Forecasting Core IP Traffic Using ARIMA-GARCH

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Abstract: The rapid expansion of Internet-based services, including cloud computing, video streaming, IoT, and emerging 5G/6G applications, has increased both the volume and complexity of core IP network traffic. Accurate short-term traffic forecasting is essential for capacity planning, congestion control, and quality of service assurance. Core IP traffic exhibits non-stationarity, burstiness, and time-varying variance, which limits the effectiveness of traditional ARIMA models that assume constant residual variance. This paper proposes a hybrid ARIMA–GARCH framework, where ARIMA models the conditional mean and GARCH captures residual volatility and heteroscedasticity. The approach is evaluated using real traffic data from multiple origin–destination OD pairs issued from the American Abilane network and various ARIMA configurations. Results demonstrate that ARIMA–GARCH consistently achieves high forecasting accuracy, with RMSE and MSE generally below 5% and regression coefficients exceeding 98%. First-order differencing effectively captures seasonal patterns, whereas over-differentiation significantly degrades performance, highlighting the importance of appropriate parameter selection. Mixed ARIMA(1,1,1) models deliver the lowest MSE values, down to 0.01%, confirming the method's robustness. Overall, the proposed framework provides a reliable, flexible, and practical solution for modeling and predicting core network traffic, enabling better network management, proactive congestion mitigation, and optimized QoS.

Keywords: *IP Traffic Forecasting, ARIMA, GARCH.*

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I. INTRODUCTION

The continuous growth of Internet-based services, including cloud computing, video streaming, Internet of Things (IoT), and emerging 5G/6G applications, has led to a significant increase in traffic volume and complexity within core IP networks. For network operators, this rapid evolution imposes stringent requirements in terms of capacity planning, congestion avoidance, and quality of service (QoS) assurance. As a result, accurate forecasting of core IP traffic has become a critical research challenge and a key enabler for efficient network management.

Core IP traffic exhibits complex temporal characteristics such as non-stationarity, strong autocorrelation, burstiness, and sudden traffic spikes. These properties are often accompanied by time-varying variance, reflecting alternating periods of calm and intense network activity. Traditional traffic forecasting approaches, widely used in network engineering, primarily focus on modeling the average behavior of traffic flows while assuming constant variance over time. However, such assumptions rarely hold in real operational networks, leading to suboptimal prediction accuracy and inefficient resource utilization.

Among classical time-series models, the AutoRegressive Integrated Moving Average (ARIMA) model has been extensively applied to network traffic forecasting due to its ability to capture linear dependencies, trends, and seasonal patterns. Despite its popularity, ARIMA inherently assumes homoscedastic residuals, which limits its effectiveness when applied to traffic data characterized by volatility clustering and heteroscedastic behavior. Empirical studies on IP traffic measurements have shown that variance dynamics play a crucial role in understanding and predicting traffic evolution, especially in core network environments where aggregated flows amplify bursty behavior.

To address these limitations, models from financial econometrics, particularly the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family, have been introduced to model time-varying volatility in time-series data. GARCH models are well suited to capture conditional variance dynamics and volatility clustering, which are frequently observed in real-world traffic traces. However,

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when applied alone, GARCH models do not adequately represent the mean structure of traffic series, which is essential for accurate forecasting.

Motivated by these observations, this paper proposes a hybrid ARIMA–GARCH modeling framework for forecasting core IP traffic. The ARIMA component is employed to model the conditional mean of the traffic series, capturing its temporal dependencies and long-term dynamics, while the GARCH component is used to model the conditional variance of the residuals, effectively characterizing traffic volatility. By jointly modeling both the mean and variance processes, the proposed approach provides a more realistic and robust representation of core IP traffic behavior.

The main objective of this work is to investigate whether incorporating volatility modeling through GARCH can significantly improve traffic forecasting accuracy compared to conventional ARIMA-based approaches. Using real core network traffic data, the proposed model is rigorously evaluated through standard statistical tests, including stationarity analysis and ARCH effects detection, as well as performance metrics such as RMSE, MAE, and MAPE. The results demonstrate that the ARIMA–GARCH model achieves superior forecasting performance, particularly during high-variability traffic periods.

The contributions of this paper are threefold. First, it provides an in-depth statistical characterization of core IP traffic, highlighting the presence of heteroscedasticity and volatility clustering. Second, it proposes and validates a hybrid ARIMA–GARCH forecasting framework tailored to core IP networks. Third, it demonstrates the practical benefits of the proposed model for network planning, proactive congestion management, and QoS optimization.

The remainder of this paper is organized as follows. Section II presents related work on IP traffic forecasting. Section III describes the ARIMA–GARCH modeling methodology. Section IV introduces the dataset and experimental setup. Section V discusses the results

II. RELATED WORK

Many works still using this technique as summarized in the table1:

Table 1 Related Work:

Study / Reference	Year	Model(s)	Traffic Type / Data	Key Findings
Raja et al. – Enhanced ARIMA for Network Traffic	2025	Enhanced ARIMA (statistical + ML components)	Network traffic	Enhanced ARIMA combined with machine learning improves MAPE (1.23%) and forecasting precision over conventional ARIMA alone; hybrid approach addresses non-linear dynamics. JISEM
ivySCI – Real-Time ARIMA–GARCH Traffic Prediction	2024	ARIMA–GARCH (with Box–Cox transformation)	Real-time IP traffic	Hybrid ARIMA–GARCH with data transformation stabilizes variance and heteroskedasticity, improving real-time forecasting accuracy in volatile traffic contexts. Ivysci
Kochetkova et al. – SARIMA & Holt-Winters Network Traffic	2023	SARIMA, Holt-Winters (statistical baselines)	Mobile network traffic	SARIMA performs well for download traffic, Holt-Winters for upload traffic, demonstrating effectiveness of classical statistical models for short-term mobile traffic forecasts. MDPI
DOAJ – FARIMA–GARCH Model for Traffic Prediction	2025	FARIMA–GARCH	Real network traffic	FARIMA–GARCH integrates fractional differencing and volatility forecasting, outperforming FARIMA in RMSE and interval forecast quality. Directory of Open Access Journals
General Survey – Network Traffic Prediction Models	2025	Mixed: statistical, ML, deep learning	Various network datasets	Hybrid approaches combining statistical and machine learning methods provide better scalability and real-time performance in network traffic forecasting. IJFMR

III. METHODOLOGY

The methodology used in this study is resumed below, we use input data issued from a real well known network the American network Abilene, for which we study its Traffic Matrix (TM) forecasting using a linear correlation. The statistical time series ARIMA which is hybridized with a nonlinear GARCH Method let's have a look on the theoretical notions.

➤ *ARIMA/GARCH Model Development*

Recent studies in economics have widely employed ARIMA–GARCH time-series models to forecast market behavior. In this work, these models are applied to IP traffic forecasting, where network traffic measurements are treated as time-series data.

The ARIMA (Auto-Regressive Integrated Moving Average) model is based on the analysis of time series, which are defined as sequences of observations of a variable recorded over time. In our case, the time series X_t represents

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the traffic volume measured every five minutes over a period of seven days.

A time series X_t can be decomposed as:

$$X_t = m_t + S_t + Y_t \quad (1)$$

Where m_t denotes the trend component of the series. If the trend is linear, it can be expressed as $m_t = a + bt$. The term S_t represents the seasonal component, which is periodic such that $S_t = S_{t+d}$, and Y_t is a random residual component assumed to have zero mean.

In practice, most time series exhibit **seasonality and non-stationarity**, which must be addressed prior to accurate forecasting. A correlogram is commonly used to determine whether a time series is stationary. For a stationary series, the autocorrelation function (ACF) decays rapidly from its initial value of unity at lag zero. In contrast, for a non-stationary series, the ACF decreases gradually over time.

An autoregressive process of order p, denoted AR(p), is defined as:

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \quad (2)$$

Where $\theta_1, \theta_2, \ldots, \theta_p$ are parameters to be estimated, and ε_t is a Gaussian white-noise process. Using the lag operator B, Equation (2) can be rewritten as:

$$\left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p\right) y_t = \varepsilon_t \quad (3)$$

Similarly, a moving average process of order q, MA(q), is expressed as:

$$y_t = \varepsilon_t - \phi_1 \varepsilon_{t-1} - \phi_2 \varepsilon_{t-2} - \cdots - \phi_q \varepsilon_{t-q} \quad (4)$$

Which can also be written as:

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_q B^q)\varepsilon_t = y_t \quad (5)$$

The MA component represents a time series that fluctuates randomly around its mean.

By combining the AR and MA components, the ARMA(p, q) model is obtained:

$$\left(1 - \theta_1 B - \cdots - \theta_p B^p\right) y_t = \left(1 - \phi_1 B - \cdots - \phi_q B^q\right)\varepsilon_t \quad (6)$$

A time series y_t is said to be stationary if the following conditions are satisfied:

- $E(y_t) = m$, independent of time
- $Var(y_t) = \gamma(0) < \infty$, constant over time
- $Cov(y_t, y_{t-h}) = \gamma(h)$, independent of t

However, most real-world time series are non-stationary. If differencing the series once results in stationarity, the process is said to be integrated of order one. More generally, a process is integrated of order d if $(1 - B)^d y_t$ is stationary, where d is called the **degree of integration**.

The ARIMA(p, d, q) model extends the ARMA model by incorporating differencing and is particularly effective for forecasting future values of non-stationary time series. The general form of the ARIMA model is given by:

$$\phi(B)\nabla^d z_t = \theta(B) a_t \quad (7)$$

Where $\phi(B)$ is the autoregressive operator of order p, $\theta(B)$ is the moving average operator of order q, $\nabla^d = (1 - B)^d$ is the differencing operator, and B denotes the lag operator.

Once the time series has been stationarized, residual autocorrelation must be corrected by identifying appropriate AR and MA terms.

To model volatility, the ARCH (Auto-Regressive Conditional Heteroskedasticity) and GARCH (Generalized ARCH) models were introduced by Engle (1982) and Bollerslev (1986), respectively. These models address time-varying variance commonly observed in econometric and traffic data. The ARCH model can be viewed as an extension of the ARIMA framework and is expressed as:

$$x_t = \sum_{i=1}^{p+d} \phi_i x_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (8)$$

Where $\{\varphi_i\}_{i=1}^{p+d}$ *and* $\{\theta_k\}_{j=1}^{q}$: are the autoregressive coefficients and the moving average parameters, respectively. p is the autoregressive order, d the differentiation order and q the moving average order

The innovation ε_t is assumed be an independent and identically distributed normal random variable with zero mean and the σ^2 variance *does not change over time*.

An ARCH model is an ARIMA with conditionally heteroscedastic disturbances for the conditional variance this latter can be governed by:

$$\begin{cases} \varepsilon_t = \eta_t \sigma_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2 \end{cases} \quad (9)$$

m is heteroscedasticity order,ARCH($\boldsymbol{m}$)

When ARCH model is governed by:

$$\mathrm{x_t} = \sum_{\mathrm{i}=1}^{\mathrm{p+d}} \varphi_{\mathrm{i}} \mathrm{x}_{\mathrm{t-i}} + \sum_{\mathrm{j}=1}^{\mathrm{q}} \theta_{\mathrm{j}} \varepsilon_{\mathrm{t-j}} + \varepsilon_{\mathrm{t}}$$

$$\varepsilon_t = \eta_t \sqrt{h_t} \quad (10)$$

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η_t is supposed to be a random normal variable independent and identically distributed zero mean $E(\eta_t) = 0$, with unit variance ($Var\ (\eta_t) = 1$), the m+1 parameters are $\{\alpha_k\}_0^m$. The disturbances (ε_t) are assumed to be uncorrelated but not independent, the amount h_t denotes the conditional variance σ^2 of innovation ε_t as :

$$\boldsymbol{\sigma_t^2 = h_t = E(\varepsilon_t^2|\varepsilon_{t-1})}$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

➢ *ARIMA Model Results and Discussion*

In order to construct the best ARIMA model for our case we have to determine the ARIMA parameters, we firstly will see if the series is stationary or nonstationary, a correlogram is achieved by the autocorrelation function (ACF) is used to determine which integration parameter do we'll usethe Fig.5which shows that the ACF decay swiftly from its initial value of unity at zero lag and dies down extremely slowly.

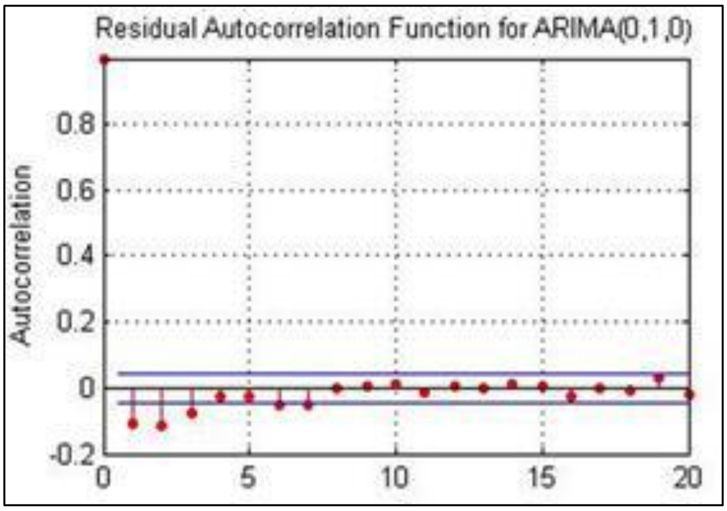

Fig 1 ACF of ARIMA(0,1,0) OD #46

In GARCH (m, s) termwe refer to the mixed presence of GARCH and ARCH terms with the process orders m and s respectively. Very often the standard GARCH (1,1) is used in reason of its compatibility with the classification of volatility where there are big changes (very variable variance) in the initial estimate of the parameters [22].

We carried out several experiments to see what appropriate model with which OD node that gives good estimates that we draw in the following tables. To compare those different ARIMA/GARCH process, our estimation will be evaluated henceforth by a criteria such as: MAPE (Mean Absolute Percentage Error)), NMSE (Normalized Mean Square Error), MSE (Mean Square Error), RMSE (Root Mean Squared Errors), MAE (Mean Absolute Error) and R^2 (coefficient of determination),

Table 2 Statistical Results of Different ARIMA(p,d,q)/GARCH(1,1) Model OD #49

ARIMA	RMSE	NMSE	R^2	STANDARD DEVIATION (SD)
(1,0,0)	5.508e-02	2.0016e-02	0.9844	-3.2030e-02
(0,0,1)	3.755e-02	9.3071e-03	0.9864	8.3178e-03
(1,0,1)	**3.490e-02**	**8.0386e-03**	**0.9881**	**7.0994e-04**
(0,1,0)	2.171e-01	3.1107e-01	0.6699	2.7705e-05
(1,1,0)	2.581e-01	4.3964e-01	0.7108	6.2261e-04
(1,1,1)	7.363e-02	3.5773e-02	0.9634	7.1202e-04
(2,1,1)	1.059e-01	7.4015e-02	0.8756	9.3392e-04
(1,1,2)	5.326e-01	1.8717e+00	0.5753	7.0451e-04
(2,1,2)	2.468e-01	4.0194e-01	0.6395	1.2921e-03
(0,2,0)	5.038e-01	1.6749e+00	0.3845	9.4335e-04
(1,2,0)	5.739e-01	2.17333+00	0.5306	7.5589e-04
(0,2,1)	3.258e-01	7.0068e-01	0.5788	9.9610e-04

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Table 2 clearly indicates that the ARIMA(1,0,1)/GARCH(1,1) model provides the best performance, achieving the lowest error rates (RMSE and MSE below 5%) without differencing, along with a very low NMSE of 0.8%. In addition, this model exhibits a high regression accuracy of 98.8%, confirming its superiority over the ARMA model. The ARIMA(1,0,0) model corresponds to a pure autoregressive process (p = 1, d = 0, q = 0), which reflects the influence of previous observations on the current value over time.

It should also be noted that the Partial Autocorrelation Function (PACF) is bounded between −1 and 1. As its magnitude increases, the influence of the corresponding lag—and consequently the effects on subsequent lags—becomes more significant.

Table 3 Statistical Results of Different ARIMA(p,d,q)/GARCH(1,1) Model for OD#42

ARIMA	RMSE %	MSE %	NMSE %	MAPE	MAE %	R^2%
(1,0,0)	44,72	20	80	92,93	44,44	94,51
(0,0,1)	**11,26**	**1,2**	**5,08**	**17,64**	**8,44**	**98,66**
(1,0,1)	45,24	20,47	82,08	9,39	44,95	93,55
(1,1,0)	**14,29**	**2,04**	**8,18**	**22,42**	**10,72**	**98,30**
(0,1,1)	45,25	20,47	82,08	9,39	44,95	93,55
(1,1,1)	**4,19**	**0,17**	**0,7**	**6,14**	**2,93**	**97,42**
(1,2,0)	16,36	2,67	10,73	25,64	12,26	95,96
(0,2,1)	5,33	0,28	1,14	7,47	3,57	94,53
(1,2,1)	5,36	0,28	1,15	7,54	3,6	94,50

For the forecasting of traffic of the **OD #42 pair**, Table 3 shows that the selected ARIMA models yield error rates within a highly acceptable range, with regression coefficients exceeding **98%**. Among these models, the **ARIMA(1,1,1)** configuration, which represents a mixed ARIMA model, achieves the **lowest mean squared error (MSE) of 0.17%**, indicating superior performance. In comparison, the autoregressive model **ARIMA(1,1,0)** attains an MSE of **2.04%** with a regression rate of **98.30%**. Meanwhile, the moving average model **ARIMA(0,0,1)** also performs competitively, achieving an MSE of **1.2%** and a regression rate exceeding **98.66%**.

These results suggest that, for this dataset, the time series can be accurately predicted using multiple ARIMA configurations, all of which provide satisfactory performance levels

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Table 4 Statistical Results of Different ARIMA(p,d,q)/GARCH(1,1) Model for the OD#01 Traffic

ARIMA	RMSE %	MSE%	NMSE %	MAPE	MAE %	R^2%
(1,0,0)	4 ,96	0,24	18,45	36,35	2,47	89,83
(0,0,1)	**9,94**	**0,98**	**7,42**	**117**	**7,99**	**97,45**
(1,0,1)	5,88	0,34	25,96	5,11	3,47	83,93
(1,1,0)	**10,7**	**1,14**	**85,89**	**92,89**	**6,28**	**95,70**
(0,1,1)	**7,57**	**0,57**	**42,7**	**64,56**	**4,3**	**97,13**
(1,1,1)	**4,02**	**0,16**	**12,17**	**32,63**	**2,21**	**96,78**
(1,2,0)	13,95	1,94	1,46	119	8,3	88,18
(0,2,1)	5,40	0,29	21,88	36,13	2,4	88,82
(1,2,1)	5,76	0,33	24,91	41,26	2,8	87,36

Table 4 summarizes the ARIMA modeling results for the OD#01 dataset. The pure MA model ARIMA(0,0,1) achieves an MSE of 0.98% with a regression coefficient of 97.45%. However, the best-performing model is ARIMA(0,1,1), which reduces the MSE to 0.57% while maintaining a comparable regression coefficient (97.13%). The mixed models ARIMA(1,1,0) and ARIMA(1,1,1) also exhibit strong performance, with MSE values below 1.2% and regression coefficients exceeding 95%. The improvement observed after first-order differencing confirms the presence of seasonal components in the data. Specifically, ARIMA(0,0,1) improves to ARIMA(0,1,1), reducing the MSE from 0.98% to 0.57%, while ARIMA(1,1,0) evolves into the mixed model ARIMA(1,1,1), achieving a significant MSE reduction from 1.14% to 0.16%. With second-order differencing ($d = 2$), the models maintain good accuracy, yielding an MSE of approximately 0.28% and regression coefficients above 94%, indicating residual seasonality in the time series.

Table 5 Statistical Results of Different ARIMA(p,d,q)/GARCH(1,1) model,OD#117 Traffic

ARIMA	RMSE %	MSE%	NMSE %	MAPE	MAE %	R^2%
(1,0,0)	**5,15**	**0,26**	**5,02**	**26,9**	**4,76**	**98,07**
(0,0,1)	**3,1**	**0,09**	**1,8**	**16,81**	**2,9**	**99,48**
(1,0,1)	25,88	6,70	126	116,76	20,65	94,51
(1,1,0)	17	3,10	58,4	69,1	12,2	67,73
(0,1,1)	**0,93**	**0,87**	**0,16**	**2,78**	**0,49**	**99,8**
(1,1,1)	**1,04**	**0,01**	**0,2**	**2,89**	**0,51**	**99,75**
(1,2,0)	39,71	15,77	2,97	144	25,5	37,82
(0,2,1)	19,9	3,97	74,8	45,5	9,64	59,81
(1,2,1)	29,5	87,5	1,65	99,2	17,5	45,07

Table 5 presents the error metrics for the OD#117 dataset. The MA model ARIMA(0,0,1) achieves high accuracy, with a regression coefficient of 99.48%, which improves to 99.80% after first-order differencing in ARIMA(0,1,1). A pure AR model, ARIMA(1,0,0), also performs well, yielding an MSE of 0.26% and a regression coefficient of 98.07%. The mixed ARIMA(1,1,1) model provides the best performance, with a minimal MSE of 0.01% and a regression coefficient of 99.75%.

Second-order differencing ($d = 2$) leads to over-differentiation and severe performance degradation, with MSE values reaching 87.5% for ARIMA(1,2,1) and 39.71% for ARIMA(1,2,0), and regression coefficients below 50%.

The results across Tables 3,4 and 5 confirm the effectiveness of the ARIMA/GARCH approach, which consistently yields low prediction errors and high regression accuracy while closely tracking the traffic matrix dynamics.

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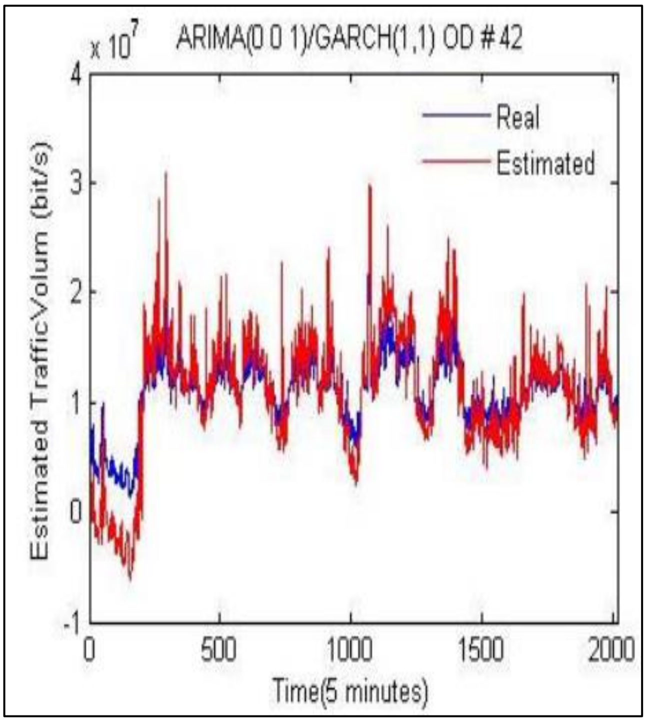

Fig 2Traffic predicted by ARIMA(0,0,1)Model

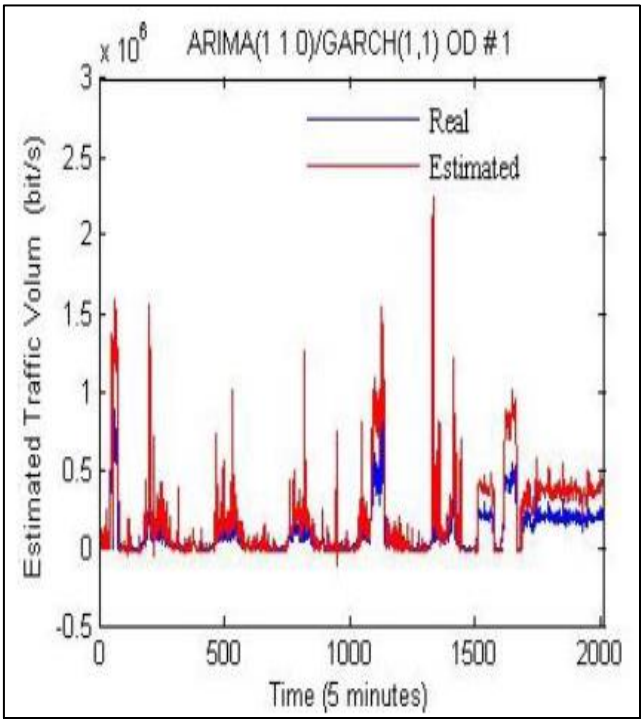

Fig 4 Estimation by ARIMA(1,1,0)Model

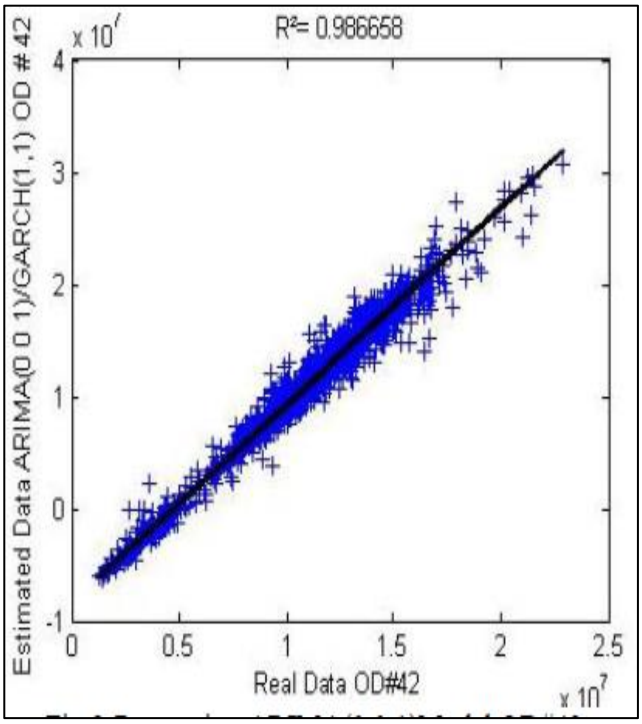

Fig 3 Regression ARIMA(0,0,1)Model OD#42

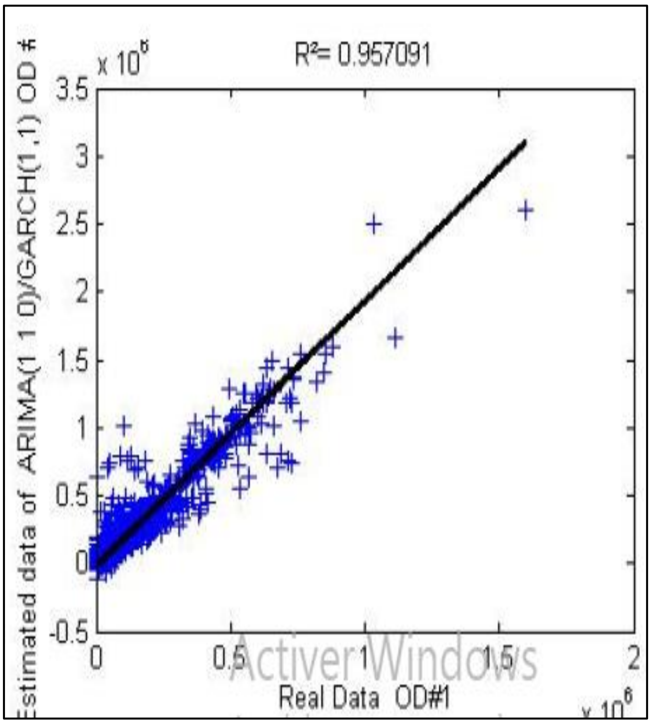

Fig 5 Regression ARIMA(1,1,0)Model OD#01

V. CONCLUSION

In this article we apply the techniques of ARIMA/GARCH to forecast a large scale IP network Traffic we have been used to study the issue by estimating its traffic matrix then we have proceeded to compare the results obtained by several scenario

We conducted a study to different values of the parameters p, d, q of OD# data.

This study confirms the effectiveness of the ARIMA/GARCH framework for short-term traffic prediction across multiple OD pairs. The results demonstrate that combining ARIMA with GARCH consistently yields low prediction errors and high regression accuracy, with RMSE and MSE values generally below 5% and regression coefficients exceeding 98%. Stationary traffic series are accurately modeled without differencing, while first-order differencing effectively captures seasonal components in non-stationary series, leading to significant error reductions, particularly with mixed ARIMA(1,1,1) models that achieve MSE values as low as 0.01%. In contrast, second-order differencing results in over-differentiation and severe performance degradation, highlighting the importance of appropriate model order selection. Overall, the proposed ARIMA/GARCH approach proves robust, flexible, and well suited for accurately tracking traffic dynamics in large-scale communication networks.

Several ARIMA models may well model the data of a time series of a given OD and can carry out an effective forecasting, the solutions probably are not unique.

The existence of seasonality often requires more differentiation, so we have to increase the d parameter each time. Our testing revealed instances of over-differentiation and case of sub-differentiation.

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