

How to Calculate SMAPE in Excel: A Step-by-Step Guide

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Understanding the Symmetric Mean Absolute Percentage Error (SMAPE)

The **Symmetric Mean Absolute Percentage Error (SMAPE)** stands as a cornerstone metric within the fields of statistics and data science, specifically employed to rigorously measure the predictive accuracy of various models. Unlike simpler measures that rely solely on absolute error, SMAPE provides a percentage measure of error, making it highly valuable for comparing forecasting performance across different datasets or models, regardless of scale. Its symmetrical nature is key, addressing known limitations found in other percentage error metrics, thus offering a more robust and unbiased assessment of forecasting quality, crucial for applications ranging from supply chain management to financial planning.

Forecasting accuracy is paramount for effective business decision-making, and selecting the appropriate error metric is half the battle. When evaluating the performance of a time series forecasting model, for instance, we require a standardized measure that penalizes errors consistently, irrespective of whether the actual value is very high or very close to zero. The primary function of SMAPE is to normalize the absolute difference between the forecast and the actual observation by dividing it by the average of the two values. This standardization ensures that the percentage error remains bounded between 0% and 200%, providing a reliable scale for interpretation, where a result closer to 0% signifies superior predictive power.

For practitioners utilizing forecasting models in high-stakes environments, such as retail inventory optimization or energy demand prediction, the ability to calculate and interpret SMAPE efficiently is essential. While sophisticated statistical software often calculates this metric automatically, understanding the underlying mathematical mechanics and implementing the calculation within a ubiquitous platform like Microsoft Excel allows for greater transparency, customization, and auditing of model results. The subsequent sections will guide you through the precise steps required to derive this sophisticated error metric using fundamental Excel functions, transforming raw data into actionable insights regarding model performance.

The Mathematical Foundation of SMAPE

The calculation of the **Symmetric Mean Absolute Percentage Error** is defined by a specific mathematical formula designed to achieve error symmetry. This formula takes the absolute difference between the forecasted value and the actual value, divides that difference by the average of the absolute actual value and the absolute forecasted value, and then averages this normalized error over all observations. This sophisticated structure is what differentiates it from simpler metrics, ensuring that the metric is symmetric and does not unduly favor over-forecasting or under-forecasting.

The complete mathematical definition of the SMAPE is as follows:

$$\text{SMAPE} = (1/n) * \sum(|\text{forecast} - \text{actual}| / ((|\text{actual}| + |\text{forecast}|)/2)) * 100$$

Let us meticulously break down the components of this critical formula:

Σ - This is the summation symbol, indicating that the normalized error calculation must be performed individually for every data point and then aggregated (summed up) across the entire dataset.

n - This represents the total **sample size**, corresponding to the number of observations or periods being analyzed in the forecasting exercise.

actual - This is the true, observed **data value** that occurred during the corresponding time period.

forecast - This is the **forecasted data value**, which is the model's prediction for the corresponding time period.

|...| - The absolute value signs ensure that the error and the denominator remain positive, preventing complex division errors and ensuring that the metric measures deviation magnitude regardless of direction.

Understanding the role of the denominator, $((|\text{actual}| + |\text{forecast}|)/2)$, is critical. This term represents the arithmetic mean of the actual and forecasted values. By normalizing the error using this average, the SMAPE effectively measures the error as a percentage of the typical size of the observation for that period. This symmetry is particularly important when dealing with datasets that have periods of extremely low values, which can otherwise skew error calculations based purely on the actual value (as is the case with standard MAPE).

Why Use SMAPE Over Other Error Metrics?

While numerous metrics exist for evaluating forecasting performance, such as the Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE), the **SMAPE** offers distinct advantages, particularly in scenarios where the actual values fluctuate significantly. The core limitation of the standard MAPE is its inherent asymmetry: it heavily penalizes negative errors (when the actual value is larger than the forecast, resulting in under-forecasting) far more severely than positive errors (over-forecasting). This asymmetry causes MAPE to become infinitely large or undefined when the actual value is zero or near zero, rendering it unsuitable for intermittent demand or low-volume data series.

In contrast, **SMAPE** was specifically developed to mitigate the asymmetry issues of MAPE. By utilizing the average of the actual and forecasted values in the denominator, it ensures that the error contribution is bounded, symmetric, and well-behaved even when actual sales volumes drop to zero. For businesses operating in volatile markets, or those tracking products with high seasonality leading to zero demand in certain periods, SMAPE provides a much more stable and reliable measure of average error magnitude. A lower value for SMAPE consistently indicates a superior model fit, making it an excellent comparative tool for model selection.

Furthermore, while the **Mean Absolute Error (MAE)** provides an easily interpretable error measurement in the original units of the data (e.g., dollars or units), it lacks scalability. MAE cannot be used directly to compare the performance of a model forecasting high-value items (like cars) with a model forecasting low-value items (like screws), as the error magnitude is dependent on the price or volume scale. Since SMAPE normalizes the error into a percentage, it allows for direct, apples-to-apples comparisons of forecasting models across disparate product lines and scales, solidifying its status as a highly versatile and professional metric for aggregated performance evaluation.

Step 1: Preparing Your Data in Excel

Before calculating the SMAPE, the first crucial step is organizing your raw data within an Excel spreadsheet structure that facilitates the subsequent calculation steps. We must define clearly labeled columns for the independent variable (often the time period, such as months or quarters), the observed **actual data value**, and the corresponding **forecasted data value** provided by your predictive model. For this demonstration, we will utilize hypothetical sales data collected over 12 consecutive sales periods to illustrate the process effectively.

Ensure your Excel sheet is set up with three primary columns, typically labeled "Period," "Actual Sales," and "Forecasted Sales." Consistency in data entry is vital; ensure that each actual sales figure aligns precisely with the forecast generated for that specific period. This alignment forms the backbone of the error calculation. For optimal readability and future analysis, it is recommended to begin inputting the data in cell A1, utilizing the row below for the header labels. The preparation stage is detailed below, showing the initial layout of the 12 data points:

	A	B	C	D	E	F	G
1	Month	Actual	Forecasted				
2	January	12	11				
3	February	13	13				
4	March	14	14				
5	April	15	14				
6	May	15	15				
7	June	22	16				
8	July	27	18				
9	August	28	27				
10	September	30	29				
11	October	35	32				
12	November	30	34				
13	December	34	33				
14							
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Once the data is accurately entered--the **actual** values residing, for example, in Column B and the **forecast** values in Column C--we can proceed to the calculation of the intermediate components. This systematic arrangement allows Excel to reference the necessary data points efficiently when constructing the complex SMAPE formula across the entire dataset. A well-structured input sheet prevents compounding errors and streamlines the computation process significantly.

Step 2: Calculating the Absolute Percentage Error Component

The most intricate part of calculating SMAPE involves deriving the symmetric absolute percentage error for each individual data point. This calculation is the core component that must be summed up before averaging. We must create a new column, which we can label "SMAPE Difference," where we will implement the per-period error formula: $|forecast - actual| / ((|actual| + |forecast|)/2)$. This formula must be translated into Excel syntax using the appropriate functions, specifically the **ABS** function to handle absolute values and basic arithmetic operators for division and addition.

To begin this step, navigate to the first row of your data (e.g., row 2, if row 1 holds headers) and input the following formula into the designated "SMAPE Difference" column (e.g., cell D2), assuming actual values are in B2 and forecasted values are in C2. The explicit formula structure in

Excel is designed to mirror the mathematical definition precisely, ensuring symmetry by averaging the magnitude of the predicted and actual values in the denominator. This robust approach ensures the metric is defined even when one of the values is zero.

The required formula for calculating the intermediate difference for a single period in Excel is:

$$=ABS(C2-B2) / ((ABS(B2)+ABS(C2))/2)$$

It is crucial to wrap the subtraction in the numerator with **ABS()** and ensure both the actual (B2) and forecast (C2) values in the denominator are also wrapped in **ABS()** before they are summed and divided by 2. Once this formula is correctly entered into the first cell (D2), it must be dragged down to apply consistently across all 12 sales periods. This action generates the individual normalized percentage error for every observation in the sample, which are the necessary inputs for the final aggregation step. The resulting calculations should appear as shown in the following figure, demonstrating the column D population:

	A	B	C	D	E	F	G	H
1	Month	Actual	Forecasted	SMAPE differences				
2	January	12	11	0.087	=ABS(C2-B2)/((ABS(B2)+ABS(C2))/2)			
3	February	13	13	0.000				
4	March	14	14	0.000				
5	April	15	14	0.069				
6	May	15	15	0.000				
7	June	22	16	0.316				
8	July	27	18	0.400				
9	August	28	27	0.036				
10	September	30	29	0.034				
11	October	35	32	0.090				
12	November	30	34	0.125				
13	December	34	33	0.030				
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Step 3: Aggregating the Results and Final Calculation

After successfully calculating the individual SMAPE difference components for every observation in Step 2, the final phase involves aggregating these values and applying the final normalization step to derive the overall **SMAPE** for the entire model. This process encompasses two main mathematical operations: first, summing all the differences calculated in Column D (the summation, Σ), and second, dividing this total sum by the sample size (n) and multiplying by 100 to express the result as a percentage.

To perform the summation, we utilize the standard **SUM** function in Excel, applied to the entire range of calculated differences (e.g., D2:D13). The total sample size, denoted by n , is simply the count of periods, which in this example is 12. The final SMAPE formula, therefore, becomes the sum of Column D divided by 12, multiplied by 100. It is often helpful to place this final calculation outside the main data table, perhaps in cell F2, for clarity and immediate visibility of the model's accuracy.

The complete Excel formula to calculate the final **SMAPE** value, assuming the differences are stored in the range D2:D13 (for $n=12$ observations), is:

```
=SUM(D2:D13) / 12 * 100
```

Upon executing this calculation, the result provides the average percentage error, symmetrically adjusted, for the given forecasting model across the measured period. The resulting figure, when displayed in Excel, should clearly articulate the model's performance. For the data provided in this example, the final calculated SMAPE for this particular model turns out to be **9.89%**. This value signifies that, on average, the forecast deviates from the actual sales by approximately 9.89% when measured symmetrically, offering a clear benchmark for model evaluation and comparison against other predictive techniques.

	A	B	C	D	E	F	G
1	Month	Actual	Forecasted	SMAPE differences			
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9	August	28	27	0.036			
10	September	30	29	0.034			
11	October	35	32	0.090			
12	November	30	34	0.125			
13	December	34	33	0.030			
14			SMAPE	0.0989	=SUM(D2:D13)/COUNT(D2:D13)		
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Interpretation and Limitations of the SMAPE Value

Interpreting the calculated **SMAPE** value is straightforward: the closer the value is to zero, the higher the **predictive accuracy** of the model. A result of 0% indicates a perfect forecast where the actual and predicted values match exactly for every period. Conversely, higher SMAPE percentages indicate poorer fit and larger forecasting errors. The interpretation must always be relative to the industry and the inherent volatility of the data being forecasted. For instance, a 10% error might be considered excellent in the highly unpredictable stock market, but unacceptable in a stable, mature manufacturing environment.

The principal advantage of SMAPE, its symmetry, helps provide a more reliable measure than **MAPE** when zero or near-zero observations occur. However, it is essential to recognize that SMAPE, like any statistical metric, is not without its limitations. Specifically, SMAPE slightly over-penalizes under-forecasts compared to over-forecasts in some specific theoretical edge cases, although its behavior is far more balanced than MAPE. Furthermore, if both the actual and

forecasted values are extremely large, the percentage change might appear minor even if the absolute error is substantial, which is a common characteristic of percentage error metrics.

In practice, SMAPE is often used in conjunction with other error metrics, such as MAE or Root Mean Square Error (RMSE), to provide a comprehensive evaluation of model performance. While SMAPE excels at comparing models across different scales due to its percentage basis, MAE offers context in the original units, helping stakeholders understand the tangible cost or volume of the error. Integrating SMAPE calculation into an accessible platform like Excel ensures that analysts have the necessary tools to derive robust and defensible conclusions about their forecasting methodologies. Always aim for the lowest possible SMAPE when optimizing model parameters.

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