test whether the advantage of an optimization algorithm is consistent across climate regimes.

Table 1: Study locations and descriptive statistics of daily GHI, 2015–2024

City	Province	Lat., Lon.	Rainfall regime	Mean (kWh/m²/day)	SD	CV (%)	Highest month	Lowest month	Lag-1 ACF
Makassar	South Sulawesi	−5.14, 119.43	Monsoonal	5.38	1.26	23.5	Sep (6.47)	Jan (4.61)	0.59
Kupang	East Nusa Tenggara	−10.17, 123.61	Monsoonal, semi-arid	5.91	1.13	19.0	Oct (7.03)	Jun (4.96)	0.69
Ambon	Maluku	−3.70, 128.18	Anti-monsoonal	4.96	1.28	25.8	Nov (5.76)	Jul (3.61)	0.55
Jayapura	Papua	−2.53, 140.72	Equatorial	4.90	1.34	27.4	Oct (5.32)	Jul (4.53)	0.12

Note: values in brackets are 2015–2024 monthly means (kWh/m²/day); SD = standard deviation; CV = coefficient of variation; ACF = autocorrelation function.

The target variable is the all-sky global horizontal irradiance at the surface (ALLSKY_SFC_SW_DWN, kWh/m²/day) from CERES SYN1deg. The auxiliary variables are clear-sky irradiance (CLRSKY_SFC_SW_DWN), the clearness index (ALLSKY_KT), downward longwave radiation (ALLSKY_SFC_LW_DWN), 2 m air temperature (T2M), 2 m dew point (T2MDEW), daily temperature range (T2M_RANGE), 2 m wind speed (WS2M), and surface pressure (PS), with meteorological variables taken from the MERRA-2 reanalysis. The 2015–2024 series are complete for all four cities. Daily extraterrestrial radiation (R_a) was not downloaded but computed astronomically from latitude and day of year following Equation 21 of FAO-56 (Allen et al., 1998).

3.2. Preprocessing and Feature Construction

Missing values (code −999) would be linearly interpolated for gaps of up to three days; none occurred within the study period. The model forecasts radiation on day t using only

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

information available at the end of day t−1, plus astronomical quantities for day t that can be computed deterministically. Seventeen features were constructed: (1) radiation lags GHI_{t-1}, GHI_{t-2}, GHI_{t-3}, GHI_{t-7} and the 7-day moving average up to t−1; (2) R_a on day t and the seasonal terms $\sin(2\pi \cdot DOY/365.25)$ and $\cos(2\pi \cdot DOY/365.25)$; (3) sky conditions on day t−1, namely the clearness index, clear-sky irradiance, and downward longwave radiation as a cloud-cover proxy; and (4) day t−1 meteorology, namely T2M, T2MDEW, dew point depression (T2M − T2MDEW) as a humidity proxy, T2M_RANGE, WS2M, and PS. The first seven days of 2015 were lost to lagging, leaving 2,915 training days. All features and the target were standardized with means and standard deviations computed from the training data only, to prevent information leakage.

3.3. *Data Splitting and Temporal Cross-Validation*

Data from 8 January 2015 to 31 December 2022 were used for training, and data from 2023–2024 (731 days) formed a test set that was never used during optimization. The split is chronological rather than random, because shuffling time series yields overly optimistic error estimates (Bergmeir & Benítez, 2012). Within the training data, the fitness of each candidate was computed by three-fold expanding-window cross-validation: training on 2015–2019 and validating on 2020, training on 2015–2020 and validating on 2021, and training on 2015–2021 and validating on 2022. The fitness to be minimized is the mean RMSE of the three folds:

$$F(C, \varepsilon, \gamma) = \frac{1}{3}\sum_{k=1}^{3} \mathrm{RMSE}_k \left(\mathrm{SVR}_{C,\varepsilon,\gamma}\right) \tag{6}$$

3.4. *Hyperparameter Optimization*

The three hyperparameters were searched on a base-10 logarithmic scale so that ranges spanning several orders of magnitude were explored evenly (Table 2). Every method received a nearly equal budget: 300 fitness evaluations per metaheuristic run and 343 for grid search. Grid search was deliberately given a slightly larger budget so that any advantage of the metaheuristics could not come from a looser budget. Each SVR fit was capped at 50,000 LIBSVM iterations so that extreme combinations (large C with small ε) did not dominate computing time; in preliminary runs such combinations produced high validation error, so the cap is not expected to shift the optimum. Because metaheuristics are stochastic, each algorithm was run ten times per city with seeds 1–10. The run with the best validation fitness was refitted on all 2015–2022 data and evaluated on 2023–2024, while the spread of the ten fitness values was used to assess stability.

Table 2: Hyperparameter search space and optimizer settings

Item	Setting
Search space for C	$\log_{10} C \in [-1, 3]$, i.e. 0.1–1,000
Search space for ε	$\log_{10} \varepsilon \in [-3, 0]$, i.e. 0.001–1
Search space for γ	$\log_{10} \gamma \in [-4, 1]$, i.e. 0.0001–10
Default SVR	$C = 1$, $\varepsilon = 0.1$, $\gamma = 1/(p \cdot \mathrm{Var}(X))$ (scikit-learn default)
SVR-Grid	7 × 7 × 7 log-uniform points = 343 evaluations
SVR-PSO	20 particles × 15 iterations = 300 evaluations; w decreases linearly 0.9 → 0.4; $c_1 = c_2 = 2$; maximum velocity 20% of range
SVR-GWO	20 wolves × 15 iterations = 300 evaluations; a decreases linearly 2 → 0
SVR-WOA	20 whales × 15 iterations = 300 evaluations; a decreases linearly 2 → 0; b = 1
All metaheuristics	10 independent runs (seeds 1–10); boundary handling by clipping; at most 50,000 LIBSVM iterations per fit

Note: ε and γ apply to standardized (z-score) variables; p = number of features.

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

3.5. *Benchmarks, Evaluation Metrics, and Statistical Tests*

In addition to the default SVR and SVR-Grid, a persistence forecast ($GHI_t = GHI_{t-1}$) served as the minimum benchmark commonly used in solar forecasting; a model that cannot beat persistence adds no operational value. Test performance was measured by the RMSE, MAE, normalized RMSE (nRMSE), coefficient of determination (R^2), and skill score (SS) relative to persistence:

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(y_t - \hat{y}_t)^2}, \quad \text{MAE} = \frac{1}{m}\sum_{t=1}^{m}|y_t - \hat{y}_t|, \quad \text{nRMSE} = \frac{\text{RMSE}}{\bar{y}} \times 100\% \tag{7}$$

$$R^2 = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y})^2}, \qquad \text{SS} = 1 - \frac{\text{RMSE}_{\text{model}}}{\text{RMSE}_{\text{persistence}}} \tag{8}$$

Differences in accuracy between models were tested with the Diebold–Mariano (DM) test (Diebold & Mariano, 1995) using a squared-error loss and the Harvey–Leybourne–Newbold small-sample correction (Harvey et al., 1997) for a one-day horizon. Differences in stability among the three metaheuristics (ten fitness values each) were tested with the Friedman test, followed by Holm-corrected Wilcoxon signed-rank tests if the Friedman test was significant at $\alpha = 0.05$.

3.6. *Software and Research Workflow*

All analyses were carried out in Python 3 with scikit-learn (whose SVR is based on LIBSVM), NumPy, pandas, and SciPy. PSO, GWO, and WOA were implemented directly in NumPy following Equations 3–5 so that every setting was controlled and reproducible. Figure 1 summarizes the workflow: the test set is separated before optimization begins and is used only once, at the evaluation stage, so the test results reflect performance on genuinely unseen data.

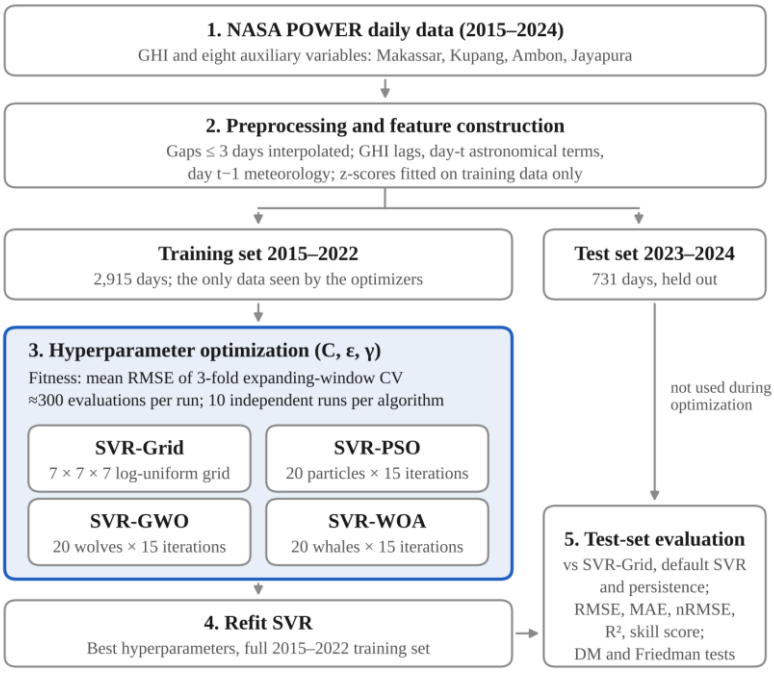


Figure 1: Research workflow

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

4. Results and Discussion

4.1. *Data Characteristics*

Daily radiation in 2015–2024 was highest in Kupang (mean 5.91 kWh/m²/day) and lowest in Jayapura (4.90 kWh/m²/day) (Table 1). Kupang was also the most stable from day to day, whereas Jayapura was the hardest to predict, with a lag-1 autocorrelation of only 0.12. Seasonal patterns follow each city's rainfall regime. Makassar and Kupang peak at the end of the dry season (September–October) and reach their minima in the wet season. Ambon shows the reversed pattern typical of the anti-monsoonal region: radiation drops sharply in June–August to 3.61 kWh/m²/day in July, 37% below its November peak. Jayapura has the smallest seasonal amplitude (4.53–5.32 kWh/m²/day), so its daily variability is driven more by rapidly changing local cloudiness than by season. This agrees with its very low autocorrelation and is the main reason why the persistence forecast fails there.

4.2. *Optimal Hyperparameters and Stability*

The three metaheuristics found almost identical hyperparameter combinations in every city, and their validation RMSE was 0.2–0.7% lower than that of grid search (Table 3). This indicates that PSO, GWO, and WOA reached the same optimum region within 300 evaluations. Two patterns stand out. First, the optimal γ was very small (0.0002–0.007) in all cities; an RBF kernel with such a small γ behaves almost linearly, meaning that the relationship between the features and next-day radiation is largely captured by a smooth function. Second, the metaheuristics consistently chose a wider ε than grid search (0.50–0.55 against 0.316 in Makassar, Ambon, and Jayapura). A wider tube makes SVR ignore small errors and generally rely on fewer support vectors. In Ambon and Jayapura, C and γ varied considerably between metaheuristics (for example, C = 477–1,000 in Jayapura), yet validation RMSE differed only in the fourth decimal. This reveals a flat fitness surface along a C–γ ridge, on which a large C with a small γ can substitute for a smaller C with a larger γ.

Table 3: Optimal hyperparameters and stability over ten independent runs

City	Method	C	ε	γ	Best validation RMSE	Mean ± SD (10 runs)
Makassar	SVR-Grid	215.44	0.316	0.00068	1.0006	–
Makassar	SVR-PSO	3.95	0.538	0.00651	0.9939	0.9942 ± 0.0003
Makassar	SVR-GWO	2.65	0.538	0.00667	0.9939	0.9957 ± 0.0048
Makassar	SVR-WOA	2.31	0.539	0.00713	0.9939	0.9958 ± 0.0047
Kupang	SVR-Grid	10.00	0.316	0.00464	0.7930	–
Kupang	SVR-PSO	22.08	0.345	0.00387	0.7899	0.7908 ± 0.0023
Kupang	SVR-GWO	18.05	0.342	0.00465	0.7898	0.7910 ± 0.0024
Kupang	SVR-WOA	14.91	0.341	0.00452	0.7899	0.7912 ± 0.0022
Ambon	SVR-Grid	10.00	0.316	0.00464	1.0185	–
Ambon	SVR-PSO	181.78	0.550	0.00114	1.0119	1.0126 ± 0.0010
Ambon	SVR-GWO	85.84	0.550	0.00174	1.0118	1.0123 ± 0.0003
Ambon	SVR-WOA	65.82	0.547	0.00197	1.0117	1.0126 ± 0.0013
Jayapura	SVR-Grid	2.15	0.316	0.00464	1.1981	–
Jayapura	SVR-PSO	477.16	0.500	0.00026	1.1954	1.1975 ± 0.0047
Jayapura	SVR-GWO	743.74	0.499	0.00022	1.1951	1.1958 ± 0.0004
Jayapura	SVR-WOA	1,000.00	0.499	0.00019	1.1951	1.1959 ± 0.0007

Note: ε and γ on the standardized scale; RMSE in kWh/m²/day, mean of the 2020, 2021, and 2022 validation folds on the original scale.

The three algorithms were equally stable: the Friedman test on the ten fitness values was not significant in any city (Makassar $\chi^2 = 1.4$, $p = 0.497$; Kupang $\chi^2 = 3.8$, $p = 0.150$; Ambon $\chi^2 = 1.4$, $p = 0.497$; Jayapura $\chi^2 = 0.6$, $p = 0.741$), and all Holm-corrected Wilcoxon p-values exceeded 0.25. The visible differences in spread were local and inconsistent across cities: PSO was the most consistent in Makassar but the most dispersed in Jayapura, where one run stopped at 1.2108, while GWO and WOA each had one run in Makassar trapped near 1.009. In every case the worst run was at most 1.6% worse than the best, and 50–85% of the total

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https://doi.org/10.35877/jetech5578

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ISSN : 2776-7914 (Print) / 2807-3045 (Online)

improvement in mean fitness was achieved within the first five iterations. With a three-dimensional search space and 300 evaluations, all three algorithms are therefore reliable enough to be run once in practice.

4.3. *Test-Set Accuracy and Significance*

All SVR variants outperformed the persistence forecast, with skill scores of 0.13–0.28 (Table 4), and the advantage of the metaheuristic SVRs over persistence was significant in all four cities (DM statistics from −3.54 to −10.24, $p < 0.001$). However, the metaheuristic-optimized SVRs were not always the best models: SVR-Grid was the most accurate in Makassar and Ambon, the two were equivalent in Kupang, and the metaheuristics were slightly better only in Jayapura. Against SVR-Grid, the metaheuristics were significantly worse in Makassar and Ambon, not different in Kupang, and significantly better in Jayapura. Against the default SVR, their improvement was significant only in Jayapura (DM from −4.72 to −4.77, $p < 0.001$; elsewhere $p = 0.106$–0.859).

Table 4: Test-set performance (2023–2024) and Diebold–Mariano test against SVR-Grid

City	Model	RMSE	MAE	nRMSE (%)	R^2	SS	DM vs SVR-Grid (p)
Makassar	Persistence	1.123	0.787	20.9	0.273	0.000	–
Makassar	Default SVR	0.920	0.668	17.1	0.511	0.180	–
Makassar	SVR-Grid	0.895	0.658	16.6	0.538	0.203	–
Makassar	SVR-PSO	0.911	0.687	16.9	0.521	0.189	3.08 (0.002)
Makassar	SVR-GWO	0.911	0.685	16.9	0.521	0.189	3.09 (0.002)
Makassar	SVR-WOA	0.911	0.685	17.0	0.521	0.188	3.10 (0.002)
Kupang	Persistence	0.868	0.544	14.8	0.420	0.000	–
Kupang	Default SVR	0.755	0.479	12.9	0.561	0.130	–
Kupang	SVR-Grid	0.740	0.491	12.6	0.578	0.147	–
Kupang	SVR-PSO	0.741	0.496	12.6	0.577	0.146	0.34 (0.734)
Kupang	SVR-GWO	0.741	0.495	12.6	0.577	0.146	0.39 (0.698)
Kupang	SVR-WOA	0.741	0.496	12.6	0.577	0.146	0.42 (0.671)
Ambon	Persistence	1.173	0.899	23.9	0.193	0.000	–
Ambon	Default SVR	0.987	0.783	20.1	0.429	0.159	–
Ambon	SVR-Grid	0.960	0.767	19.6	0.460	0.182	–
Ambon	SVR-PSO	0.985	0.800	20.1	0.432	0.161	4.88 (< 0.001)
Ambon	SVR-GWO	0.985	0.799	20.1	0.432	0.161	4.93 (< 0.001)
Ambon	SVR-WOA	0.985	0.799	20.1	0.432	0.161	4.98 (< 0.001)
Jayapura	Persistence	1.803	1.411	37.5	−0.747	0.000	–
Jayapura	Default SVR	1.367	1.070	28.4	−0.005	0.242	–
Jayapura	SVR-Grid	1.304	1.027	27.1	0.086	0.277	–
Jayapura	SVR-PSO	1.296	1.030	26.9	0.098	0.281	−2.60 (0.009)
Jayapura	SVR-GWO	1.297	1.031	27.0	0.096	0.280	−2.15 (0.032)
Jayapura	SVR-WOA	1.297	1.030	26.9	0.096	0.281	−2.32 (0.021)

Note: RMSE and MAE in kWh/m²/day; SS = skill score relative to persistence; grey cells mark the best value per city; DM = Harvey–Leybourne–Newbold-corrected statistic (two-sided p, n = 731), negative values favour the metaheuristic model.

Forecast difficulty differed widely between cities. Kupang was the easiest to predict (nRMSE 12.6%), in line with its long dry season and stable radiation. Jayapura was the hardest (nRMSE ≈ 27%): its persistence R^2 was negative (−0.75), and even the best SVR explained only about 10% of the daily variance. Nevertheless, Jayapura obtained the highest skill score (0.28), because the failure of persistence there left the most room for improvement. The three metaheuristic variants produced practically identical forecasts in every city (RMSE differences ≤ 0.002 kWh/m²/day), consistent with their similar hyperparameters. Relative to the default SVR, metaheuristic optimization reduced RMSE by 0.2% (Ambon), 1.0% (Makassar), 1.9% (Kupang), and 5.2% (Jayapura), whereas grid search reduced it by 2.0–4.6% in all four cities.

4.4. *Why the Validation Advantage Did Not Transfer*

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

The metaheuristics lowered validation RMSE by 0.2–0.7% relative to grid search in all four cities, but on the test set this improvement persisted only in Jayapura and reversed in Makassar and Ambon (Figure 2). To verify that the validation advantage was not an artifact of a single fold, RMSE was recomputed for each validation year using the SVR-Grid and SVR-PSO configurations. The PSO configuration was better in 11 of the 12 folds; the only exception was Jayapura in 2022 (1.107 against 1.103 kWh/m²/day). The advantage was therefore consistent throughout 2020–2022 but did not carry over to 2023–2024.

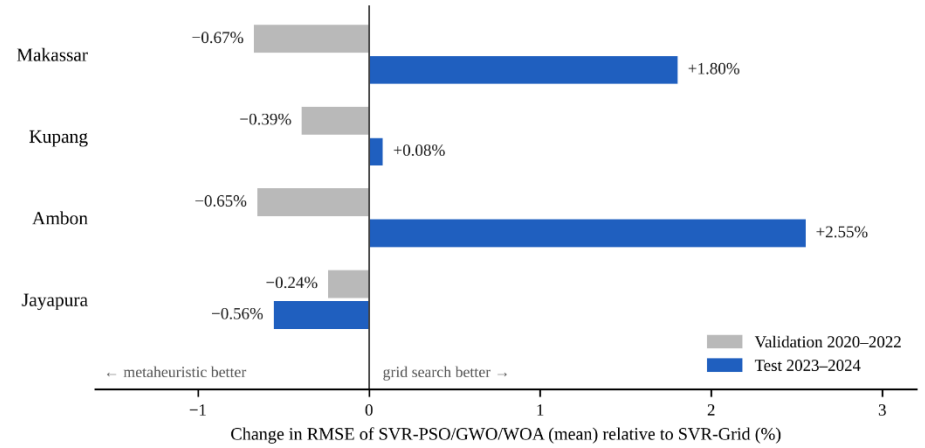


Figure 2: Change in RMSE of the metaheuristic-optimized SVRs (mean of PSO, GWO, and WOA) relative to SVR-Grid on validation and test data

The most plausible explanation is a shift in climatic conditions between the validation and test periods. The validation years 2020–2022 coincided with a three-year La Niña (2020–2023), which was followed by a strong El Niño from mid-2023 (NOAA Global Ocean Monitoring and Observing Program, 2023). Mean annual radiation in 2023 in Makassar (5.55 kWh/m²/day) and Ambon (5.03 kWh/m²/day) lay above the range of their validation years (5.08–5.34 and 4.77–4.87), and these are the two cities where the metaheuristics lost to grid search. In Kupang, the 2023 value (5.94) remained within the validation range (5.71–5.96), and the two approaches were equivalent. In Jayapura, the 2023 value (4.83) lay slightly below the validation range (4.99–5.15), and the metaheuristics kept their advantage. This pattern is consistent with the hypothesis that the wide ε selected by the metaheuristics was overly adapted to the cloudier La Niña years; with only four cities, however, it should be tested further before being treated as causal.

The choice of metaheuristic did not determine the outcome. PSO, GWO, and WOA reached the same optimum region, did not differ significantly in stability, and produced test forecasts within 0.002 kWh/m²/day of each other. This agrees with the no free lunch theorem (Wolpert & Macready, 1997): in a flat three-dimensional search space, different search mechanisms offer no meaningful advantage. The result differs from claims of a single superior algorithm in some earlier studies (Fan et al., 2020; Yasin et al., 2020), and from the gain of a GA-tuned SVM reported by Rais and Yuniar (2025); such differences may arise because those studies compared tuned models with untuned ones, ran each algorithm once, or used random data splits.

In practical terms, the largest source of accuracy was the use of SVR itself (skill scores of 0.13–0.28 against persistence), while hyperparameter tuning of any kind added a smaller gain of 2.0–4.6% for grid search over the default SVR. Because the computational cost is equivalent (300 against 343 evaluations), a logarithmic grid search, already the usual tuning procedure in Indonesian SVR applications (Annas et al., 2023; Isnaeni et al., 2022; Rahmat et al., 2023; Ruliana et al., 2024), is a strong and transparent benchmark for tuning a three-hyperparameter SVR, and metaheuristics are likely to be more useful when the search space is larger, for example when feature selection is optimized jointly with the hyperparameters (Antonanzas-Torres et al., 2015). For PV planning, one-day-ahead errors of 12.6% in Kupang

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https://doi.org/10.35877/jetech5578

ISSN : 2776-7914 (Print) / 2807-3045 (Online)

and about 17% in Makassar are informative enough for scheduling energy storage, whereas an nRMSE of about 27% in Jayapura indicates that daily forecasts based on satellite data and previous-day meteorology remain inadequate where cloud cover changes rapidly.

Several limitations apply. First, the target is satellite-derived NASA POWER radiation, which has a positive bias of 3–7% against surface measurements in Indonesia (Harsarapama et al., 2020), and the results have not been validated against pyranometer data. Second, the optimization budget was limited to 300 evaluations per run because of computational constraints, although the convergence curves show that most of the improvement was reached early. Third, rainfall was not available as a feature in the data used. Fourth, the cross-validation covered only three years, all within a La Niña phase.

5. Conclusion

This study compared SVR models tuned by PSO, GWO, and WOA for one-day-ahead forecasting of daily solar radiation in Makassar, Kupang, Ambon, and Jayapura. All SVR variants significantly outperformed the persistence forecast, with skill scores of 0.13–0.28 and test RMSE of 0.74–1.30 kWh/m²/day; accuracy was highest in Kupang (nRMSE 12.6%) and lowest in Jayapura (nRMSE ≈ 27%). PSO, GWO, and WOA converged to nearly identical hyperparameters with statistically indistinguishable stability, so the choice of metaheuristic did not affect accuracy. Although the metaheuristics reduced validation RMSE by 0.2–0.7% relative to grid search, this advantage was not consistent on the test set: it was significantly better in Jayapura, equivalent in Kupang, and significantly worse in Makassar and Ambon, a reversal that coincided with the transition from La Niña in the validation period to El Niño in the test period.

Under an equivalent computational budget, a logarithmic grid search is therefore a strong benchmark for tuning a three-hyperparameter SVR, and the superiority of an optimization method should be reported on out-of-sample test data with significance tests rather than on validation error alone. Future work should use cross-validation schemes spanning several ENSO phases, optimize feature selection jointly with the hyperparameters, add rainfall and ground pyranometer data to correct satellite bias, and compare these results with deep learning models such as LSTM, including hybrid statistical–deep learning schemes that have improved forecasts of other Indonesian series (Rais, Sumarno, et al., 2026), at the same locations.

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ISSN : 2776-7914 (Print) / 2807-3045 (Online)

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