Short-Term Internet Network Traffic Patterns in Greece: A High-Frequency Time-Series Analysis

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Abstract

This study examines short-term Internet traffic patterns in Greece within the context of time-series dynamics and digital infrastructure behavior, aiming to identify temporal structures, daily cycles, and variability in network traffic. Using high-frequency data collected at 5-minute intervals over three months, this study adopts a multi-scale time-series analysis approach to investigate short-term Internet traffic dynamics. The analysis aggregates traffic data at hourly and daily levels and applies descriptive statistical analyses and visualization techniques, including hourly aggregation, daily averages, boxplots, and heatmaps. The findings reveal a strong and consistent diurnal pattern, with minimum traffic during the early morning hours (02:00–05:00) and peak demand in the evening (18:00–21:00). Inbound and outbound traffic exhibit near-perfect symmetry, indicating balanced network flows. Although mean traffic remains stable, significant short-term fluctuations and increased variability during peak periods are observed, highlighting both the stability and the dynamic nature of network behavior.

Keywords: Internet traffic, time-series analysis, high-frequency data, diurnal patterns

1. Introduction

The rapid expansion of digital technologies and the increasing reliance on Internet-based services have significantly transformed communication networks and digital infrastructure worldwide. Internet traffic, as a key indicator of both technological activity and human behavior, plays a central role in understanding network performance, capacity requirements, and system resilience. In modern economies, the ability to monitor and analyze traffic patterns at high temporal resolution has become essential for efficient network management, optimization, and policy development. The existing literature on Internet traffic analysis has primarily focused on aggregated data at daily or monthly frequencies. While such approaches are adequate for identifying long-term trends, they are insufficient for capturing short-term fluctuations and dynamic behavioral patterns. Several studies have applied time-series models, including autoregressive integrated moving average (ARIMA) and machine learning techniques, to forecast traffic demand and detect anomalies. However, high-frequency analyses—particularly those based on sub-hourly data—remain relatively limited due to constraints related to data availability and methodological complexity. Moreover, most studies concentrate on large-scale or international datasets, whereas country-specific high-frequency analyses remain scarce. In the case of Greece, despite significant advancements in digital infrastructure and widespread Internet adoption, there is a notable lack of empirical research examining short-term Internet traffic dynamics at high temporal resolution. This gap limits the understanding of intra-day variability, peak demand behavior, and traffic symmetry within the national network context. The objective of this study is to investigate short-term Internet traffic patterns

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in Greece using high-frequency time-series data recorded at 5-minute intervals over three months. Specifically, the analysis identifies temporal structures, including diurnal cycles, variability patterns, and the relationship between inbound and outbound traffic flows. By employing descriptive statistical methods and visualization techniques, the study provides a detailed, data-driven understanding of network behavior at a granular level [1, 2].

The novelty of this study lies not only in confirming the presence of well-documented daily Internet traffic cycles, but also in making two further contributions. On the one hand, in contrast to earlier studies, which are based mostly on aggregated traffic statistics measured daily, the current study applies a high-frequency database comprising 24,378 observations recorded every five minutes, making it possible to analyze the dynamics of network traffic over much shorter time spans. On the other hand, while earlier research analyzed the temporality and symmetry of incoming and outgoing traffic flows separately, the current study analyzes both aspects simultaneously, providing empirical evidence of the balance between two-way network traffic flows. The use of various aggregation levels (hourly, daily, and weekly), together with visualization, allows identifying regularities, variability, and short-term fluctuations in network traffic that are difficult to reveal using low-frequency data.

Understanding how Internet traffic evolves over short time intervals is crucial for both theoretical insights into network functioning and practical applications such as network optimization, capacity planning, cybercrime prevention, and digital policy development [3, 4]. Recent advances in data availability have enabled researchers to shift their focus from aggregated indicators to the short-term dynamics of network activity. [5–8]. Consequently, the analysis of high-frequency time series data enables more precise and reliable identification of patterns in network activity dynamics [9, 10].

This study focuses on Greece, which constitutes a particularly relevant example due to significant progress in digital infrastructure development and Internet penetration over the past decade. Greece is of special interest because it combines high broadband Internet penetration, increasing reliance on digital services, and evolving consumer behavior patterns. However, there remains insufficient evidence regarding the dynamics of Internet traffic in Greece. The objective of this study is to examine the short-term behavior of Internet traffic in Greece through the analysis of a high-frequency time-series dataset comprising 5-minute interval records over several months [11, 12].

The analysis adopts a descriptive statistical approach to identify Internet usage patterns across different times of the day and days of the week, and assess traffic flow balance. Particular attention is given to detecting regularities in Internet traffic at specific hours and days, along with evaluating the symmetry between inflow and outflow volumes. The dataset contains more than twenty thousand observations, and various visualization tools—such as hourly and daily profiles, boxplots, and heatmaps—are employed to provide a multifaceted examination of traffic dynamics [13-16]. These techniques facilitate the identification of patterns while revealing irregularities that may not be captured through statistical analysis alone [17].

The significance of this research can be considered from three perspectives. First, it is among the few studies providing an empirical analysis of high-frequency Internet traffic in Greece. Second, it characterizes traffic patterns and demonstrates the presence of daily cycles and behavioral regularities. Third, it highlights the importance of considering not only average but also peak network traffic to fully understand load and variability [18, 19].

The remainder of the paper is organized as follows. The next section presents a review of the literature on short-term Internet traffic analysis. This is followed by the methodology section, which describes the data and analytical approach. The empirical findings are then presented and discussed, followed by the conclusion, which outlines key findings, implications, and directions for future research.

2. Literature Review: Short-Term Internet Traffic Patterns

Studies of short-term Internet traffic patterns have largely focused on specific environments rather than providing a comprehensive view of this type of demand profile. Research on traffic affecting large regions, including Europe, follows a

similar pattern. One notable study examined short-term traffic dynamics in Europe; however, that analysis primarily employed ARIMA models, which limit the scope of further practical applications of the identified patterns. Studies focusing on high-frequency analysis of Internet traffic within network environments remain relatively scarce, particularly given the complexity of network operations and demand dynamics in such contexts. Among high-frequency analyses, attention has generally been concentrated on a specific characteristic of the Internet—its capacity to handle large volumes of churn traffic [20, 21]. High-frequency data have also been used to identify patterns and predict periods of elevated traffic levels in specific environments. In Greece, developments in Internet infrastructure have been closely accompanied by increases in data traffic. When examining annual volume patterns, most studies highlight a gradual shift in aggregate traffic flows toward southern and southeastern Europe; however, high-frequency demand patterns remain insufficiently explored.

An analysis that aligns the high-frequency nature of many services and forecasting techniques with the specific characteristics of the Greek Internet environment represents a novel contribution in this area [1, 7, 11, 25, 22, 23]. Among studies of Internet traffic, those investigating short-term (e.g., sub-hourly, daily, weekly) dynamics often emphasize high-frequency background noise and operational disturbances rather than the broader seasonal and trend components typically examined in long-term analyses. Despite the availability of extensive sources of discrete high-frequency measurements (e.g., Internet service provider (ISP), Internet exchange (IX), content delivery network (CDN), and cloud facility data), their utilization in Internet traffic studies remains limited, and key attributes of such datasets are still largely unexplored.

Furthermore, the application of wavelet-based multi-scale analysis makes it possible to provide a solution to the problem of dealing with non-stationary environments and the scaling properties of teletraffic, which is not always possible in other models [4, 8, 14, 15, 17, 24, 25]. Research on short-term Internet traffic patterns overlaps with a substantial body of literature documenting their characteristics across several major regions, particularly within Europe. Common areas of investigation include overall traffic flows, load distributions, diurnal patterns, day-of-week effects, seasonal influences, major Internet disruptions, and parametric incident detection [23, 24]. In Europe, studies of availability and periodicity—based on analyses of seasonal and aperiodic basal rhythm (ABR) components—have demonstrated that background traffic is predominantly seasonal. Furthermore, monthly traffic comparisons across major European ISPs reveal pronounced decreases during the summer period, while sub-weekly analyses using 5-minute interval monitoring identify dominant diurnal patterns, peak periods, day-of-week effects, and seasonal declines [25]. Within the short-term Internet traffic literature, most studies have employed high-frequency modeling frameworks focused on non-continuous traffic, where observations are represented as discrete time series with relatively few data points per day. Other granular analyses in the field examine seasonal, weekly, weekly–diurnal, and daily–diurnal patterns, as well as forecasting techniques for European ISP traffic.

In recent years, there has been a growing number of studies applying time-series methods to Internet activity and data. Most of these methods utilize techniques such as the leader's approach for dimensional reduction prior to performing hierarchical clustering on the call activity data. Moreover, wavelet-based decomposition techniques have started being combined with more advanced methods of change point detection, such as iterated cumulative sums of squares, to identify several changes in variance within the sequences of data. These methods help in breaking down complicated data into regularity and randomness, thereby increasing the predictive power of the mobile traffic data analysis in the cellular environment. Such an approach is important because of the heterogeneity of subscribers' consumption behavior, which can be divided into a limited number of profiles [24, 26].

Traffic patterns observed in Greece share many similarities with results obtained from similar studies conducted in other countries. Previous studies have identified a strong Internet traffic cycle during the day, where traffic decreases in the early morning and peaks in the late afternoon and evening, reflecting human behavioral and working patterns. The daily periodic pattern observed in this study through autocorrelation and seasonal decomposition analysis is common in all modern uses of

the Internet. However, what this study adds to the current knowledge about Internet traffic is country-specific data derived from high-resolution traffic data that show that traffic in Greece behaves in a stable pattern while having a balanced symmetry between incoming and outgoing traffic patterns.

For example, in China, empirical research has shown that 9,600 cell towers exhibit only five distinct temporal patterns, demonstrating a high level of regularity in urban human behavior. This implies that it is possible to improve clustering by matching those patterns to certain elements of urban ecology [27]. Large-scale studies in France have shown that clustering cellular traffic demand patterns leads to a much better match between the network's digital signatures and ground-truth land-use data. They successfully apply the method of eigenvector composition in order to find hidden connections between places and their purposes within the city [28]. Studies carried out in the US clearly show that this methodology extends to metropolitan comparisons, where identifying periodicity helps characterize mobile service requirements more generally [29, 30].

3. Methodology

The present study adopts a quantitative research methodology centered on high-frequency time-series analysis of Internet traffic dynamics in Greece. The methodological approach is primarily descriptive and analytical, focusing on identifying patterns of periodicity and variability in network traffic. The dataset comprises high-frequency observations of Internet traffic recorded at 5-minute intervals between January 11, 2026, and April 6, 2026, resulting in a total of 24,378 observations. This dataset provides a detailed representation of changes in network dynamics over a period of approximately three months. Two primary variables are considered: inbound traffic and outbound traffic, both measured in absolute Internet traffic units.

The analysis is conducted using a multi-scale analysis methodology in order to describe traffic evolution by reconciling the fine-grain scale of the signal dynamics and the coarse scale of the network behavior. Such an approach employs visual diagnostic tools to identify temporal traffic structures and patterns across multiple time scales. The use of high-frequency data enables the differentiation of regular background traffic from short-term irregular fluctuations. As a result, decomposition of these complex signals provides a better way of estimating their periodicities, which continue to be important in predicting future bandwidth demands. In addition, identification of different components of the traffic helps establish methods for more reliable anomaly detection systems capable of distinguishing between legitimate traffic peaks and malicious attacks. Furthermore, the use of the visibility graph technique makes it possible to transform such complicated traffic data series into topological networks with different structural characteristics depending on various application scenarios. The proposed topological network serves as an analysis tool that makes it possible to classify various network types according to their resilience to various attacks and stresses caused by traffic. In doing so, the proposed methodology provides a systematic framework for characterizing short-term Internet traffic dynamics using high-frequency observations.

Methodologically, the analysis is structured around three main components: descriptive statistics, time-series aggregation, and visual analytics. First, descriptive statistical measures are computed to characterize central tendency and dispersion. These include metrics such as mean values, maximum values, and other distributional properties for both inbound and outbound traffic flows. This step enables the assessment of the magnitude, balance, and variability of network traffic. Second, the time-series data are analyzed through aggregation across multiple temporal dimensions in order to uncover underlying patterns in traffic behavior [23, 24]. Third, visual analytics techniques are applied to the data. This includes line charts, boxplots, and heatmaps, which are used to visualize traffic behavior across different temporal scales and to reveal patterns, variability, and anomalies that descriptive statistics and aggregation alone may not capture.

Visual analysis is especially valuable for high-frequency data because it enables identifying patterns and anomalies that cannot be captured via purely numerical descriptions. Furthermore, the methodology places particular emphasis on comparing inbound and outbound traffic streams. Through an analysis of both time series, researchers assess the level of symmetry and

coordination observed in the dynamics of the analyzed processes. Such a comparison is crucial for determining whether traffic is balanced or whether there are any discrepancies in directional dynamics. The proposed methodology is exploratory and descriptive in nature; it does not aim to develop any econometric models to identify any causal relations. The methodology used is suitable, considering that the purpose of the study is to analyze short-term trends in the behavior of Internet traffic based on high-frequency data.

Even though the dataset offers an extensive analysis of the network, several limitations should be considered. The analysis focuses on one period in one particular geographical location; hence, the findings may not be generalized to different time periods and countries. Furthermore, the lack of other explanatory variables may affect the interpretation of the results.

Data were collected from the Greek Internet Exchange (GR-IX) via the Greek Open Data Portal (data.gov.gr). This portal offers open access to Internet traffic data measurements in Greece. The period covered by the data is from 11 January 2026 to 6 April 2026. Internet traffic data were measured at 5-minute intervals, leading to 24,378 data points. The data consist of incoming and outgoing Internet traffic. Before the data analysis, the dataset was checked for consistency of time stamping, duplicates, and missing data points [6].

As the GR-IX dataset contains traffic volume data only, without information on network capacity, this research is concerned solely with traffic demand. Accordingly, it is not possible to estimate either network capacity or utilization rates from the available dataset. The examined variables represent the volume of Internet traffic, measured in bytes (B), within each 5-minute observation period.

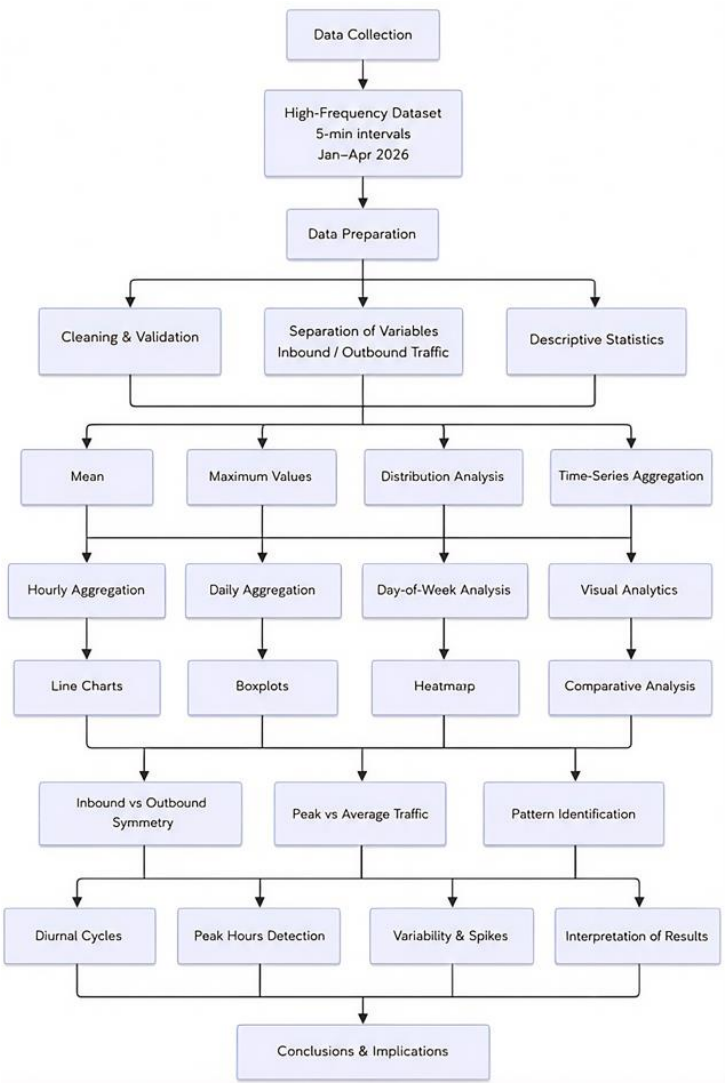

Fig. 1 Methodological framework for high-frequency Internet traffic analysis (Authors' scheme)

This research uses an organized approach and a step-by-step methodology to achieve the desired outcomes, as demonstrated in the flow chart presented in Fig. 1. The first step in the study is the acquisition of high-frequency Internet traffic data that occurs every 5 minutes from January to April 2026. This enables a detailed understanding of the network activity and observe the changes in the dynamics of such a system on an almost real-time basis. After the data has been collected from the system, data preparation is done to clean and validate the data to make sure it is accurate. In addition, data is classified into two major categories: inbound and outbound traffic. The next stage involves the application of descriptive statistical analysis. Key statistical measures, including mean values, maximum values, and distribution characteristics, are computed to provide an initial understanding of the magnitude, dispersion, and balance of Internet traffic. This step is essential for identifying the fundamental properties of the dataset and establishing a baseline for further analysis.

The analysis first applies time series aggregation methods using multiple time units, such as hourly, daily, and weekly levels. This enables the identification of patterns within the time series, for instance, daily (diurnal) patterns and weekly patterns. Patterns within the traffic behaviors at different time scales are captured to account for systematic variations that occur due to human behaviors and patterns of network usage. Visual analytics are then implemented to aid in the understanding of the collected data. Different types of graphs, such as line charts, plots, and heat maps, are used to visualize traffic behaviors and variations. Line charts show the progression of traffic with respect to time, while plots capture the variation within the hour. Heat maps help to visualize the intensity of traffic across different hours and weeks.

In addition to the above, the methodological approach encompasses the use of a comparative analysis tool that centers on the association of inbound and outbound traffic. The analysis attempts to identify how symmetrical or dissimilar the two flows are, as well as the difference between peak and average traffic volumes. Such comparisons help determine whether the network functions in a symmetric manner or not during specific times. Following the earlier-mentioned steps, pattern recognition is performed to characterize important aspects related to time, such as daily cycles, peak traffic periods, and high variance or spike periods.

The results are discussed in light of network performance and management issues related to digital infrastructure. In this regard, the interpretation process involves an analysis of the collected findings based on statistical, temporal, and graphical methods. This will allow reaching several conclusions and making important recommendations that would be useful for network providers, policy-makers, and researchers. Such implications could be very valuable for enhancing capacity planning and management efforts in relation to high-frequency Internet traffic behavior. In summary, this methodology involves a coherent sequence of steps, ranging from collecting initial data to drawing important conclusions based on statistical analysis and time series modeling.

4. Empirical Findings: Greece in Focus

Daily-to-sub-hourly Internet traffic flows exhibit a clear periodic structure, associated rhythm, and well-defined amplitude. Yet, certain peak usage periods and atypical surges are also observed [28, 9, 29, 30, 19]. Because the analysis relies on aggregated traffic volumes alone, these surges are characterized in the following sections in terms of their magnitude, timing, and variability rather than attributed to specific external events [1–5].

Descriptive statistics of the high-frequency Internet traffic data set that is being analyzed in this research are presented in Table 1. This data set contains approximately three months of Internet traffic collected on a 5-minute basis and provides a comprehensive representation of the dynamics of short-term Internet traffic in Greece. This data set contains information on the period of the research, the total number of observations, as well as the mean and maximum values of inbound and outbound Internet traffic.

Table 1 High-frequency analysis of Internet traffic dynamics in Greece (authors' table and European data [6])

	Value
Study period starts	1/11/2026 0:00
Study period end	4/6/2026 20:55
Number of 5-min observations	24,378
Mean inbound traffic	481,144,512,450.30
Mean outbound traffic	481,146,214,510.87
Maximum inbound traffic	1,092,843,329,104
Maximum outbound traffic	1,092,690,805,720

Table 1 shows the period and the basic descriptive statistics of Internet traffic in Greece. The dataset covers the interval from 11 January 2026 to 6 April 2026 and includes 24,378 five-minute observations. This indicates a high-frequency time series with a detailed representation of short-term traffic dynamics over nearly three months. The large number of observations provides a strong basis for examining both regular patterns and short-lived fluctuations in network activity. The average inbound and outbound values are almost identical, at 481,144,512,450.30 and 481,146,214,510.87, respectively. This close similarity suggests that the network traffic was highly balanced in both directions throughout the study period. Similarly, the maximum values are also extremely close, with inbound traffic reaching 1,092,843,329,104 and outbound traffic reaching 1,092,690,805,720. The table therefore indicates a stable, high-volume traffic environment with strong bidirectional balance and occasional large spikes in activity.

Table 2 Summary of inbound Internet traffic patterns by day of week and hour of day (Authors' table)

Aspect	Interpretation
Overall pattern	The heatmap shows a clear diurnal rhythm in inbound Internet traffic, with low activity in the early morning and higher activity later in the day.
Lowest traffic period	Traffic is consistently weakest during the early morning hours, especially between 02:00 and 05:00.
Highest traffic period	The highest levels of traffic occur in the evening, particularly between 18:00 and 21:00.
Day-of-week variation	The traffic pattern is broadly similar across all days of the week, indicating a stable weekly structure.
Variability	Traffic becomes more intense and more variable during peak evening hours, while overnight usage remains low and stable.
Main interpretation	The figure demonstrates a strong and regular daily usage cycle, with peak demand concentrated in the late afternoon and evening.

Notes: Values are based on average inbound traffic aggregated by hour of day and day of week. The color intensity in the heatmap represents relative traffic magnitude, with darker colors indicating lower traffic and lighter colors indicating higher traffic.

Table 2 summarizes the main pattern shown in the heatmap of inbound Internet traffic by day of week and hour of day. It explains that traffic follows a strong daily cycle, with very low activity in the early morning and much higher activity later in the day. The summary facilitates interpretation of the heatmap by presenting its main findings in a concise format. The results also show that the lowest traffic occurs between 02:00 and 05:00, when network use is minimal, while the highest traffic is observed in the evening, especially between 18:00 and 21:00. This indicates that Internet demand is concentrated in the later part of the day, which is consistent with normal user behavior after work or daily routines.

The weekday structure is also relatively stable, with similar traffic patterns observed throughout the week. In addition, the variability of traffic increases during peak hours. During these periods, traffic is not only higher but also more variable, while overnight traffic remains low and stable. This suggests that the network experiences more intense and less predictable load during busy periods. Overall, the table provides a concise interpretation of the heatmap and highlights the regular daily and weekly structure of inbound traffic.

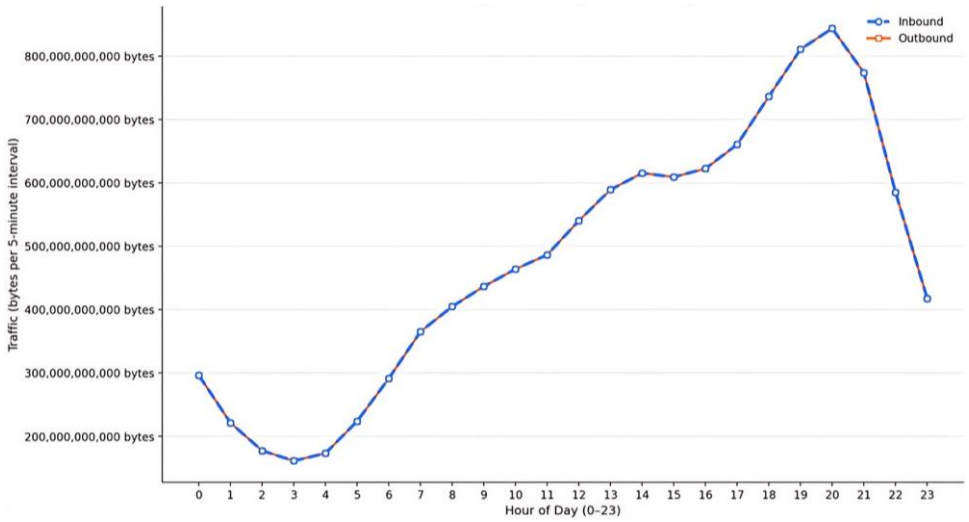

Fig. 2 Average traffic by hour of day (Authors' scheme)

Fig. 2 shows the average traffic entering and leaving the Internet within the daily cycle. A distinct circadian rhythm is observed, with the lowest traffic volume occurring at 03:00 and remaining relatively low until 05:00. Following this time, the traffic volume gradually increases due to higher network activity. Inbound and outbound traffic are highly synchronized and closely overlap. There is a sharp peak in traffic volumes during the evenings, when traffic peaks in the range of 20:00 - 21:00, indicating that the period of maximum user activity is between these hours. Traffic levels then decline progressively after the peak period and complete one day's cycle in the nighttime. Overall, the figure demonstrates that Internet usage has an established and consistent pattern, with low demand during the nighttime, an increase during the daytime, and a sharp peak during the evenings.

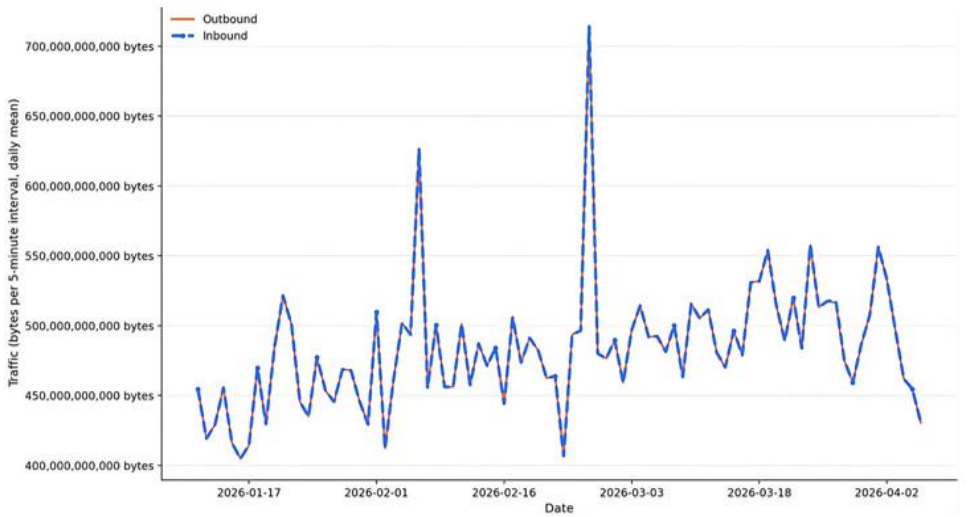

Fig. 3 Daily mean Internet traffic in Greece (Authors' scheme)

Fig. 3 presents the daily mean Internet traffic in Greece over the study period, showing both inbound and outbound traffic. The two series move almost identically, indicating a high degree of symmetry between traffic entering and leaving the network. This close overlap suggests that the network experienced balanced bidirectional usage throughout the observation window, with no sustained divergence between inbound and outbound flow. The series fluctuates from day to day, but the general level of traffic remains fairly stable across the period. Most daily values lie within a relatively narrow band, which indicates that the network load was consistent over time rather than subject to prolonged disruptions or structural shifts. At the same time, a few notable spikes are visible, especially in mid-February and again near the end of February, when traffic rises sharply above the surrounding daily pattern. These peaks may reflect short-lived episodes of unusually high network activity. Toward the end of the period, traffic appears to increase modestly for several days before declining again in early April. This pattern suggests a

slight upward movement in activity during March, but without a strong long-term trend. In summary, the figure shows a generally stable daily traffic profile with occasional pronounced peaks, and it confirms that inbound and outbound traffic followed nearly the same temporal behavior throughout the study period.

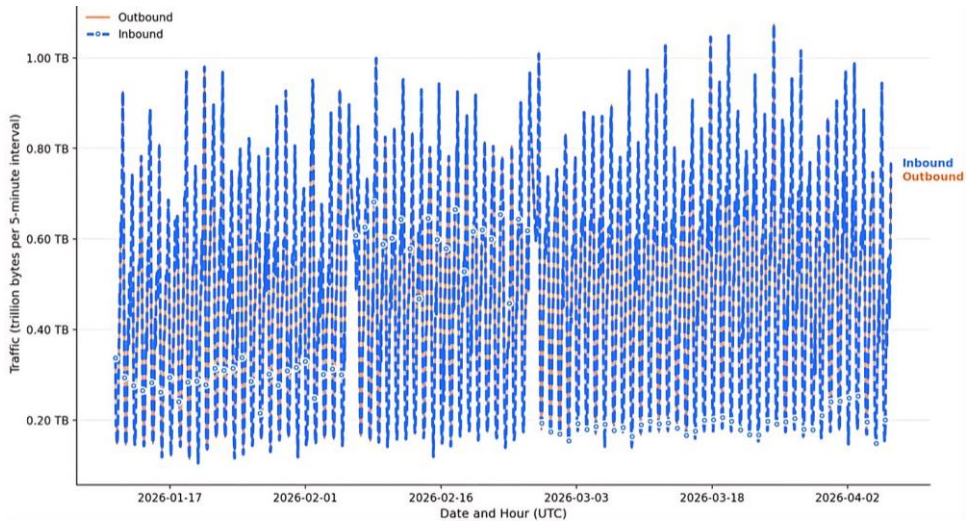

Fig. 4 Hourly average Internet traffic in Greece (Authors' scheme)

Fig. 4 shows the average Internet traffic in Greece on an hourly basis for the whole duration of the study as a time series. Each data point is an average of Internet traffic in one hourly interval based on the corresponding 5-minute readings within that interval. Therefore, each day results in 24 hourly averages instead of one daily average. The repeated cycles evident in the figure can thus be seen as the normal cycles of hour-to-hour variations of Internet traffic and not a result of any problems with the daily average readings.

Inbound and outbound traffic follow practically the same path through the whole period of the study, showing a significant symmetry between the two. The considerable overlap of the two series shows that the inbound and outbound traffic were balanced to a large extent in response to any changes in network demand. There is a clear presence of a diurnal pattern throughout the whole period under observation. Traffic is lowest in the early morning, from about 02:00 to 05:00, then rises steadily through the morning and afternoon before reaching its peak in the evening, particularly between 18:00 and 21:00. This periodicity is consistent with typical human activity, with demand peaking during evening hours. Beyond this daily pattern, short-term rises and falls occur due to normal fluctuations in network traffic; these do not indicate structural change in the network but simply reflect varying demand at different hours. Figure 4 thus clearly illustrates stable two-way traffic in Greece, a consistent diurnal pattern, and ongoing short-term fluctuations.

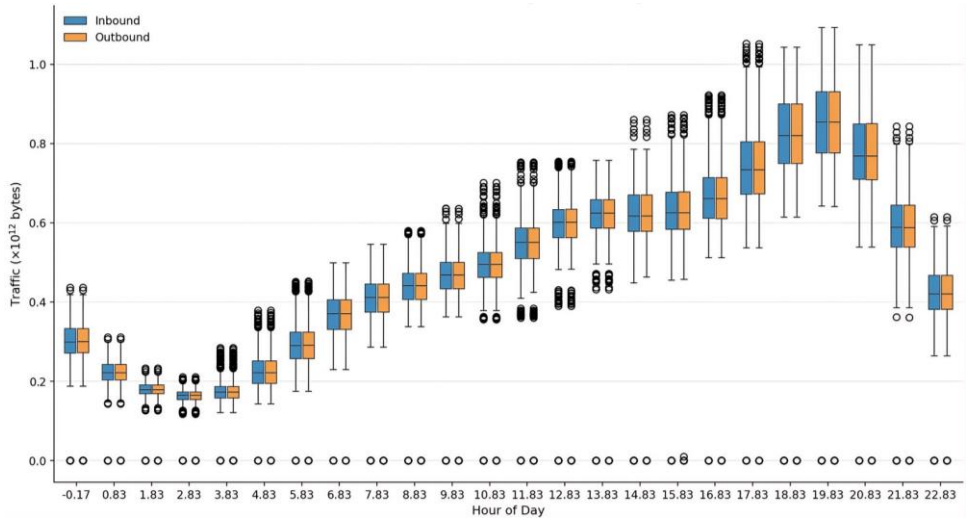

Fig. 5 Traffic variation by hour of day (Authors' scheme)

Fig. 5 illustrates the distribution of Internet traffic by hour of day for both inbound and outbound flows. Each boxplot summarizes the median, interquartile range, and outliers for a given hour, allowing the reader to assess not only the typical traffic level but also its variability throughout the day. The inbound and outbound distributions are very similar across all hours, which indicates that traffic entering and leaving the network followed nearly identical temporal patterns during the study period. A clear diurnal cycle is visible in the figure. Beyond the timing of the daily cycle already reported in Table 2 and Fig. 4, the boxplots add information on the dispersion of traffic within each hour. During the overnight hours, the distributions are the most compact of the day, with both the median and the interquartile range at their narrowest. Dispersion then widens progressively as activity builds through the late morning and afternoon. The evening hours display the widest distributions of the day, with the interquartile ranges and upper whiskers at their maximum extent and a visibly larger number of high outliers. Traffic during these hours is therefore not only higher but also markedly more volatile, whereas the overnight hours remain stable as well as low. Therefore, Fig. 5 demonstrates a strong and regular daily traffic rhythm, with synchronized inbound and outbound behavior and pronounced peak-time variability.

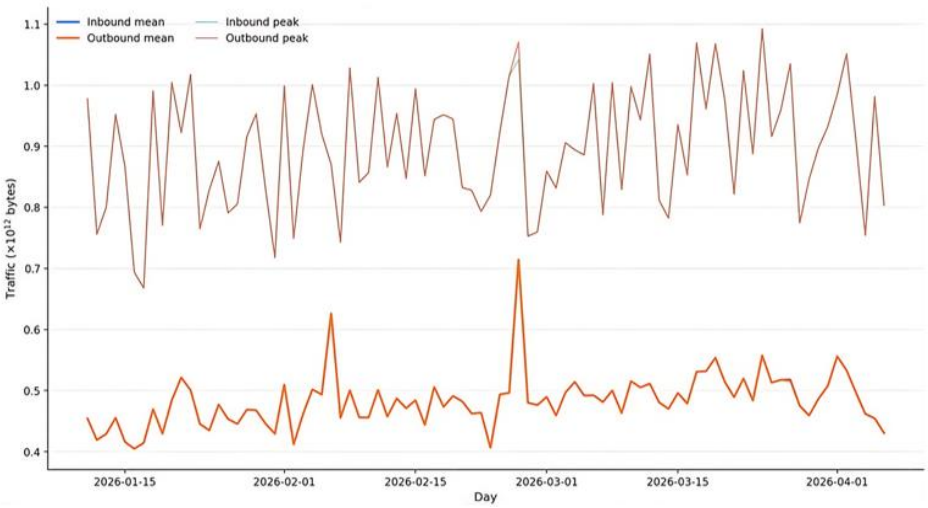

Fig. 6 Daily mean and peak Internet traffic (Authors' scheme)

Fig. 6 presents the daily mean and daily peak Internet traffic for inbound and outbound directions over the study period. The mean series for inbound and outbound traffic remains very close to each other throughout the timeline, indicating that the overall volume of traffic entering and leaving the network was highly balanced. In general, the mean traffic level shows moderate day-to-day variation, but no dramatic long-term shift, which suggests a relatively stable baseline of network usage across the period. In contrast, the peak traffic series shows much stronger fluctuations than the mean series. This is expected, as peak values capture the highest traffic observed within each day and therefore reflect short-lived surges in network activity. Several pronounced spikes are visible, especially around late February and throughout March, when peak traffic rises substantially above the surrounding daily levels. These spikes indicate occasional bursts of unusually intense network demand, possibly linked to specific events, user behavior patterns, or temporary congestion periods. The figure suggests that while typical daily traffic remained fairly steady, the network experienced intermittent high-intensity load events.

The similarity between inbound and outbound mean traffic implies symmetric traffic behavior, while the larger variability in peak traffic highlights the presence of occasional extremes that are not captured by average values alone. The comparison highlights the difference between routine network usage and exceptional traffic surges in the dataset. The noted spikes in traffic show that despite the overall stability of the network, there are instances when the demand for the Internet grows significantly higher than usual. In this regard, it should be noted that the current study focuses solely on the aggregated traffic data, which makes it impossible to link any particular spike to an external event. However, it should also be pointed out that the obtained results show that frequent measurement of traffic makes it possible to note such changes that cannot be detected by analyzing daily or weekly traffic data.

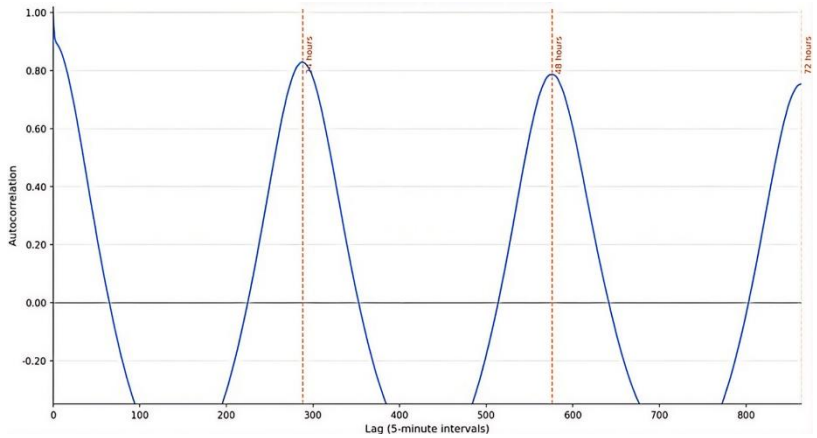

Fig. 7 Autocorrelation function of inbound Internet traffic in Greece (Authors' scheme)

Fig. 7 shows the autocorrelation function (ACF) of the inbound Internet traffic process, thereby providing evidence of temporal dependence and periodicity of the traffic process. The autocorrelation starts very high at small lags, implying that traffic data obtained from short periods of time have a high degree of correlation. This indicates that for high-frequency Internet traffic, the network use does not change abruptly between two consecutive 5-minute periods of time. There is a strong daily periodicity in the autocorrelation function. Since the traffic data is taken every 5 minutes, 288 lags refer to 24 hours. The positive autocorrelation at lag 288, along with the peaks at lags 576 and 864, which correspond to 48 and 72 hours, respectively, indicates that traffic during a particular time of day is highly similar to traffic at the same time on the following days. The autocorrelation drops between the two peaks and turns negative at some intermediate lags until it increases once again, until the arrival of the next 24-hour cycle. Such behavior can be explained by the change in states from periods when the network was relatively inactive to periods when the network was very busy throughout the day. For example, traffic during the early morning period shows a negative correlation with traffic during evening peak times.

The fact that the autocorrelation persists in more than one daily cycle suggests that the Internet traffic pattern was quite stable during the entire observation period. Instead of being characterized by randomness, the time series demonstrates a very high level of regularity, since users behave according to the fixed daily pattern. This evidence is consistent with the previous graphs and provides additional proof that the main feature of the series is its strong seasonality on the daily scale. The results of the ACF analysis confirm the conclusion that Internet traffic in Greece has a stable repetitive pattern, which is important for network traffic control and capacity planning.

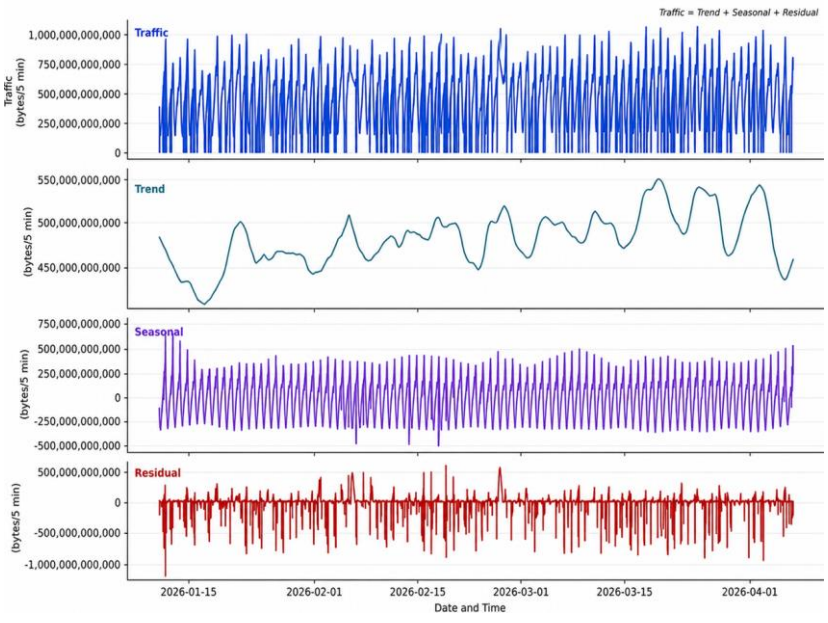

Fig. 8 Seasonal-trend decomposition of high-frequency inbound Internet traffic in Greece (Authors' scheme)

Fig. 8 shows the STL decomposition of the high-frequency series of inbound Internet traffic in Greece. The STL decomposition separates the inbound Internet traffic series into four components, namely the original series, the long-term trend, the seasonal part, and the residuals. The trend component indicates that there was no structural change in the inbound Internet traffic, as the trend shows stable Internet traffic throughout the time period under consideration. The STL decomposition is consistent with the patterns observed in the previous figures, suggesting that the inbound Internet traffic was characterized by a strong periodic structure showing regular daily cycles. STL also shows the presence of irregular fluctuations in the series that could not be accounted for by the trend and seasonal patterns. In other words, these were temporary fluctuations in the Internet traffic series. Thus, the STL decomposition shows that the variation of Internet traffic is associated with systematic seasonality, while the trends and irregularities are small.

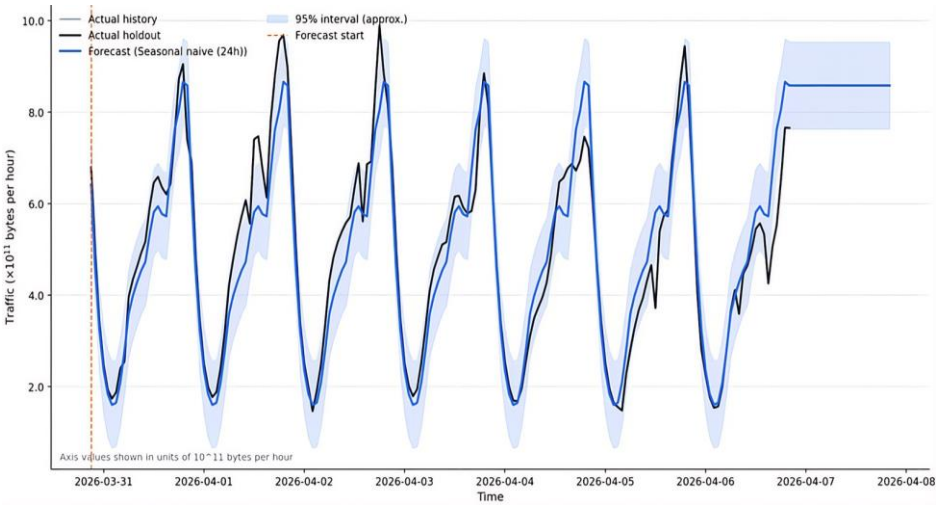

Fig. 9 Hourly inbound Internet traffic forecast based on seasonal naïve (24-hour) time-series model (Authors' scheme)

Fig. 9 presents the hourly forecast of inbound Internet traffic in Greece based on a Seasonal Naïve forecasting model with a 24-hour seasonal period. The model captures the daily seasonality of traffic by assuming that the traffic in a particular hour is similar to that of the corresponding hour on the previous day. In Fig. 9, the black line depicts the actual traffic, whereas the blue line corresponds to the forecasted values. The shaded region corresponds to the estimated 95% prediction interval that represents the uncertainty related to future data. The forecast is able to predict the significant daily variability found in the empirical data, namely, the early morning low points of traffic and the late-night peaks. Despite the inability of this simple benchmark model to make any predictions about short-term volatility and unpredictable traffic spikes, it can be seen that daily seasonality serves as a reasonable baseline for short-term forecasting.

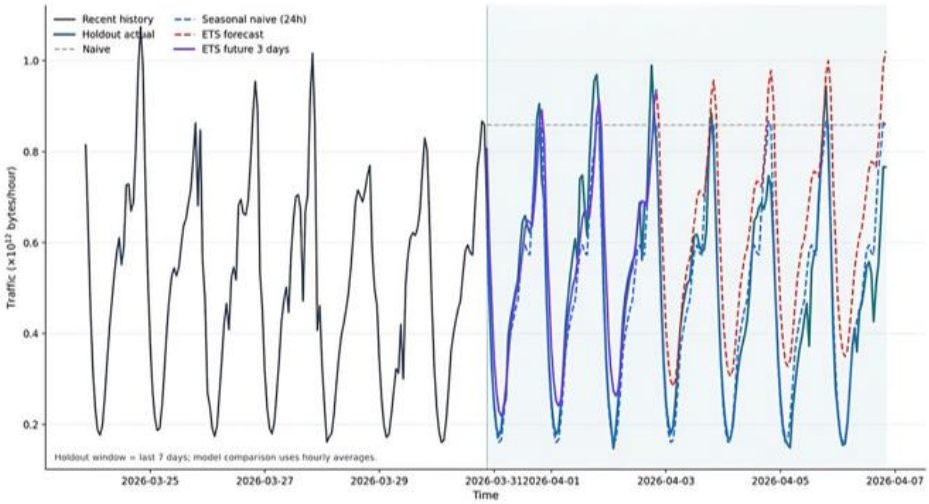

Fig. 10 Predicting outbound Internet traffic using naïve, seasonal naïve, and ETS forecasting models

Fig. 10 shows the forecast of outbound Internet traffic in Greece with three time-series forecasting methods: Naïve, Seasonal Naïve with a seasonal period equal to 24 hours, and the ETS model. The figure compares the observed values, the holdout sample, and the forecasts produced by each forecasting method, allowing their predictive performance to be evaluated. The Seasonal Naïve model shows an adequate reproduction of the daily pattern in the traffic, but the ETS model incorporates not only the seasonal component, but also the level of the series, making the forecast smoother for several days. In turn, the Naïve model assumes that future values remain unchanged and thus is less suitable for representing temporal dynamics. The conclusion from the analysis is that forecasting models, taking into account the daily seasonality, give considerably better forecast accuracy than the models without any consideration of temporal patterns.

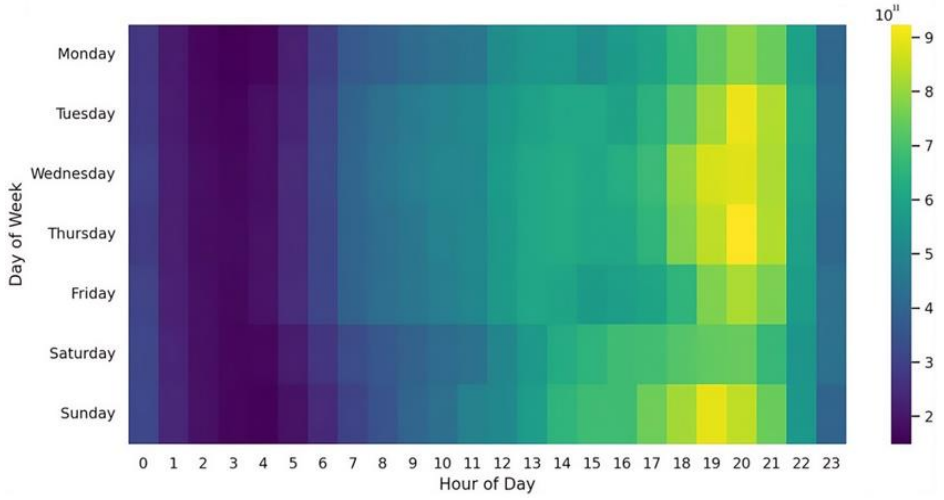

Fig. 11 Mean inbound traffic by day of week and hour (Authors' scheme)

Fig. 11 illustrates the average inbound Internet traffic across the days of the week and the hours of the day. A strong daily rhythm is immediately visible, with traffic remaining low during the early morning hours and gradually increasing throughout the morning and afternoon. The darkest colors appear around the early hours of the day, indicating minimal network activity, while the lighter green and yellow tones emerge later in the day, showing substantially higher traffic levels. The heaviest traffic generally occurs during the evening hours, especially between 18:00 and 21:00, when the heatmap shows the highest values across most days of the week. This suggests that Internet usage peaks in the evening, likely reflecting periods of heightened user activity after work or daily routines. The pattern is highly consistent from Monday through Sunday, which indicates that the daily traffic cycle is largely stable and not strongly altered by the day of the week. At the same time, there are some small differences across weekdays. Midweek days (particularly Wednesday and Thursday) appear to show slightly stronger evening traffic than the early part of the week, while weekend traffic also remains high but with a somewhat broader spread across the afternoon and evening hours. Overall, Fig. 11 demonstrates a clear and regular diurnal pattern in inbound traffic, with consistent peak activity concentrated in the late afternoon and evening across the entire week.

5. Policy and Operational Implications

Addressing the problem of network resilience, as a connected aspect of demand predictability, four high-frequency traffic-focused considerations have been identified:

(1) The resilience of the Greek Internet infrastructure can be improved if comprehensive, high-frequency traffic-flow data on the network are monitored and considered by the National Authority for Communication and Post, as well as the Telecommunication Regulatory Authority.

(2) Network service providers and, more generally, the telecommunication sector can better plan and size their external infrastructure if these high-frequency periods of load, churn, and stress are taken into account.

(3) Demand can be shaped to smooth extreme load spikes around well-identified, critical external events or periods.
(4) These high-frequency signals can serve as alerts to network operators for traffic management during possible multi-usage overloads [18–26].

Maintaining sufficiently fast reaction-response capabilities that provide short-term flexibility in internal routing is also necessary for quickly and cost-effectively absorbing traffic turmoil. The timing of tourism-related Internet traffic surges is predictable, allowing for advance allocation of internal support resources. Short-term and critical-phase traffic management systems can assist in maintaining user quality and infrastructure stability.

Enabling demand shaping through agreements with users and encouraging trusted-content distribution may contribute to improving overall Greek network traffic patterns. Daily traffic appears to utilize only about half of the available capacity of Greece's international links, suggesting that off-peak capacity could be provisioned cost-efficiently and with less environmental impact than expanding peak-time infrastructure. Available capacity during the early morning hours may allow large file transfers and operating-system or business-application updates to be scheduled at lower cost. Shifting such activities to specific days or off-peak hours may help reduce processing times and lower the marginal cost of service delivery. More consistent workloads in transmitted data volumes would reduce churn-related problems, and smoothing the traffic distribution would make service-provisioning times more predictable, thereby facilitating overall network planning.

Demand shaping may only partially address congestion issues, however, since a large share of data traveling toward the same destination within a limited time period still increases the risk of congestion. Traffic management capable of absorbing incoming load directed at the same destination at the same time—even when this exceeds normal off-peak capacity—would also help. A resilience-testing tool that simulates and evaluates the performance of distributed network elements under such extreme conditions can further improve awareness of likely bottlenecks. Level-of-service measures for different traffic types during periods when incoming demand exceeds available capacity, and congestion must be tolerated, can then guide such management [9–17].

Enhanced monitoring at specific network nodes may allow anonymized information to be shared with other relevant facilities, supporting broader high-frequency anomaly detection across the network. In this instance, the benefits of high-frequency anomaly detection outweigh the costs associated with such additional instrumentation. Although not intended for routine network control, the demand information obtained is of considerable value for managing irregular events, since demand cannot be shifted away from high-stress periods when it naturally exceeds capacity. These represent the two primary opportunities for demand shaping identified here. Sharing anonymized data with commercial vendors (e.g., IBM, Google) that already aggregate user information and commonly invest in demand-shaping technologies could also provide these providers with a more accurate picture of overall market demand.

Table 3 Empirical findings (Authors' table)

Aspect	Conclusion	Implications
Overall Traffic Behavior	Stable traffic with no major structural shifts.	Indicates a mature and reliable digital infrastructure.
Inbound vs Outbound Traffic	Near-perfect symmetry between inbound and outbound traffic flows.	Suggests balanced network usage and efficient bidirectional communication.
Diurnal Patterns	Strong daily cycle with low traffic (02:00–05:00) and peak traffic (18:00–21:00).	Enables precise capacity planning and load balancing.
Weekly Patterns	Traffic patterns are consistent across all days of the week.	Indicates predictable user behavior and stable demand structure.
Peak Traffic	Occasional extreme spikes significantly exceed average traffic levels.	Highlights the need for flexible infrastructure and peak-load management.
Variability	Higher variability during peak hours; low variability during night hours.	Suggests increased uncertainty and risk during high-demand periods.

Table 3 Empirical findings (Authors' table) (continued)

Aspect	Conclusion	Implications
Temporal Structure	Clear hourly and daily periodicity	Temporal Structure
Traffic Distribution	Average values do not fully capture network stress due to peak fluctuations.	Necessitates inclusion of both mean and peak metrics in the analysis.
Network Stress Periods	Short-lived surges represent critical stress points in the system.	Important for real-time monitoring and anomaly detection systems.
Visualization Insights	Heatmaps and boxplots reveal patterns not visible in raw statistics.	Supports visual analytics for high-frequency data analysis.
Demand Concentration	Internet usage is concentrated in evening hours.	Allows targeted optimization of resources during peak demand.
Infrastructure Resilience	Network demonstrates strong resilience with stable baseline performance.	Confirms robustness but also the need for handling extreme events.
Policy Implications	High-frequency monitoring can improve decision-making and infrastructure planning.	Useful for regulators and digital policy development.
Methodological Insight	High-frequency time-series analysis provides deeper insights than aggregated data.	Encourages adoption of granular data approaches in future research.

Table 3 summarizes the principal findings of the empirical analysis. One of the important outcomes of the research is the discovery of a highly structured pattern, characterized by clear diurnal rhythms and predictability. The fact that there are predictable low periods of activity in the mornings and high demands in the evenings indicates that the Internet traffic is closely linked to people's daily activities. An equally relevant conclusion is the high degree of symmetry between the traffic flows going into and out of the network. This demonstrates that the Greek Internet structure works efficiently and effectively, and there are no lasting discrepancies between the two types of data flow. Indeed, the symmetry can be considered a sign of a highly developed infrastructure where data exchange takes place evenly, irrespective of whether there are increased demands. Nevertheless, the research results show that whereas the average amounts of traffic are steady, peak traffic loads change significantly, and there are surges of network activity at certain times. Another significant factor is variability, one of the key features of Internet traffic. In the case of Greece, nighttime traffic shows stability, whereas peak traffic displays high variability.

Network stress is reflected not just by mean traffic levels but also by peak traffic volumes. Hence, using average indicators alone may result in undervaluing the loads of networks and their risks, making the need to use indicators related to the peaks and variability when constructing networks. From a methodological perspective, this study shows the advantages of time series analysis with visualization methods. Methods like heatmaps and plots allow the discovery of peculiarities of traffic changes that cannot be uncovered with aggregated indicators only. In other words, the application of visualization methods along with high-frequency time series analysis is useful for analyzing network behavior.

In conclusion, the significance of the above findings can be further expanded into practical implications within the areas of networking management and policy-making. First of all, the determination of peak traffic hours and variability can be useful for capacity management and overall traffic management. At the same time, the information derived from conducting high-frequency analyses can help make sound digital infrastructure policies based on data. All in all, the research contributes to a better understanding of Internet traffic dynamics.

6. Limitations and Future Research

Although this study provides a comprehensive analysis of high-frequency Internet traffic, several limitations should be acknowledged. The analysis is carried out within a specific time period and the geographical region (Greece). Such an approach may narrow the scope of the results obtained to this particular case and not be relevant in a wider time span or another region. Second, there is only a descriptive approach in this paper, without using any causality or predictive econometric models that could better explain the dynamics of Internet traffic. The absence of control variables such as demographics, application types, weather, or significant events may make it difficult to uncover the hidden patterns. Future research may address these limitations in time and geographic scope and apply advanced tools such as ARIMA, machine learning, or causality approaches.

7. Conclusion

The current research investigated short-term Internet traffic patterns in Greece using high-frequency time-series data at 5-minute intervals over three months. The study applied descriptive statistical analysis and visualization techniques, including hourly aggregation, daily averages, and heatmaps, to identify temporal structures, variability, and directional characteristics of network traffic. By focusing on high-resolution data, the study provided a detailed understanding of intra-day dynamics and short-term fluctuations in Internet usage, offering both methodological and empirical insights into digital infrastructure behavior. The contribution of the current study does not primarily lie in confirming the existence of daily Internet traffic cycles, which have already been shown before, but rather in presenting an empirical description of Internet traffic behavior in Greece at a high temporal resolution based on sub-hourly measurements. It shows the constancy of two-way traffic flows, determines the short-term variation in traffic, and shows the benefits of performing high-frequency analysis for monitoring Internet traffic. The main conclusions of the study are summarized as follows:

(1) Internet traffic in Greece exhibits a strong and consistent diurnal pattern, with minimum activity during early morning hours (02:00–05:00) and peak demand in the evening (18:00–21:00).
(2) There is a high degree of symmetry between inbound and outbound traffic, indicating balanced bidirectional network flows and efficient system operation.
(3) Overall traffic levels remain stable over time, suggesting a robust and mature digital infrastructure without significant structural shifts.
(4) Despite this stability, the network experiences significant short-term spikes, reflecting intermittent periods of high demand that are not captured by average values.
(5) Traffic variability is substantially higher during peak hours, indicating increased uncertainty and potential stress on the network during periods of intensive usage.
(6) High-frequency analysis proves to be methodologically valuable, as it reveals patterns and fluctuations that are not observable in lower-frequency or aggregated data.
(7) The findings have important practical implications for network management, particularly in capacity planning, load balancing, and real-time monitoring of network performance.

The analysis offers a detailed examination of short-term Internet traffic trends in Greece, emphasizing the balance between stability and variation observed in the daily Internet traffic patterns. The results of this study provide deeper insights into the characteristics of Internet traffic and support more informed decisions based on the analyzed data.

Conflicts of Interest

The authors declare no conflict of interest.

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