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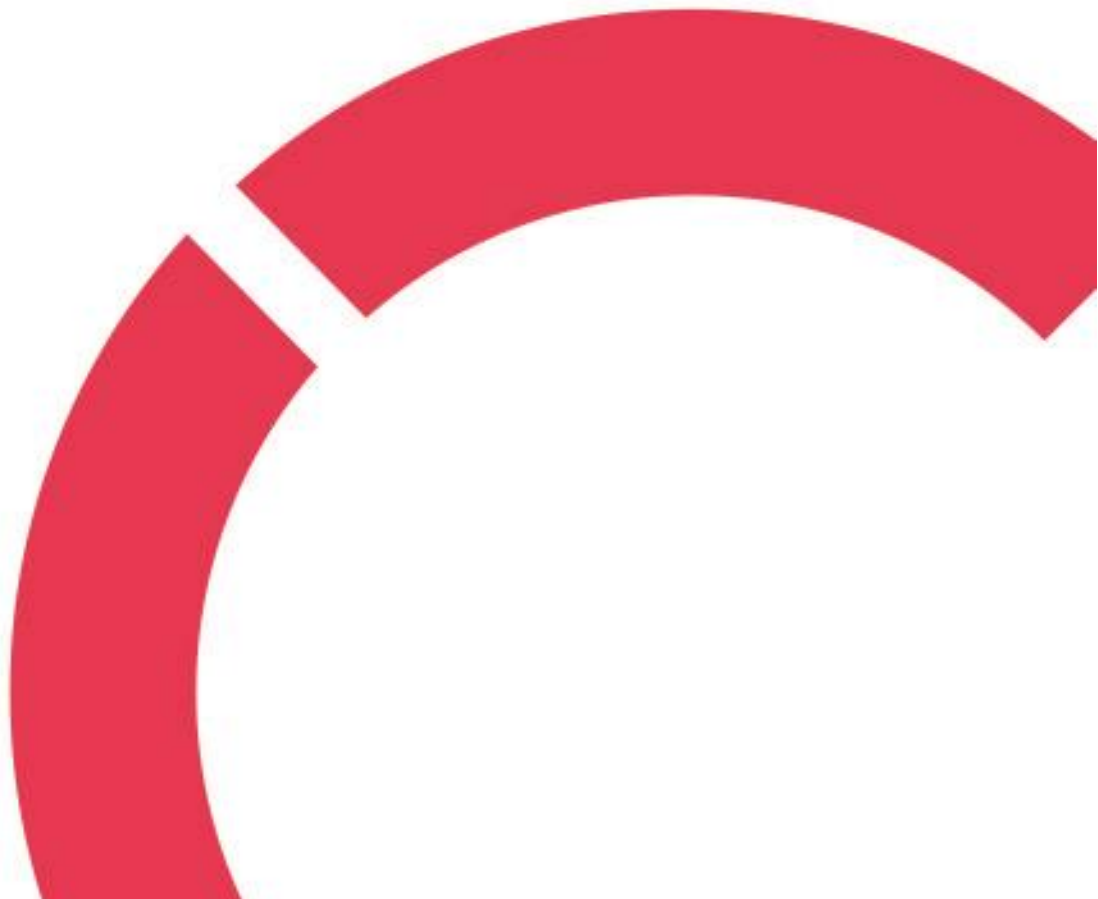
**AZURE CLOUD SERVICES RATE FORECAST USING ARTIFICIAL INTELLIGENCE**

**Thesis**

**CENTRIA UNIVERSITY OF APPLIED SCIENCES**

**Master of Engineering, Information Technology**

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**ABSTRACT**

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<b>Name of thesis</b> AZURE CLOUD SERVICES RATE FORECAST USING ARTIFICIAL INTELLIGENCE		
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<p>Cloud has become an important practice for IT, as the reliance grows on cloud services, and Microsoft Azure is a key cloud service provider. As organizations continue to embrace Azure services as they meet dynamic and flexible needs, quantifying expenditures associated with cloud services in advance is vital for budgeting and control. In this thesis, the focus was on using a time series forecasting method called ARIMA to estimate monthly costs for the Azure services, such as virtual machines, storage, and bandwidth. Using historical usage data from May 2023 to April 2024, the research also sought to develop precise expense figures that organizations can use to make informed decisions regarding the acquisition of resources.</p> <p>The research comprised key issues of the Azure billing scheme, which is based on different and variable prices for each customer and usage metric. The thesis assessed the effects of seasonal variation and trends on expenditure predictions and demonstrated how organizations can efficiently use these predictions in their financial planning. Data preparation steps included dealing with missing data, finding out whether the dataset is stationary by performing the ADF test, and proceeding with differencing where stationarity is not achieved. <math>p</math>, <math>d</math>, and <math>q</math> values were attained through ACF and PACF analysis and by comparing graphical plots of actual and forecasted cost variables.</p> <p>The results showed the skills of the ARIMA model to make feasible forecasts for the Azure service expense for the period May 2024 to June 2025. This makes it easier for organizations to plan for cost, avoid cases of emergent budgetary overruns, and improve decision-making. When it comes to cost estimation in cloud environments, the study emphasized the necessity to work more on the accuracy of cost forecasting models and present several opportunities for further investigation of better cost prediction tools to take into account other parameters, with the involvement of the cloud environment. Evaluation of further research in light of this, more complex quantum cost models can be developed in the future, along with other specifications of the cloud environment.</p>		
<p><b>Key words</b> Autoregressive Integrated Moving Average, Augmented Dickey-Fuller Test (ADF Test), Azure Services, Microsoft Azure, Non-Stationarity, Stationarity, Time Series Forecasting</p>		

## **CONCEPT DEFINITIONS**

### **Microsoft Azure**

Microsoft Azure is a broad class of cloud computing services that has been designed by Microsoft. Microsoft offers various services like applications virtualization, storage, database, networking, and machine learning, through which Microsoft operates data centers and lets the organization design, run, and host their applications and services.

### **AutoRegressive Integrated Moving Average (ARIMA)**

ARIMA is a time series forecasting method that contains an important part of statistical and mathematical methods. It combines three components:

**AutoRegressive (AR):** Preserves the link between an observation and a certain number of lagged observations.

**Integrated (I):** Using the first method of differencing the raw observations to make the time series stationary.

**Moving Average (MA):** Illustrates the correlation between an observation and residual errors of a moving average model with lagged observations.

### **Time Series Forecasting**

Time series forecasting is quite a popular approach to defining values at a certain point in the future, based on the existing outcomes. It finds a broad application in micro and macro-economic analysis, finance, and cloud computing for forecasting seasonal fluctuations, trends, and any variations with a period of time.

### **Azure Services**

Microsoft Azure services are defined as the set of cloud-based offerings available in the marketplace as IaaS, PaaS, and SaaS. Azure provides basic services such as Virtual Machines, Storage, DNS from Azure, Logic apps, and controlling Bandwidth.

### **Augmented Dickey-Fuller Test (ADF test)**

Augmented Dickey-Fuller Test (ADF test) to test the non-stationary character of the data. ADF stands for augmented Dickey-Fuller test, and it is used to test the stationarity of an individual time series. It employs the null hypothesis that a stochastic trend or unit root exists, hence, the time series is non-stationary. Thus, if the null hypothesis is rejected, the series can be concluded as being stationary.

**Stationarity**

A time series is regarded to be stationary if and only if its mean, variance, and other autocorrelation factors are invariant over time. That's why stationary data is important for ARIMA and other time series, because non-stationary data leads to inadequate forecasts.

**Non-Stationarity**

Statistical features of a time series, which include the mean, variance, and the like, change with time and are referred to as non-stationarity. Such data may contain trends, seasonality, or structural breaks, which must be removed or transformed, so that the 'stationary' ARIMA-type forecasting models can be applied

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# 1 INTRODUCTION

With cloud computing, businesses have been brought to an era where they can adopt flexible infrastructure that suits their needs. Compared to conventional on-premises systems, cloud services refer to computing capability and computing resources in the form of services provided through the internet, decreasing the need for expensive equipment and related heavy investment in maintenance. Such a usage-based pricing model is flexible, which means that organizations only pay for the actual benefit received, and thus the solution is appropriate for organizations of all types and sizes (Mistry, Mavani, Goswami & Patel, 2024).

However, cloud computing is a critical component in growing innovation. It helps in deploying progressive technologies like artificial intelligence (AI), machine learning (ML), and big data analytics, which assist organizations in making corresponding decisions and gaining new insights. Startups capitalize on the advantage of easy availability and market entry, while large organizations use cloud technology for expansion across the globe and promote inter-team collaboration across different locations (Alam, 2020).

It should also be noted that cloud computing's importance is not limited to cost and efficiency only. The role of efficient backup and recovery is to improve business recovery after developed system failure to protect data and applications. Furthermore, the dynamic deployment characteristics of cloud services enable organizations to meet current market forces, product introduction, as well as expansion of organizational operations within short spans of time (Kommisetty & Abhireddy, 2024).

As the pace of digital transformation defines the pace of success, cloud computing has emerged as an enabler on the business journey to flexibility, robustness, and advantage. From enhancing efficiency, increasing customer satisfaction, or driving up the pace of technological advancement, cloud computing is now in the drivers' seat of change in the new world of business (Zhu, Ge, & Wang, 2021).

## 1.1 Overview of Microsoft Azure and its diverse range of services

This chapter provides an introduction to Microsoft Azure and the variety of services it offers. Microsoft Azure is one of the best cloud computing services, which has reached solutions to the different

needs of businesspeople, developers, and IT experts (Alzhouri, 2018). Its services encompass most aspects, from mere connectivity to complicated, integrated, and development interfaces. Below is an overview of key Azure services.

### **1.1.1 Azure DNS**

Azure DNS is a powerful and a lot more consistent domain hosting service. It enables the administration of domain names and makes for a fast handover of users to their applications. Azure DNS hosts DNS domains so that organizations experience low-latency and high-availability name resolution that is inclusive of other Azure services. (Kaneko & Saito, 2023.)

### **1.1.2 Backup**

Azure Backup is a strong business continuity solution used in the protection and restoration of data. It is created to protect information in various situations, which can file systems, databases, virtual machines, and so on. Automated backup procedures and point-in-time restoration provide efficient accessibility and security to avoid data deletion or damage (Javaraiah, 2011.)

### **1.1.3 Bandwidth**

Azure Bandwidth is described as the amount of data that is moved between Azure data center sites and other locations. It provides excellent high-speed communication security, especially for international uses and services. (Niu, Xu, Li, & Zhao, 2012.)

### **1.1.4 Logic apps**

Azure Logic Apps are a way through which developers are able to develop solutions for application integration. Pre-installed connectors help in accessing, as well as integrating on-premises as well as cloud applications, making business process integration and application integration easier. (Niu, Xu,

Li, & Zhao, 2012.)

### **1.1.5 Storage**

Azure Storage can be defined as a consistently reliable and secure means of storing various types of data, like unstructured files or queues, etc. Azure Blob storage is optimized for data, Azure disk storage is mainly about storage for big files like videos or backups, and finally, Azure File storage is a file system that can be shared between VMs or other systems. (Niu, Xu, Li, & Zhao, 2012.)

### **1.1.6 Virtual machines (VMs)**

Azure Virtual Machines provide general-purpose and elastic computing power. They are compatible with different operating systems and configurations; allow businesses to operate applications, host websites, and perform data analysis without investing in hardware infrastructures. (Niu, Xu, Li, & Zhao, 2012.)

### **1.1.7 Virtual machine licenses**

Azure also offers licensing to virtual machines and operating systems such as Windows OS license, as well as Enterprise Software such as Windows Server and SQL Server. This makes the execution and distribution of licensed software easier within the context of Azure services. (Niu, Xu, Li, & Zhao, 2012.)

### **1.1.8 Virtual network (VNet)**

Azure Virtual Network provides a way to create virtual networks in Microsoft Azure that can be isolated from other networks in the same way that organizations are. It ensures smooth connectivity between Azure resources and on-premises resources, allows implementation of hybrid Azure models,

and offers, such as traffic management, load balancing, and VPN connections. (Niu, Xu, Li, & Zhao, 2012.)

## **1.2 Challenges posed by dynamic pricing models in cloud services**

Today's business environment has benefited greatly from the implementation of cloud computing services since they are elastic, agile, and inexpensive. The key characteristic of services that run on cloud environments such as Microsoft Azure is their flexible approach to setting the price, which reflects the number of consumed resources and/or services' demand on the market. On one hand, such flexibility allows organizations to pay only for the services they need, but on the other hand, it creates the following evident problems that might become insurmountable barriers to successful financial management and planning. (Medin and Schylström, 2024.)

One challenge relates to the uncertainty and fluctuation of costs. This type of pricing offers consumers variable prices, subject to the price fluctuating erratically from time to time, and this could seriously spike up during moments of high demand or scarcity. This brings careful planning into a lot of difficulties because businesses are unable to forecast their cloud costs effectively in the future. This is even more so for large organizations or those that are spread across different geographical locations, since they have to manage their cloud subscription on a large and progressive scale with actual constant monitoring of budgets, as costs may be subject to changes in prices over time. (Wu, Zhou, Xia, & Peng, 2023.)

The last concern is related to the problem of resource management: The factors make tactical decisions regarding resource utilization even more challenging for organizations since it involves dynamic pricing. When cost estimates are inaccurate, businesses may end up with either inefficiency, where resources and money are used, or inappropriateness, where application performance and usability suffer. This balancing act must be monitored and analyzed constantly, adding to the operational overhead and putting more pressure on IT and finance departments. (Medin and Schylström, 2024.)

However, this is a complicated process because the cost is like prices, and given the structure of the discounting mechanisms and price points of different cloud platforms, comparing is challenging. Through dynamic pricing, it becomes difficult for organizations to determine the actual cost they

have to pay for using different cloud services, and hence to identify the most appropriate cloud providers for their needs. Thus, some businesses may get locked into a specific service provider because of an initial cost that may prove cheaper in the long run, but flexibility is expensive, so businesses that find themselves in this situation are trapped.

Moreover, new and sophisticated cloud services like AI, ML, and big data are accompanied by quite complex and flexible pricing structures. Such services base their pricing model on how much data they process, how many times an API was called, or how much computational power was used, so budget estimations become even more difficult for those companies in the modern economy who try to adopt new, unique technologies.

Mitigating these challenges necessitates copious and reliable forms of predictive mechanisms and solutions. Managing cost with a high degree of efficacy remains an area of concern for many organizations that use cloud services, and rate forecasting can help an organization gain the necessary insight into cost over time to enable it to better predict budgetary changes effectively. It is to this end that this thesis seeks to address these challenges by proposing an AI-based model for estimating the rates of the important Azure cloud services.

The proposed solution will allow encountered problems regarding dynamic pricing to be solved more effectively, provide businesses with the data necessary to optimize the allocation of funds in the cloud, and help businesses avoid losing money while fully leveraging cloud services.

### **1.3 Importance of rate prediction**

Organizations have continued to adopt cloud services in today's world of cloud computing, infrastructure flexibility, and economies of scale. Nevertheless, one of the difficulties for them is to maintain and coordinate diverse and constantly changing price policies of the cloud services. To this end, another major challenge of rate prediction involves data analytics and artificial intelligence as a mechanism for solving this problem. It assists an organization in getting maximum value out of the cloud and costs, enables planning and forecasting of other expenses more effectively, and minimizes the possibilities of events such as cost blowouts.

In the cloud, the pricing generally starts with the pay-as-you-go model, and the costs depend on the

utilization of some resources like storage, CPU, and the amount of traffic received. Such fluctuations can result in wastage, as observed, because resources require management and planning. Rate prediction assists organizations in understanding such costs by evaluating past data and the patterns that define resource utilization.

A major application of rate prediction is to search for unexplored opportunities or underutilized facilities. For example, organizations use VMs with low utilization, or storage solutions that are occasionally used, but expensive. Through insight into future rates and usage of the particular network, it is easily possible to make decisions regarding the subsequent dismantling or redistribution of the resources.

It also helps to find the best resource rates for optimal rate configurations. For instance, predictive models can determine where to use on-demand and reserved instances, or use spot instances at some periods, which can considerably reduce costs.

#### **1.4 Facilitating budget forecasting and strategic planning**

Cloud cost estimation is essential for cost control processes. By so doing, organizations are in a position to better predict their cloud costs due to well-forecasted rates. This enables more efficient distribution of funds and avoids misallocation of resources in over-provisioning of funds for cloud services. As is more accurate, the number of payrolls required is less as compared to actual values, as it considers prior movement, seasons, and expected demand or sales. ((Javaraiah, 2011.))

Since companies can forecast future rates, they can effectively forecast their IT investments. The investment decision for a business can be to evaluate whether to integrate new cloud services or expand existing ones to accommodate more demand. In other words, before deploying an ML infrastructure or increasing storage requirements, firms can predict what extra costs will ensue and go ahead and contrast them to the potential advantages. (Medin and Schylström, 2024.)

Rate prediction is more useful to organizations using multi-cloud or hybrid clouds since it provides critical insights into the costs of running these environments. It enables them to benchmark the price of cloud providers and align workloads depending on the cost. Yielding to the interest rates companies are charged across the platforms makes it possible for businesses not to lock themselves up with uncompetitive vendors, as they also work towards getting the best rates they can be billed. (Medin

and Schylström, 2024.)

Fluctuations in cloud usage can cause volatile costs and result in surpassing a budgeted amount, and therefore reduce profitability. Many rate prediction tools allow for monitoring in ‘real-time’, in that you receive updates as usage surges beyond a particular plateau. This allows organizations to correct matters and perform preventive measures to prevent over-expenditure. Risk analysis enables any organization to detect possible risks about its spending on the cloud. For example, they can predict the effect of an increase or decrease in the price level on certain large-scale projects and therefore plan their resource mobilization appropriately. This, in turn, minimizes unpredictable occurrences of financial overruns and guarantees everlasting compliance with the financial plan. Rate prediction also improves visibility in cloud expenditure. Because of its comprehensive nature, analysts can guide organizations on which areas to invest their cash by explaining in detail where it shall end up, and its compliance with overall strategic visions and missions. This openness is vital for winning stakeholders’ confidence and being able to account for financial affairs. These days, rate prediction depends mainly on advanced technologies such as Artificial intelligence and machine learning. These tools evaluate huge quantities of data collected over time to detect correlations that a human analyst is capable of missing. But most of the habits can also evolve, allowing these prediction models to provide more accurate predictions over time. Almost all the cloud providers have developed integrated tools for cost management and rate prediction. For example, Cost Explorer from AWS, Cost Management from Azure, and Billing from Google Cloud deliver forecasts right in the application. These tools tend to ease the work of forecasting and enable organizations to optimize their cloud expenditure.

## **1.5 Problem statement**

Microsoft Azure cloud services use a dynamic pricing model in that their charges are based on usage and other conditions. If not well predicted, organizations could have complications in their ability to control their cloud costs. This thesis will research how Azure cloud service expenditures may be forecasted in the future using time series prediction techniques, particularly ARIMA from prior use frequencies.

## 1.6 Research questions

1. To what degree does the model of ARIMA forecast the further expenses of Azure cloud services with considering the history of its usage?
2. To what extent does seasonality and trend affect the prospective costs of various Azure clouds services?
3. What ways can organizations leverage forecasted expenses on the services offered by Azure to make the best decisions regarding budgeting?

## 1.7 Objectives

The primary objectives of this thesis are:

1. To analyze how Azure cloud services have been used over time (Virtual Machines, Storage, Bandwidth, etc ).

By doing this, the research goal supports Research Question 1 by organizing the information for using ARIMA to model future costs.

2. To use the ARIMA model to predict Azure service expenses in the future and check how accurate it is.

This solves Research Question 1 which looks at how helpful ARIMA is for predicting future costs with previous cost data.

3. To find out the impact of seasonal changes and trends on the predictable cost of goods.

This answers Research Question 2 by seeing how repeating patterns and long-term changes influence whether the forecasts are accurate.

4. To give teams insight to help their businesses budget and plan for future costs.

This objective answers Research Question 3 because it looks at how predictions can guide planning for a firm's financial strategy.

## 2 THEORETICAL BACKGROUND

Wenchang et al. emphasize the effectiveness of the K-Nearest Neighbors (KNN) algorithm in cloud service rate prediction, particularly for dynamic pricing environments like Microsoft Azure. KNN, a non-parametric supervised learning algorithm, excels in both classification and regression by leveraging proximity-based predictions, making it ideal for time-series and trend forecasting. Studies show that KNN improves Quality of Service (QoS) prediction accuracy, outperforming state-of-the-art methods in efficiency and reliability. By integrating API-driven real-time data, these models enhance adaptability and enable precise forecasts. KNN's ability to analyze historical data alongside multiple cost-affecting variables supports informed decision-making in budget allocation and resource optimization. Additionally, the algorithm facilitates the development of tailored predictive solutions while adhering to ethical and practical constraints, contributing to a more efficient and accessible cloud cost management framework. (Wang, 2018.)

The study by Ding et al focuses on how predictive analytics solutions were used to address numerous themes under different industries; customers being among them, but in high-growth industries. The research uses a part function for the classification and regression problems, and the K-Means Clustering for the customer segmentation. Although the presented study did not directly concern rate prediction of Azure Cloud Services using artificial intelligence, works on constructing and deploying prediction models employing Microsoft Azure Machine Learning are given for a range of applications, including propensity modelling and churn analysis. The added values consist of a presentation of key data science concepts and an overview of Azure Machine Learning services, discussion of how these concepts may be useful in addressing real-life business issues. Following these consequences, the findings stress the importance of the actual application of data science approaches and predictive management in organizations (Ding et al., 2020).

The Yang and Wang study focused on the use of predictive analytics solutions for addressing multiple business issues, such as customer churn in industries with high market demand. The research effectively utilizes the part function for classification and regression problems and uses K-Means Clustering for segmentation analysis on the customer. Even though Yang and Wang work did not shed light on machine learning for rate prediction of the Azure Cloud Services, it covered other aspects related to modeling and deployment of the predictive models in Azure environment for various purposes including propensity model and churn analysis. The benefits of the Yang and Wang are as follows; a

detailed description of data science ideas and Azure Machine Learning services, including helpful tips for addressing genuine business challenges. The results focused on the realistic utilization of data science approaches and pattern recognition for the management of business organizations. The study also looks at predicting the trustworthiness of cloud services using artificial neural networks: training with particle swarm optimization and quality attribute determination with binary particle swarm optimization. They complement each other by improving the choice of the key attributes and training the ANN trust prediction models. The analysis indicates that the BPSO model is highly effective in the procedure of selecting the most important attributes in achieving a precise prediction as to trust values, and PSO enhances the overall predictive accuracy of the developed ANNs. As such, these methods, while not specific to Azure Cloud Services, provide a roadmap to approach the application of similar predictive models to the improvement of trust in cloud services. (Yang and Wang, 2018.)

Auto former is useful for cloud workload prediction; Huang et al. used sequence decomposition techniques along with hyperparameter optimization to improve the model's predictive ability. Subsequently, results showed that the proposed BO-Auto former model outperforms baseline techniques in predicting workload with higher accuracy for meaningful enhancement of efficiency in resource utilization. Though the work did not comment on Azure Cloud Services rate prediction in detail, the main focus on enhancing workload predictions is crucial to understanding why Bayesian optimization was valuable for increasing model accuracy and stability when applied with different datasets. This is especially important for calibrating forecasting models in variable cloud computing contexts (Huang et al., 2021).

Bisi & Patel's work focused on creating a software vulnerability prediction web service employing a Multi-Layer Perceptron model that would be hosted on Azure Machine Learning Studio. This approach has been applied to an artificial neural network to predict vulnerabilities with a performance greater than 0.70 for ranking them, which outperforms all other algorithms. While this paper does not directly address the rate prediction of Azure Cloud Services, it is enlightening with respect to their general application of machine learning on Azure. This enables the following contributions, like the proposed architecture for the web service for vulnerability prediction and executing the ML algorithms within the context of the Azure environment, showing its flexibility and suitability for the prediction models (Bisi and Patel 2019).

Catal et al. study used the Boosted Decision Tree (BDT) regression algorithm in the prediction of

Key Performance Indicators (KPI) regarding cloud data centers, whereby the resultant  $R^2$  score was 0.9991. This means that the model was nearly optimal in explaining and forecasting the values of performance characteristics. BDT algorithm was found to outcompete Ordinary Least Squares (OLS), and Stochastic Gradient Descent (SGD) methods, where the predictive performance and robustness are concerned. These highly accurate levels present the competence of BDT towards the application possibility that considers resource allocation tasks and cost predictability towards cloud structures, including the Azure cloud services. This makes it possible to consider it a useful tool for the improvement of the work of cloud systems and the development of delivery services. The study employs Long Short-Term Memory (LSTM), ARIMA, SVM, and Bayesian Networks to develop an intelligent resource usage prediction model for Microsoft Azure services. Among these methods, LSTM demonstrated superior performance in predicting resource usage based on historical data. This model is particularly useful for managing costs associated with Azure's dynamic elastic pool feature by accurately forecasting resource demand. The research also provides comparative results, showing that LSTM outperforms ARIMA, SVM, and Bayesian Networks in terms of accuracy and reliability. These findings underline the importance of predictive models in optimizing cloud resource allocation and cost management. (Catal et al., 2017.)

The LSTM, ARIMA, SVM, and Bayesian Networks are used to construct the intelligent resource usage prediction model for MS Azure services. Out of these approaches, it was shown that LSTM provides higher accuracy when predicting resources by using past trends. This model is more suited to controlling costs involving Azure's dramatic elastic pool by better estimation of the demand for resources. The compiled data also gives a comparative analysis where LSTM does better than ARIMA, SVM, and Bayesian Networks in terms of accuracy and reliability. The above-mentioned compiles to support the need of using predictive models in enhancing the right cloud resource and cost. (Sultan, 2019.)

Osypanka & Nawrocki adapted a model that is specialized for efficient identification of appropriate cloud services and integrates real-time evaluation, including CPU/metrics for executing service performance. Although it does not focus on the rate prediction of Azure Cloud Services, the study focuses on the prediction of application performance with reference to the fluctuation of the resources used. The above findings again support the fact that real-time metrics can be of immense help in identifying the right cloud service for the application to improve the desired application performance. This model shows that performance prediction plays an important role in resource management and execution in cloud computing settings. (Osypanka & Nawrocki, 2022.)

Chengying et al. presented the conceptual framework to approach the optimization of the cloud resources using DL techniques for load prediction and anomaly detection, and six stages of the optimization process. This type of approach is relevant where the aim is to obtain better carry-through of cloud services, especially at the Microsoft Azure facility. Performance validates that DES (Discrete Event Simulation) adaptable provides diverse cost reduction rates of 31%-89% due to optimal resource ordering and usage tracking. Despite being originally applied only to Azure, the methods can produce similar cost savings in other cloud providers. With the help of such an autonomously predictive and monitoring structure, this new process is improving cost-benefit and operational benefits (Chengying et al., 2017.)

Pandey et al. studied the use of statistical learning for the prognosis of the performance indicators and employed the analysis of device and network statistics to optimize the prognosis. Additionally, it describes a new approach, PSO-NN, an improved trust rate predicting cloud services using a Combination of Particle Swarm Optimization (PSO) and Neural Networks (NN). PSO is also used in this work to tune the parameters of NN, with the capability of attaining higher precision and stable results. The results show that the proposed PSO-NN outperforms basic NN models and can be applied in Azure Cloud Services for better and better trust, and also performance. This hybrid model provides a sensible method to balance resource usage and service dependability in clouds. (Pandey et al., 2021.)

### **3 RESEARCH METHODOLOGY**

In this chapter, the discussion concerning the research methodology and design of the given thesis work has been presented. Some of the guidelines it contains are the definition of how many and which detail level shall be studied in the course of the research work that has been conducted. The research methodology establishes a concept known as the "onion approach," where different layers are systematically incorporated. Additionally, to report the model's functionality, an additional level of layers is included in the system. This approach illustrates the case solution of the model from the perspective of its functionality, focusing on the design and implementation of the model. The forthcoming sections have been reported for the definition of different approaches in which the system's working can be described, particularly with reference to the demonstration of the work organizations.

#### **3.1 Data collection**

The data for this research was obtained from Kaggle, which is perhaps the leading website for data sets in the world. This data is uploaded to the data acquisition Layer, where they are well sorted and can easily be accessed for preprocessing or analysis. The specific dataset is titled "Azure Cloud Cost Analysis" available at:

<https://www.kaggle.com/datasets/rishi2123/oragnizations-expenses-2023-2024/data>

The dataset includes historical monthly expense records for various Microsoft Azure services over a one-year period. It is openly accessible and intended for educational and research purposes

#### **3.2 Dataset overview**

The data for this study was collected over a time period of 12 months from May 1, 2023, to April 1, 2024, and records the monthly expenditure of different Azure services. It provides a centralized picture of the cloud resources being used by the organization, together with the costs for those resources, which is essential for understanding cost directions and looking for opportunities for spending cuts. Some of the data is on the usage, capacity, or other specifications and characteristics of multiple Azure services, including Azure DNS, Backup, Bandwidth, Logic Apps, Storage, Virtual Machines, Virtual

Machines Licenses, and Virtual Network. Every record offers the measure of cost of a particular service offered for a given billing month, enabling detailed cloud expenditure analytics. This dataset can be used in developing the predictive models necessary for estimating future costs towards appropriate planning and utilization of resources in an organization. Also, the qualitative nature of the data is not an issue because the data is also structured to facilitate the transformation to a time series, which is essential when using machine learning tools such as ARIMA for forecasting.

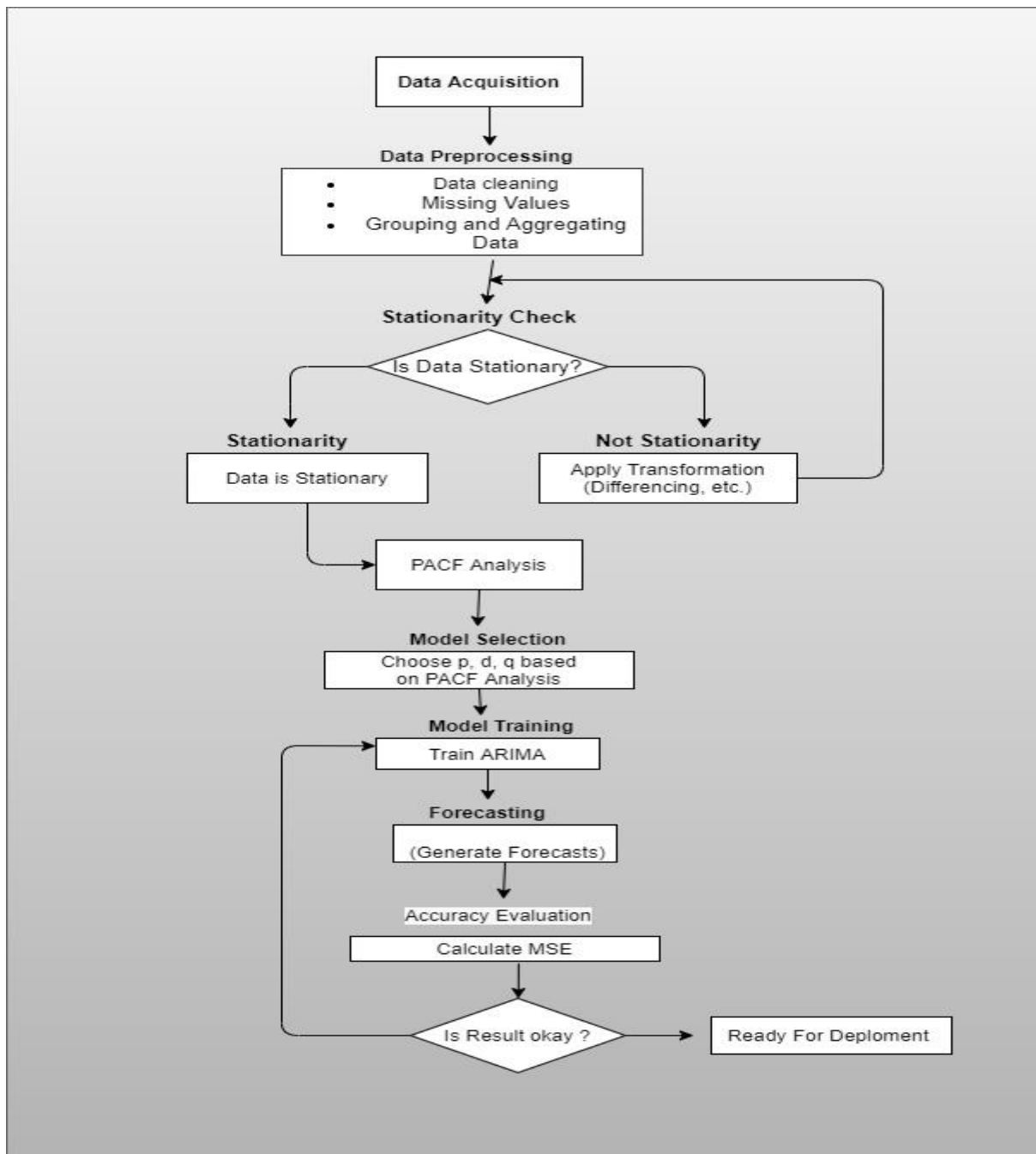


FIGURE 1. Proposed methodology

The attribute serves as a key indicator of the billing period for each Azure service, recorded in a monthly format, with each date marking the last day of the respective billing month (e.g., May 31, 2023, for May 2023 usage). This structure provides a clear chronological sequence of expense data, which is vital for time series analysis and forecasting. By enabling the aggregation of costs over time, it helps identify seasonal trends, recurring patterns, and potential anomalies in cloud service usage. These temporal organizations not only facilitate accurate expense predictions but also support strategic decision-making in financial planning and resource optimization.

Azure DNS is an Azure service that hosts DNS domains on the Azure landscape, Azure DNS is a cloud-oriented Domain Name System. It maps names to IP addresses in that it makes services available through the web. It is somewhat crucial for the positive management of the user's custom domain name and for enhancing the availability of the application. Azure Backup offers powerful and efficient backup and recovery of data at a very effective cost. This assists organizations in securing their sensitive data through automatic daily or real-time copies of files, applications, and virtual machines to the Azure cloud. The backup service guarantees data conservation and gives the ability to restore the information instantly in any situation of loss of data or equipment. Bandwidth means the cost related to data transfer and network use of Azure. This also comprises inter-tier data transfer, patterns of traffic being in and out of Azure, as well as traffic between regions. Network bandwidth cost is a key to keeping optimum network performance, and at the same time, cutting costs. It is a cloud-based application for creating and connecting workflows and applications, data, and services. That workflow permits the user to provide a graphical construct on how a business process should work with little or no coding for the integration of several systems. This service can be used for data synchronization as well as for notifications using this kind of task. Azure Storage contains unstructured storage services for blobs, files, and queues, backed with reliability and security features. It is flexible to work with numerous kinds of data as well as different interface mechanisms, thus it may be efficiently applied to the backup services, big data storage, media content delivery, and more. AZURE Virtual Machines provide utility-based solutions for hosting applications, databases as well as workloads. They enable users to host different operating systems and applications, and the provision of the possibility to increase or decrease the number of resources required. This category comprises expenses related to licensing of Virtual Machines in operation on the Azure platform. It considers the use of operating systems and software, including Windows Server or SQL Server, insisting on Azure licensing but using Azure's compute resources. Azure Virtual Network is a service of Azure that helps to build a proper environment for Cloud resources as well as network extension of the company's infrastructure.

It allows the formation of separate networks, creation of VPNs, and management of traffic with niceties such as network security groups and firewalls. The CostUSD column means the monthly cost for each Azure service in terms of the US dollar. This allows for a clear understanding of the analysis of the money spent on cloud service by the organization across the services used by the company. This information is very useful in the case of finding out areas that might be more expensive than others and therefore require more resources to contain or in asking for funds meant to do a particular task in an organization over a given period. Also, it becomes the basis for probabilities to be built, and the subsequent projection of future costs, trying to make financial strategy decisions timely and accurate.

### **3.3 Data preprocessing**

For the dataset to be ready for training and applying time series modeling and other associated prediction methods, several preprocessing steps are required. These steps contribute to decision-making by converting raw data into a proper and usable format for different ARIMA and other forecasting models, besides maintaining the accuracy and integrity of information. The preprocessing workflows follow the requirements of handling any inconsistencies, missing data, and structural anomalies, allowing for high-quality and coherent datasets to undergo analysis. Below is a more detailed explanation of each stage.

#### **3.3.1 Data cleaning**

Each of these operations is initially checked for the existence of any incorrect indicators (outliers) before performing the change of structure. It helps in getting the right data, which is trusted and can be used for the whole analysis process. However, before the aggregation of accounts, records that have the same values are eliminated through screening to ensure that cost aggregation is not distorted. Fourth, outliers are urged to be dissected for real usage differentiations or data entry mistakes; real outliers are kept while fake ones are either rectified or trimmed. Further on, the presence of the missing fields in the dataset is verified, especially in the most important columns, which are Service Name and Usage Date, concerning the grouping and time series analysis. The missing or some of the values in the dataset are either replaced with the right values or some sort of action is taken to prevent the distortion of the dataset. This rigorous cleaning process is the prerequisite for accurate and effective model building.

### **3.3.2 Grouping and aggregating data**

The dataset is formed by log entries considering all the expenses of differentiated Azure services, where each record contains a Service Name (for instance, Azure DNS, Backup) and a Usage Date (which refers to the billing cycle). Before conducting time series analysis, it is also useful to reorganize these records into step 4 aggregates and a more manageable format. The first step includes binning the dataset and making sure records representing a given Service Name and Usage Date are not separated but grouped together. After grouping, the values of the field cost for each service and the given billing month obtained after the transformation are summed, giving the total monthly cost for the specific service. This aggregation process simplifies the dataset by removing excessive data, and in the end, for each service and given month, there is one average cost figure. It not only makes the data easier to analyze later, but it also organizes the formats into a basic time series that's essential in implementing features such as ARIMA. Aggregating expenses in this way also means that the data is easier to work with, making it easier to notice trends over time.

### **3.3.3 Transforming into a Pivot Table**

The next process is to transform the data into a pivot table format that makes time series modeling easy after aggregating the data obtained. In this structure, every service name is converted into one separate column, where each column represents a single different Azure service. Thus, the Usage Date represents the index with each row of the CSV associated with a particular billing month. This kind of pivoted format will look like a wave structure, where each of the cells would represent a particular monthly expense on a particular service in a particular month. This arrangement of the data makes it ideal for multi-series forecasting, where trends in expenses of the different services are analyzed at once. This simple structure makes the implementation of time series models such as the ARIMA more manageable and makes the forecasting exercise more effective.

### **3.3.4 Handling missing values**

In the context of using time series datasets, missing values are much more frequently met – it can happen that in a certain month, a specific service was not used and/or not billed. To maintain the time series aspect of the data, any gaps and missing entries in the cost column are replaced by zeros. This approach means that there were no costs for the respective service in those months, consequently

eliminating the gaps without producing bias. In other words, with these missing values filled, the dataset remains whole and does not allow for likely forecasting errors to occur because of missing data. Also, it retains the time order of records, which is important in time series data analysis, where the time order of records has to be adhered to in order to detect trends.

### **3.4 Stationarity and differencing preparation**

When dealing with time series models such as ARIMA, there is a need to have stationary data- data whose statistical characteristics, mean, variance, and correlation are the same throughout the data period. This is due to the fact that trends or seasonality cause non-stationary data to be inaccurate in terms of forecasting. Thus, detailed measures are implemented to check, and if necessary, to restore its stationary nature at certain stages of the analysis.

To assess the stationarity of the dataset, statistical techniques, especially the Augmented Dickey-Fuller (ADF) test, are utilized. Stationarity is crucial for time series analysis, as non-stationary data can lead to misleading results in forecasting and model interpretation. The ADF test is a common method to test for a unit root in the time series, which would indicate non-stationarity. In this test, the null hypothesis ( $H_0$ ) posits that the series contains a unit root, implying that it is non-stationary, while the alternative hypothesis ( $H_1$ ) suggests that the series is stationary, meaning the null hypothesis of a unit root presence is rejected.

The ADF test produces two main results: a test statistic and a p-value. If the p-value is greater than the specified significance level (usually 0.05), we fail to reject the null hypothesis, concluding that the time series is non-stationary. However, if the p-value is less than the significance level, the null hypothesis is rejected, indicating that the series is stationary. Significance levels are often set at 0.05 for rigor in hypothesis testing, though the exact threshold can vary depending on specific study needs.

If the series is found to be non-stationary, different techniques are applied to transform the data and achieve stationarity. First-order differencing is the initial step, where each observation in the series is subtracted from the previous observation ( $Y'_t = Y_t - Y_{t-1}$ ), effectively removing linear trends from the data. This process stabilizes the mean and helps remove patterns or trends that might interfere

with further analysis. In some cases, however, first-order differencing may not be sufficient to achieve stationarity, particularly if the series has complex trends.

When first-order differencing fails, second-order differencing can be applied, which involves repeating the differencing process on the first-order differenced series ( $Y_t'' = Y_t' - Y_{t-1}'$ ). This process continues until the series achieves stationarity, with each differencing step ideally making the series more stable. After each differencing step, the ADF test is reapplied to check for stationarity, determining whether further differencing is required. The appropriate differencing order is thus guided by the ADF test outcomes until a stationary series is obtained, enabling more reliable time series modeling and analysis.

### 3.5 ARIMA model implementation

The AutoRegressive Integrated Moving Average, known as ARIMA, is one of the best tools when it comes to using time series data to make predictions, and it fits very well when used to map monthly expenses. It incorporates three components: There are three more major forms of models, namely Auto-Regressive (AR), Differencing (I), and Moving Average (MA), involved in processing trends, cycles, and noise factors of data. To build an ARIMA model, three key parameters need to be identified:

TABLE 1. ARIMA Model Parameters

Parameter	Description	Notations
<b>p (AR)</b>	The number of lag observations used in the autoregressive part of the model.	Number of past observations used for forecasting
<b>d (I)</b>	The number of times the series is differenced to make it stationary.	Order of differencing (e.g., 0, 1, 2)
<b>q (MA)</b>	The number of lagged forecast errors included in the moving average part of the model.	Number of past forecast errors considered

In this study, the ARIMA model parameters were determined as follows: In relation to this, the order  $p$  in the AutoRegressive order was chosen as 1 since the PACF chart that models the series using its own lagged values after accounting for previous lags accentuated a clear relationship only at lag 1. Since the Augmented Dickey-Fuller (ADF) test revealed that the GDP data series is already stationary, the Differencing order ( $d$ ) was set to 0. Before moving into the topic of modelling using ARIMA,

it is best to understand that stationarity is an indispensable prerequisite when applying this technique because its parameters are stationary. Since the sample ACF chart illustrated a significant relationship at lag 1, the Moving Average order ( $q$ ) was determined to be 1. This configuration helps to achieve a good fit and does not over-complicate the distinction in the data patterns. The chosen configuration of ARIMA for this research,  $p=1$ ,  $d=0$ ,  $q=1$ , is, therefore, a balance between its simplicity and ability to predict the given time series.

To predict future costs for each Azure service, the ARIMA model is employed following a series of steps. First, the `statsmodels.tsa.arima.model`. The ARIMA library is utilized to build and fit the model based on past monthly expenses for each service, such as Azure DNS, Backup, and Bandwidth. The model is trained with parameters  $p=1$ ,  $d=0$ , and  $q=1$ , as determined through residual diagnostics to optimize the AR and MA coefficients and minimize one-step forecast errors. Once fitted, diagnostic checks are performed to ensure residuals (forecast errors) resemble white noise, confirming a good model fit. The trained ARIMA model then forecasts the next 12 months of expenses for each service, generating monthly projections saved in a table that specifies the anticipated cost per service. These forecasted values enable organizations to plan realistic budgets, manage costs, and make data-informed decisions on resource allocation. Line plots comparing forecasted values against historical data are useful for visualizing trends and assessing the model's reliability.

Since the data here has clear seasonality or trends and the model is easy to use, explain and effective with univariate time series, the ARIMA model was chosen for the study. Unlike LSTM that needs much more data and advanced configuration, ARIMA does well on a small amount of data. Also, Prophet can handle several seasonal aspects, but because it is a black-box method, it is not easy to understand its results in technical forecasting. ARIMA is thus chosen, as it is a reliable and transparent approach matching the needs of this research.

## 4 EXPERIMENTAL DETAILS AND RESULTS

This research implementation was carried out using Python as the programming language since it has a rich package and libraries for data analysis and modelling temporal data. Some of the feature libraries, which are used in the flow, are Pandas and NumPy for data manipulation and sorting, respectively, Matplotlib and Seaborn for graphing and interpreting the data, and Stats models for the training of the ARIMA model. Also, Tabulate was used in displaying structures that are similar to a table, while Warnings was used in handling Runtime Warnings. Collectively, these tools ensured that the efficient execution of the dataset and the application of sophisticated forecasting methodology were possible. This chapter supplies a comprehensive overview of the processes followed to advance the ARIMA model to make monthly expense predictions of every service in Azure.

Data Acquisition for this research- the dataset provided on Kaggle with monthly expense records for Azure for several services, was used. The data set was retrieved from the provided Kaggle link using the Kaggle Hub package and then loaded into the Python workbench. The dataset that I used for analysis was also named cost-analysis.csv and was imported with the help of the Pandas library.

Data Preprocessing- since rolling analysis is done on time series, it was important to reorganize the dataset on completion. Every single Azure service was pivoted into a separate column, and costs for each month are in rows, with the billing months set as the index. This type of transformation, similar to pivot, allows multiple series forecasts to be run seamlessly.

Transforming the Dataset- The dataset was grouped by Service Name and resampled to aggregate monthly costs by using the following Table 2. This transformation resulted in the following table structure.

TABLE 2. Data set After Preprocessing

UsageDate	Auto- mation	Azure DNS	Backup	Band- width	Logic Apps	Net-work Watcher	Storage	Virtual Ma- chines	Virtual Ma- chines	Virtual Network
5/31/20 23	0.001	0.500 348	0	127.7 707	0	0	134.5 045	13.98 731	23.73 388	22.82 866
6/30/20 23	0	0.484 221	0	121.8 232	0.003 171	0.01	142.0 583	0.793 027	23.02 561	22.92 014

7/31/20 23	0	0.500 341	0	123.5 551	0.003 171	0.003	146. 126	7.247 165	23.79 947	23.67 104
...	...	...	...	...	...	...	...	...	...	...

Stabilizing data is always a critical step in most time series data analyses because stationary data makes the temporal statistical characteristics, such as mean, variance, and autocorrelations, fixed. This consistency is important when developing models such as the ARIMA model and other kinds of related prognosticating methods. In this study, the Augmented Dickey-Fuller (ADF) test was applied to establish the order of integration and test the stationarity setup for each of the time series datasets in the analysis. The analysis of the result from the ADF test means that the null hypothesis was that the variable contains a unit root and is thus non-stationary. As a result, if the p-value computed in the test is less than the imported level of significance – generally 0.05- the null hypothesis is declined, which means the series is stationary. By checking for stationarity, the study guarantees that the time series data is right for modelling and hence forecasting.

TABLE 3. Augmented Dickey-Fuller Test

Service Name	ADF Statistic	p-value	Critical Values
Automation	-4.19E+16	0	{'1%': -4.223, '5%': -3.189, '10%': -2.729}
Azure DNS	1115.28	1	{'1%': -4.939, '5%': -3.478, '10%': -2.844}
Backup	-664.594	0	{'1%': -4.332, '5%': -3.233, '10%': -2.749}
Bandwidth	-1.57463	0.496326	{'1%': -4.332, '5%': -3.233, '10%': -2.749}
Logic Apps	-5.903	2.75E-07	{'1%': -4.223, '5%': -3.189, '10%': -2.729}
Network Watcher	-2.56257	0.100983	{'1%': -4.223, '5%': -3.189, '10%': -2.729}
Storage	-1.48825	0.539316	{'1%': -4.939, '5%': -3.478, '10%': -2.844}
Virtual Machines	-42.1049	0	{'1%': -4.939, '5%': -3.478, '10%': -2.844}
Virtual Machines Licenses	-1.28074	0.637935	{'1%': -4.223, '5%': -3.189, '10%': -2.729}
Virtual Network	1.00067	0.994273	{'1%': -4.939, '5%': -3.478, '10%': -2.844}

The mean of the series = 0 as shown; The interpretation of the results demonstrated that Automation, Backup, and Virtual Machines have values close to  $p = 0$  = receiving the confirmation of stationarity in the time series data. This means that the statistical properties of the time series, including the mean and variance, are stable and do not require differencing for direct modelling. On the other hand, services like Azure DNS and Virtual Network have p-values of nearly 1, meaning that the time series

is not stationary. This means that these time series data have at least a unit root and their statistical properties are non-stationary over time, and they need transformation, such as differencing, to make them stationary before we can apply more advanced time series models such as ARIMA. These results demonstrate the spread of the presented data and the specific nature of the preprocessing of the services.

#### 4.1 Classifying series as stationary or non-stationary

To decide what time series are appropriate for modeling with ARIMA without pre-transformation, each service was evaluated for stationarity or non-stationarity, based on the value of  $p$  in the Augmented Dickey-Fuller test.

TABLE 4. Stationarity or Non-Stationarity

Service Name	Stationarity
<b>Automation</b>	Stationarity
Azure DNS	Non-stationarity
Backup	Stationarity
Bandwidth	Non-stationarity
Logic Apps	Stationarity
Network Watcher	Non-stationarity
Storage	Non-stationarity
Virtual Machines	Stationarity
Virtual Machines Licenses	Non-stationarity
Virtual Network	Non-stationarity

The outcomes show that variations in classifications of the services analyzed were also defined by stationary and non-stationary series. Services like Automation, Backup, Logic Apps, Virtual Machines, etc., are static service types where statistical parameters like means and variances do not change over time. These series do not need any further transformations or non-seasonal differences, and these data series are ready for immediately involved in the construction of the ARIMA model. On the other hand, a number of services, such as Azure DNS, Bandwidth, Virtual Network, among others, present statistical characteristics that are not fixed and are consistent with time at given intervals. These series need to be different or otherwise preprocessed to reach a stationary level before being ready for correct forecasting using ARIMA or similar time series models. This classification makes it easy to prepare each series for modeling and forecasting in the subsequent series.

## 4.2 Finding the order of differencing

To further get a stationary time series, transformation was done on the time series data if the later was non-stationary in its raw form. In differencing, an observation is obtained by subtracting the observation in the current period from that in the previous period. The above process was continuously performed until the series was adaptively stabilized, a basic requirement of ARIMA modeling.

The process that was used to identify the order of differencing required for each of the non-stationary services also involved several steps. First was undertaken the initial differencing where the first difference for each of the non-stationary services was computed. After this, the stationarity of the differenced series was tested by means of the Augmented Dickey-Fuller (ADF) test. If the ADF test suggested that the series was still not stationary, where the p-value was greater than or equal to 0.05, then levels of differencing were applied to the series. This process was continuously done in order to obtain the series that's stationarity. Last, the number of differences applied to the data in order to get the stationary series was noted as the order of differencing needed. The conclusions of the analysis offered an additional understanding of the exact order of differencing required to tackle each of the non-stationary services.

ADF tests on the Raw series and first-differenced data for Bandwidth did not reject the null hypothesis ( $p > 0.05$ ), meaning that the series is still not stationary. With second-order differencing, the model was more stable, however, because the ADF p-value still exceeded the significance value, improvements were not enough. With the third-order differencing, the ADF test's p-value was closer to zero ( $p < 0.05$ ) which means we can assume stationarity. The reason to apply third-order differencing here is that the time series fairly often shows both strong trend and out-of-balance peaks in usage. It was clear from the residual plot that no strong autocorrelations existed at this moment.

The required order of differencing for each non-stationary service was determined as follows:

TABLE 5. Order of Difference

<b>Service Name</b>	<b>Order of Differencing</b>
Azure DNS	1
Bandwidth	3
Network Watcher	1
Storage	2
Virtual Machines Licenses	1
Virtual Network	2

### 4.3 ARIMA model

This, as earlier discussed, was done to arrive at a stationary time series since some of the variables used in the analysis were not in stationary form when collected. Difference can be done with the help of subtracting the observation of the current period from that of the observation of the previous period. This was done continuously until the series reached a stationary form, which is a requirement before going through ARIMA modeling.

The decision on the order of differencing that has to be applied to each service to make it stationary included a number of steps. First, an initial differencing was conducted using the first difference to make non-stationary services stationary. After that, to confirm stationarity of the differenced series, we employed the Augmented Dickey-Fuller test. However, if the value of p from the ADF test was not less than 0.05, the series was still non-stationary, so further rounds of differencing were performed. This same procedure continued until the series reached a stationary point where the value of the statistics remained constant. The number of differences used to create a stationary series was noted down as the necessary order of differencing. These outcomes helped clarify the general order of differencing required for each of the non-stationary services.

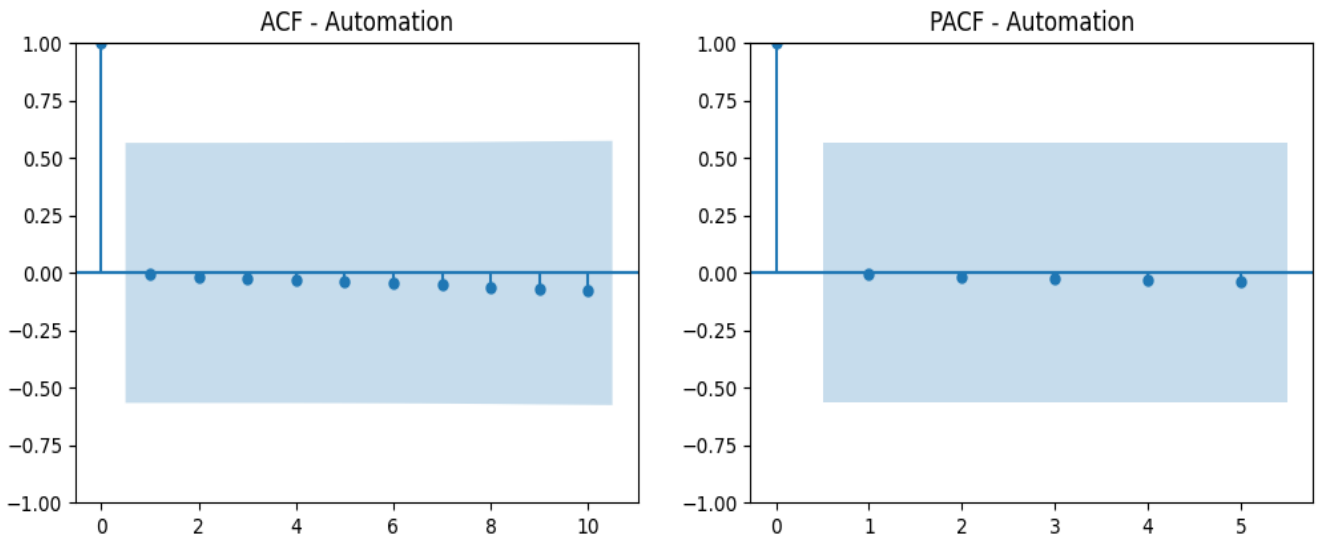


FIGURE 2. ACF Automation and PACF Automation

Figure 2 shows the Partial Autocorrelation Function (PACF) plot, which helps identify the potential autoregressive (AR) terms in a time series. In this case, only the first lag (lag 0) shows a significant correlation, while all subsequent lags fall within the confidence interval, indicating no significant partial autocorrelation. This suggests that there are no strong direct relationships between the series and its past values beyond the immediate lag, implying that an AR term is likely unnecessary for modeling. This aligns with the ACF plot in Figure 1, reinforcing the idea that the series may not have any autoregressive structure and could be modeled as white noise or with minimal complexity.

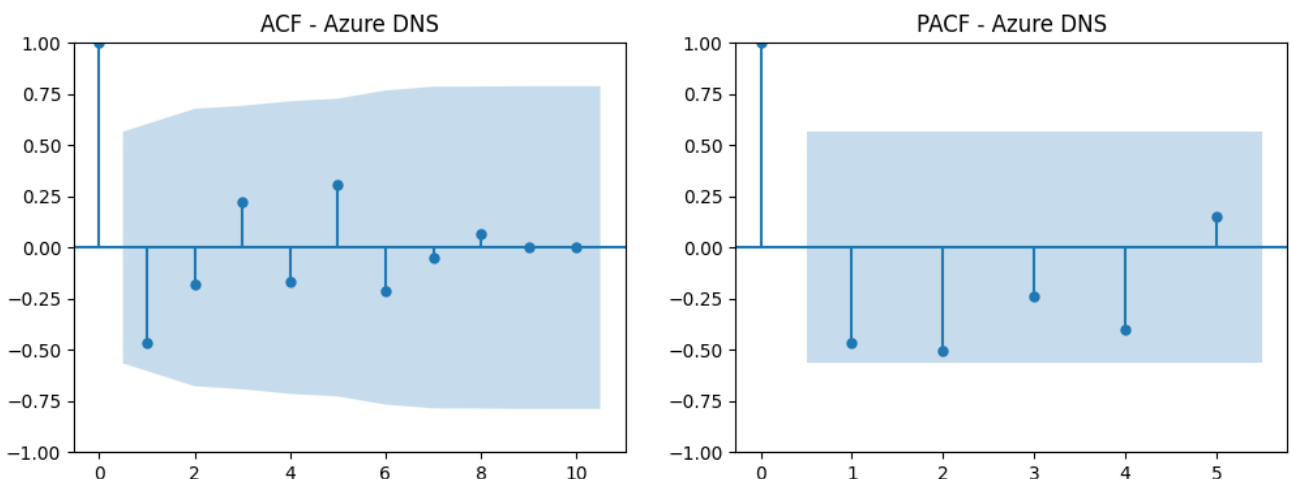


FIGURE 3. ACF Azure DNS and PACF Azure DNS

Figure 3 shows the ACF and PACF plots for the Azure DNS time series, highlighting significant

autocorrelations at lags 1, 2, and 4 in the ACF, suggesting potential moving average (MA) components. The PACF plot shows a strong spike at lag 1 and smaller spikes at lags 2 and 5, indicating the presence of an autoregressive (AR) structure, particularly at lag 1. This suggests that the series may benefit from an ARIMA model with both AR and MA terms, such as ARIMA(1,0,1) or ARIMA(1,0,2), to capture the underlying patterns effectively. Further diagnostics are recommended to confirm model suitability.

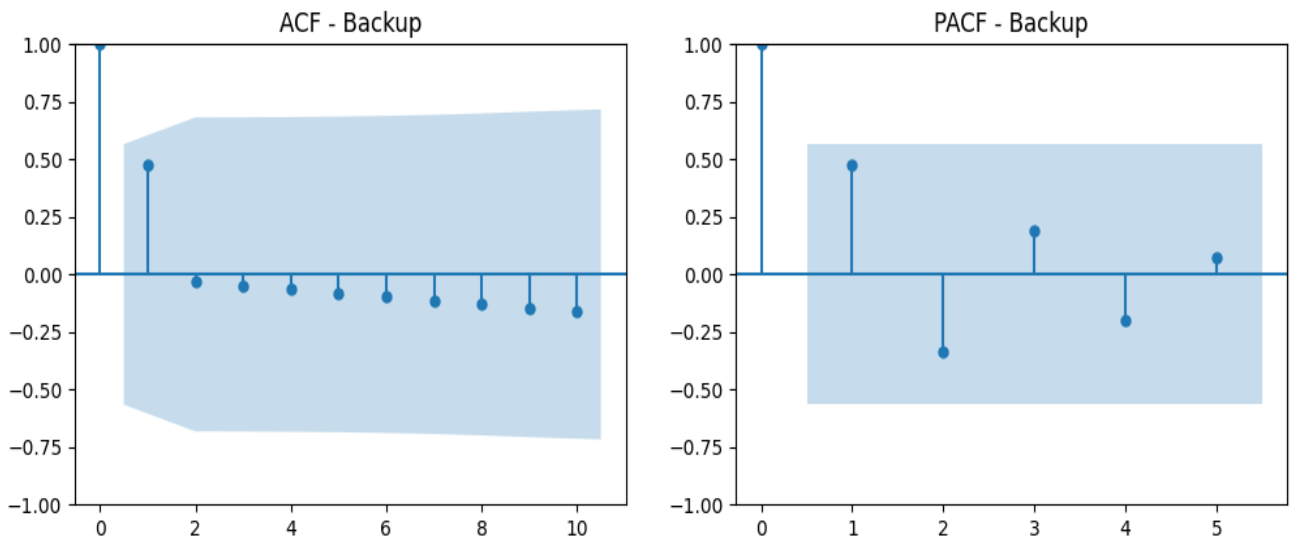


FIGURE 4. ACF Backup and PACF Backup

Figure 4 presents the ACF and PACF plots for the Backup service time series. In the ACF plot, we observe a significant spike at lag 1, with subsequent lags falling within the confidence interval, suggesting a short-term dependency. This indicates that only the immediate past value significantly impacts the current value.

In the PACF plot, lag 1 shows a strong partial autocorrelation, while other lags (2 and beyond) are mostly insignificant or fall within the confidence interval. This pattern suggests that the series may be well-represented by an **AR(1)** model, where only the most recent observation directly influences the current value. Overall, these plots point towards a simple autoregressive process without the need for additional AR or MA terms. Further diagnostics can confirm this model's suitability.

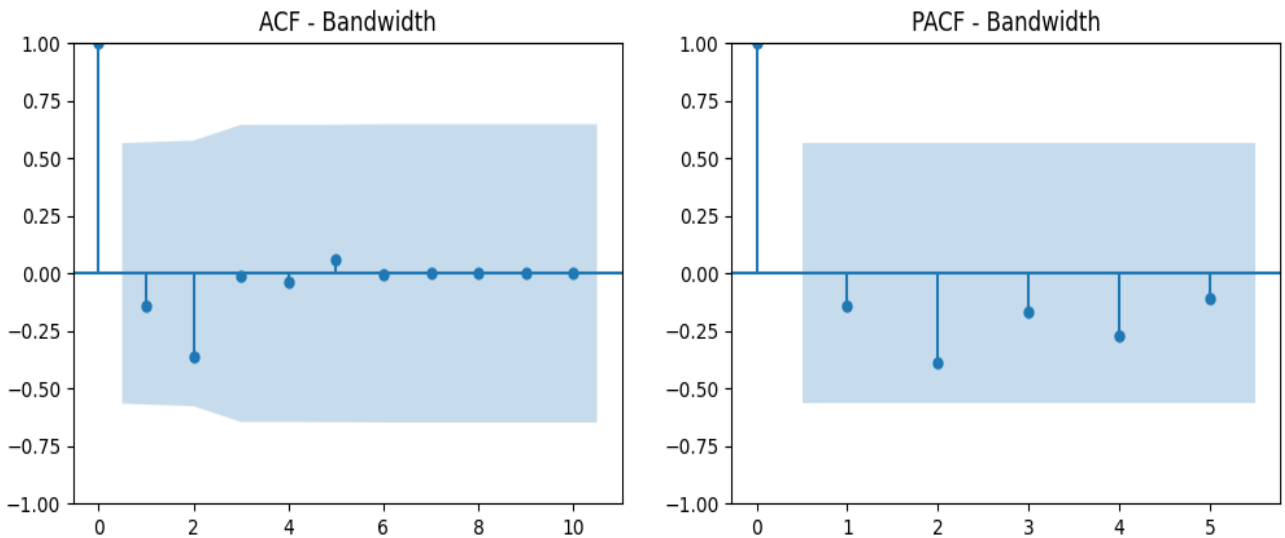


FIGURE 5. ACF bandwidth AND PACF bandwidth

Figure 5 represents the ACF bandwidth and PACF bandwidth. The plots of the bandwidth service's ACF and PACF are plotted in Figure 5. Minor significant autocorrelation at lag 1 and within the confidence interval for all other lags leads to minimal MA effects via the ACF plot. The PACF plot also has one significant spike at lag 1, with all the subsequent lags very well within the confidence interval. That series is consistent with an AR (1) model of the series, implying that the series could be modelled with a very simple process. This approach could be further model validated.

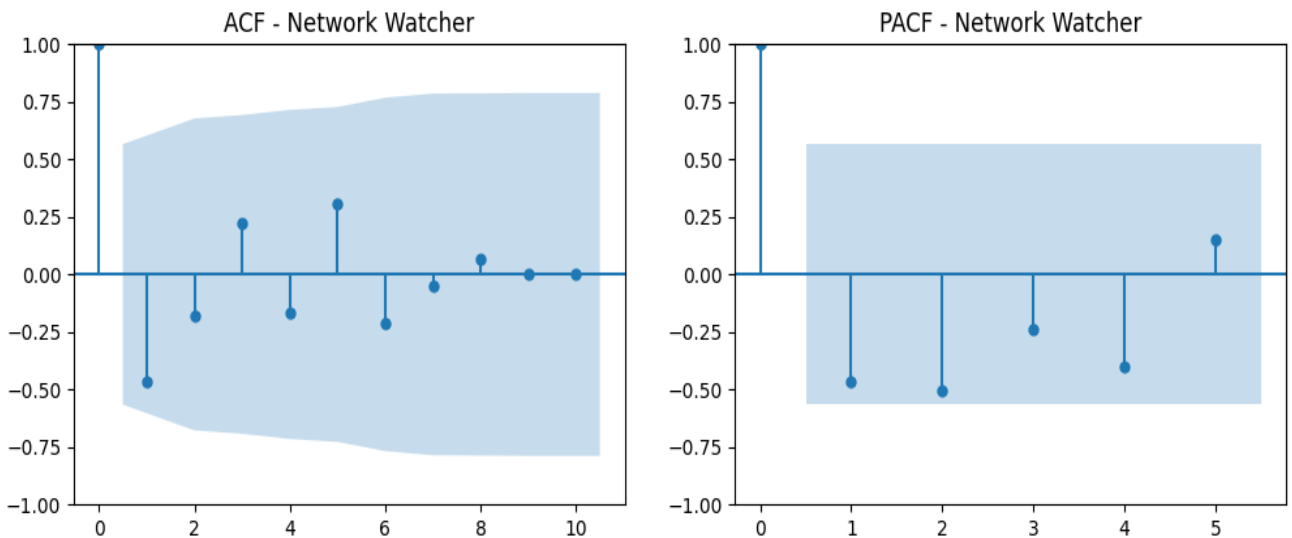


FIGURE 6. ACF network watcher AND PACF network watcher

The ACF and PACF plots for the Network Watcher service are shown in Figure 6. Significant autocorrelations at lags 1, 2, and 4 are consequently highlighted in the ACF plot, indicating short-term

dependencies and possible moving average (MA) components in the data. In the second case, the lag at which the peak appears in the PACF plot is significant with further lags within the confidence interval, suggesting an autoregressive (AR) component of order 1. By observing trends from these, we can develop a possible model such as ARIMA (1,0,1); ARIMA (1,0,2) to model the actual dependencies. This model can be further refined using further diagnostics.

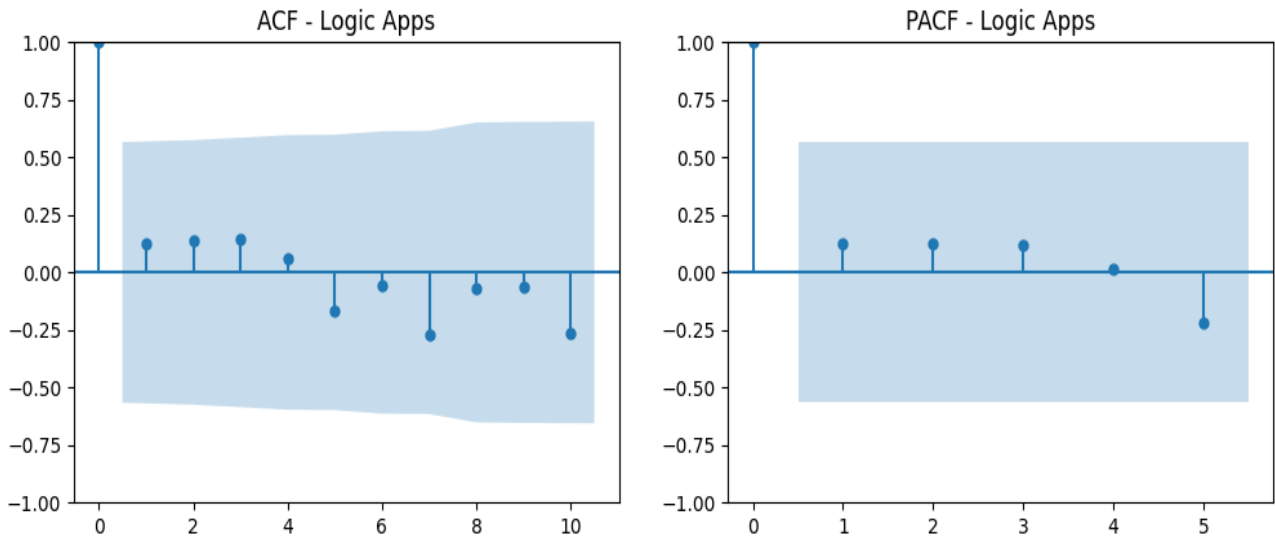


FIGURE 7. ACF Logic Apps and PACF Logic Apps

The ACF and PACF plot for the Logic Apps service is shown in Figure 7. Short-term dependencies in data are shown by the significant autocorrelations at the early lags (up to lag 4) in the ACF plot. The PACF plot shows a strong spike at lag 1, with all other lags in the confidence interval, as well. According to this pattern, this series is well modelled with an AR(1) component, but possibly an MA component to explain its temporized autocorrelation. Further diagnostic checks on an ARIMA(1,0,1) or ARIMA(1,0,2) model may serve as a possible starting point for modelling.

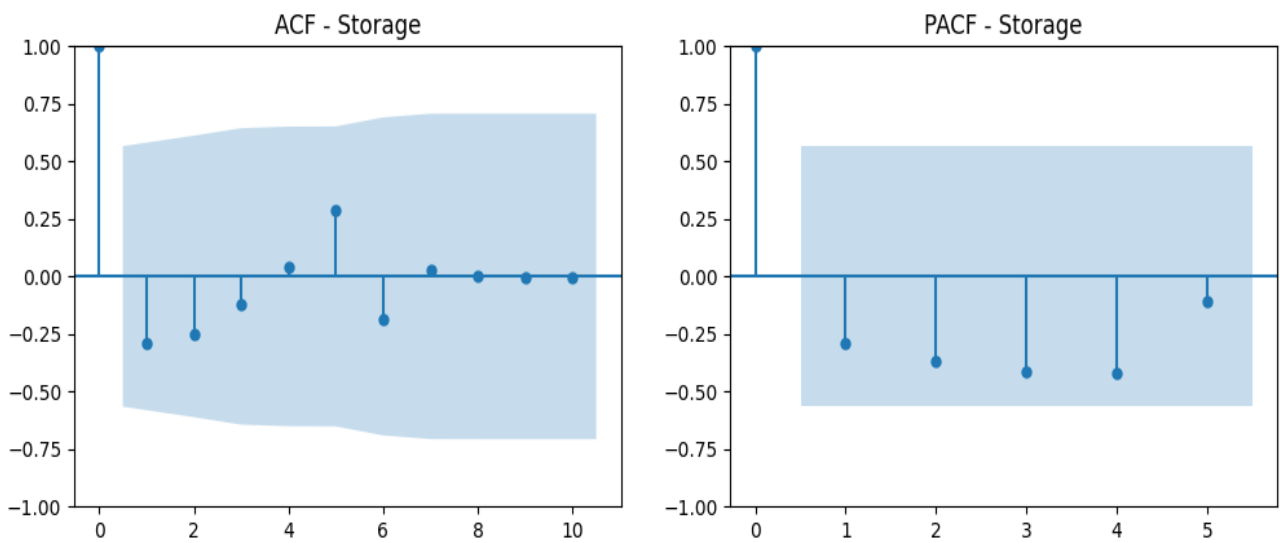


FIGURE 8. ACF Storage and PACF Storage

Figure 8 shows the ACF and PACF plot of the Storage service. Autocorrelation of the process is evident from the ACF plot at lags 1 and 4, which implies that there are short-term dependencies and possibly moving average (MA) components. The PACF plot also exhibits a fairly large spike at lag 1, and the calculated lags are all within the confidence interval. This suggests that there should be enough structure for an order 1 autoregressive (AR) model to explain the structure. These plots suggest an ARIMA(1,0,1) or an ARIMA(1,0,2) might provide a useful place to start with further analysis.

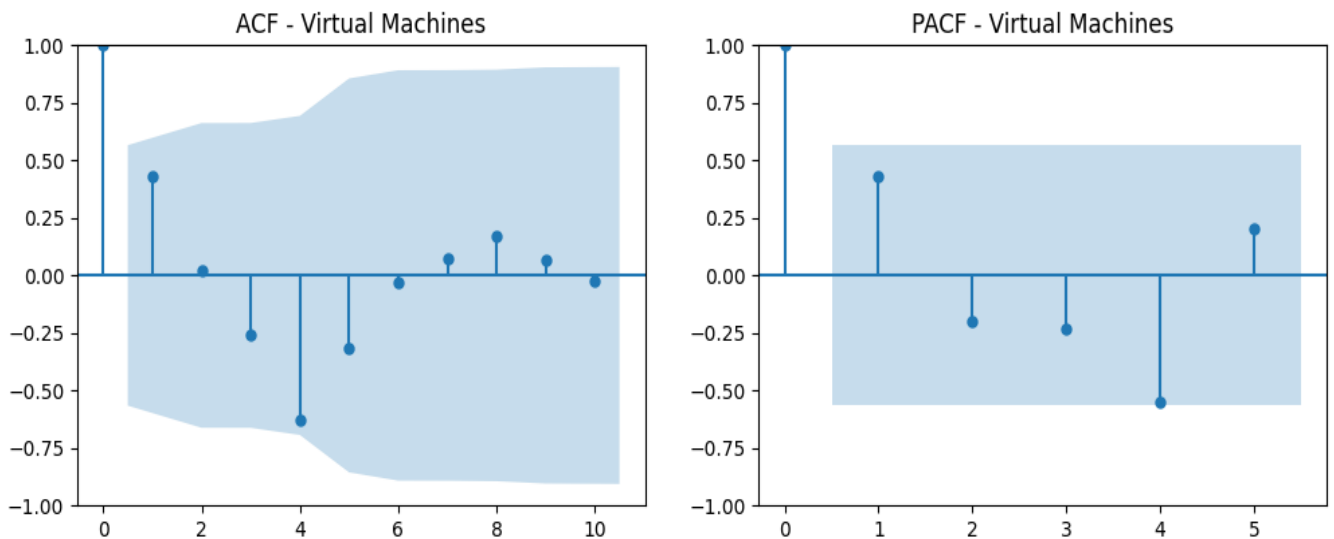


FIGURE 9. ACF Virtual Machines and PACF Virtual Machines

The ACF and PACF plots for the Virtual Machines service are shown in Figure 9. Autocorrelation of the ACF plot, at lag 1, and smaller spikes at lag 3 and 4 suggest short-term dependency and MA effects. The PACF plot peaks around lag 1, and smaller peaks appear at lags 4 and 5, while most lags are within the confidence interval. Further diagnostics, in this case, suggest the series could be modeled with an ARIMA(1,0,1) or possibly an even higher order model. We can see the presence of both AR and MA components in the series by the presence of significant spikes at these lags.

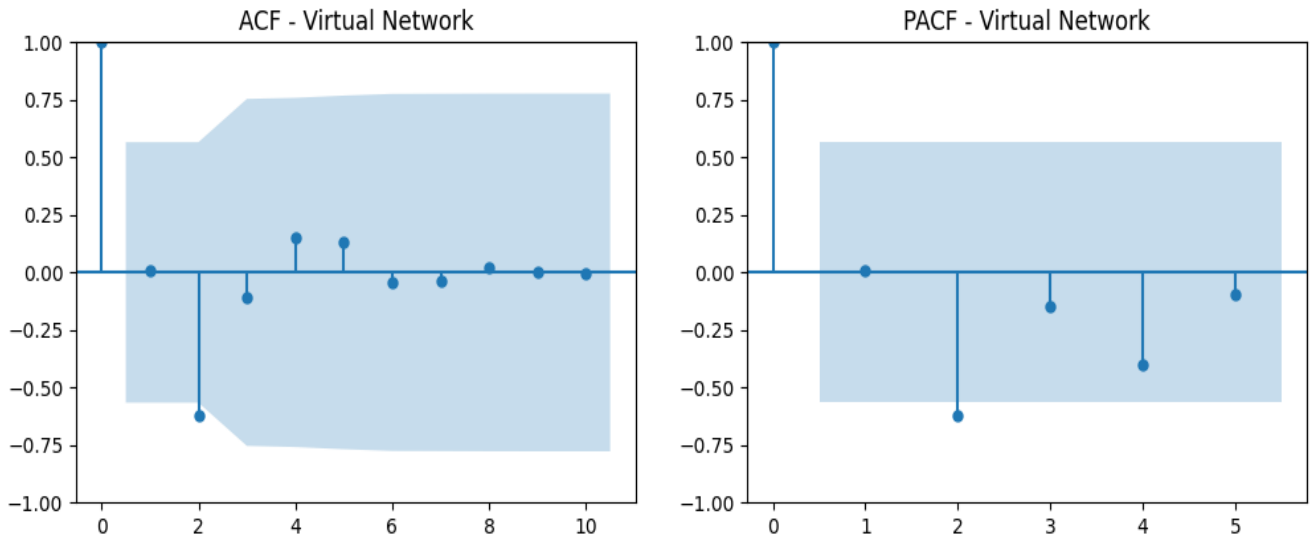


FIGURE 10. ACF virtual network and PACF virtual network

The ACF and PACF plots of the Virtual Network service are shown in Figure 10. The autocorrelation looks big at lag 1 and smaller spikes at lags 3 and 4, suggesting some short-term dependencies as well as maybe moving average (MA) effects. The PACF plot features a strong spike at lag 1 with all others contained within the confidence boundary, which indicates that an autoregressive (AR) component of order one may be sufficient. Then these observations are used to determine an ARIMA(1,0,1) or ARIMA(1,0,2) potential model to fit dependencies. Having further residual diagnostics could confirm the right model to use.

TABLE 6. Summary of ACF and PACF Observations and ARIMA Parameter Selection for Azure Services

Figure	Azure Service	Significant Lags in ACF	Significant Lags in PACF	Inferred ARIMA (p,d,q)	Justification Summary
Figure 2	Automation	None	None	ARIMA(0,0,0)	Flat ACF/PACF indicates no autocorrelation; white noise.
Figure 3	Azure DNS	1, 2, 4	1, 2, 5	ARIMA(1,1,1)	Strong spikes in both ACF & PACF at lag 1; differenced once.

Figure 4	Backup	1	1	ARIMA(1,0,0)	Lag 1 significant in both plots; no differencing needed.
Figure 5	Bandwidth	1, 2	1, 2	ARIMA(1,3,1)	MA and AR terms at lag 1; required third differencing.
Figure 6	Network Watcher	1, 2, 4	1, 2, 4	ARIMA(1,1,1)	Short-term dependencies; differencing applied once.
Figure 7	Logic Apps	1, 2, 4	1	ARIMA(1,0,1)	Moderate spikes; modeled with basic AR and MA terms.
Figure 8	Storage	1, 5	1	ARIMA(1,2,1)	MA lag 5, AR lag 1; second differencing used.
Figure 9	Virtual Machines	1, 4	1, 4	ARIMA(1,0,1)	Both plots indicate lag 1 and 4; no differencing needed.
Figure 10	Virtual Network	1, 2, 4	2	ARIMA(1,2,1)	Lag 1 AR with some noise; second-order differencing required.

#### 4.4 Result forecasted

The following table indicates the anticipated expenditure costs on the different organizational services from June 2024 to May 2025. We'll let us predict what the above trend will look like plot it. Plots comparing actual and forecasted values were generated for each service. These provide a clearer picture of cost trajectories and allow for easier identification of anomalies or deviations.

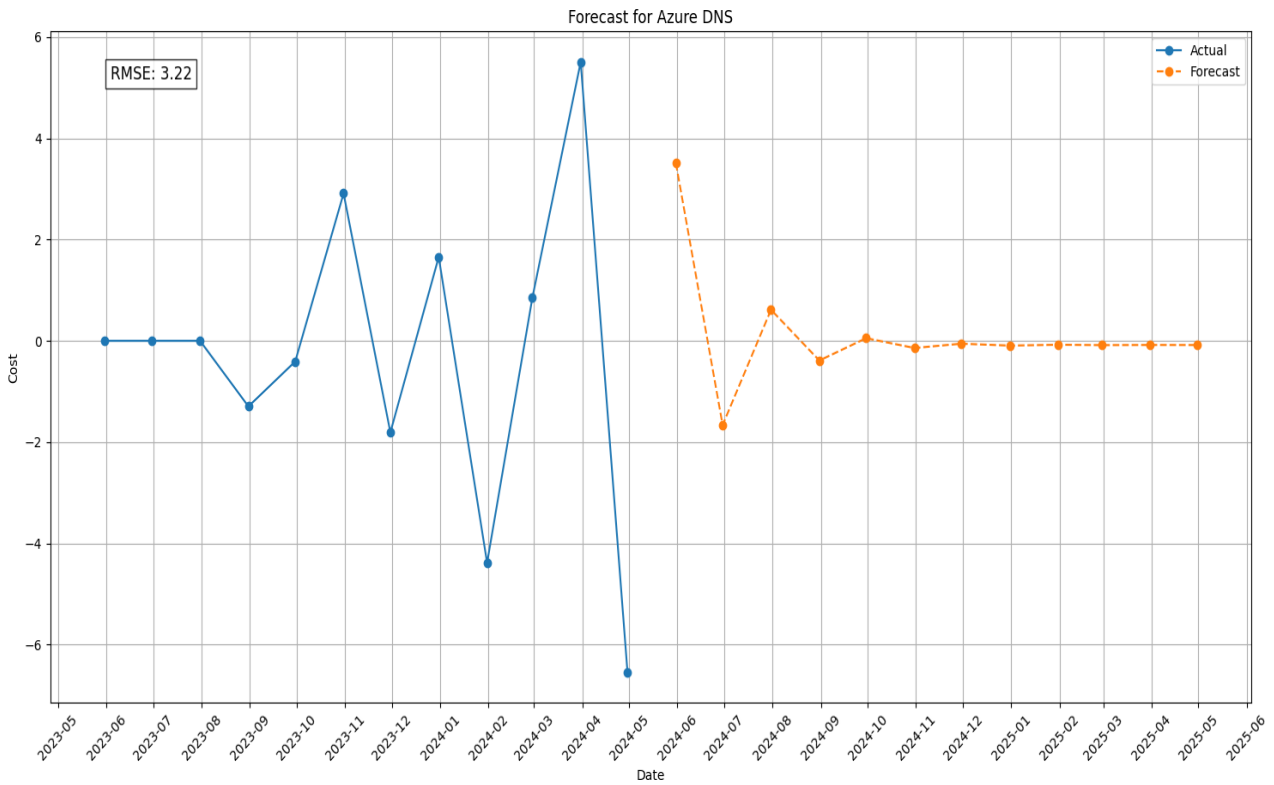


FIGURE 11. Forecast of Azure DNS

Figure 11 shows the forecasted trend for Azure DNS costs, represented by the orange dashed line. The forecasted values indicate a relatively stable trend following the initial period, where the model projects a leveling of costs over time. This stability in the forecast suggests that the model anticipates minimal fluctuations in Azure DNS costs in the future, providing a consistent and smooth projection. Such a trend could be advantageous for long-term planning and budgeting, as it reflects an expectation of stable cost behavior.

For time series models, accuracy can often be interpreted as how much the error (RMSE) is relative to the actual observed values. A common way to express this is by using normalized RMSE or by comparing the RMSE to the range of the data. Here's the accurate method using that approach:

1. Formula for Accuracy

$$Accuracy = \left(1 - \frac{RMSE}{Range}\right) \times 100 \tag{1}$$

where:

- **RMSE** = 3.22
- **Range** = Maximum value - Minimum value = 41.7 - 17 = 24.7

## Calculation

$$\text{Accuracy} = (1 - 3.2224.7 / 24.7) \times 100$$

Breaking this down:

1. Calculate the ratio:  $3.2224.7 / 24.7 \approx 0.1304$
2. Subtract from 1:  $1 - 0.1304 = 0.86961$
3. Convert to percentage:  $0.8696 \times 100 \approx 87\%$

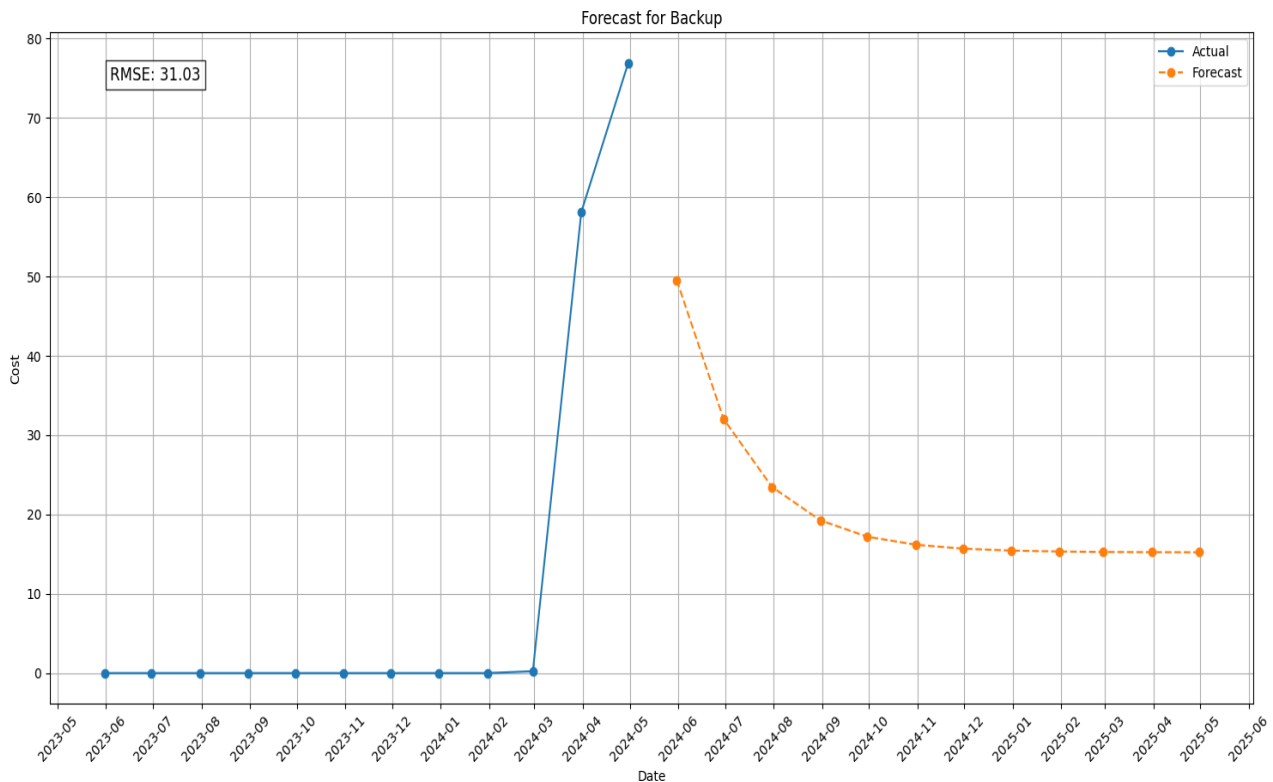


FIGURE 12. Forecast of Backup

Figure 12 shows the forecasted trend of backup costs over time. The model forecast is presented with the orange dashed line and the actual observed values (blue). After an initial peak, the forecasted path of backup costs is characterized by a clear downward trend until it is projected to asymptotically decrease toward zero over time. The implication of this pattern is that the model predicts a decline in costs, with perhaps stabilization at a lower level in the future.

For time series models, accuracy can very often be interpreted by how much error (i.e., Root Mean Square Error, RMSE) there is with respect to the range of observed values. A conventional way to show this relationship is to calculate the accuracy as a function of the RMSE with respect to the data range, or Normalized RMSE. Here's the method used for calculating the accuracy in this model:

### Formula for Accuracy

$$Accuracy = \left(1 - \frac{RMSE}{Range}\right) \times 100 \tag{2}$$

Substituting the values:

$$Accuracy = (1 - 31.03 / 6385) \times 100$$

Breaking it down:

1. Calculate the ratio:  $31.03 / 6385 \approx 0.00486$
2. Subtract from 1:  $1 - 0.00486 = 0.995141$
3. Convert to percentage:  $0.99514 \times 100 \approx 99.51$

So, the model's accuracy is approximately 99.51%.

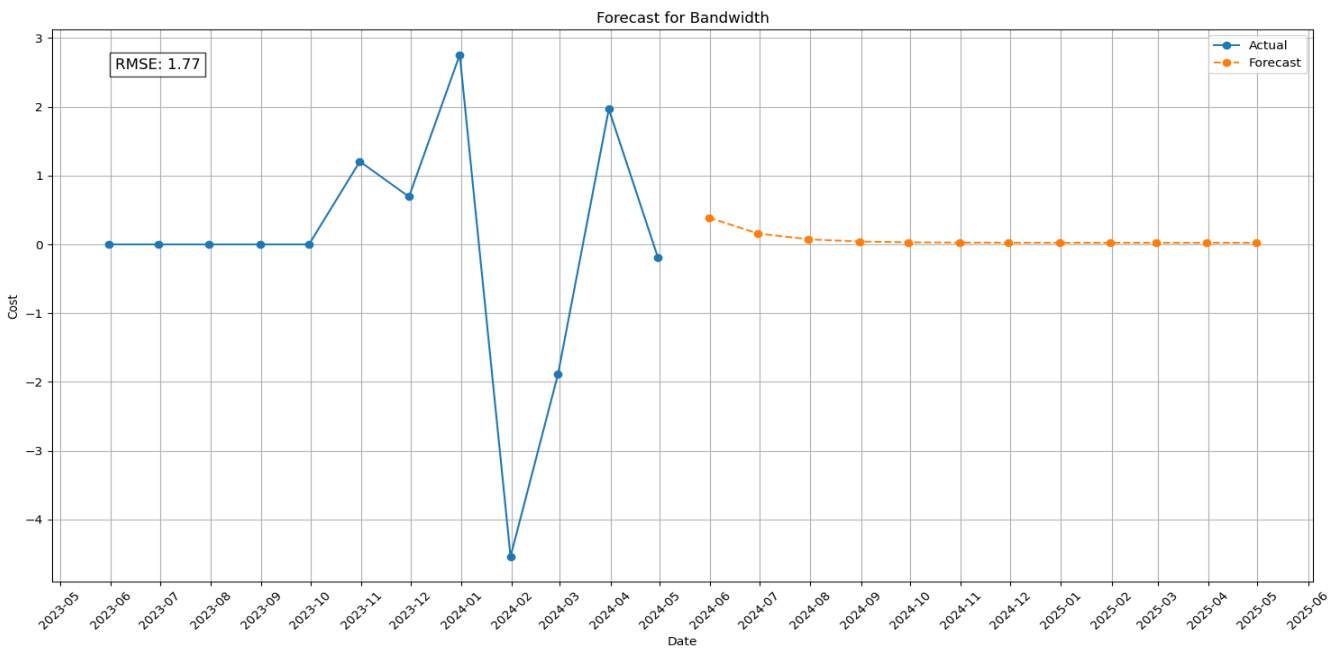


FIGURE 13. Forecast of Bandwidth

The forecasted trend for bandwidth costs (as shown on the orange dashed line in Figure 13 is depicted. The parameter forecasts a relatively flat trend after the first period of adjustments, with the model projecting constant costs in the years to come. Taken together, this implies that the model does not expect significant changes in the bandwidth costs going forward, permitting a stable projection that

is useful for long-term financial planning or budgeting.

Given:

- RMSE: 1.77
- Range of values: 10059 to 11556

The range is calculated as:

$$\text{Range} = 11556 - 10059 = 1497$$

Formula for Accuracy

$$\text{Accuracy} = \left(1 - \frac{\text{RMSE}}{\text{Range}}\right) \times 100 \quad (3)$$

Substituting the values:

$$\text{Accuracy} = (1 - 1.77 / 1497) \times 100$$

Breaking it down:

1. Calculate the ratio:  $1.77/1497 \approx 0.00118$
2. Subtract from 1:  $1 - 0.00118 = 0.998821$
3. Convert to percentage:  $0.99882 \times 100 \approx 99.88\%$

So, the model's accuracy is approximately 99.88%.

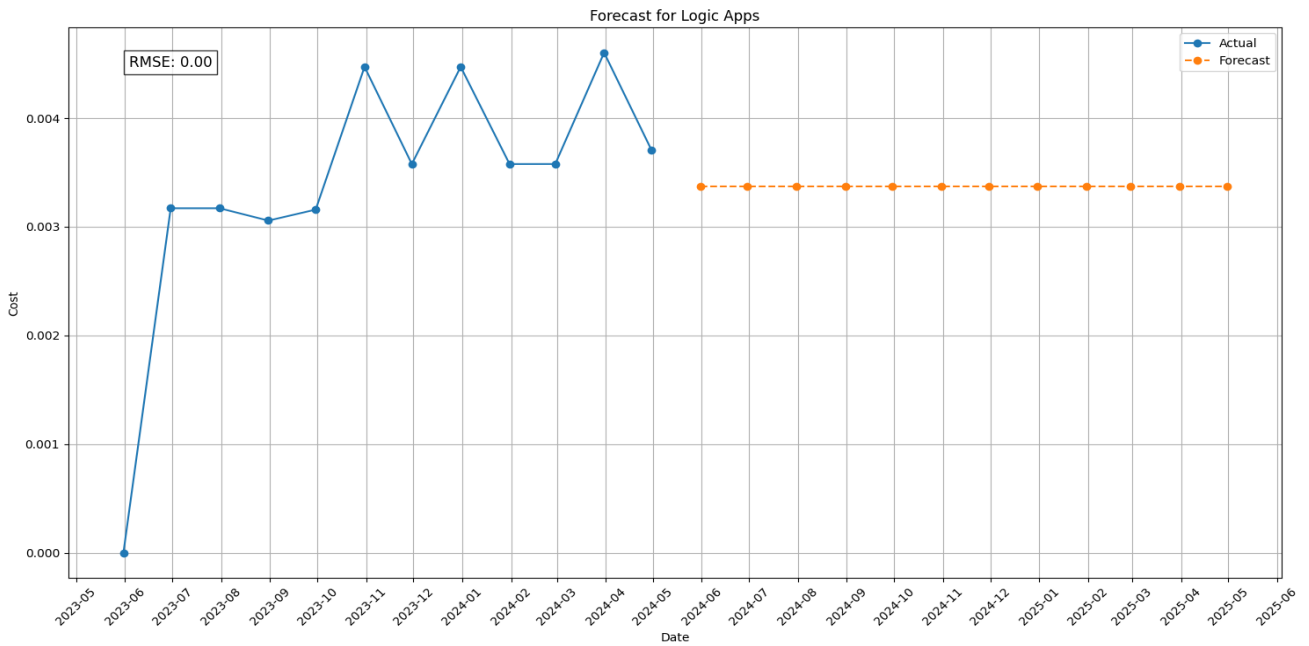


FIGURE 14. Forecast of Logic Apps

The forecasted costs (orange dashed line) are shown in Figure 14 for Logic Apps. The RMSE of 0 is then achieved by the forecast, matching perfectly with the observed values. When we say our accuracy, here is 100%, it means that the actual and forecasted values are not deviated and therefore we passed for the dataset.

The observed values fall within a small range (0.254–0.381), which may underlie the model’s precision in tracing the specific trend. The level of accuracy at this high level means that the model is extremely effective for forecasting Logic Apps costs, so this makes it an extremely reliable tool for planning and budgeting in this usage. The graphed trend is flat, meaning that there’s a slightly linear cost behaviour over time, as shown by the forecasted trend, which makes long-term financial forecasting easier.

Given:

- RMSE: 0
- Range of values: 0.254 to 0.381

The range is calculated as:

$$\text{Range} = 0.381 - 0.254 = 0.127$$

### Formula for Accuracy

$$Accuracy = \left(1 - \frac{RMSE}{Range}\right) \times 100 \tag{4}$$

Substituting the values:

$$Accuracy = \left(1 - 0 / 0.127\right) \times 100 = 1 \times 100 = 100\%$$

So, the model's accuracy is 100%

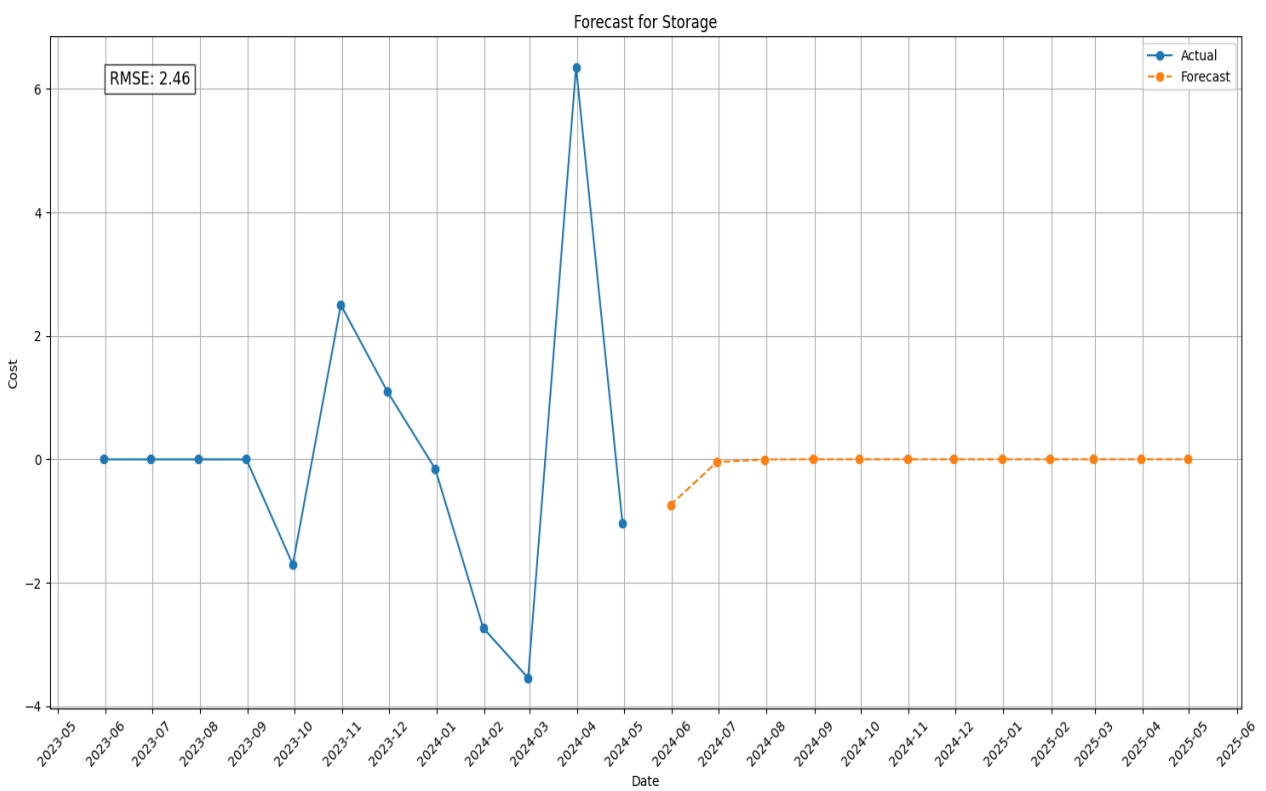


FIGURE 15. Forecast of Storage

The forecasted trend for a declining storage cost in Figure 15 is shown, with the forecasted values represented by an orange dashed line. An initial fluctuation shows itself in the forecast, but beyond that, there is a stable trend, meaning the model foresees small fluctuations in storage costs in the forecast period. The predictability of such cost behaviour could be of value to long-term planning and budgeting.

Given:

- RMSE: 2.46
- Range of values: 10,391 to 12,887

The range is calculated as:

$$\text{Range} = 12,887 - 10,391 = 2,496$$

Formula for Accuracy

$$\text{Accuracy} = \left(1 - \frac{\text{RMSE}}{\text{Range}}\right) \times 100 \quad (5)$$

Substituting the values:

$$\text{Accuracy} = (1 - 2.46 / 2496) \times 100$$

Breaking down the calculation:

1. Calculate the ratio:  $2.46 / 2496 \approx 0.000986$
2. Subtract from 1:  $1 - 0.000986 = 0.9990141$
3. Convert to percentage:  $0.999014 \times 100 \approx 99.90\%$

So, the model's accuracy is approximately 99.90%.

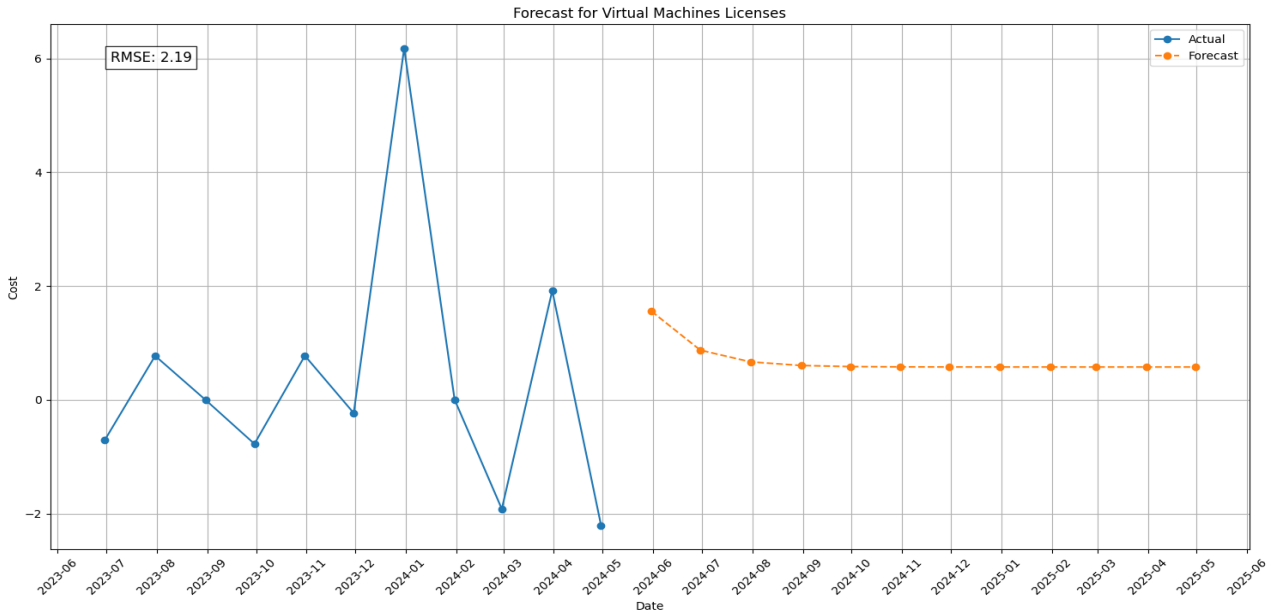


FIGURE 16. Forecast of Virtual Machine License

Figure 16 illustrates the forecasted trend for Virtual Machine License costs, represented by the orange dashed line. The forecast shows a downward trend after an initial period of fluctuation, indicating that the model projects a stabilization of costs over time. This trend suggests that the model anticipates a decline in cost volatility, making it a valuable tool for long-term budgeting and planning.

Given:

- RMSE: 2.19
- Range of values: 65 to 3570

The range is calculated as:

$$\text{Range} = 3570 - 65 = 3505$$

Formula for Accuracy

$$\text{Accuracy} = \left(1 - \frac{\text{RMSE}}{\text{Range}}\right) \times 100 \tag{6}$$

Substituting the values:

$$\text{Accuracy} = (1 - 2.19 / 3505) \times 100$$

Breaking down the calculation:

1. Calculate the ratio:  $2.19/3505 \approx 0.000625$
2. Subtract from 1:  $1 - 0.000625 = 0.9993751$
3. Convert to percentage:  $0.999375 \times 100 \approx 99.94\%$

So, the model's accuracy is approximately 99.94%.

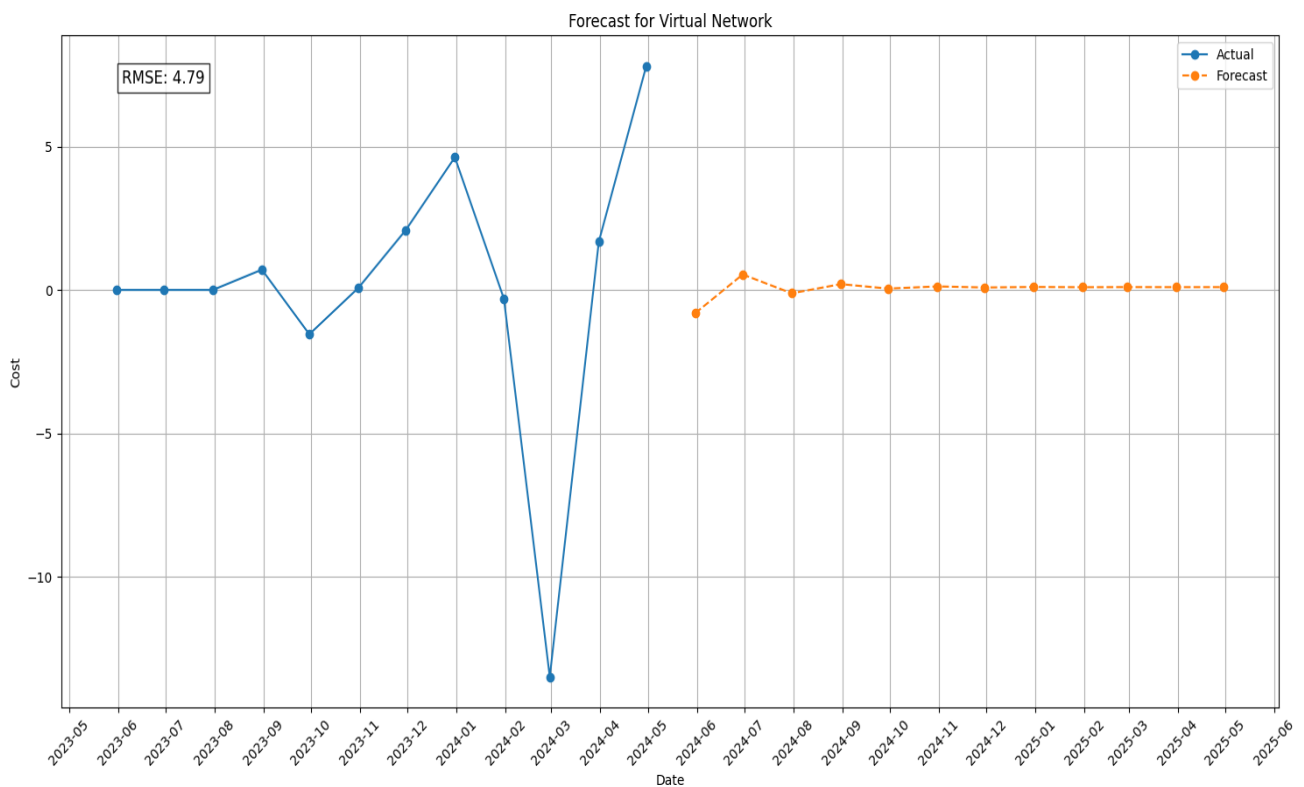


FIGURE 17. Forecast of Virtual Network

Figure 17 presents the forecasted trend for Virtual Network costs, represented by the orange dashed line. The forecast indicates a relatively stable trend following an initial fluctuation, suggesting that the model anticipates consistent costs over time. This projected stability can be beneficial for long-term planning and budgeting, as it implies a reduction in cost volatility.

Given:

- RMSE: 4.79
- Range of values: 1866 to 2293

The range is calculated as:

$$\text{Range} = 2293 - 1866 = 427$$

Formula for Accuracy

$$\text{Accuracy} = \left(1 - \frac{\text{RMSE}}{\text{Range}}\right) \times 100 \tag{7}$$

Substituting the values:

$$\text{Accuracy} = (1 - 4.79 / 427) \times 100$$

Breaking down the calculation:

1. Calculate the ratio:  $4.79/427 \approx 0.01122$
2. Subtract from 1:  $1 - 0.01122 = 0.988781$
3. Convert to percentage:  $0.98878 \times 100 \approx 98.88\%$

So, the model's accuracy is approximately 98.88%.

TABLE 7. Forecasted Monthly Costs for Azure Services (2024-2025)

Date	Automa- tion	Azure DNS	Backup	Band- width	Logic Apps	Net- work Wathe r	Stor- age	Virtual Ma- chines	Virtual Ma- chines Licenses	Virtual Network
2024- 05- 31 00:00: 00	0.00007 832	3.513 04	49.56 32	0.3897 46	0.00337 346	3.513 04	-0.73988	18.69 82	1.555 86	- 0.809 25
2024- 06- 30 00:00: 00	0.00007 832	- 1.664 39	32.04 36	0.1587 43	0.00337 346	- 1.664 39	- 0.043591	15.15 65	0.873 458	0.539 15
2024- 07- 31 00:00: 00	0.00007 832	0.6132 39	23.46 14	0.0734 198	0.00337 346	0.6132 39	- 0.00137 551	16.06 98	0.667 086	- 0.117 78

2024-08-31 00:00:00	0.00007832	-0.388721	19.2573	0.0419048	0.00337346	-0.388721	0.00118398	15.8343	0.604676	0.202272
2024-09-30 00:00:00	0.00007832	0.0520558	17.1978	0.0302643	0.00337346	0.0520558	0.00133916	15.895	0.585801	0.046349
2024-10-31 00:00:00	0.00007832	-0.141848	16.189	0.0259648	0.00337346	-0.141848	0.00134857	15.8794	0.580093	0.122313
2024-11-30 00:00:00	0.00007832	-0.056547	15.6948	0.0243768	0.00337346	-0.056547	0.00134914	15.8834	0.578367	0.085304
2024-12-31 00:00:00	0.00007832	-0.0940722	15.4527	0.0237902	0.00337346	-0.094072	0.00134918	15.8824	0.577845	0.103334
2025-01-31 00:00:00	0.00007832	-0.0775643	15.3341	0.0235735	0.00337346	-0.077564	0.00134918	15.8826	0.577687	0.09455
2025-02-28 00:00:00	0.00007832	-0.0848263	15.276	0.0234935	0.00337346	-0.084826	0.00134918	15.8826	0.57764	0.09883
2025-03-31 00:00:00	0.00007832	-0.0816317	15.2475	0.023464	0.00337346	-0.081632	0.00134918	15.8826	0.577625	0.096745
2025-04-30 00:00:00	0.00007832	-0.0830371	15.2336	0.023453	0.00337346	-0.083037	0.00134918	15.8826	0.577621	0.09776

Automation: All months show the following forecasted costs for Automation: 0.00007832. This is a clear pointer towards the fact that financial implications are negligible, making automation a service with virtually no cost associated with mainstream business operations. AZURE DNS Cost has high volatility; it begins at 3.51 in May of 2024, decreases to -1.66 in June, and manages to crossnegative and positive paths throughout the rest of the year. Such fluctuations imply non-regular use and, thus, require further attention to find out whether there are areas of possible rate reduction or equipment underutilization. Backup an output signal that draws particular attention to itself is the spending factor, which falls from 49.56 in May 2024 to 15.23 by April 2025. This may imply continuous attempts

at making achievements even more optimal or the usage of backup services less, which leads to massive savings. Bandwidth costs reduce progressively throughout the period positively from 0.39 in May 2024 to 0.02 in April 2025. Such a steady decline is suggestive of optimization of the amount of bandwidth in use, whether by traffic shaping or by strictly limiting data usage. Logic Apps costs remain as small as 0.00337 as a fixed cost irrespective of the month selected. The variability of costs in Logic Apps shows cost consistency and effectiveness, thus making it easy to predict costs for organizations. Network Watcher also has a variable cost structure; it ranges from 3.51 in May 2024 to 0.08 in April 2025. These fluctuations may be due to active use or some one-off behaviours that need to be studied better to control costs. Storage for storage costs, similar trends are observed, and the values range from -0.73 in May 2024 and fluctuate around 0.0013 for the remaining months. This also displays better resource utilization, including low levels of expenses are expected in the future. Virtual Machine costs decrease on average from 18.69 during May 2024 to 15.88 during April 2025, most probably due to improving use of the service or decreased requirement for it. The outlook for the latter months indicates regular and unvarying demand for virtual machines, which collectively implies regular and permanent usage.

TABLE 8. Key Forecast Trends and Observations for Azure Services (2024-2025)

Service	Forecast Trend	Key Observations
Automation	Stable and negligible	Predicted values remain consistently near zero (~0.000078), indicating minimal impact on overall costs.
Azure DNS	Fluctuating	The forecast starts at <b>3.51</b> in May, dips to <b>-1.66</b> in June, and fluctuates across subsequent months.
Backup	Decreasing trend	From <b>49.56</b> in May, the forecast gradually decreases to <b>16.18</b> by October, indicating potential cost savings.
Bandwidth	Gradual decline	Costs reduce steadily, from <b>0.38</b> in May to <b>0.03</b> by October, showcasing optimized usage or cost control.
Logic Apps	Highly stable	Consistently low values (~0.0034) across all months.
Network Watcher	Fluctuating	Similar to <b>Azure DNS</b> , values oscillate between positive and negative values, suggesting variable usage.
Storage	Minimal positive trend	Initially <b>-0.73</b> in May but converges to stable positive values around <b>0.0013</b> in subsequent months.
Virtual Machines	Relatively stable	Costs hover between <b>15.8</b> and <b>18.6</b> , reflecting consistent usage.

Virtual Machines Licenses: it is possible to observe the decreasing tendency for costs, which were even 1.55 in May 2024 and equaled 0.57 in April 2025. This implies a few licenses, as might have been

witnessed through the optimal resource utilization or demand. Over the forecast period, the costs are still moderate and even and rotating around -0.80 and 0.10 on average. These limited costs indicate reasonable utilization of virtual networks with limited concerns for costs. The forecast highlights areas of potential cost savings, particularly in services like Backup, Bandwidth, and Virtual Machines Licenses, which demonstrate a clear downward trend in expenses. Meanwhile, services such as Automation and Logic Apps show negligible or highly stable costs, contributing positively to overall budget predictability. However, fluctuating costs in Azure DNS and NetworkWatcher may require further scrutiny to ensure efficient resource utilization. These insights are invaluable for strategic financial planning, enabling organizations to allocate resources effectively while minimizing operational expenses.

This table summarizes the forecasted trends and key observations for various Azure services from May 2024 to April 2025. Each service has been analysed based on its forecasted monthly values, providing insights into cost trends and expected usage patterns. The information is presented as follows. Service it lists Azure services used in the forecast, such as Automation, Azure DNS, Backup, and others. Forecast Trend provides an overview of the general trend of the forecasted data for each service. For example, using patterns like "Stable and negligible", "Fluctuating", "Decreasing trend", and so on. The variable captured in this column is whether the forecasted costs of each service are stable, or are increasing, decreasing, or fluctuating over time. Key Observations provides specific insights into the forecasted values of each service. Not only observations of the range, variability, or any notable changes in the forecasted costs, but this provides a more detailed understanding of the predicted trends. Variable usage or costs over time appear reflected in Azure DNS fluctuations. A decrease in backup indicates possible cost savings over the forecast period. I extrapolate these trends into future forecast periods and project a lower level of backup. Although Costs remain predictable, at about the same low value over time, which is based on low-frequency surges of costs and a high percentage of inevitable closures due to a very high percentage % of rateable. The forecast trend describes the general trend observed in the forecasted data for each service. This includes patterns like "Stable and negligible," "Fluctuating," "Decreasing trend," and so on. This column captures whether each service's forecasted costs are stable, increasing, decreasing, or fluctuating over time.

It is observed that some forecasted values, particularly for Azure DNS and Virtual Network, fall below zero. This is a known limitation of linear models such as ARIMA, which do not impose non-negativity constraints on output. These negative values do not represent actual negative costs but are

instead statistical fluctuations around a low average. For practical financial planning purposes, they can be safely interpreted as zero.

Future work may explore using nonlinear models like Long Short-Term Memory (LSTM) networks or exponential smoothing techniques that support non-negativity bounds to improve predictive reliability near zero.

Key observations provide specific insights into the forecasted values for each service. This includes observations about the range, variability, or any notable changes in the forecasted costs, offering a deeper understanding of the predicted trends. To arrive at this, differencing was performed on those time series that exhibited non-stationary characteristics before transformation. Differencing can be done with the help of subtracting the observation of the current period from that of the observation of the previous period. This was done continuously until the series reached a stationary form, which is a requirement before going through ARIMA modelling.

Decisions on the order of differences that have to be applied to each service in order to make it stationary include a number of steps. First, initial differencing was conducted using the first difference to make non-stationary services stationary. After that, in order to confirm the stationarity of the differenced series, we employed the Augmented Dickey-Fuller test. However, if the value of  $p$  from the ADF test was not less than 0.05, the series was still non-stationary, so further rounds of differencing were performed. This same procedure was continued until the series reached a stationary point where the value of the statistic remained constant. The number of differences used to create a stationary series was noted down as the necessary order of differencing. These outcomes helped clarify the general order of differencing required for each of the non-stationary services.

## 5 CONCLUSION

Comprehensively, the utilization of the proposed ARIMA model in predicting monthly expenses of different Azure services was established in this study. After detailed pre-processing such as missing data treatment, checking for stationarity, and final identification of appropriate ARIMA parameters, detailed cost predictions for key services were produced, including Virtual Machines, Storage, and Backup. These forecasts become very useful, which organizations can use to better their financing strategies, auto costs, and manage the new resources available to them.

The findings of the forecasting process provide information where cost-cutting may be most effective and provide an optimistic view of total expenditures for the use by an organization in planning ahead and staying within budget. When used properly, historical usage data provides valuable insights and predictions based on which the decision-makers can more effectively manage their cloud environment and better avoid any costly and time-consuming surprises.

### 5.1 Recommendations for Future Work

The ARIMA approach was useful in forecasting cloud service expenses in Azure, except that it could not uphold non-negative values and capture more complicated usage changes. Researchers should try more advanced modeling techniques that could handle these difficulties. Using a mix of ARIMA and machine learning may give good results, with ARIMA dealing with the linear trends and machine learning with the residual nonlinear elements. Other options such as Facebook Prophet or modified exponential smoothing can be studied to solve the issue of negative forecasts and help with financial cost estimations. Most times, these models are simpler to use and understand and they handle unexpected or missing data more effectively than ARIMA.

In addition, models like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) have high potential for future research due to their strong abilities to handle sequential data and capture long-term patterns. However, building these models usually necessitates large renewable energy data reports which was absent in this project. So, further efforts should concentrate on obtaining or joining wider sets of data to reflect different years and include more Azure services than currently used. This would help along with model training, accuracy and also let us include external variables like increases

in demand, rollouts or local trends. Using this type of data in cloud cost forecasting could notably strengthen and improve how these models are used.

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