

What is Considered a Good Value for MAPE?

Authored by
Mohammed loot

November 6, 2025

RECOMMENDED CITATION

Mohammed loot (2025). *What is Considered a Good Value for MAPE?*. PSYCHOLOGICAL STATISTICS. Retrieved from <https://statistics.arabpsychology.com/?p=11438>

Measuring the effectiveness of predictive algorithms is crucial in data science and business operations. One of the most frequently employed metrics for assessing [forecasting](#) accuracy is the **Mean Absolute Percentage Error**, widely known by its acronym, [MAPE](#).

MAPE offers an intuitive, percentage-based view of error, making it highly valuable for communication across different business units. It essentially tells us the average difference between the forecasted values and the actual outcomes, expressed as a percentage of the actual values.

However, despite its widespread use and clarity, practitioners often struggle with a fundamental question: **What value is considered a good MAPE?** This article explores the calculation of MAPE, analyzes the factors that influence acceptable error levels, and provides critical context for interpreting this key performance indicator.

Understanding the MAPE Formula

The calculation of [MAPE](#) is straightforward, focusing on the absolute error relative to the actual observation. This normalization by the actual value is what transforms the error into a percentage, simplifying interpretation.

The formula to calculate MAPE is as follows:

$$\text{MAPE} = (1/n) * \sum(|\text{actual} - \text{forecast}| / |\text{actual}|) * 100$$

Where the components of the formula represent:

Σ - The summation operator, indicating the sum of all calculated percentage errors.

n - The sample size or the total number of periods being evaluated.

actual - The observed, or true, data value.

forecast - The predicted data value generated by the model.

For example, if a model produces a [MAPE](#) of 15%, it means that, on average, the predictions deviate from the actual outcomes by 15%. This ease of interpretation contributes significantly to MAPE's popularity, especially when presenting results to non-technical stakeholders.

The Relative Nature of "Good" MAPE

The immediate and often frustrating answer to what constitutes a "good" MAPE value is: **It depends entirely on the context.** There is no universal threshold--such as 5% or 10%--that dictates success or failure for all models across all domains. While mathematically, a MAPE of 0% is ideal (perfect prediction), achieving such a result is rarely possible in real-world environments.

A low MAPE is always preferable to a high one, but the acceptability of the value hinges on several critical factors. These factors include the inherent volatility of the data being modeled, the industry standards, and crucially, how the model performs compared to simpler, baseline methods.

To properly evaluate model performance using MAPE, we must analyze the following two contextual factors:

The inherent volatility and characteristics of the specific industry.

The comparison of the model's MAPE against simple, established benchmark [forecasting](#) models.

These two considerations provide the necessary framework for determining if a calculated error rate is reasonable or indicative of a poor model fit.

MAPE Variation by Industry and Context

The level of acceptable forecasting error varies dramatically across industries because different economic sectors possess vastly different levels of predictability and stability. Companies commonly use MAPE to gauge the accuracy of demand forecasts for inventory planning and supply chain optimization.

Consider the contrast between sectors. A utility company forecasting electrical demand might deal with relatively stable, cyclical data influenced primarily by weather and seasonal trends. Such stability allows sophisticated models to achieve very high accuracy, meaning an acceptable MAPE might be extremely low--perhaps under 3% or 4%.

Conversely, a retail company operating in a highly promotional environment, where pricing changes weekly, seasonal items are introduced frequently, and competitor actions are unpredictable, faces enormous data volatility. In this scenario, demand is inherently harder to predict. A model applied here might yield a MAPE of 15% or even 20%, yet still be considered "good" or highly valuable because the cost of error is factored against the difficulty of the prediction task. Higher error rates are simply the reality of chaotic data environments.

Therefore, when interpreting MAPE, it is essential to understand the typical volatility of the metrics being forecasted within that specific sector. Benchmarking against industry peers, where possible, provides a more realistic measure of success than applying an arbitrary global standard.

Benchmarking Against Simple Forecasting Models

One of the most robust methods for validating a new or complex forecasting model is to compare its MAPE not against a fixed number, but against the MAPE achieved by simple, unintelligent forecasting models. If a sophisticated model, which requires extensive resources and computational power, cannot significantly outperform a simple baseline, its complexity is

unwarranted.

There are two well-known and powerful simple forecasting models that serve as essential benchmarks:

The Average Forecasting Method

This rudimentary model predicts that the value for the next time period will be the simple arithmetic average of all previously observed data points. Although seemingly too simplistic for modern data analysis, the average method establishes a strong baseline, particularly for data that lacks clear trends or seasonality.

The Naïve Forecasting Method

The naïve method assumes that the value for the next upcoming period will be identical to the value observed in the most recent prior period. This method is surprisingly effective for data exhibiting strong trends or high persistence (where the current value is highly correlated with the last value). It requires minimal calculation and often performs better than expected.

When developing a novel forecasting technique, the calculated MAPE must demonstrate a statistically significant improvement over the MAPE generated by both the average and naïve methods. If the new model's error rate is comparable to or only marginally better than these simple benchmarks, the model should not be considered useful for deployment, regardless of the absolute value of its MAPE.

Critical Limitations and Drawbacks of MAPE

While MAPE is user-friendly and highly interpretable, it is not without significant mathematical flaws. Practitioners must be aware of these limitations to avoid making costly modeling errors or misinterpreting results:

Division by Zero: The formula for the absolute percentage error involves dividing the absolute difference by the actual value ($|\text{actual} - \text{forecast}| / |\text{actual}|$). If the actual value in any period is zero, the calculation becomes mathematically undefined. This makes MAPE unsuitable for data sets where observations of zero occur frequently (e.g., intermittent demand, transactions in low-traffic periods).

Asymmetric Bias (Penalizing Positive Errors More Heavily): MAPE exhibits an inherent asymmetry. It heavily penalizes forecasts that are significantly higher than the actual value (over-forecasting) but limits the penalty for forecasts that are lower than the actual value (under-forecasting). Since the actual value serves as the denominator, an actual value of 100 with a forecast of 200 yields a 100% error. Conversely, an actual value of 200 with a forecast of 100

yields only a 50% error. This bias means MAPE inherently favors models that tend to under-forecast.

Bias with Low-Volume Data: MAPE can produce misleadingly high error rates when dealing with low-volume or sporadic data. For example, if the actual demand for a niche product is 2 units and the forecast is 1 unit, the absolute percentage error is calculated as $|2-1| / |2| = 50\%$. This 50% error appears alarmingly high, even though the forecast was only inaccurate by a single unit. In such scenarios, the practical implication of the error is minimal, but the MAPE value exaggerates the inaccuracy.

Due to these drawbacks, especially the division by zero and the asymmetric bias, MAPE should be used with extreme caution, particularly in highly volatile or low-volume environments.

Alternative Metrics for Forecasting Accuracy

When MAPE's limitations become prohibitive, alternative metrics that measure error on a non-percentage basis are often preferred. These metrics typically calculate the error in the original units of measurement, avoiding the issues associated with the denominator being zero or low:

Mean Absolute Deviation (MAD): [MAD](#) calculates the average of the absolute differences between the actual and forecasted values. MAD is easy to interpret (the error is expressed in the same unit as the data) and avoids the division by zero problem.

Root Mean Squared Error (RMSE): [RMSE](#) squares the errors before averaging them, which places a significantly heavier penalty on large errors compared to smaller ones. This makes RMSE particularly useful when models must avoid large, catastrophic forecasting misses.

Choosing the appropriate error metric is a foundational step in model validation. While MAPE offers simplicity, its contextual dependencies and mathematical flaws necessitate careful consideration of industry benchmarks and a thorough review of its performance against simpler alternatives before accepting its value as "good."

Additional Resources

[What is Considered a Good RMSE Value?](#)