

# Calculating Mean Absolute Percentage Error (MAPE) in Excel: A Step-by-Step Guide

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The **Mean Absolute Percentage Error** (MAPE) stands as one of the most crucial and widely adopted metrics for rigorously quantifying the performance and reliability of predictive systems across various industries. This powerful statistical measure provides a clear, universally scalable assessment of **forecasting accuracy**, translating complex deviations between predicted outcomes and actual results into an easily digestible percentage value. For organizations heavily reliant on quantitative **models**--particularly in sectors like finance, supply chain management, and detailed demand planning--the ability to accurately evaluate forecast alignment with real-world outcomes is paramount to operational success.

MAPE is highly favored within the global business community primarily due to its inherent interpretability and intuitive nature. Unlike alternative error metrics that yield results expressed in the native units of the data (such as calculating the error in dollars, units, or volume), MAPE standardizes the error calculation. By expressing the average error as a percentage, it enables straightforward and meaningful cross-comparison between drastically different time series, product lines, or even entirely distinct business functions. Mastering the calculation and correct interpretation of **MAPE** is a foundational requirement for anyone involved in optimizing or managing predictive processes.

## Understanding Mean Absolute Percentage Error (MAPE)

The fundamental goal of **MAPE** is to precisely assess the magnitude of error, expressing it directly as a percentage of the actual observed value. By focusing specifically on the absolute difference between the actual observed value and the corresponding forecasted value, the metric ensures that positive and negative deviations do not neutralize each other when aggregated. This critical feature provides a true, unbiased representation of the average magnitude of deviation. This percentage format allows analysts and managers to quickly grasp the inherent forecasting risk associated with their underlying predictive **model**. For instance, stating that a system has a MAPE of 8% immediately communicates that, on average, the predictions deviate from reality by eight percent--a clear, actionable insight.

MAPE is often prioritized over alternative measures, such as Mean Squared Error (MSE), precisely because its results are both unit-independent and highly accessible to non-technical stakeholders. When accuracy results are presented to leadership, a simple percentage (e.g., 15%) is far more digestible and actionable than a complex squared error value (e.g., 2,500 units squared). This inherent ease of communication significantly facilitates better strategic decision-making and helps build crucial confidence in the integrity of the underlying **forecasting model**. However, it is essential to acknowledge that MAPE's reliance on dividing by the actual value introduces specific analytical challenges, particularly when data points approach or equal zero.

To achieve optimal **forecasting accuracy**, the primary objective is always to minimize the

calculated **MAPE** value. A result that is closer to zero signifies that the predicted values are consistently and tightly aligned with the realized actual values. Consequently, the standard method for comparing two competing forecasting techniques involves selecting the technique that consistently yields the lower **MAPE**, thereby identifying the statistically superior predictive tool. This foundational principle guides numerous statistical evaluations in complex fields ranging from inventory control to large-scale sales planning.

## The Mathematical Foundation of MAPE

The formula used to calculate the **Mean Absolute Percentage Error** is derived through a structured, two-step procedure: first, determining the absolute percentage error for every single observation point, and second, calculating the arithmetic average of these individual errors across the entire evaluated dataset. This systematic approach ensures that every observation contributes equally to the final metric, regardless of the overall sample size or the specific magnitude of the values within the sample.

The standard mathematical expression for calculating **MAPE** is presented as follows:

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

A detailed understanding of the components within this formula is essential for accurate application:

**Σ (Sigma)** - This symbol represents the mathematical operation of "summation," indicating that we must aggregate the calculated error terms across all data points included in the evaluation sample.

**n** - This variable quantifies the total **sample size**, or the total count of observations pairs (actual versus forecast) used in the performance assessment.

**actual** - This refers to the observed, verifiable, real-world data value recorded at a specific time point or period.

**forecast** - This is the predicted or expected data value generated by the **forecasting model** corresponding to that exact same time point.

**|actual - forecast| / |actual|** - This crucial inner component calculates the **absolute percent error** for a single observation. It normalizes the raw difference by dividing it by the absolute actual value. The subsequent multiplication by 100 is used to convert the final ratio into a percentage format.

The elegant structure of the formula outlines a clear, two-stage calculation process: isolating the error magnitude for each individual period (the absolute percentage error), and then systematically aggregating these errors by computing their arithmetic average. This ensures that the resulting **MAPE** value accurately reflects the typical magnitude of error experienced by the predictive system across the entire evaluation horizon, thereby serving as a robust measure of overall **forecasting accuracy**.

## How to Calculate MAPE in Excel: Step-by-Step Methodology

While sophisticated statistical software often automates complex calculations, mastering the efficient calculation of **MAPE** using Microsoft **Excel** remains a fundamental and highly valuable skill. Understanding this manual, step-by-step procedure provides deep clarity regarding the underlying mathematics and offers essential flexibility when analyzing custom or irregularly structured data. We will systematically dissect the calculation into three distinct and manageable phases: thorough data preparation, calculating the individual absolute percent errors for each data point, and finally, aggregating these results to determine the final metric.

This practical guide assumes you are working with a prepared dataset that contains paired observations--specifically, a column detailing the actual historical values and a corresponding column containing the predicted values generated by your **forecasting model**. Following these precise steps will empower you to quickly and accurately calculate the MAPE for your specific dataset, yielding a clear and actionable metric of **forecasting accuracy**.

### Step 1 & 2: Preparing Data and Calculating Absolute Percent Error

The initial and crucial phase of calculating **MAPE** involves structuring the raw data correctly within the **Excel** spreadsheet environment. Proper organization ensures that subsequent formulas can reference the necessary cells easily, consistently, and without error.

**Step 1: Input the actual values and the corresponding forecasted values into two separate, adjacent columns.** It is highly recommended to clearly label these columns, perhaps using "Actual" and "Forecast," to maintain impeccable data organization and readability. For the purpose of this illustrative example, we will assume that the Actual values reside in Column B and the Forecasted values are located in Column C, with the data starting consistently from Row 2.

	A	B	C	D	E	F
1	<b>Month</b>	<b>Actual</b>	<b>Forecasted</b>			
2	January	34	37			
3	February	37	40			
4	March	44	46			
5	April	47	44			
6	May	48	46			
7	June	48	50			
8	July	46	45			
9	August	43	44			
10	September	32	34			
11	October	27	30			
12	November	26	22			
13	December	24	23			
14						
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**Step 2: Calculate the absolute percent error for every single row observation.** This calculation is the most mathematically intensive step. Recall that the absolute percent error for any individual observation is defined by the formula:  $|\text{actual} - \text{forecast}| / |\text{actual}|$ . We must carefully translate this precise mathematical expression into a functional [Excel](#) formula, utilizing the native `ABS` function (which computes the absolute value) and standard cell referencing practices.

For the first data point, located in Row 2, where the actual value is in cell B2 and the forecast is in cell C2, the formula must be entered into cell D2 as follows: `=ABS(B2-C2)/ABS(B2)`. It is important to note that we intentionally omit multiplication by 100 at this stage; instead, we will apply the percentage formatting directly to the resulting column later, which is cleaner and mathematically equivalent.

The resulting calculation, showing the calculated absolute percent error (formatted as a percentage) in Column D, and the exact formula used for pedagogical clarity in Column E:

	A	B	C	D	E	F
1	<b>Month</b>	<b>Actual</b>	<b>Forecasted</b>	<b>Absolute Percent Error</b>	<b>Formula</b>	
2	January	34	37	8.82	=ABS(B2-C2)/B2*100	
3	February	37	40			
4	March	44	46			
5	April	47	44			
6	May	48	46			
7	June	48	50			
8	July	46	45			
9	August	43	44			
10	September	32	34			
11	October	27	30			
12	November	26	22			
13	December	24	23			
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This derived formula must subsequently be applied efficiently to every remaining row within the dataset. The most common method involves dragging the formula handle down the column. This process successfully generates a complete column of values, each representing the magnitude of error for its respective period, which serves as the necessary input for the final aggregation step required to determine the overall Mean Absolute Percentage Error.

	A	B	C	D	E
1	<b>Month</b>	<b>Actual</b>	<b>Forecasted</b>	<b>Absolute Percent Error</b>	<b>Formula</b>
2	January	34	37	8.82	=ABS(B2-C2)/B2*100
3	February	37	40	8.11	=ABS(B3-C3)/B3*100
4	March	44	46	4.55	=ABS(B4-C4)/B4*100
5	April	47	44	6.38	=ABS(B5-C5)/B5*100
6	May	48	46	4.17	=ABS(B6-C6)/B6*100
7	June	48	50	4.17	=ABS(B7-C7)/B7*100
8	July	46	45	2.17	=ABS(B8-C8)/B8*100
9	August	43	44	2.33	=ABS(B9-C9)/B9*100
10	September	32	34	6.25	=ABS(B10-C10)/B10*100
11	October	27	30	11.11	=ABS(B11-C11)/B11*100
12	November	26	22	15.38	=ABS(B12-C12)/B12*100
13	December	24	23	4.17	=ABS(B13-C13)/B13*100
14					

### Step 3: Aggregating Results to Determine Final MAPE

Once the absolute percent error has been accurately calculated for every single observation point in the designated Column D, the final step required to determine the overall Mean Absolute Percentage Error is remarkably straightforward: simply calculate the arithmetic average of all the individual percentage error values. This single operation fulfills both the summation ( $\Sigma$ ) and the division by the sample size ( $1/n$ ) requirements mandated by the mathematical definition of MAPE.

Within **Excel**, calculating this average is accomplished using the robust, built-in `AVERAGE` function. Assuming that the range containing all the calculated absolute percentage errors spans from cell D2 to D11, the final aggregation formula should be written as: `=AVERAGE(D2:D11)`. This single, efficient function simultaneously sums all the individual errors and divides the total by the count of observations, thereby yielding the precise final Mean Absolute Percentage Error result.

The visual representation of calculating MAPE by finding the average of the values in column D:

	A	B	C	D	E
1	<b>Month</b>	<b>Actual</b>	<b>Forecasted</b>	<b>Absolute Percent Error</b>	Formula
2	January	34	37	8.82	=ABS(B2-C2)/B2*100
3	February	37	40	8.11	=ABS(B3-C3)/B3*100
4	March	44	46	4.55	=ABS(B4-C4)/B4*100
5	April	47	44	6.38	=ABS(B5-C5)/B5*100
6	May	48	46	4.17	=ABS(B6-C6)/B6*100
7	June	48	50	4.17	=ABS(B7-C7)/B7*100
8	July	46	45	2.17	=ABS(B8-C8)/B8*100
9	August	43	44	2.33	=ABS(B9-C9)/B9*100
10	September	32	34	6.25	=ABS(B10-C10)/B10*100
11	October	27	30	11.11	=ABS(B11-C11)/B11*100
12	November	26	22	15.38	=ABS(B12-C12)/B12*100
13	December	24	23	4.17	=ABS(B13-C13)/B13*100
14			<b>MAPE</b>	6.47	=AVERAGE(D2:D13)
15					
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In the context of this specific illustrative example, the resulting **MAPE** for the predictive **model** is precisely calculated to be **6.47%**. This quantified result signifies that, on average, the forecasted values deviated from the actual values by slightly less than seven percent. This relatively low value suggests a commendably high degree of predictive reliability, making the model a trustworthy tool for critical operational planning purposes within this specific data environment.

## Critical Considerations and Limitations of Using MAPE

While **MAPE** is highly esteemed across industries for its intuitive percentage-based interpretability, it is essential for practitioners to recognize that it is subject to significant inherent limitations. Analysts must be acutely aware of two primary potential drawbacks that can lead to skewed or mathematically undefined results, particularly when analyzing certain types of time series data. Applying MAPE without careful consideration of these issues can result in a fundamentally inaccurate assessment of the predictive model's true performance capabilities.

**Division by Zero: The Undefined Error Condition.** The core calculation structure requires dividing the absolute error by the absolute actual value (specifically,  $|\text{actual} - \text{forecast}| / |\text{actual}|$ ). Consequently, if any of the actual observed values are exactly zero, the metric becomes mathematically undefined for that specific period. This scenario is common in real-world applications involving retail inventory, supply chain demand, or financial datasets where periods of zero sales or zero demand frequently occur. If an actual data point equals zero, the calculation results in an attempt to divide by zero, which yields an error message (such as #DIV/0! within [Excel](#)). This computational failure prevents the calculation of a collective MAPE unless these zero-actual periods are either systematically excluded (which introduces selection bias) or handled through specialized algorithmic adjustments, such as introducing a small "epsilon" value or opting for alternative error metrics like the Symmetric Mean Absolute Percentage Error (SMAPE).

**Inherent Bias with Low Volume Data.** MAPE is known to exhibit a significant, systematic bias when the actual values being observed are very small, a scenario commonly referred to as low-volume data. The formula structure imposes a disproportionately severe penalty on forecasting errors when the actual magnitude is low. For instance, consider a minor forecast miss: if the actual demand for a niche product is 2 units and the forecast was 1 unit, the absolute percent error is calculated as  $|2-1| / |2| = 50\%$ . Conversely, if the actual demand is 1,000 units and the forecast is 999 units, the absolute percent error is a negligible  $|1000-999| / |1000| = 0.1\%$ . Despite both forecasts being off by only one unit, MAPE assigns an extremely large penalty (50%) to the low-volume error. This characteristic can falsely inflate the overall MAPE, giving the misleading impression that the forecasting system is performing poorly, especially when dealing with small numbers. Furthermore, this structural bias means MAPE inherently favors forecasts that are slightly underestimated compared to the actual values (a negative bias).

Due to these well-documented limitations, seasoned analysts frequently recommend confining the use of MAPE only to data series that demonstrably do not contain zero or near-zero values, and where the volume of data is consistently high enough to mitigate extreme percentage volatility stemming from minor unit errors.

## Alternative Measures of Forecasting Accuracy

Given the potential analytical pitfalls associated with MAPE, particularly those concerning zero values and low data volume, statisticians and data scientists routinely employ alternative error metrics to gain a more comprehensive and robust assessment of a predictive model's true performance. The selection of the most appropriate metric must be heavily influenced by the specific context of the forecast and the unique statistical characteristics of the data being modeled.

One robust and popular alternative is [Mean Absolute Deviation](#), commonly abbreviated as **MAD**. Unlike MAPE, MAD calculates the arithmetic average of the absolute errors without the step of normalizing them by the actual value. This results in an error measure that is consistently expressed in the original, native units of the data (e.g., dollars, kilograms, or units sold). While MAD sacrifices the desirable unit-free interpretability of MAPE, it completely bypasses the problematic division-by-zero issue and is significantly less sensitive to the high volatility caused by low-volume outliers. Thus, **MAD** offers a highly stable and straightforward measure of the average unit error. Calculating **MAD** in [Excel](#) is simplified, involving merely taking the average of the `ABS(actual - forecast)` column.

Another critically important metric is [Root Mean Squared Error](#) (RMSE). RMSE is notably sensitive to large forecasting errors because the calculation involves squaring the error terms before averaging them, and then taking the square root of the result. This mathematical characteristic is exceptionally beneficial in practical applications where large forecasting misses carry disproportionately high costs or risks (such as inventory stock-outs, or critical financial miscalculations). Although RMSE is generally less intuitive for lay stakeholders than a simple percentage like MAPE, it provides a powerful indicator of the severity and frequency of the largest errors produced by the model. Analysts frequently utilize a combination of these metrics--MAPE, MAD, and RMSE--to achieve a truly comprehensive and balanced understanding of a model's overall [forecasting accuracy](#).

*For those seeking to further explore unit-based error measurements, a foundational understanding of the methodology for calculating [MAD](#) is strongly recommended. Read about how to calculate MAD in Excel.*

## Additional Resources for Predictive Analytics Mastery

Further dedicated research into the principles of time series analysis, along with rigorous statistical validation techniques, will significantly enhance your analytical ability to correctly select, implement, and utilize the most appropriate accuracy metrics tailored to your specific organizational needs. Achieving mastery in fundamental tools like [Excel](#) for executing these core calculations is an absolutely foundational skill set required for success in the rapidly evolving field

of predictive analytics.