European Research Studies Journal
Volume XXVII, Special Issue 2, 2024

pp. 103-113

Monte Carlo Simulation as a Demand Forecasting Tool

Submitted 18/02/24, 1st revision 16/03/24, 2nd revision 20/04/24, accepted 16/05/24

Bartosz Przysucha[1], Piotr Bednarczuk[2], Włodzimierz Martyniuk[3],
Ewa Golec[4], Michał Jasieński[5], Damian Pliszczuk[6]

Abstract:

Purpose: *This article aims to evaluate the effectiveness of Monte Carlo simulation as a tool for demand forecasting.*
Design/Methodology/Approach: *The study analyzes historical data on product sales, fits a theoretical distribution, and then applies Monte Carlo simulation to forecast demand for the next 15 days.*
Findings: *The result of the research shows that Monte Carlo simulation can outperform more straightforward methods such as averaging, particularly in the presence of uncertainty or randomness*
Practical Implications: *The study demonstrates how Monte Carlo simulation can improve demand forecasting accuracy, which is crucial for optimizing various business operations.*
Originality/Value: *This study's novelty lies in demonstrating the practical application of Monte Carlo simulation for demand forecasting and comparing its performance against traditional methods.*

Keywords: *Monte Carlo simulation, demand forecasting, business operations, sales prediction, uncertainty management.*

JEL codes: *C15, C53, E27, D81, L11, M11.*

Paper type: *Research article.*

[1]*Corresponding Author: Management Faculty, Lublin University of Technology, Lublin, Poland, e-mail: b.przysucha@pollub.pl;*
[2]*WSEI University, Lublin, Poland, e-mail: Piotr.Bednarczuk@wsei.lublin.pl;*
[3]*WSEI University, Lublin, Poland, e-mail: Wlodzimierz.Martyniuk@wsei.lublin.pl;*
[4]*WSEI University, Lublin, Poland, e-mail: Ewa.Golec@wsei.lublin.pl;*
[5]*Wyższa Szkoła Biznesu - National Louis University, e-mail: mjasienski@wsb-nlu.edu.pl;*
[6]*Netrix, Lublin, Poland, e-mail: damian.pliszczuk@netrix.com.pl;*

1. Introduction

Forecasting future demand is critical to effective business decisions (Pliszczuk, 2021). Accurate demand forecasts are essential for planning and managing various aspects of business, including production, inventory, distribution, finance, marketing, and human resources.

The ability to predict future demand with a high degree of accuracy helps companies align their business processes with customer needs, optimize resource allocation, improve operational efficiency, and increase their competitiveness in the market (Chopra and Meindl, 2007). To remain competitive, companies must forecast future demand to manage their production capacity, inventory levels, and other aspects of their business, including finance, marketing, human resources, and supply chain operations (Grima, Spiteri, and Thalassinos, 2020).

Accurate forecasts are also essential for suppliers, business partners, and stakeholders across the company's ecosystem, ensuring compliance, minimizing risk, and reducing discrepancies between supply and demand (Thalassinos and Pociovalisteanu, 2007; Ugurlu *et al.,* 2014).

When all phases of the business work together to create a typical forecast, the resulting accuracy improves, leading to more flexible, efficient, and profitable operations. This coordinated approach to forecasting can also enhance a company's ability to respond to market changes, adapt to new trends, and better meet customer needs (Thalassinos *et al.,* 2009; Thalassinos and Thalassinos, 2006).

Forecasts always involve a degree of uncertainty, so companies need to account for forecast errors when planning their operations (Spencer, 2014). Long-term forecasts are less accurate than short-term forecasts (Brauer, 2013), while aggregate forecasts are more accurate than individual forecasts.

In addition, companies farther away from the end customer in the supply chain often experience more significant distortions in the information they receive, highlighting the importance of collective forecasting based on direct sales to the end customer (Khojasteh, 2018).

Seasonality and cyclicality are vital factors affecting demand (Snepenger, 1990). Seasonality refers to predictable changes in demand at regular intervals, such as increased demand for certain products during the holiday season. Cyclicality refers to long-term patterns associated with business cycles, affecting demand for products or services. Considering these factors in forecasts helps companies better manage their resources and operations.

However, unforeseen situations such as natural disasters, pandemics, or other unexpected events can significantly disrupt predicted demand patterns.

Such conditions are difficult to forecast because they do not have regular, repeatable patterns. Companies must be prepared for such events by having flexible action plans and including a margin of error in their forecasts (Fiksel, 2015).

Therefore, companies should consider forecasting in a broader context and strive to improve the accuracy of their forecasts by working with supply chain partners and using sales data from end customers. This will minimize risk and increase the efficiency of their operations.

Demand forecasting requires a balance between objective data and subjective judgment. Although this article discusses quantitative forecasting methods, qualitative factors also play an important role in final forecasts.

Various factors influence demand, including previous demand patterns, advertising plans, economic conditions, price discounts, and competitor actions (West and Milan, 2001). Understanding these factors is essential to selecting an appropriate forecasting methodology.

Forecasting methods can be divided into four main categories: qualitative methods, time series methods, causal methods, and simulation methods (Weigend, 1994). The choice of an appropriate method depends mainly on the specifics of the problem and the context.

This article mainly focuses on time series forecasting methods suitable for future demand related to historical demand patterns. Demand can be divided into systematic and random components (McCausland, 2009), where the systematic component reflects expected demand, and the random component accounts for variability. Forecasting aims to estimate the systematic component and filter out the noise.

This article also explores the application of the Monte Carlo method to demand forecasting. The Monte Carlo method is a versatile simulation technique that can model and predict various outcomes, especially when there is significant uncertainty. Using the Monte Carlo method, companies can better predict future demand, improve supply chain efficiency, and increase overall business performance.

2. Demand Modeling Using Monte Carlo Simulation

In this section, we will show how Monte Carlo simulations can predict future product sales (Barbu and Zou, 2020). Initially, we will analyze historical data on the amount of products sold and then use it to estimate a theoretical distribution of the variable.

Then, using the assumed distribution, we will run a Monte Carlo simulation to determine the predicted amount of sales for the next 15 days.

2.1 Monte Carlo Method

In the face of considerable uncertainty in the forecasting or estimation process, Monte Carlo simulation can prove to be a much better solution than, for example, calculating an average. The technique was first developed by Stanislaw Ulam (Barbu and Zou, 2020), a Polish mathematician who worked, among other things, on the Manhattan Project (Reed, 2019). After the war, Ulam played countless solitaire games, taking an interest in plotting the results of each match to observe their distribution and determine the probability of winning. When he shared his idea with John von Neumann, the two collaborated to develop a Monte Carlo simulation (Eckhardt, 1987).

Monte Carlo simulations are used to model the probability of various outcomes of processes that cannot be easily predicted due to random variables (Barbu and Zou, 2020). Monte Carlo simulation aims to repeat random samples to obtain specific results continuously. This method considers an uncertain variable and assigns a random value to a particular distribution.

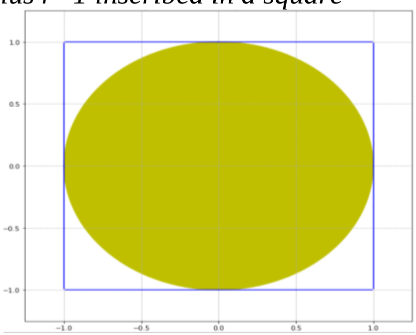
The model is then run, and the result is obtained. This process is repeated many times, assigning random values to the variable according to a particular distribution. The results are averaged once the simulation is complete to obtain an estimate.

To briefly illustrate how the simulation works, a classic example of using some form of Meotda Monte Carlo to approximate the value of a $number$ will be given. The idea behind this task is based on the fundamental formula for the area of a circle

$$P = \pi r^2,$$

where r denotes the radius of the circle. For simplicity and easier visualization, we will assume that $r = 1$ and place the circle's center at the coordinate system's origin. In addition, for better understanding, such a circle is inscribed in a square with a side equal to r, which gives us the situation shown in Figure 1.

Figure 1. *A circle of radius r=1 inscribed in a square*



Source: *Own creation.*

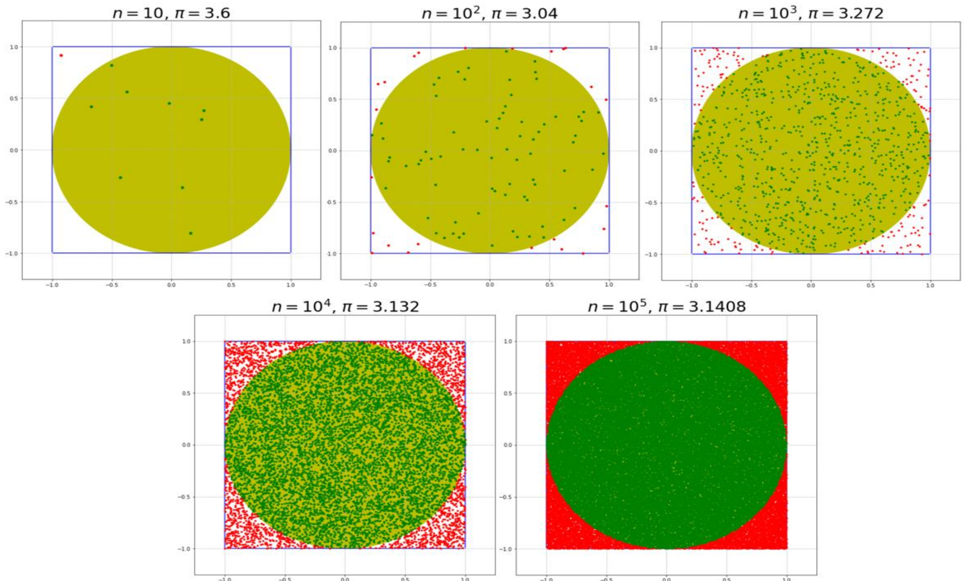
Since r, równa się, 1, the area of the circle is pi, andthe area of the square is 4.

Therefore, using the Monte Carlo method, we need to calculate the number of consecutively drawn points from the interval [-1,1] that belong to a circle ($\mathrm{pn}_{\mathrm{circle}}$) and those that belong to the surface of a square ($\mathrm{pn}_{\mathrm{square}}$), which gives:

$$\frac{Area_{circle}}{Area_{square}} = \frac{pn_{circle}}{pn_{square}},$$

$$\pi \approx 4\,\frac{pn_{circle}}{pn_{square}}.$$

Figure 2. *Simulation results for determining the π number approximation.*



Source: *Own creation.*

By performing successive simulations of the coordinates x, y steps, respectively, along with the location of the drawn numbers. The number of steps and the simulation's approximation of the number pi has been given in the titles of each graph.

2.2 Identification of Demand Volume

In the case under review, we only have data on the products sold in the time series. Based on these, a theoretical distribution that best represents this variable will be estimated, and then a Monte Carlo simulation will be carried out using the adopted distribution to determine the total sales volume for the next period.

2.3 Data Preparation

Due to dynamic changes in the sales area due to various factors, such as promotions, new offers, or changing customer demand, we will analyze data from the last three months. Our goal is to predict the aggregate value of demand for the next 15 days. It's worth noting here that this type of analysis usually calculates the dependent variable with several other variables whose distributions we try to predict.

Then, we simulate each of these variables to obtain an appropriate prediction. In this case, however, we present a solution based solely on analyzing the dependent variable whose distribution we are studying. The form of the analyzed dataset is shown in Figure 3.

Figure 3. *The dataset under consideration*

	Ilosc
2019-07-01	436.0
2019-07-02	987.0
2019-07-03	796.0
2019-07-04	683.0
2019-07-05	632.0
...	...
2019-10-11	778.0
2019-10-12	767.0
2019-10-13	756.0
2019-10-14	745.0
2019-10-15	1397.0

Source: *Own creation.*

2.4 Testing and Fitting the Distribution

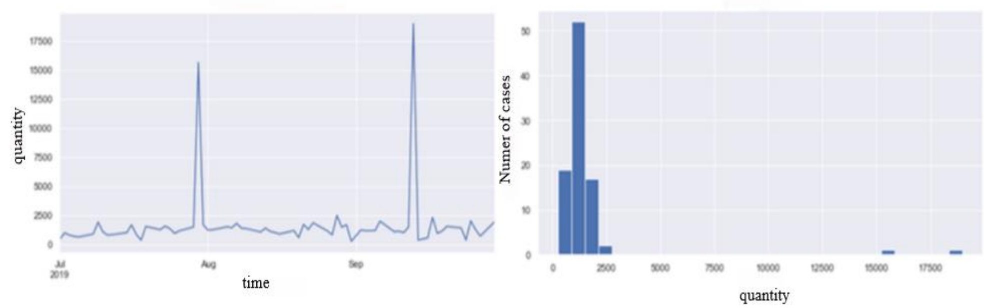
As described earlier, we will analyze the distribution of the variable "Quantity" over three months. Below is a graph and a histogram of this variable's value over time.

In Figure 4, you can see that there are two distinct spikes in sales over the period under consideration. To fit the theoretical distribution to the empirical one, we use a python library called distfit. To evaluate the fit, the Residual Sum of Squares of the differences will be calculated according to the formula:

$$RSS = \sum_{i=1}^{n} \left(y_i - f(x_i)\right)^2,$$

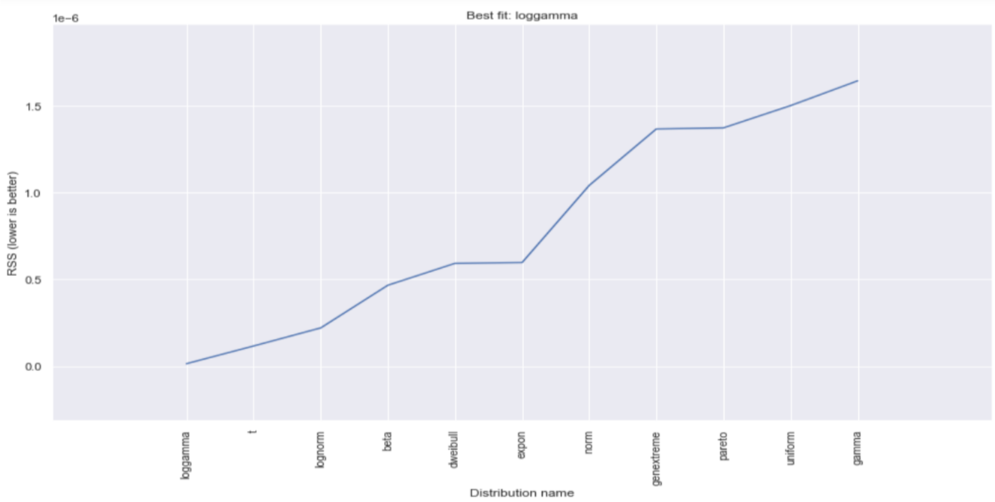
where y_i is the i-th value of the predicted variable and $f(x_i)$ i-th value of the explanatory variable. This measure describes the predicted deviation from actual empirical values vs. fitted theoretical values. Accordingly, low RSS values mean a good fit for the adopted data distribution. Thus, using the library above, it is possible to find distributions closest to the actual distribution of the given variable. Figure 5 shows a graphical interpretation of the RSS for the following distributions.

Figure 4. *Graph of values and histogram of the variable quantity*



Source: *Own creation.*

Figure 5. *Matching distributions to the variable quantity*



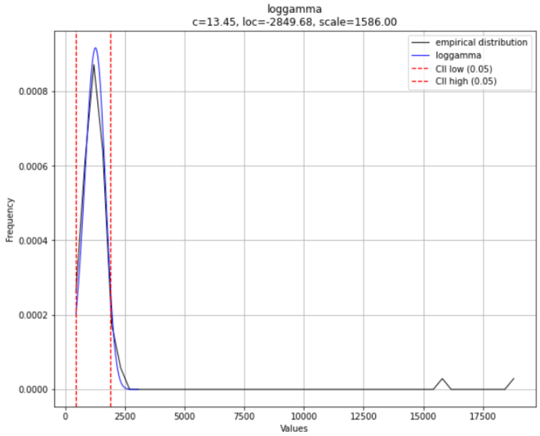
Source: *Own creation.*

The calculations show that the loggamma distribution best represents the real distribution. According to its definition, a variable has such a distribution if its natural logarithm has a gamma distribution. In addition to the shape and scale parameters derived from the gamma distribution, the parameter c is therefore added, so that the density function then takes the following form (scipy.stats.loggamma — SciPy v1.7.0 Manual):

$$f(x, c) = \frac{\exp(cx - \exp(x))}{\Gamma(c)}.$$

The estimated parameters $c = 13.45$, $loc = -2849.68$ and $scale = 1586.00$, along with a plot of the fit of such a distribution to the empirical distribution, are shown in the following figure.

Figure 6. *Fitting the log gamma distribution to the data*



Source: *Own creation.*

The next step is to check whether the assumed distribution is indeed not significantly different from the empirical distribution. To do this, we performed the Kolmogorov-Smirnov test at a confidence level of 95%. This test showed that the difference between the considered distributions is insignificant, so we can use the theoretical log gamma distribution to represent our variable in the Monte Carlo simulation.

3. Running a Simulation

After carefully examining the distribution of the variable under consideration and adjusting the theoretical distribution accordingly, the simulation proceeded. According to the results obtained, a variable corresponding to the test for fifteen days was drawn, taking the appropriate parameters of the log gamma distribution.

Then, the cumulative demand value from the drawn 15 days was calculated. This procedure was repeated several times - in this case, 100,000 trials were assumed - and the resulting cumulative demand was divided by this number of trials. The method used was compared with the post-factum average.

Thus, an average daily value calculated based on three months multiplied by 15 was determined. During the fifteen days studied, the total number of products sold was 18483. A comparison of the performance of the simulation and the adoption of the average is shown in the following Table 1.

Table 1. *Result of simulation and Average calculation*

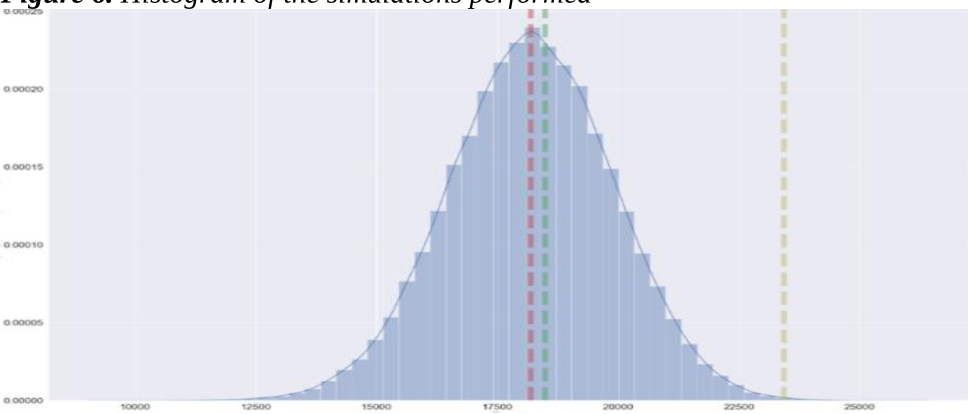
Methods	Value	Relative error (%)
Monte Carlo Simulation	18188	1.596
Average	23445	26.846

Source: *Own creation.*

As you can easily see, the simulation result is better than simply calculating the average. Of course, the average result is also subject to error due to jumps in the data. Still, the simulation using the Monte Carlo method was able to detect the trend and adequately depict the actual demand.

The following Figure 6 shows the histogram of the simulations carried out. The green color indicates the exact value of demand, the red indicates the value obtained through simulation, and the yellow indicates the value calculated from the average.

Figure 6. *Histogram of the simulations performed*



Source: *Own creation.*

Of course, such a simulation will not consider seasonal or holiday effects, but it is a simple alternative to much more complex solutions - and often a better one, too.

4. Conclusions

Demand forecasting is critical to business management, especially in production, inventory, distribution, finance, marketing, and human resource management. The introduction of Monte Carlo simulation as a forecasting tool allows companies to predict better future demand, which in turn helps optimize business processes, increase operational efficiency, and improve competitiveness in the market.

As the examples presented in this article show, Monte Carlo simulations are more accurate than calculating an average. This method proves much more effective when significant uncertainty or random variables exist. In addition, with this method, companies can minimize risks, better respond to market changes, and better meet customer needs.

At the same time, it is worth noting that demand forecasts are always subject to a certain degree of uncertainty. Companies should, therefore, strive to improve the accuracy of their estimates by working with supply chain partners and using various data sources. This will minimize the risk of forecast errors and increase the efficiency of their operations.

Ultimately, the Monte Carlo method can be an effective tool for forecasting demand, especially in the face of seasonal variability, cyclicality, and unpredictable events such as natural disasters, pandemics, or other unexpected events. By using this method, companies can better prepare for uncertainty and improve overall business performance.

References:

Barbu, A., Zhu, S.C. 2020. Monte Carlo Methods. Springer.

Brauer, M. 2013. The effects of short-term and long-term oriented managerial behavior on medium-term financial performance: Longitudinal evidence from Europe. Journal of Business Economics and Management, 14. DOI:10.3846/16111699.2012.703965.

Chopra, S., Meindl, P. 2007. Supply chain management : strategy, planning, and operation. Pearson Prentice Hall.

Eckhardt, R. 1987. Stan Ulam, John von Neumann, and the Monte Carlo Method. Los Alamos Sci., 15, no. (Special Issue), 131-137.

Fiksel, J. 2015. Resilient by Design: Creating Businesses That Adapt and Flourish in a Changing World. Resilient by Design.

Grima, S., Spiteri, J.V., Thalassinos, E.I. 2020. Risk management models and theories. Frontiers in Applied Mathematics and Statistics, 6, 8.

Khojasteh, Y. 2018. Supply Chain Risk Management. Singapore: Springer Singapore.

McCausland, W.J. 2009. Random Consumer Demand. Economica, London School of Economics and Political Science, vol. 76(301), 89-107.

Pliszczuk, D., Lesiak, P., Zuk, K., Cieplak, T. 2021. Forecasting Sales in the Supply Chain Based on the LSTM Network: The Case of Furniture Industry. European Research Studies Journal, 24, 627-636. https://doi.org/10.35808/ersj/2291.

Reed, B.C. 2019. The History and Science of the Manhattan Project (Undergraduate Lecture Notes in Physics) 2nd Edition.

scipy.stats.loggamma — SciPy v1.7.0 Manual. https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.loggamma.html#scipy.stats.loggamma.

Snepenger, D., Houser, B., Snepenger, M. 1990. Seasonality of demand. Annals of Tourism Research, Volume 17, Issue 4, 628-630, ISSN 0160-7383. https://doi.org/10.1016/0160-7383(90)90037-R.
Spencer, R.W. 2014. Managing Under Uncertainty. Research-Technology Management, 57(5), 53-54. https://doi.org/10.5437/08956308X5705007.
Thalassinos, E.I., Thalassinos, P.E. 2006. Stock markets' integration analysis. European Research Studies Journal, 9(3-4), 3-13.
Thalassinos, E.I., Pociovalisteanu, D. M. 2007. A time series model for the Romanian stock market. European Research Studies Journal, 10(3-4), 57-72.
Thalassinos, E.I., Hanias, M.P., Curtis, P.G., Thalassinos, Y.E. 2009. Chaos theory: Forecasting the freight rate of an oil tanker. International Journal of Computational Economics and Econometrics, 1(1), 76-88.
Ugurlu, E., Thalassinos, E.I., Muratoglu, Y. 2014. Modeling volatility in the stock markets using GARCH models: European emerging economies and Turkey. International Journal of Economics & Business Administration, 2(3), 72-87.
Weigend, A.S. 1994. Time Series Prediction: Forecasting the Future and Understanding the Past (1st ed.). Routledge. https://doi.org/10.4324/9780429492648.
West, L., Milan, M. 2001. The Supply and Demand Factors. In: The Reflecting Glass. Palgrave Macmillan, London. https://doi.org/10.1057/9780230506084_2.