



## IMPLEMENTATION OF GATED RECURRENT UNIT (GRU) WITH PARTICLE SWARM OPTIMIZATION (PSO) FOR PALM OIL PRICE PREDICTION

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### ABSTRACT

Palm oil is a major agricultural commodity whose price fluctuates over time, creating uncertainty for planning and decision-making. This study develops a time-series prediction model for Palm Oil Futures prices by implementing a Gated Recurrent Unit (GRU) and optimizing selected GRU hyperparameters using Particle Swarm Optimization (PSO). The dataset was obtained from Investing.com and contains 2,376 daily observations covering 2 June 2016 to 2 June 2026, with Date and Price used as the principal attributes. The research workflow includes data cleaning, chronological train-test splitting, Min-Max normalization, sequence construction, baseline GRU development, PSO-based hyperparameter optimization, final model training, and evaluation using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Three split scenarios (70:30, 80:20, and 90:10) and two sequence lengths (14 and 28) were examined before the final configuration was selected. PSO searched GRU Units and Dense Units in the ranges 64-128 and 32-64, respectively. The best baseline configuration achieved RMSE 2.890, MAE 2.303, and MAPE 6.681%, while the optimized GRU-PSO achieved RMSE 1.956, MAE 1.653, and MAPE 6.689%. Thus, PSO reduced RMSE by about 32.3% and MAE by about 28.2%, while MAPE increased slightly. The final model was also used to generate a seven-day short-term forecast.

**Keywords:** Gated Recurrent Unit, hyperparameter, palm oil price, Particle Swarm Optimization, time series

### INTRODUCTION

Palm oil is a strategic agricultural commodity in tropical regions and plays an important role in food and industrial supply chains. Indonesia is among the countries in which palm oil is widely cultivated, supported by tropical climatic conditions that are suitable for oil palm growth. Palm oil is also a major raw material for edible oil production, so changes in palm oil prices can propagate into downstream products and affect economic decision-making ([1] [2]).

Despite its strategic role, palm oil prices are characterized by fluctuations that make future price movements difficult to anticipate. Historical price data therefore provide an important basis for identifying temporal patterns and generating short-term forecasts. In this study, the forecasting problem is treated as a time-series problem because each observation is ordered chronologically and the current value is related to information

contained in previous observations. The dataset is sourced from Investing.com, which provides historical Palm Oil Futures data, and the study focuses on the Date and Price attributes.

Deep learning approaches are increasingly used for sequential data because they can learn nonlinear temporal representations. Previous comparative work on stock-price time series found that GRU outperformed Linear Regression and LSTM, obtaining lower RMSE, MSE, and MAE values in that experimental setting [3]. GRU is a recurrent neural architecture that uses reset and update gates and generally has a simpler structure than LSTM, making it attractive when computational efficiency is important ([4] [5]).

However, GRU performance depends on hyperparameter configuration. The number of recurrent units and dense units can affect model capacity and consequently prediction error. Manual selection may not identify a strong configuration efficiently. Particle Swarm Optimization (PSO) provides a population-based search strategy in which candidate solutions are represented by particles that update their positions using personal-best and global-best information. Previous research has shown that PSO can improve predictive or classification performance by searching for more suitable hyperparameter combinations ([6] [7]).

An important research gap is identified from previous work using the same general palm-oil dataset. The earlier study by [8] applied Linear Regression and Random Forest and reported relatively high RMSE values, indicating room for improvement on the time-series prediction task. The present study extends the temporal coverage through 2 June 2026 and investigates a combination of GRU and PSO, with an explicit comparison between an unoptimized GRU baseline and a GRU model using PSO-selected hyperparameters. The contribution of this work is therefore the empirical evaluation of whether PSO-based hyperparameter selection improves GRU prediction performance for the selected palm-oil price series, together with a short-term seven-day forecast.

## **RELATED WORKS**

### **GRU for Time-Series Prediction**

GRU is a recurrent neural network architecture designed to model sequential information. Compared with LSTM, GRU uses two principal gates, namely the reset gate and update gate, to regulate the flow and retention of information. The reset gate controls the influence of previous hidden information when forming new representations, while the update gate determines how much information from the previous state should be retained. This compact structure can reduce computational requirements while preserving the ability to model temporal dependencies ([9] [10]).

For time-series forecasting, GRU receives observations in temporal order and carries a hidden state from one time step to the next. This enables the model to learn patterns such as trends and fluctuations across sequential observations. Prior studies have reported successful GRU applications for stock indices, stock prices, and other sequential forecasting problems ([11] [9]).

### **Hyperparameter Optimization with PSO**

Hyperparameter optimization aims to identify model configurations that provide favorable validation performance. The thesis compares PSO with Gravitational Search Algorithm (GSA) at the conceptual level. GSA is inspired by gravitational interaction and can explore complex solution spaces, but the thesis notes higher computational complexity and slower convergence in some settings ([12] [13]). PSO, in contrast, represents candidate configurations as particles and uses personal-best (pBest) and global-best (gBest) information to guide the search. In this study, PSO is used specifically to optimize GRU Units and Dense Units.

The research literature summarized in the thesis also indicates that PSO can be effective for hyperparameter optimization in other models. For example, [6] reported improved classification performance after PSO-based SVM optimization, while the 2026 Bi-LSTM study summarized in the thesis reported improved predictive error after PSO-based hyperparameter search. These studies motivate the use of PSO as a complementary optimization layer rather than replacing the forecasting model itself.

**Table 1. Selected previous studies and their relevance to the present study**

| Study                        | Model / method                      | Key finding                                                  | Relevance / gap                                                |
|------------------------------|-------------------------------------|--------------------------------------------------------------|----------------------------------------------------------------|
| citra resita (2022)          | Linear Regression;<br>Random Forest | RMSE remained relatively high on palm-oil price data         | Motivates a stronger time-series model on the same data source |
| Khalis Sofi et al. (2021)    | Linear Regression;<br>LSTM; GRU     | GRU produced the lowest reported RMSE, MSE, and MAE          | Supports the use of GRU for sequential price prediction        |
| Danestiara et al. (2024)     | GRU                                 | GRU successfully modeled LQ45 closing-price time series      | Shows GRU applicability to financial time series               |
| Adrian & Laksana (2025)      | SVM + PSO                           | PSO improved model performance through hyperparameter search | Supports PSO as a hyperparameter optimizer                     |
| Hyperparameter et al. (2026) | Bi-LSTM + PSO                       | PSO-based configuration reduced predictive error             | Shows optimization can complement deep-learning forecasting    |

The comparison indicates that prior studies separately provide evidence for GRU-based time-series prediction and PSO-based hyperparameter optimization. The distinctive focus of the present study is their combination on the selected palm-oil price series, followed by a controlled comparison of the baseline and optimized configurations.

## METHODOLOGY

### Research Design and Proposed Method

The study follows an experimental quantitative design for univariate time-series prediction. The dataset was obtained from Investing.com and contains 2,376 observations covering 2 June 2016 to 2 June 2026. The raw dataset contains Date, Price, Open, High, Low, Vol., and Change % fields. For the forecasting task, the study retained Date and Price as the principal variables and treated Date as the chronological index. The thesis reports that the data are used in chronological order so that earlier observations are used to learn patterns and later observations are reserved for evaluation.

## Data Preprocessing

Data cleaning converted Date to a datetime representation, used Date as the time index, sorted observations chronologically, removed the unused Open, High, Low, Vol., and Change % columns, and converted Price to a numeric form after removing punctuation characters. The cleaned series was therefore structured for sequential modeling. The thesis reports 2,376 usable observations after cleaning.

Train-test splitting was evaluated using 70:30, 80:20, and 90:10 chronological scenarios. The corresponding counts reported in the thesis were 1,663/713, 1,900/476, and 2,138/238 for training/testing. The 90:10 scenario was selected for subsequent experiments because it provided the best overall configuration for the later GRU and GRU-PSO comparison within the experimental setup.

Normalization used Min-Max scaling to map values to the 0-1 range. Sequence construction was then performed with a time step of 28 for the final model selection. The resulting final sequence shapes were 2,111 training samples and 211 testing samples, each with 28 time steps and one feature. The thesis also reports an earlier screening stage that compared time steps of 14 and 28.

## GRU Model

The forecasting network contains one GRU layer, one Dense hidden layer with ReLU activation, one Dropout layer with a rate of 0.1, and one output Dense layer with a single unit. The model is compiled using the Adam optimizer and mean squared error as the training loss. The baseline configuration uses 64 GRU units, 32 Dense units, and a learning rate of 0.001. This baseline is used as the reference configuration before PSO optimization.

For the selected experiments, the study evaluates time steps 14 and 28, batch sizes 32 and 64, and epochs 50, 100, 150, and 200. Early stopping is used in training so that the best observed validation weights can be restored when the validation loss no longer improves. The final best baseline configuration reported by the thesis is time step 28, batch size 64, and epoch 150.

In the proposed workflow, the baseline model serves two purposes. First, it establishes how the GRU performs when its principal architectural settings are chosen without the PSO search. Second, it provides a reference point for judging whether the optimized configuration actually changes predictive performance. This before-and-after design is important because a lower error from the optimized model can be interpreted only when the baseline is trained and evaluated under a comparable experimental setting.

The GRU architecture was kept intentionally compact. A single recurrent layer processes the historical sequence, followed by a Dense layer that transforms the recurrent representation before a one-unit output layer produces the price estimate. The Dropout layer with a rate of 0.1 is included to reduce the risk of excessive reliance on individual hidden representations during training. The same model-building function is reused for the baseline and PSO candidates, so the principal structural difference between the two final models is the hyperparameter configuration rather than an unrelated architectural change.

The PSO objective is based on validation loss rather than the final test metrics. Each particle represents a candidate pair of GRU Units and Dense Units. For each candidate, a GRU model is constructed, trained on the training sequences, and evaluated on the validation portion available in the implementation. The minimum validation loss observed during the candidate training becomes the fitness value that PSO attempts to minimize.

Personal-best and global-best updates then guide subsequent particle movement toward promising regions of the search space. After optimization, the best pair is transferred to the final GRU-PSO model for the controlled performance comparison.

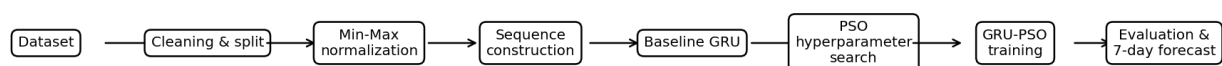
The optimization search is deliberately limited to GRU Units and Dense Units. The thesis fixes the learning rate at 0.001 so that the search remains two-dimensional and computationally manageable. The bounds of 64–128 recurrent units and 32–64 dense units provide a constrained but meaningful range around the baseline architecture. The use of a swarm size of five and three maximum iterations also reflects a practical trade-off between search coverage and computational cost. Consequently, the reported optimum should be understood as the best configuration found within this defined search space, not as an assertion that no better configuration exists outside the tested bounds.

### Particle Swarm Optimization

PSO is used to search the two hyperparameters that define model capacity: GRU Units and Dense Units. The search bounds are 64-128 for GRU Units and 32-64 for Dense Units. Learning rate is fixed at 0.001 and is not included in the optimization space. The objective function trains a candidate GRU configuration and returns the minimum validation loss observed during training. The thesis implementation uses a swarm size of 5 and a maximum of 3 iterations for the optimization stage. The best solution found is 128 GRU Units and 51 Dense Units.

### Experimental Procedure

The experimental sequence is: (1) load and clean the dataset; (2) split the data chronologically; (3) construct sequences; (4) normalize the input and target values; (5) evaluate candidate data-split and time-step settings; (6) train the baseline GRU; (7) run PSO on GRU Units and Dense Units; (8) train the final GRU-PSO model using the best PSO configuration; (9) compare GRU and GRU-PSO using RMSE, MAE, and MAPE; and (10) use the selected GRU-PSO model for a seven-day forecast.



**Figure 1. Research workflow for GRU prediction and PSO hyperparameter optimization**

For reproducibility, the study keeps the final data order chronological from the earliest observation in June 2016 to the latest observation in May 2026 used in the modeling dataset. The forecast output is then extended from the latest available sequence. This chronological treatment is consistent with the underlying assumption that future observations should not influence the representation learned from earlier observations.

## RESULTS AND DISCUSSION

## Dataset and Experimental Selection

The dataset contains 2,376 daily observations from June 2016 to June 2026. The exploratory split experiments showed that model performance varies with both the proportion of training data and sequence length. Across the tested split and time-step combinations, the thesis selected 90:10 for the main experiment. For the baseline GRU, the best screening result reported at this stage was obtained at 80:20 with time step 14, whereas the subsequent parameter search under the 90:10 setup selected time step 28 for the final baseline. For GRU-PSO, the 90:10, time-step-14 configuration performed strongly during the initial screening, but the later controlled parameter search selected time step 28, batch size 32, and epoch 200 as the best final configuration.

**Table 2. Best screening results by model**

| Model   | Best split / time step | RMSE   | MAE    | MAPE   |
|---------|------------------------|--------|--------|--------|
| GRU     | 80:20 / 14             | 20.804 | 18.629 | 9.020% |
| GRU-PSO | 90:10 / 14             | 9.422  | 7.874  | 6.607% |

The screening stage was used to identify a practical experimental direction before the final parameter search. The thesis shows that model error changed substantially across split ratios and time steps, which means that the amount of historical information supplied to the model and the size of the held-out period can affect the observed performance. The 90:10 split provided the largest training set among the tested scenarios, with 2,138 observations for training and 238 observations for testing. This chronological design is important for time-series forecasting because it avoids randomly mixing future observations into the training set and preserves the temporal ordering of the series.

Sequence length was also treated as an experimental factor. A time step determines how many consecutive historical observations are presented to the GRU as one input sequence. In the thesis, time steps of 14 and 28 were compared. The final experiment selected 28 because the parameter search under the selected split produced the lowest final errors at that sequence length. Thus, the selected time step was not assumed in advance; it emerged from the experimental comparison together with the training configuration. This distinction is useful in the journal manuscript because it separates the methodological choice from the final reported result.

The preprocessing stage is also essential to reproducibility. The raw dataset contains price values represented as text with punctuation, as well as additional market fields that are not used by the final forecasting model. The thesis therefore converts the date field to a datetime representation, orders observations chronologically, removes the unused market columns, and converts the price field to a numeric representation. After cleaning, the final modeling data contain the chronological date index and the price series. Min-Max normalization then maps the numerical values to a common 0-1 range before sequence construction and neural-network training.

The final sequence generation uses 28 observations per input window and one target value. The thesis code produces 2,111 training sequences and 211 testing sequences after the time-step transformation. These sequence dimensions are used to define the recurrent input shape. Because the task is univariate, each time step contains one price feature. The model therefore learns temporal dependencies from the historical price sequence rather than from a set of exogenous explanatory variables.

## PSO Optimization Result

PSO converged to a configuration of 128 GRU Units and 51 Dense Units within the defined search bounds. These settings were subsequently fixed for the final GRU-PSO model. The result indicates that the optimizer selected a larger recurrent representation than the baseline while keeping the Dense layer within the prescribed range. Because the objective was based on validation loss, the selected combination was the configuration that produced the lowest observed objective value during the swarm search.

## Baseline versus GRU-PSO Performance

**Table 3. Final comparison of the best GRU and GRU-PSO configurations**

| Model         | Time step | Batch size | Epoch | RMSE  | MAE   | MAPE   |
|---------------|-----------|------------|-------|-------|-------|--------|
| GRU (Non-PSO) | 28        | 64         | 150   | 2.890 | 2.303 | 6.681% |
| GRU-PSO       | 28        | 32         | 200   | 1.956 | 1.653 | 6.689% |

The optimized model achieved lower RMSE and MAE than the baseline. RMSE decreased from 2.890 to 1.956, corresponding to an approximate reduction of 32.3%, while MAE decreased from 2.303 to 1.653, a reduction of approximately 28.2%. These reductions indicate that, under the final experimental configuration, the GRU-PSO predictions were closer to the observed prices than the baseline predictions. In contrast, MAPE changed from 6.681% to 6.689%, an increase of only 0.008 percentage points. Because both values remain below 10%, the thesis categorizes both as very good according to its MAPE interpretation scale.

The mixed behavior across metrics is important. PSO improved absolute-error-based measures (RMSE and MAE), but the relative percentage error represented by MAPE did not improve. This means the conclusion that PSO improved the model should be expressed in metric-specific terms rather than as an unconditional improvement across every metric. The result is consistent with the thesis conclusion that optimization can affect different evaluation criteria differently.

The choice of a seven-day forecast horizon is consistent with the short-term nature of the modeled series. The forecast is generated recursively from the trained GRU-PSO model and is intended to extend the historical pattern into the immediate future. The thesis reports a smooth progression across the seven forecast dates rather than abrupt oscillation. This behavior should be interpreted cautiously: a smooth trajectory can be appropriate when the most recent historical sequence is stable, but it does not guarantee that unexpected market shocks will be captured because those shocks may not be encoded in the historical price-only input.

From an applied perspective, the prediction output can serve as an initial quantitative reference for short-term planning, but it should be combined with contextual information before operational or financial decisions are made. The thesis explicitly limits the study to historical price information and does not separately model weather conditions, export policies, exchange rates, global commodity movements, or other macroeconomic factors. This limitation is consistent with the research boundary and also identifies a clear direction for future work using multivariate time-series inputs.

### Prediction Behavior and Short-Term Forecast

The thesis reports that the GRU-PSO prediction curve generally follows the actual price curve in the testing period, with larger discrepancies appearing around sharper price movements. A sample of ten testing observations also shows that GRU-PSO often has a smaller absolute difference from the actual value than the baseline. For example, on 13 May 2025, the actual price was 3,923.00, the baseline predicted 3,954.73 (absolute difference 31.73), and GRU-PSO predicted 3,915.13 (absolute difference 7.87). This sample-level comparison supports the aggregate RMSE and MAE results, although the full evaluation metrics remain the primary basis for model assessment.

**Table 4. Seven-day forecast generated by GRU-PSO**

| Date       | Predicted price |
|------------|-----------------|
| 2026-05-29 | 4,522.64        |
| 2026-05-30 | 4,526.14        |
| 2026-05-31 | 4,528.44        |
| 2026-06-01 | 4,530.20        |
| 2026-06-02 | 4,531.65        |
| 2026-06-03 | 4,532.92        |
| 2026-06-04 | 4,534.08        |

The seven-day forecast shows a relatively stable short-term trajectory with a gradual increase from 4,522.64 to 4,534.08 across the forecast horizon. The thesis interprets this pattern as a short-term tendency toward stability with a slight increase rather than an extreme movement. Because the model uses historical price observations and does not explicitly include external drivers such as global market conditions, trade policy, exchange rates, or other macroeconomic variables, the forecast should be treated as a statistical indication of short-term temporal behavior rather than a complete economic forecast.

### Training Stability and Error Behavior

The training and validation-loss visualization provides a complementary view of the numerical evaluation. The thesis reports a sharp decline in training loss during the early stages of GRU-PSO training, followed by a more stable pattern at lower loss values. The relatively small separation between training and validation loss near the later training stages was interpreted as evidence that the model was learning a useful representation without a strong visual indication of severe overfitting. Early stopping was also incorporated so that training could stop when validation loss ceased to improve and the best observed weights could be retained.

The final comparison also demonstrates why a single evaluation metric should not be used in isolation. RMSE and MAE are expressed on the price scale and directly represent absolute prediction deviations, whereas MAPE expresses the error relative to the actual price. In the final experiment, PSO improved the two absolute-error measures but did not reduce MAPE. The most defensible interpretation is therefore that PSO improved the final GRU configuration in terms of RMSE and MAE, while the percentage-error performance remained essentially unchanged. This metric-specific conclusion is consistent with the numerical evidence and avoids overstating the optimization effect.

The sample-level predictions support the aggregate metrics. For several dates shown in the thesis, the optimized model produces a smaller absolute difference from the actual price than the baseline model. This behavior is visible in both the numerical comparison table and the prediction-versus-actual plot. Nevertheless,

individual observations should be regarded as illustrative rather than sufficient evidence on their own; the overall RMSE, MAE, and MAPE values calculated over the testing period remain the principal quantitative evidence used to compare the models.

### Study Limitations

Several limitations should be considered when interpreting the results. First, the modeling variables are limited to the historical price series and the date index, so the model does not directly represent external determinants of palm-oil prices. Second, the PSO search is intentionally restricted to two hyperparameters—GRU Units and Dense Units—while the learning rate is fixed at 0.001. Third, the optimization uses a small swarm size and a limited maximum number of iterations to control computational cost. These choices make the experimental design focused, but a larger search space or additional hyperparameters could potentially identify other competitive configurations. Finally, the seven-day forecast represents short-term statistical extrapolation from historical patterns and should not be interpreted as a guaranteed market outcome.

### Discussion in Relation to Previous Studies

The results extend the findings of the previous palm-oil study that used Linear Regression and Random Forest on related historical data. Whereas that work reported relatively high RMSE values, the present study obtained substantially lower errors under its final GRU configuration and then reduced RMSE and MAE further after PSO optimization. The result also aligns with the broader evidence that GRU is suitable for sequential price prediction ([3] [11]). The contribution of the present study is not simply the use of GRU, but the addition of a PSO search layer and a direct before-versus-after comparison on the extended dataset.

At the same time, the findings should not be overstated. The study uses a single primary price series and excludes external explanatory factors. In addition, the PSO search was intentionally constrained to two hyperparameters and a small swarm configuration to control computational cost. These design choices make the experiment focused and reproducible, but they also limit the space of configurations that could be explored.

## CONCLUSION

This study implemented GRU and GRU-PSO models for Palm Oil Futures price prediction using 2,376 daily observations from Investing.com covering 2 June 2016 to 2 June 2026. The research workflow included chronological preprocessing, normalization, sequence construction, baseline modeling, PSO-based hyperparameter search, final model training, and evaluation using RMSE, MAE, and MAPE.

The final baseline configuration used time step 28, batch size 64, and 150 epochs, while the optimized model used time step 28, batch size 32, and 200 epochs together with PSO-selected values of 128 GRU Units and 51 Dense Units. GRU-PSO reduced RMSE from 2.890 to 1.956 and MAE from 2.303 to 1.653, while MAPE changed slightly from 6.681% to 6.689%. Therefore, PSO provided a clear improvement on the RMSE and MAE criteria in the final experiment, but it did not reduce MAPE. The final GRU-PSO model was then used to generate a seven-day forecast showing a relatively stable short-term increase.

Future work should extend the historical dataset, compare GRU-PSO with other deep-learning architectures, and investigate alternative hyperparameter optimization methods. Incorporating external variables such as macroeconomic, market, exchange-rate, or policy indicators may also provide a richer forecasting framework.

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### 1. GENERATIVE AI DISCLOSURE

Generative AI and AI-assisted tools were used to support manuscript organization, language polishing, and formatting preparation. The authors reviewed the manuscript and remain fully responsible for the accuracy, originality, citations, interpretation, and integrity of the submitted work.

### 2. DATA AVAILABILITY STATEMENT

The study uses historical Palm Oil Futures data obtained from Investing.com. The data source is publicly accessible at <https://www.investing.com/commodities/palm-oil>. The processed dataset used in this study is derived from that source.

### 3. AUTHOR CONTRIBUTIONS

The author declares that there is no conflict of interest relevant to this work.

### 4. CONFLICT OF INTEREST

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