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Exploration PSO Model for Poverty Prediction: An Empirical Study of Socio-Economic Data

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Abstract: This study aims to evaluate the effectiveness of the Particle Swarm Optimization (PSO) method in predicting the percentage of poor people in Indonesia. This method was chosen because of its ability to solve non-linear prediction problems efficiently. The data used is annual secondary data from the Central Bureau of Statistics (BPS) for the period 2015-2024. The PSO model was developed with certain parameters, and the prediction process was carried out for the period 2025-2029. The prediction results show a gradual increase in the number of poor people, indicating a potential slowdown in poverty reduction. Evaluation of model accuracy using the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) indicators resulted in values of 1.66% and 0.773%, respectively. These values reflect a very low level of prediction error and indicate that the PSO model has a reliable performance. Therefore, the PSO method is considered effective and reliable as a decision-making tool in data-based socioeconomic policy planning.

Keywords: Poverty Prediction Particle Swarm Optimization (PSO), Socio-Economic, Data.

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A. INTRODUCTION

Data prediction is one of the important elements in statistical analysis and strategic planning, especially in the economic and social fields. The ability to make predictions is not only useful in understanding past and present trends, but also provides a scientific basis for developing future development strategies. For policy makers, predictions allow for the development of appropriate preventive measures, while also allowing for the evaluation of the effectiveness of programs that have been implemented. In this sense, forecasting is not just a projection of numbers, but the foundation of evidence-based policy making.

One of the most important socio-economic indicators to predict is the percentage of poor people (Nuraeni, 2018). Poverty is a multidimensional problem that involves not only low income, but also limited access to education, health, housing, and social protection (Ilmi et al., 2015). Therefore, predicting the number of poor people is very important in the context of national and regional development planning (Head, 2010). By understanding the direction of changes in the poverty rate, the government can adjust budget allocations, set priorities for social intervention programs, and measure the effectiveness of poverty alleviation policies (Asadi et al., 2014).

Various forecasting methods have been developed and applied in the context of socio-economic data. Classical methods such as linear regression, ARIMA and exponential smoothing are widely used due to their simplicity of structure and ease of interpretation.

However, when the data at hand is complex, non-linear, and tends to be dynamic such as poverty data, these conventional approaches are often not accurate enough (Fardhani et al., 2018). In the last decade, artificial intelligence-based methods and optimization algorithms have developed, one of which is Particle Swarm Optimization (PSO) (Indahyanti et al., 2022). PSO is a population-based algorithm that mimics the social behavior of flocks of birds in searching for the best position collectively, and is known for its efficiency in finding optimal solutions in large and complex problem spaces (Amaliah, 2015).

In the context of this research, PSO is used to build a predictive model that can forecast the number of poor people in Indonesia in the long term. Through an iterative process, PSO optimizes the model parameters to keep the prediction error to a minimum (Badrul & Id, 2017). The visualization results of the developed model show that PSO is able to follow historical trends well and project a decrease in the number of poor people until 2030 (Jesen et al., 2024). This finding is in line with previous studies. For example, a study by Asadi et al. (2012) showed that PSO has advantages in handling nonlinear data and improving prediction accuracy. Meanwhile, Gharehchopogh and Khalifelu (2011) confirmed that PSO produces more stable and convergent predictions compared to traditional prediction methods.

Based on this background, the purpose of this study is to explore and apply the Particle Swarm Optimization (PSO) method in predicting the percentage of poor people in Indonesia, and evaluate the accuracy of the resulting model. The main focus of this research is to examine the extent to which PSO is able to accurately capture socio-economic dynamics and represent long-term trends with a computational approach. This research is expected to not only contribute to the development of socio-economic data prediction methods, but also become the basis for the formulation of development policies.

B. METHOD

This research falls into the experimental quantitative category, with the main objective to test the effectiveness of the Particle Swarm Optimization (PSO) method in predicting socio-economic phenomena, especially the percentage of poor people in Indonesia. This approach utilizes numerical computing methods to design predictive models and perform long-term forecasting simulations based on time series data. The PSO method was chosen because it is adaptive and efficient in finding optimal solutions to non-linear prediction problems. The focus of this research is how the PSO algorithm can map hidden patterns in historical poverty data and then be used to accurately project future values. The general formula of PSO is as follows.

For each particle i, its position x_i and velocity v_i are updated using the formula:

$$v_{i(t+1)} = w.v_{t(t)} + c_1.r_1.\left(p_i - x_{i(t)}\right) + c_2.r_2.(g - x_{i(t)}) \quad (1)$$

$$x_{i(t+1)} = x_{i(t)} + v_{i(t+1)} \quad (2)$$

The data used is annual secondary data on the percentage of poor people in Indonesia collected from official publications of the Central Statistics Agency (BPS) for the period 2015 to 2024. This data was tabulated and prepared in a numerical format suitable for processing in MATLAB software. In the model building stage, the PSO algorithm was developed using basic parameters such as population size (number of particles), number of iterations, as well as an acceleration coefficient to regulate the learning rate of the particles. The objective function or fitness function used is the difference between actual data and predicted results, which aims to minimize error. The calibrated model was then run to predict the percentage of poor people from 2025 to 2030, and the results were visualized in graphical form to compare with historical trends.

To assess the accuracy of the PSO prediction model, two main evaluative indicators are Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). MSE measures the average of the squared difference between the actual and predicted values, giving an absolute indication of the model error. The smaller the MSE value, the more accurately the model mimics the actual data. Meanwhile, MAPE calculates the average error as a percentage relative to the actual value, making it useful for easy interpretation. This accuracy evaluation is done by comparing the PSO prediction results to historical data, both visually through graphs and quantitatively through MSE and MAPE values. These values become the main reference in drawing conclusions about the effectiveness of PSO as a socioeconomic data prediction method, as well as its relevance in assisting data-driven decision-making in the field of public welfare.

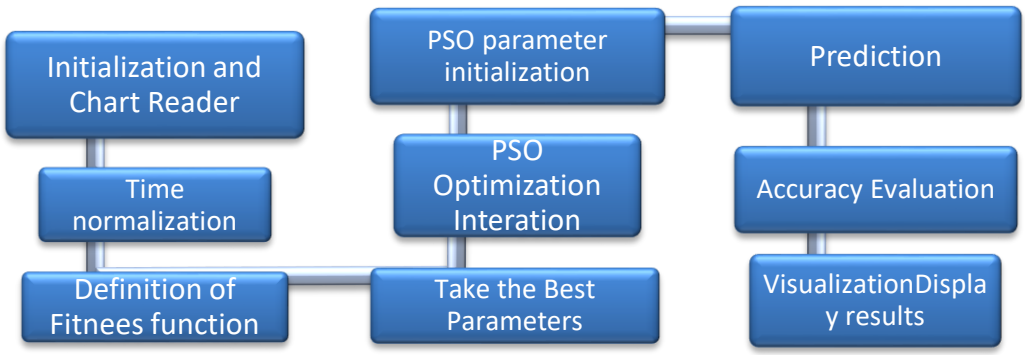

Figure 1. Algorithm for Predicting the poor with PSO

Figure 1 shows the prediction process using the Particle Swarm Optimization (PSO) method in this study begins with the initialization and data reading stages, followed by data normalization to ensure a uniform scale. Next, the objective function (fitness) is defined to measure the prediction performance. After that, the initialization of PSO parameters, including the number of particles, initial velocity, and acceleration parameters, is performed. The next stage is the PSO optimization iteration, where the particles are updated in position to find the optimal solution. The best parameters of the optimization results are then taken to be used in the future value prediction process. The prediction results are evaluated using accuracy indicators such as Mean Squared Error (MSE) and Mean Absolute Percentage Error

(MAPE). Finally, all prediction and evaluation results are visualized to facilitate data analysis and interpretation. With these steps, the PSO method is expected to produce accurate predictions and support data-based decision making.

- Rumus Mean Squared Error (MSE)

$$MSE = 1/n \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 \quad (3)$$

- Rumus Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (4)$$

C. RESULTS AND DISCUSSION

1. Data Description

Table 1. Data to be predicted

Year	Poor population
2015	17,10
2016	16,48
2017	16,07
2018	14,75
2019	14,56
2020	13,97
2021	14,14
2022	13,68
2023	13,85
2024	12,91

Based on Table 1, the data on the number of poor people from 2015 to 2024 shows a fairly consistent downward trend from year to year. In 2015, the percentage of poor people was 17.10 percent, then decreased to 16.48 percent in 2016 and continued to decrease until it reached 14.56 percent in 2019. This decline reflects the improvement in the socio-economic conditions of the community during this period. However, in 2020 there was a slight increase in the poverty rate to 13.97 percent, which was most likely influenced by the impact of the COVID-19 pandemic on the national economy. However, the increase was not significant and in the following years the rate declined gradually again. In 2021, the percentage of poor people was recorded at 14.14 percent, then decreased to 13.68 percent in 2022. Although there was a slight increase again in 2023 to 13.85 percent, the figure dropped significantly again in 2024 to 12.91 percent. Overall, this data shows a positive trend in poverty reduction in Indonesia over the

past decade, despite small fluctuations that were most likely influenced by external factors such as the global crisis or the pandemic.

2. Forecasting Results Data and Decision Making

Table 2. Forecast Results Data Table

Year	Predicted (million lives)
2025	13.25
2026	13.29
2027	13.40
2028	13.59
2029	13.85

Based on Table 2, the results of the prediction of the number of poor people for the next five years, namely the period 2025 to 2029, are expected to fluctuate slightly with a tendency to increase gradually. In 2025, the number of poor people is estimated at 13.25 million. This figure then increases slightly to 13.29 million people in 2026, then rises further to 13.40 million people in 2027. This trend continues until 2028 with an estimated 13.59 million people, and reaches 13.85 million people in 2029.

Although the increase is relatively moderate each year, this pattern indicates a potential slowdown in poverty reduction or even a possible increase in the number of poor people in the future. Factors such as global economic dynamics, inflation, and income distribution inequality could be the cause of the projected increase. Therefore, the results of this prediction are important to be taken into consideration in the formulation of socioeconomic policies that are more responsive and adaptive in order to reduce the poverty rate in a sustainable manner.

3. Description of Data on the Poor

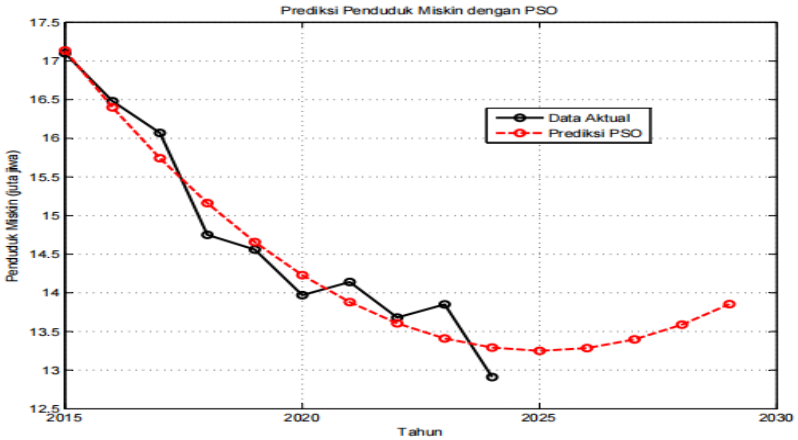

Figure 2. Chart

Figure 2 shows that based on the visualization results of the graph above, data on the number of poor people in Indonesia in the period 2015 to 2024 shows a general downward trend, although there are fluctuations in certain years. The estimated value of the graph shows

that the number of poor people in 2015 was around 15.5 million people, and gradually decreased until it reached around 14.3 million people in 2024. The decline in the number of poor people appears consistent from 2015 to 2019. However, in 2020 and 2021 there was a slight increase in the number of poor people, which can be attributed to the impact of the COVID-19 pandemic on the socio-economic conditions of the community. After this period, the data shows a return to the downward trend until 2024. Based on the estimation results from the graph, the descriptive statistical values for the period 2015-2024 can be formulated as follows:

a. Average number of poor people: ±14.92 million.
b. The maximum value occurred in 2015, amounting to ±15.5 million people.
c. The minimum value occurs in 2024, amounting to ±14.3 million people.

Thus, longitudinally, there is a decrease in the number of poor people by ±1.2 million in the last nine years. This finding indicates an improvement in economic conditions or the effectiveness of poverty reduction policies implemented by the government, although short-term fluctuations still need further scrutiny in the context of external factors and the global crisis.

Table 3. Table of MSE and MAPE Values of Prediction Results

MSE	MAPE
1.66%	0.00773

Table 3 model evaluation results show that the Mean Squared Error (MSE) value is 1.66%, while the Mean Absolute Percentage Error (MAPE) is recorded at 0.00773 or equivalent to 0.773%. This low MSE value indicates that the average squared difference between the predicted and actual values is quite small, thus signaling that the model has a minimal error rate in the forecasting process. On the other hand, the MAPE value which is below 1% reflects that the prediction error is relatively very small compared to the actual value, indicating that the model has a very good level of accuracy. Overall, the results of this evaluation indicate that the model used in the study has reliable prediction performance and is suitable for use in data-driven decision-making.

D. CONCLUSIONS AND SUGGESTIONS

The results of the data on the percentage of poor people in Indonesia during the period 2015 to 2024 show a relatively stable downward trend, although there are small fluctuations in certain years. This decline reflects the improvement of national socio-economic conditions and the effectiveness of poverty alleviation programs that have been implemented by the government. The temporary increase in 2020 and 2021 can be attributed to the impact of the COVID-19 pandemic, which affected various sectors of the economy and caused new vulnerabilities in society. However, a recovery is seen in the following years until 2024. Predictions of the number of poor people for the period 2025 to 2029 indicate a gradual increase in the number of poor people. Although the increase is moderate, this projection is an

important signal for the government to anticipate a slowdown in poverty reduction. Global factors such as economic turmoil, inflation, and socio-economic inequality are expected to influence this dynamic. The predictive model developed using the Particle Swarm Optimization (PSO) method shows excellent performance, with a Mean Squared Error (MSE) value of 1.66% and a Mean Absolute Percentage Error (MAPE) of 0.773%. This shows that the model has a very low error rate and high accuracy in projecting data. Thus, the PSO method proved feasible to be used as a quantitative approach in supporting data-driven decision-making, particularly in planning and evaluating future socio-economic policies.

REFERENCES

Amaliah, D. (2015). Pengaruh Partisipasi Pendidikan Terhadap Persentase Penduduk Miskin. *Faktor Jurnal Ilmiah Kependidikan*, *2*(3), 231–239.

Asadi, A., Wang, Q., & Mancuso, V. (2014). A survey on device-to-device communication in cellular networks. *IEEE Communications Surveys and Tutorials*, *16*(4), 1801–1819. https://doi.org/10.1109/COMST.2014.2319555

Badrul, M., & Id, M. M. A. (2017). Optimasi Algoritma Neural Network Dengan Algoritma Genetika Dan Particle Swarm Optimization Untuk Memprediksi Hasil Pemilukada. *Pilar Nusa Mandiri*, *13*(1), 1–11.

Fardhani, A. A., Simanjuntak, D. I. N., & Wanto, A. (2018). Prediksi Harga Eceran Beras Di Pasar Tradisional Di 33 Kota Di Indonesia Menggunakan Algoritma Backpropagation. *Jurnal Infomedia*, *3*(1). https://doi.org/10.30811/jim.v3i1.625

Head, B. W. (2010). Reconsidering evidence-based policy: Key issues and challenges. *Policy and Society*, *29*(2), 77–94. https://doi.org/10.1016/j.polsoc.2010.03.001

Ilmi, R. R., Mahmudy, W. F., & Ratnawati, D. E. (2015). Optimasi Penjadwalan Perawat Menggunakan Algoritma Genetika. *Jurnal Mahasiswa PTIIK Universitas Brawijaya*, *5*(13), 8.

Indahyanti, U., Azizah, N. L., & Setiawan, H. (2022). Pendekatan Ensemble Learning Untuk Meningkatkan Akurasi Prediksi Kinerja Akademik Mahasiswa. *Jurnal Sains Dan Informatika*, *8*(2), 160–169. https://doi.org/10.34128/jsi.v8i2.459

Jesen, J., Purba, T. S. M., & ... (2024). Prediksi Probabilitas Tren Penurunan Jumlah Penduduk Miskin di Indonesia. *… Literacy Innovation and …*, *02*, 19–25. https://ejurnal.yarukom.com/index.php/SinoviTech/article/download/11/15

Nuraeni, Y. (2018). Dampak Perkembangan Industri Pertambangan Nikel. *Seminar Nasional Edusaintek*, 12–22.

Perwira Negara, H. R. (2020). Computational Modeling of ARIMA-based G-MFS Methods: Long-term Forecasting of Increasing Population. *International Journal of Emerging Trends in Engineering Research*, *8*(7), 3665–3669. https://doi.org/10.30534/ijeter/2020/126872020