

Exploring short-term optical variability of blazars using *TESS*

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ABSTRACT

We present a first systematic time series study of a sample of blazars observed by the Transiting Exoplanet Survey Satellite (*TESS*). By cross matching the positions of the sources in the *TESS* observations with those from Roma-BZCAT, 29 blazars including both BL Lacerate objects and flat-spectrum radio quasars were identified. The observation lengths of the 79 light curves of the sources, across all sectors on which the targets of interest have been observed by *TESS*, range between 21.25 and 28.2 d. The light curves were analysed using various methods of time series analysis. The results show that the sources exhibit significant variability with fractional variability spanning between 1.41 per cent and 53.84 per cent. The blazar flux distributions were studied by applying normal and log-normal probability density function models. The results indicate that optical flux histogram of the sources are consistent with normal probability density function with most of them following bimodal distribution as opposed to unimodal distribution. This suggests that the days-time-scale optical variability is contributed either by two different emission zones or two distinct states of short-term activity in blazars. Power spectral density analysis was performed by using the power spectral response method and the true power spectra of unevenly sampled light curves were estimated. The power spectral slopes of the light curves ranged from 1.7 to 3.2.

Key words: accretion, accretion discs – radiation mechanisms: non-thermal – methods: statistical – galaxies: active – BL Lacertae objects: general – galaxies: jets.

1 INTRODUCTION

Imaging of most galaxies shows that their observed optical luminosities are due to the constituent stars that are almost uniformly distributed throughout the galaxy. Such galaxies are called normal galaxies. On the other hand, a fraction of all observed galaxies emit substantial radiation from their central region or nuclei and thereby outshine the entire galaxy. The core region of such active galaxies are widely known as Active Galactic Nuclei (AGNs). These sources are one of the most luminous objects in the Universe with their luminosities of the order of 10^{47} ergs s⁻¹. Historically, the distant AGNs were mistaken with the nearby stars; hence they were termed as quasar.

At the time of their discovery around 1963 (Shields 1999), scientists quickly realized that the high luminosity of AGNs could not be powered from nuclear processes. Today, it is widely accepted that such galaxies host supermassive black holes (SMBH) at the centre with gravitational potential strong enough to pull surrounding

matter comprised of gas, dust, and stars to form an accretion disc. The combination of strong gravitational potential and magnetic fields from these BHs and loss of angular momentum of infalling materials result in the release of tremendous amount of energy that is sufficient to support bipolar relativistic jets. The jets transport a part of the total energy into the intergalactic medium in the form of kinetic energy of the constituent particles.

A small fraction of AGNs (~ 10 per cent) (Urry & Padovani 1995) extensively emit in radio frequency and are known as radioloud sources. Blazars are a subpopulation of radioloud AGNs that expel powerful relativistic jets closely aligned to the line of sight. The term ‘blazar’ was first introduced by Edward Spiegel at the Pittsburgh Conference on BL LAC Objects in the year 1978 (Wolfe 1978). On the basis of equivalent width (EW) of the optical emission lines (Urry & Padovani 1995), Flat Spectrum Radio Quasars (FSRQ) along with the BL Lacertae (BL Lac) objects normally constitute the blazar class of AGNs. These two radio galaxy types are widely known to be distinct in morphology such that the parent population of FSRQs are the Fanaroff–Riley type II radio galaxies (FRIIs), and that of BL Lacs are the FRIs (for some exceptions, see e.g. Rector & Stocke 2001; Kharb, Lister & Cooper 2010).

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Blazars are one of the most variable extragalactic objects with a strong broad-band emission ranging from radio to TeV energies. The emitted non-thermal radiation exhibits rapid flux and polarization variability on diverse time-scales, typically a few minutes to decades. Strong Doppler boosted relativistic jets that are viewed at small angles, i.e. $\lesssim 5^\circ$ for BL Lac and $\lesssim 10^\circ$ for FSRQ, cause relativistic beaming which is responsible for dominant radiation processes in blazars (Lähteenmäki & Valtaoja 1999). Such a Doppler beaming of the jets amplifies the apparent luminosity and shortens the apparent variability time-scales, lending the sources distinct properties that can be analysed and constrained in the framework of time-domain astrophysics. As a result, the study of flux change from blazars become ideal probe to the central regions of AGN.

On the basis of the presence of emission lines over the broad-band continuum emission, blazars are grouped into two subclasses. The more luminous type is known as flat-spectrum radio quasars (FSRQ), which show emission lines over the continuum. The synchrotron peak of the sources lies in the lower frequency; and the external Compton (EC) scenario is thought to be more plausible scenario in explaining the high-energy emission (Fossati et al. 1998). This is because FSRQs have abundant seed photons originating from Accretion Disc (AD), Broad Line Region (BLR), and Dusty Torus (DT). On the other hand, the less powerful type of sources, known as BL Lac objects, show weak or no such lines. In these sources, the peak of the synchrotron emission lies in the optical to X-ray regions, and the origin of high energy emission, ranging from tens of keV to TeV energies, is most likely due to the synchrotron self-Compton (SSC) effect. Possible reasons for the apparent low luminosities (compared to FSRQs) of these sources are the lack of strong circumnuclear photon fields and comparatively low accretion rates. Apart from FSRQ-BLLac dichotomy, blazars can also be classified according to their synchrotron peak frequency (ν_{peak}^S). According to this scheme of classification, blazars can be high synchrotron peaked blazars (HSP; $\nu_{\text{peak}}^S > 10^{15}$ Hz), intermediate synchrotron peaked blazars (ISP; $10^{14} < \nu_{\text{peak}}^S < 10^{15}$ Hz), or low synchrotron peaked blazars (LSP; $\nu_{\text{peak}}^S < 10^{14}$ Hz) (Abdo et al. 2010).

Blazar variability in general is observed to be erratic in nature. But the source light curves display persistent activity along with superimposed intermittent flares distinguished by a well-defined rise and decline in the flux level. One of the defining properties of blazar is the variability over diverse time-scales. The observed variability broadly can be categorized as intraday variability (IDV) where time-scales range from a few minutes to several hours and flux changes by a few tenths of magnitude (e.g. Wagner & Witzel 1995). Short term variability (STV) can be observed in the time-scales ranging from several days to months, whereas Long Term variability (LT) persist over the time-scales ranging from a few months to decades (Fan et al. 2009; Gaur et al. 2015; Gupta et al. 2016). In addition to the aperiodic flux variability, several sources are known to show quasi-periodic modulations in their multiwavelength (MWL) observations (see Bhatta et al. 2016, and the references therein).

The literature is full of several blazar models that possibly can shape the variability observed in the MWL observations of the sources. The models can be broadly classified into two groups: In the *intrinsic* scenario the flux modulations in the sources can be ascribed to a number of processes e.g. the interaction of shocks with the turbulent regions or magnetic field anomalies existing in the jet (e.g. Marscher 2013; Calafut & Wiita 2015), or the generation of ultrarelativistic mini-jets within the jet (e.g Giannios, Uzdensky & Begelman 2009). On the other hand, according to the extrinsic models of variability projection, geometrical effects could play dominant role in producing the observed variability features. For

example, as the viewing angle to a moving, discrete emitting region changes, Doppler boosting of the emitted radiation also changes (e.g. Larionov, Villata & Raiteri 2010; Raiteri et al. 2013). Also the geometrical effects could play to result in an overall bending of the jets, either through instabilities (Pollack, Pauls & Wiita 2016), or through orbital motion (Valtonen & Wiita 2012). Blazar variability over longer time-scales also could be a combination of both intrinsic and extrinsic mechanisms: shocks propagating down the twisted jets and plasma blobs travelling through some helical structure in the magnetized jets are some of the examples (see Camenzind & Krockenberger 1992; Raiteri et al. 2017).

A detailed study of optical variability can add to the understanding of blazar processes. For example, using variability studies jet structures and location of the emitting region in relation to the central engine can be estimated. Variability at the shortest measurable time-scales should provide information on emitting regions at the smallest spatial scales. This can be used to test any relation with the emission at higher frequencies. Optical variability of blazars in various time-scales have been studied mainly using the ground-based telescopes: intraday time-scales (Wagner & Witzel 1995; Heidt & Wagner 1996; Bhatta & Webb 2018; Kalita, Gupta & Gu 2021; Webb et al. 2021), long-term time-scale (Fan et al. 2009; Nilsson et al. 2018; Valverde et al. 2020; Bhatta 2021).

In this paper, optical variability properties of 29 blazars using high cadence and largely continuous observations from the *Transiting Exoplanet Survey Satellite* (TESS) have been studied. The paper is structured as follows: In Section 2, the TESS data acquisition and processing is described. In Section 3 we present the TESS light curves. Section 4 the time series analysis of TESS data and the results are presented. In Section 5, we discuss some of the possible scenarios to explain the observed results. Finally, Section 6 summarizes our work.

2 OBSERVATIONS BY TESS

Launched on 2018 April 18, the *Transiting Exoplanet Survey Satellite*'s (TESS) mission is to find exoplanets orbiting the brightest dwarf stars (Ricker et al. 2015). In addition, the primary mission allows scientists from a wider astrophysics community to request targets for research on roughly 10 000 additional objects through each cycle of its Guest Investigator programme.¹ TESS instruments² consist of four wide-field charge-coupled device (CCD) cameras that can image a region of the sky measuring $24^\circ \times 96^\circ$. For a minimum of 27 d and maximum of 356 d, the cameras estimate the brightness of $\sim 15\,000$ –20 000 stars every 2 min. TESS science data have a nominal cadence of 2 min. The Full Frame Images (FFIs) are calibrated by the Science Processing Operations Center (SPOC) and are collected at 30 min cadence. These data are then made available to the public in the form of Target Pixel Files (TPFs) and calibrated light curves. TESS has its own catalogue of data and it contains mostly observations taken by TESS for luminous objects. The data collected by TESS is available in MAST portal or through Astroquery (Ginsburg et al. 2019). There is a substantial difference in the trend between the light curves obtained from Simple-Aperture Photometry (SAP) and the Pre-search Data Conditioning SAP (PDCSAP). PDCSAP flux is filtered and processed to remove trends that are known to affect exoplanet detection. This implies the removal of long-term trends by using Co-trending Basis Vectors (CBVs). However, this process, in

¹<https://heasarc.gsfc.nasa.gov/docs/tess/primary.html>

²<https://heasarc.gsfc.nasa.gov/docs/tess/documentation.html>

Table 1. The observation periods for the sectors concerned with Table 2.

Sector	Dates of observation	Hemisphere
14	07/18/19-08/15/19	N
15	08/15/19-09/11/19	N
16	09/11/19-10/07/19	N
17	10/07/19-11/02/19	N
18	11/02/19-11/27/19	N
19	11/27/19-12/24/19	N
20	12/24/19-01/21/20	N
21	01/21/20-02/18/20	N
22	02/18/20-03/18/20	N
23	03/18/20-04/16/20	N
24	04/16/20-05/13/20	N
25	05/13/20-06/08/20	N
26	06/08/20-07/04/20	N
27	07/04/20-07/30/20	S
28	07/30/20-08/26/20	S
29	08/26/20-09/22/20	S
30	09/22/20-10/21/20	S
31	10/21/20-11/19/20	S
32	11/19/20-12/17/20	S
33	12/17/20-01/13/21	S
34	01/13/21-02/09/21	S
35	02/09/21-03/07/21	S
36	03/07/21-04/02/21	S
37	04/02/21-04/28/21	S
38	04/28/21-05/26/21	S
39	05/26/21-06/24/21	S
40	06/24/21-07/23/21	N
41	07/23/21-08/20/21	N
44	10/12/21-11/06/21	N
45	11/06/21-12/02/21	N
46	12/02/21-12/30/21	N

case of blazars, may remove intrinsic source variability. To check the stability of *TESS* photometry, the light curves were also extracted from the FFI by manually selecting the aperture around a blazar source and then plotting the light curve. However, even slight difference in aperture choice led to drastically different light curves and hence the choice to use SAP flux for our study was made. Also, Raiteri et al. (2021) checked the reliability of the SAP flux for S5 0716+714 by comparing it with ground-based WEBT data and found that errors for SAP fluxes are small and range from 0.3 to 0.6 per cent. The sector wise details of the objects studied in this paper are listed in Table 1.

3 DATA

We have considered the blazars from the fifth edition of the Roma-BZCAT Multi-Frequency Catalogue of Blazars³ (Massaro et al. 2009) and looked at the *TESS* catalogue to check which of these blazars have been observed by the *TESS* spacecraft. Before analysing the light curves from *TESS*, there was a need to confirm whether the sources of the light curves are of the targeted blazars. The light-curve sources were validated by using the associated FITS photos to cross-reference the sources with the *GAIA* catalogue. The sky distribution of the cross-matched sources that are identified as blazars is presented in Fig. 1.

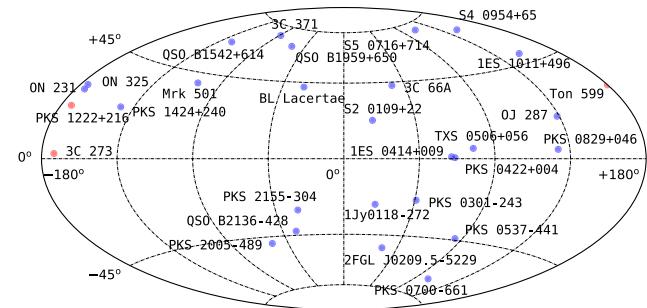


Figure 1. The sky distribution of the sources that are identified as blazars by cross-matching with the Roma-BZCAT Multi-Frequency Catalogue of Blazars. The source locations are presented in the International Celestial Reference System (ICRS) coordinates with origin at Solar System Barycenter. The sub-groups of blazars, BL Lac objects, and FSRQs are distinguished by the blue and red symbols, respectively.

Once it was certain that our objects of interest were within the default aperture, we have considered the SAP fluxes with 2 min cadence to conduct our study. Besides the 2 min exposure, SPOC pipeline also has SAP flux with 20 s exposure, starting from 2021 (Jenkins et al. 2021). Few blazars have been observed by the *TESS* multiple times i.e. they have been observed in multiple sectors. This brings the count of light curves studied here to 79, for the 29 blazars. Table 1 presents information about the sectors of the blazars included in this study.

The photometric aperture which the light curves are derived from includes extra light from nearby sources (Stumpe et al. 2012). This extra flux would hinder the transit analysis for planet detection by decreasing the apparent planet transit depth. Also, there could be cases where the aperture does not include the entire Point Spread Function (PSF) of the source. For this, the SAP fluxes were modified by using the flux fraction, a parameter linked with each cadence of the light curves. This parameter gives us the fraction of the target flux contained in the optimal aperture to the total flux of the target. This along with another parameter, crowding metric, are accounted for when the light curves are processed resulting in the PDCSAP flux (Jenkins 2017). All the data that has been quality flagged⁴ by *TESS* team were removed. This includes data points that have been flagged for reasons such as scattered light, cosmic rays, and insufficient targets for error correction. In the next step, the outliers beyond 3 sigma in the 0.1 d binned light curves for each light curve were discarded. In particular, light curves from two observations showing high and low variability are presented in the top and bottom panels, respectively, of Fig. 2. The outliers are marked in red symbols. Additional light curves are presented in Appendix A (see Fig. A1). For comparison, a representative light curve of non-variable sources (star G 224-79) is also shown in Fig. 3.

4 ANALYSIS AND RESULTS

Using the cleaned data, we have calculated fractional variability of each blazar for each sector, and optical flux distributions for each blazar have been fitted with normal and lognormal Probability Distribution Function (PDF). These plots and their corresponding fit statistics that we have calculated using Maximum Likelihood Estimator (MLE) are presented in this section. We then study the Power Spectral Density (PSD) of the blazars by modelling them

³The Roma BZCAT - 5th edition

⁴<https://outerspace.stsci.edu/display/TESS/2.0+-+Data+Product+Overview>

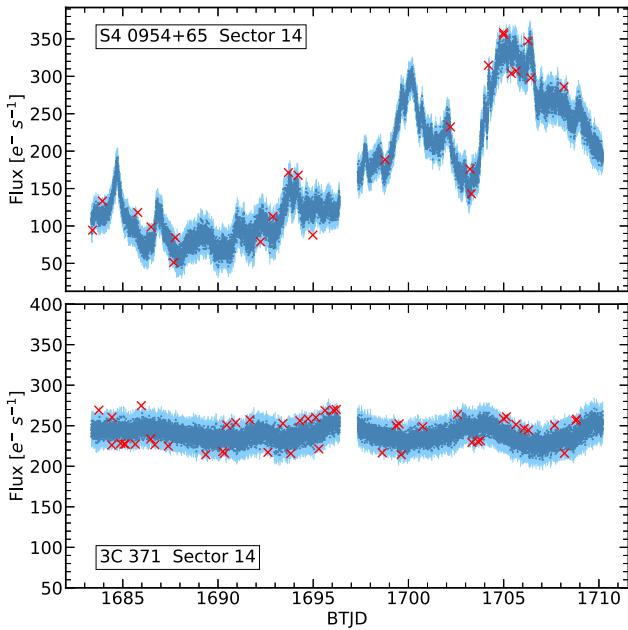


Figure 2. The top panel shows a light curve where the mean square error is lower than the variance of the flux while the bottom panel shows where the mean square error is greater.

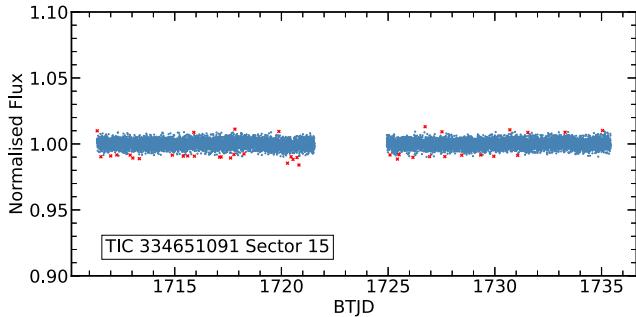


Figure 3. Shown here is the SAP flux light curve of a high proper motion star G 224-79 as an example of a star with flux not variable. This is cleaned in same way as the rest of the blazars.

using the Power Spectral Response (PSRESP) method which is a Monte Carlo technique. We use a simple power-law model to compute the true power spectra of unevenly sampled light curves and compare them against the observed power spectra to produce a reliable estimate of the goodness-of-fit of the mentioned model as described in Uttley, McHardy & Papadakis (2002). The details of the methods and the corresponding results are described below.

4.1 Fractional variability

Blazars exhibit variability that show flux changes in time-scales ranging from minutes to hours to years. In this study, we have SAP flux data for 29 blazars with 2-min cadence where the light curves are of the duration that range between 21.25 and 28.2 d. The average variability over this period can be quantified by calculating their fractional variability (FV) given by

$$F_{\text{var}} = \sqrt{\frac{S^2 - \langle \sigma_{\text{err}}^2 \rangle}{\langle x \rangle^2}}, \quad (1)$$

where $\langle \sigma_{\text{err}}^2 \rangle$ is the mean square error and is given by

$$\langle \sigma_{\text{err}}^2 \rangle = \frac{1}{N} \sum_{i=1}^N \sigma_{\text{err},i}^2, \quad (2)$$

and $\sigma_{\text{err},i}$ gives the measurement uncertainties of flux values. The uncertainty in F_{var} is given by

$$\Delta F_{\text{var}} = \sqrt{F_{\text{var}}^2 + \text{err}(\sigma_{\text{NXS}}^2)} - F_{\text{var}}, \quad (3)$$

where $\text{err}(\sigma_{\text{NXS}}^2)$ is given by

$$\text{err}(\sigma_{\text{NXS}}^2) = \sqrt{\left(\sqrt{\frac{2}{N} \frac{\langle \sigma_{\text{err}}^2 \rangle}{\langle x \rangle^2}} \right) + \left(\sqrt{\frac{\langle \sigma_{\text{err}}^2 \rangle}{N}} \frac{2F_{\text{var}}}{\langle x \rangle} \right)^2} \quad (4)$$

Vaughan et al. (2003), Bhatta & Webb (2018)

The FV of the sample sources are listed in 9th column of Table 2 and are also shown in Fig. 4. The result of the analysis shows that the mean fractional variability of the sources is 13.44 per cent with a standard deviation of 12.37 per cent, and that the source S4 0954+65 with over 50 per cent FV is found to be the most variable source whereas 3C 273 with 0.82 ± 2 per cent is the least variable of the sample sources.

4.2 Flux distribution: Lognormality and normality

Flux variability in AGNs across the electromagnetic spectrum is frequently observed in their MWL observations; however the details that describe the physical processes leading to such variability are still debated. Study of the flux distribution characterized by suitable probability density function (PDF) is one of the most important tools to constraint the physical processes. Blazar MWL, e.g. optical, X-ray and gamma-ray, flux distribution are mostly represented by normal and lognormal processes (see e.g. Bhatta & Dhital 2020; Bhatta 2021; Mohorian et al. 2022). A normal flux distribution might indicate a linear summation of components contributing to the total observed emission. On the other hand, lognormal distributions i.e. distributions which are Gaussian in the logarithm of the flux, can be obtained via multiplicative (or cascade) like processes (Uttley, McHardy & Vaughan 2005). Here we construct source flux histograms using TESS observations and subsequently the histograms are fitted with normal and lognormal PDFs.

A normal PDF is given by

$$f_{\text{normal}}(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right), \quad (5)$$

where μ and σ are the mean and the standard deviation of the normal distribution, respectively.

Similarly the lognormal PDF is written as

$$f_{\text{lognormal}}(x) = \frac{1}{xs\sqrt{2\pi}} \exp\left(-\frac{(\ln x - m)^2}{2s^2}\right), \quad (6)$$

where m and s are the mean location (expressed in units of natural log) and the scale parameters of the distribution, respectively.

We modelled the blazar optical flux distributions of the sample sources using a linear combination of the two PDFs. The method adopted here employs the expectation–maximization algorithm, which is a method for performing maximum-likelihood estimation in the presence of latent variables (Buitinck et al. 2013). For fitting lognormal models, we have transformed the data with natural logarithm and applied normal models. The Akaike’s Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used

Table 2. Descriptive statistics for the flux along with spectral indices.

Source	R.A.	Dec.	Class	Sector	Mean ($e^{-} s^{-1}$)	S.D. ($e^{-} s^{-1}$)	FV (%)	α
3C 371	271°711	69°8245	BL Lac	14	239.45	9.08	–	2.0 ± 0.23
				15	229.24	11.69	–	1.9 ± 0.58
				16	246.77	16.29	4.01 ± 4	2.0 ± 0.05
				17	221.95	15.85	5.86 ± 3	2.3 ± 0.63
				18	256.45	33.16	12.43 ± 1	3.1 ± 0.46
				20	275.63	20.67	6.32 ± 2	2.2 ± 0.37
				21	279.33	44.2	15.31 ± 1	3.0 ± 0.55
				22	282.14	33.17	10.98 ± 1	2.2 ± 0.76
				23	270.83	21.43	7.09 ± 2	2.0 ± 1.02
				24	262.8	18.25	5.2 ± 3	2.1 ± 0.77
				25	263.43	14.37	3.08 ± 4	1.9 ± 0.59
				26	267.05	12.94	1.64 ± 5	2.1 ± 0.28
				41	273.43	12.54	3.25 ± 3	2.2 ± 0.38
PKS 0700-661	105°13	−66°1792	BL Lac	27	98.35	5.42	–	2.3 ± 0.28
				28	99.98	7.96	–	2.4 ± 0.66
				29	109.77	6.9	–	2.6 ± 0.4
				30	82.59	6.07	–	2.1 ± 0.27
				31	87.99	10.29	9.6 ± 3	2.9 ± 0.54
				32	89.96	5.5	–	2.6 ± 0.33
				33	106.68	5.38	–	2.0 ± 0.21
				34	97.48	5.3	–	1.9 ± 0.21
				35	91.36	5.24	–	1.9 ± 0.35
				36	100.12	6.67	1.41 ± 7	2.5 ± 0.42
				37	96.59	8.64	5.63 ± 4	2.0 ± 0.21
				38	98.15	5.26	–	2.0 ± 0.21
				39	112.28	8.32	3.09 ± 5	1.8 ± 0.47
				41	240.56	22.51	7.38 ± 3	2.0 ± 0.83
QSO B1959+650	299°999	65°1485	BL Lac	15	245.64	38.57	14.78 ± 1	3.1 ± 0.68
				16	224.99	17.07	5.71 ± 3	2.7 ± 0.45
				17	240.75	13.35	2.68 ± 5	2.8 ± 0.71
				18	244.67	22.66	–	2.9 ± 0.46
				19	220.26	9.78	–	2.2 ± 0.14
				21	246.85	69.32	27.66 ± 0	2.9 ± 0.02
				22	232.73	21.26	6.59 ± 3	2.8 ± 0.6
				24	207.48	12.7	–	2.7 ± 0.54
				25	209.56	16.58	–	2.5 ± 0.73
				41	263.68	17.74	5.54 ± 2	2.2 ± 0.95
QSO B1542+614	235°737	61°4987	BL Lac	15	97.58	8.87	–	2.5 ± 0.61
				16	77.34	8.87	–	2.5 ± 0.71
				21	80.95	7.09	–	3.2 ± 0.72
				22	103.98	14.23	8.67 ± 4	2.7 ± 0.46
				23	79.54	9.51	–	2.9 ± 0.5
				24	76.6	10.49	–	2.2 ± 0.33
S4 0954+65	149°697	65°5652	BL Lac	14	170.79	80.94	46.65 ± 0	2.9 ± 0.58
				20	110.55	29.16	24.13 ± 2	2.4 ± 0.52
				21	110.31	60.49	53.84 ± 0	2.6 ± 0.67
				40	90.95	13.99	10.14 ± 4	1.8 ± 0.17
				41	108.97	20.62	15.59 ± 3	2.1 ± 0.95
OJ 287	133°704	20°1085	BL Lac	44	238.33	82.19	34.26 ± 0	2.8 ± 0.22
				45	212.12	78.51	36.63 ± 0	2.9 ± 0.29
				46	139.38	29.39	19.85 ± 1	3.1 ± 0.37
S5 0716+714	110°473	71°3434	BL Lac	20	2267.91	583.2	25.71 ± 0	2.8 ± 0.54
				26	1336.73	191.36	14.26 ± 0	2.1 ± 0.66
				40	979.37	107.86	10.95 ± 0	1.7 ± 0.28
				44	32.77	10.23	24.74 ± 3	3.0 ± 0.46
PKS 0537-441	84°7098	−44°0858	BL Lac	32	38.15	13.04	29.22 ± 2	2.2 ± 0.95
Mrk 501	253°468	39°7602	BL Lac	24	496.01	18.58	2.66 ± 3	2.9 ± 0.44
2FGL J0209.5-5229	32°3401	−52°4897	BL Lac	29	196.69	15.99	6.98 ± 2	2.9 ± 0.47
Ton 599	179°883	29°2455	FSRQ	22	37.73	14.7	25.57 ± 5	2.3 ± 0.91
TXS 0506+056	77°3582	5°69314	BL Lac	32	277.27	108.57	38.95 ± 0	2.7 ± 0.51
PKS 2155-304	329°717	−30°2256	BL Lac	28	786.46	25.32	2.82 ± 2	2.2 ± 0.75

Table 2 – continued

Source	R.A.	Dec.	Class	Sector	Mean ($e^{-} s^{-1}$)	S.D. ($e^{-} s^{-1}$)	FV (%)	α
QSO B2136-428	324°851	-42°589	BL Lac	28	143.03	12.48	6.87 ± 3	1.9 ± 0.52
PKS 2005-489	302°356	-48°8316	BL Lac	27	904.31	22.32	2.17 ± 2	3.1 ± 0.54
PKS 0829+046	127°954	4°49418	BL Lac	34	152.1	41.76	25.91 ± 1	2.5 ± 0.54
PKS 0422+004	66°1952	0°601754	BL Lac	32	99.96	6.43	–	1.9 ± 0.19
1ES 0414+009	64°2187	1°08997	BL Lac	32	71.25	4.82	–	1.9 ± 0.2
PKS 0301-243	45°8604	-24°1198	BL Lac	31	134.2	5.33	–	2.5 ± 0.28
1Jy0118-272	20°1319	-27°0235	BL Lac	30	112.35	4.5	–	1.7 ± 0.18
S2 0109+22	18°0243	22°7441	BL Lac	17	615.04	108.81	17.5 ± 0	2.5 ± 0.66
BL Lacertae	330°68	42°2778	BL Lac	16	1169.98	158.04	13.44 ± 0	2.1 ± 0.64
PKS 1424+240	216°752	23°8	BL Lac	23	338.28	8.86	–	2.2 ± 0.36
ON 231	185°382	28°2329	BL Lac	22	192.18	13.3	3.64 ± 5	3.0 ± 0.7
ON 325	184°467	30°1168	BL Lac	22	400.58	38.09	9.12 ± 1	2.5 ± 0.58
1ES 1011+496	153°767	49°4335	BL Lac	21	202.78	19.67	8.55 ± 2	3.0 ± 0.57
PKS 1222+216	186°227	21°3795	FSRQ	22	147.24	7.13	–	2.6 ± 0.32
3C 273	187°278	2°05239	FSRQ	46	943.71	13.38	0.82 ± 2	2.3 ± 0.23
3C 66A	35°6651	43°0355	BL Lac	18	400.4	50.75	12.36 ± 1	2.6 ± 0.65

Table 3. The best of lognormal and best of normal distribution fit statistics for the optical flux distribution using MLE method, for selected light curves. The lower values of AIC and BIC corresponding to the best fit are highlighted.

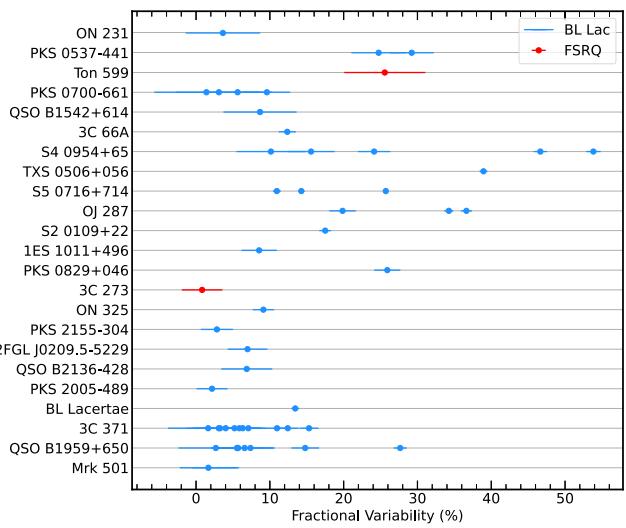
Source	Sector	Normal fit		Lognormal fit	
		AIC	BIC	AIC	BIC
PKS 0700-661	14	133535.8	133574.9	133564.1	133579.8
	26	132858.3	132897.0	132815.0	132853.7
	27	78523.6	78538.5	78538.7	78575.9
	28	85013.1	85050.1	85029.3	85066.3
	29	89599.9	89637.4	89610.5	89648.0
	30	99463.0	99501.3	99481.9	99520.2
	32	106944.1	106982.9	106963.2	107001.9
	33	108256.5	108272.1	108223.2	108238.7
	35	83553.0	83590.6	83540.0	83555.0
	36	100904.3	100942.5	100921.0	100959.1
	37	102950.7	102988.8	102972.2	103010.2
QSO B1542+614	38	110756.4	110772.0	110677.7	110693.3
	39	121667.2	121706.0	121691.7	121730.5
	16	90672.3	90709.6	90804.2	90841.6
	21	123096.4	123135.5	123058.5	123097.6
	23	92179.2	92216.5	92240.4	92277.6
PKS 0537-441	24	122202.5	122241.0	122187.0	122225.5
	32	129377.6	129416.4	129944.7	129983.6
	32	144791.5	144830.3	144795.0	144833.8
2FGL J0209.5-5229	30	126087.6	126126.2	126105.3	126143.9
	32	112436.2	112451.7	112524.7	112563.4
	32	102447.5	102463.0	102545.2	102560.7
PKS 0301-243	31	102491.4	102530.0	102495.7	102534.3
	30	97048.0	97063.4	97089.5	97105.0
	23	95963.9	96001.4	95969.4	96006.9
PKS 1222+216	22	108918.0	108956.4	108920.9	108959.4
	46	130791.1	130829.6	130794.9	130833.4

to compare both normal and the lognormal models. These estimators are given as

$$AIC = 2k - 2 \ln(L) \quad (7)$$

$$BIC = k \ln(n) - 2 \ln(L), \quad (8)$$

where k is the number of estimated parameters in the model, L is the maximum value of the likelihood function, and n is the number

**Figure 4.** Fractional variability of the source light curves, when mean squared error is less than the variance of flux. The sources are ordered in the vertical axis in the order of increasing corresponding redshifts.

of observations or the sample size. AIC is an estimator that predicts error in model selection and hence is a relative quantity to determine best-fitting models on a given data set. BIC is a criteria for model selection from a finite group of models. Models with lower AIC and BIC values better estimate a given data than other models. The AIC and BIC values we calculated by applying normal model to log-transformed data were missing the Jacobian component of log transformation. Hence, before comparing the AIC and BIC values of both the models, we have added $2\sum \ln(\text{flux})$ to the AIC and BIC of the lognormal model (Akaike 1978).

For 27 light curves of 13 blazars the AIC and BIC values as presented in Table 3 agreed on the same model for the flux distribution, which is either a single component or a two-component model. The bimodal Gaussian distribution was the most prevalent model among the flux distributions of these light curves, accounting for 17 of them. The rest of the flux distributions were comprised of single component Gaussian, single component lognormal, and bimodal lognormal models in similar proportion. The flux histograms

and their normal and lognormal fitting for selected observations showing multiple components and the corresponding residuals are shown in Fig. 5. It is interesting to note that in the case of sources PKS 0700-661 and QSO B1542+614 with multiple light curves, the best-fitting PDFs tends to vary both in terms of the components and the PDF models.

4.3 Power spectral analysis

The source light curves exhibit rapid flux variability. It is then natural to determine PSD as a function of temporal frequency, which is a measure of variability power over various time-scales. The analysis is motivated to search for any possible peaks or breaks in the source PSD, which are indications of presence of time-scales that could be characteristic to the system.

In general, discrete Fourier transforms can be employed to calculate PSD of the time series that are regularly sampled and that has large ratio of length of observation to sampling time interval. The *TESS* light curves are discretely sampled every 2 min. In some cases, the sampling times are also unevenly spaced, with a significant gap of up to 24 h in the middle of a every single sector observation. This large gap in the middle of every *TESS* light curve is caused by the observational gap that occurs when the spacecraft transmits data to the ground station on Earth during which the spacecraft is reoriented to join its Ka-band transmitter at the Earth (Vanderspek et al. 2018). Aliasing and red-noise leak will impede the power density spectrum produced by such a light curve such that the periodogram can be seen to flatten out at higher frequencies (Uttley et al. 2002). The gaps in the *TESS* data make the sampling unevenly spaced such that the PSD estimation using discrete Fourier transforms would not be accurate for the given sources. In such a context, the Lomb–Scargle (LS) method (Lomb 1976; Scargle 1982) proves to be a better estimation of the source PSD. Furthermore, in the case of the time series with uneven sampling times, the Nyquist frequency is not clearly defined. Usually, taking the mean of the sampling intervals is one of the ways of calculating it (see e.g. Scargle 1982; Horne & Baliunas 1986; Press et al. 2007). However, it is important to note that the frequency calculated in this manner is less than the true Nyquist frequency, beyond which all signals are aliased into the Nyquist range (VanderPlas 2018). So to construct the source PSD, the frequency components ranging from $\nu_{\min} = 1/T$ and $\nu_{\max} = N/2T$ were chosen, where N is the total number of data points in a light curve while T is the time baseline.

The power spectral response (PSRESP) method (Uttley et al. 2002), that is known to remove most of the artefacts of sampling patterns, was employed to derive the intrinsic PSD of a light curve along with its associated uncertainties. To implement the method, the algorithm described in Chatterjee et al. (2008) was followed. The Monte Carlo algorithm was considered to simulate the artificial light curves following the phase and amplitude randomization method described in Timmer & Koenig (1995). However, the light curves thus generated strictly follow the Gaussian distribution; whereas the blazar flux can have other forms of distributions. Therefore, to simulate light curves of given model of PSD and PDF, the method described in Emmanoulopoulos, McHardy & Papadakis (2013)⁵ was adopted. In this process, for each of the blazar light curves, 100 light curves were simulated using the best-fitting PDF model from

Section 4.2 and a single power-law model with the spectral indices ranging from 1.0 to 4.0 with a regular interval of 0.1. The simulated light curves were sampled at equal time intervals, and subsequently, the light curves were interpolated to mimic the *TESS* light curves of each of the sources.

Before computing LS periodogram, the light curves were binned using 10 min time bin and then the periodogram is computed to get the powers at frequencies up to Nyquist frequency. This is done for all of the simulated light curves and mean power spectra are calculated for all of the simulated light curves corresponding with a particular power-law model. A similar power spectrum is constructed after binning the *TESS* light curve as well. Now, to determine the PSD associated with the *TESS* light curve, a chi-square like statistics for the observed source periodogram was constructed as given below.

$$\chi^2_{\text{obs}} = \sum_{\nu=\nu_{\min}}^{\nu_{\max}} \frac{(\text{PSD}_{\text{obs}} - \overline{\text{PSD}}_{\text{sim}})^2}{(\Delta \text{PSD}_{\text{sim}})^2}. \quad (9)$$

A similar statistics for each of the simulated light curves was also defined as below.

$$\chi^2_{\text{dist},i} = \sum_{\nu=\nu_{\min}}^{\nu_{\max}} \frac{(\text{PSD}_{\text{sim},i} - \overline{\text{PSD}}_{\text{sim}})^2}{(\Delta \text{PSD}_{\text{sim}})^2}. \quad (10)$$

Then, the success fractions based on the magnitudes of χ^2 are determined for each of the power-law indices by taking the ratio of total number of χ^2_{obs} values that are smaller than $\chi^2_{\text{dist},i}$ and the total number of simulations for a simple power-law model. Then the intrinsic power spectrum of the *TESS* light curve is represented by the power-law model with the highest success fraction. The LS periodogram and the best-fitting PSD models for a few sources are shown in Fig. 6.

5 DISCUSSION

We performed a first systematic variability study of blazars observed by the *TESS* spacecraft. As mentioned earlier, there have been several studies that monitor variability of blazars in either intraday or sparsely sampled observation aimed to study variability properties in longer (a few years) time-scales. Also, there have been some efforts to obtain continuous monitor of a single source via globally coordinated observation campaigns (e.g. Bhatta et al. 2016, 2013; Acciari et al. 2020). However, such studies require considerable effort in co-coordinating campaigns demanding participation of a large number of observatories. In such context, the short cadence light curves spanning time-scales of a few days provide a unique opportunity to explore variability studies in the time-scales of a few days, given that most of the studies are either in intraday time-scales spanning a few hours or are of sparsely sampled long-term observations.

In the BL Lac sources, the optical emission as detected by the instrument mostly represents non-thermal synchrotron radiation emitted by the relativistic particle moving in the jet's magnetic field. In the leptonic emission models of blazars, the energetic particles, either electrons or positrons, could have been accelerated by the shocks propagating in the large scale jets, or by magnetic reconnection events taking place in the highly magnetized region of the jets (Giannios et al. 2009). In the internal shock scenario of the particle acceleration, the particles could be accelerated up to the energies equivalent to thousands of Lorentz factors (e.g. Marscher & Gear 1985; Kirk, Rieger & Mastichiadis 1998; Spada et al. 2001; Joshi & Böttcher 2011). Also, the particles might be accelerated in the high turbulent regions of the jet (e.g. Marscher

⁵The method was implemented using the python program based on the code at <https://github.com/samconnolly/DELightcurveSimulation>

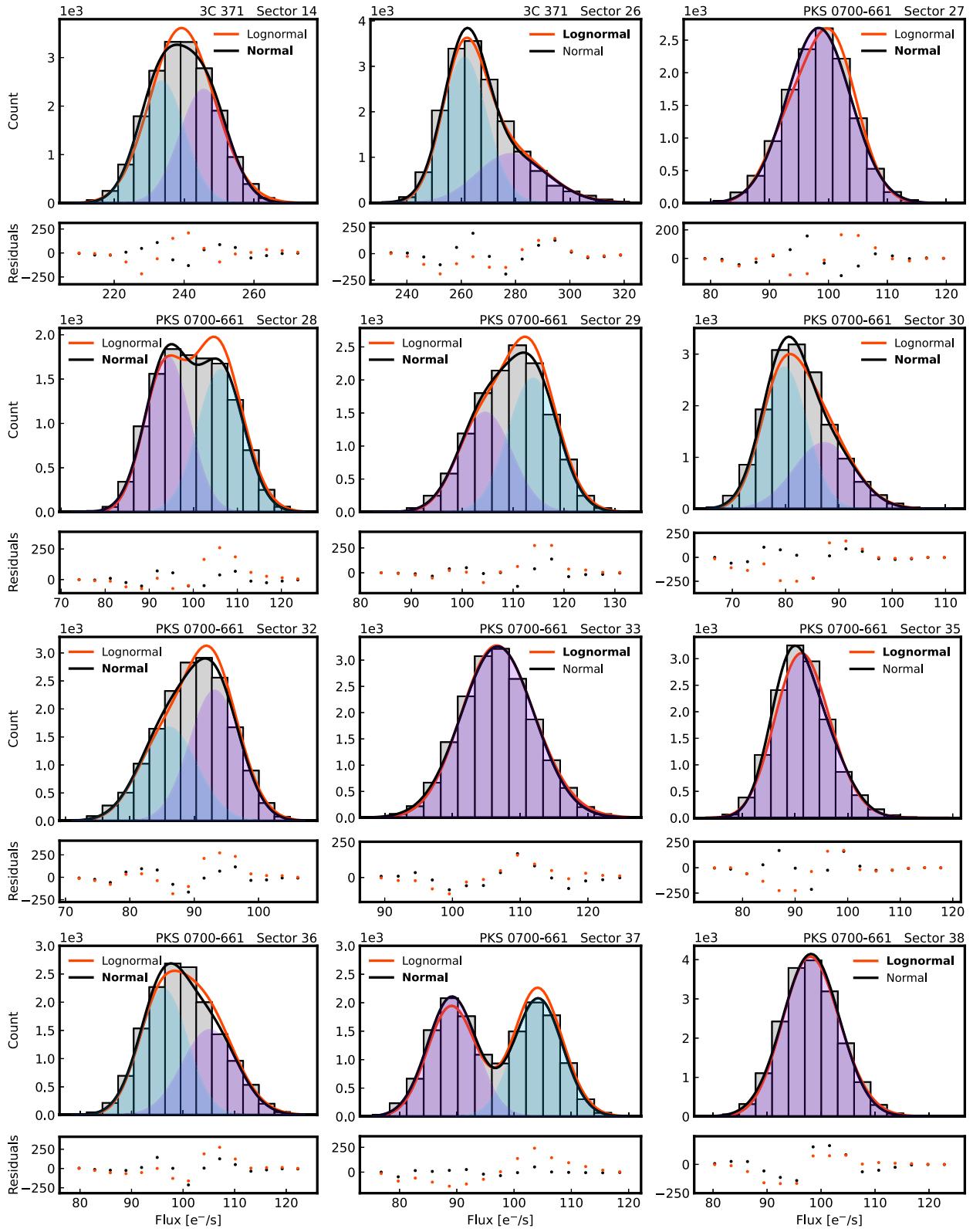
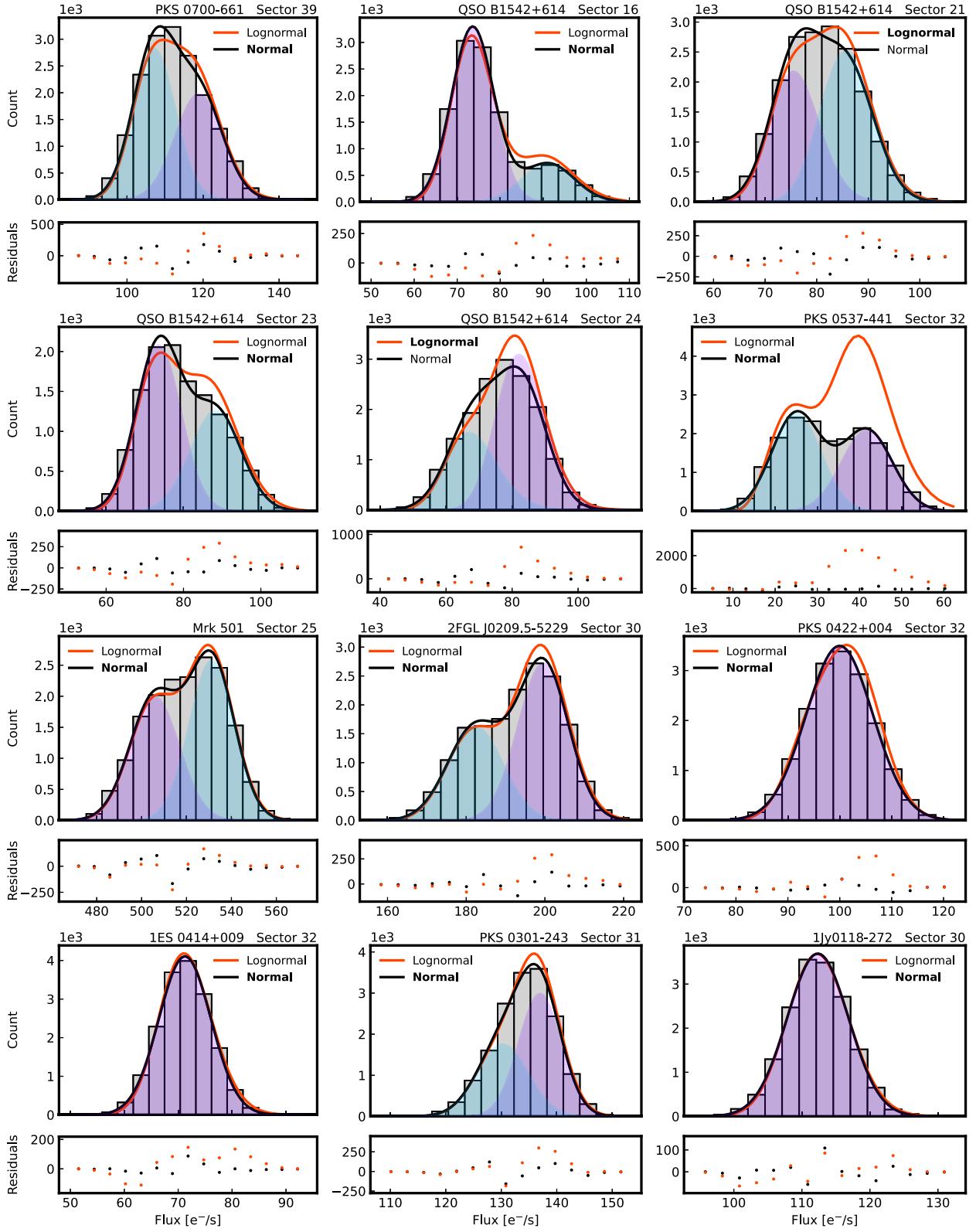


Figure 5a. Normal and lognormal PDF fitted on flux histogram for the selected light curves. The coloured distributions represent individual components of the best-fitting model (highlighted in the legend).

**Figure 5b.** (Continued.)

2013; Calafut & Wiita 2015). On the other hand, in hadronic models of blazars the synchrotron emission might have resulted from the secondary particles from the hadronic interactions, such as interaction of highly accelerated protons with the ambient photon or

particle fields (e.g. Mannheim 1993; Mücke et al. 2003). Besides the jet origin, a part of optical emission might have its origin due to the thermal emission from the accretion disc, especially in FSRQs.

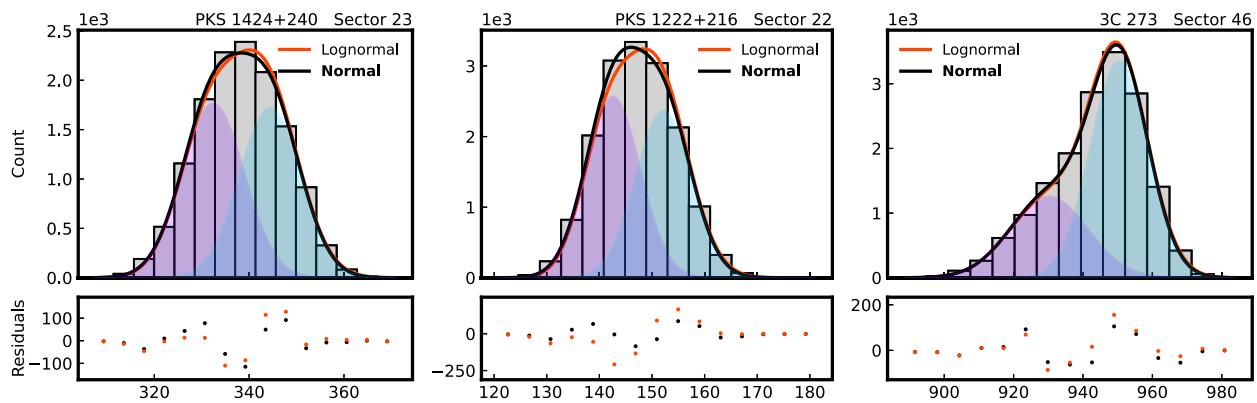


Figure 5c. (Continued.)

The observed optical variability might have been shaped by a combination of both the source intrinsic and extrinsic variable factors. In the source intrinsic cases, variability might arise due to magnetohydrodynamical instability in the jets or the disc, e.g. due to variable injection rates at the shock front (Bhatta et al. 2013; Xu et al. 2019; Webb et al. 2021), or due to intrinsic turbulent nature of the jet (Larionov et al. 2013; Böttcher & Baring 2019). In the extrinsic scenario, the observed variable flux could be a result of the geometric effects such as change in orientation, speed of the emission regions, and light crossing time-scales (see e.g. Raiteri et al. 2013, 2017; Bhatta 2018).

The results from the flux distribution analysis imply that majority of flux histograms are consistent with the bimodal normal PDF. This could be a clear evidence that the optical flux variability on time-scales of a few days are mainly contributed by two different emission zones e.g. disc and jet or two dominant turbulent regions in the jet. But it also can be speculated that the days time-scale flux modulations are driven by two distinct states of the activity in a localized region of the jet. Recent results reported by Mohorian et al. (2022) also clearly show bimodal normal flux distributions in the intraday X-ray observations of blazars Mrk 501, OJ 287, and RBS 2070. However, it should be noted that in a similar study using long-term optical observations Bhatta (2021) found that the flux histograms are consistent with mainly unimodal normal or lognormal PDFs. It appears that in the longer time-scales the observed bimodality gets smeared by the variable emission contributed by other components. As there are not many works that study the flux distribution in short time-scales, the results from this study utilizing largely uninterrupted observations from the space telescope are important in constraining the physics behind the short-term optical variability observed in blazars.

Power spectral density can reveal the stochastic nature of the variability in the form of combined emission from different realizations of a single/multiple noise-like processes. Under such a framework, the variability power spectrum can be characterized by simple power-law PSD shapes. The slope indices of the PSDs then estimate the variability amplitude over temporal frequencies. One of the primary goals of the study was to analyse the PSDs in search of the PSD breaks and potential QPOs with characteristic time-scales. Such time-scales corresponding to the observed break frequency can be linked to the physical parameters of the AGN system, e.g. size of the emission region, cooling time-scales, etc., that contribute to the observed flux variability. Similarly, QPOs in blazar could be conceived in several scenarios (see Bhatta 2019, for detailed discussion). However, we did not detect any significant PSD breaks in the *TESS* blazar observations.

Furthermore, a number of studies involving multiwavelength observations estimate the PSD and the corresponding slope index using mostly simple power law of the form of $P(\nu) \propto \nu^{-\beta}$: A study including long-term light curves of 31 blazars (Nilsson et al. 2018) estimated the average PSD slope of ~ 1.42 that is uncorrelated with the synchrotron peak frequency of the sources. Max-Moerbeck et al. (2014) in a study of the cross-correlation between the radio and the gamma-ray emission from blazar analysed 15 GHz radio light curves of a large sample of source and found the distribution of the PSD slope (spectral indices) centred around 2.3. In Gamma-ray studies using Fermi/LAT observations, the PSD slopes are found to be nearly 1.0 (Sobolewska et al. 2014; Meyer, Scargle & Blandford 2019; Bhatta & Dhital 2020). On the other hand, some works explore the jet emission models treated with computational methods. In a simplistic hydrodynamic simulation of 2D relativistic jets considering both intrinsic and extrinsic scenario, Pollack et al. (2016) observed that the PSD slopes for the bulk velocity produced variations was found to be steeper, ~ 2.5 , compared to the turbulence induced variations at ~ 2.0 . Furthermore, the study also indicated that when both intrinsic and extrinsic scenarios were considered together, the shorter time-scale variations were found to be dominated by the turbulent fluctuations contributions and the longer periods by the bulk flow changes. However, the result of Calafut & Wiita (2015) shows that the PSD slopes which are highly sensitive to the turbulent velocity are largely unaffected by the change in the viewing angle and bulk velocity. Similarly, in a more realistic case, O’ Riordan, Pe’er & McKinney (2017) based their model on turbulence in relativistic jets that are launched by magnetically arrested accretion flows (MAD) around a rapidly rotating supermassive black hole. The PSD of the modelled synchrotron and synchrotron self-Compton variable emission is in confirmation with the observed power-law spectrum at short-term time-scale. In the similar MHD simulation of large scale jets, based on MAD scenario, McKinney, Tchekhovskoy & Blandford (2012) found signatures of QPOs and PSD breaks in their simulations.

6 CONCLUSIONS

This work represents one of the first systematic studies of optical variability of blazars using observations that are nearly continuous in the time-scales of a few days. As a quantitative measure of the variable emission from the sources, we computed fractional variability of the sample sources, which spans a large range in percentage. For example, S4 0954+65 shows variability of 53.84 ± 0 per cent. The lowest variability percentage is seen in 3C 273 which is 0.82 ± 2 per cent. The average fractional variability is 13.44 per cent with an SD of

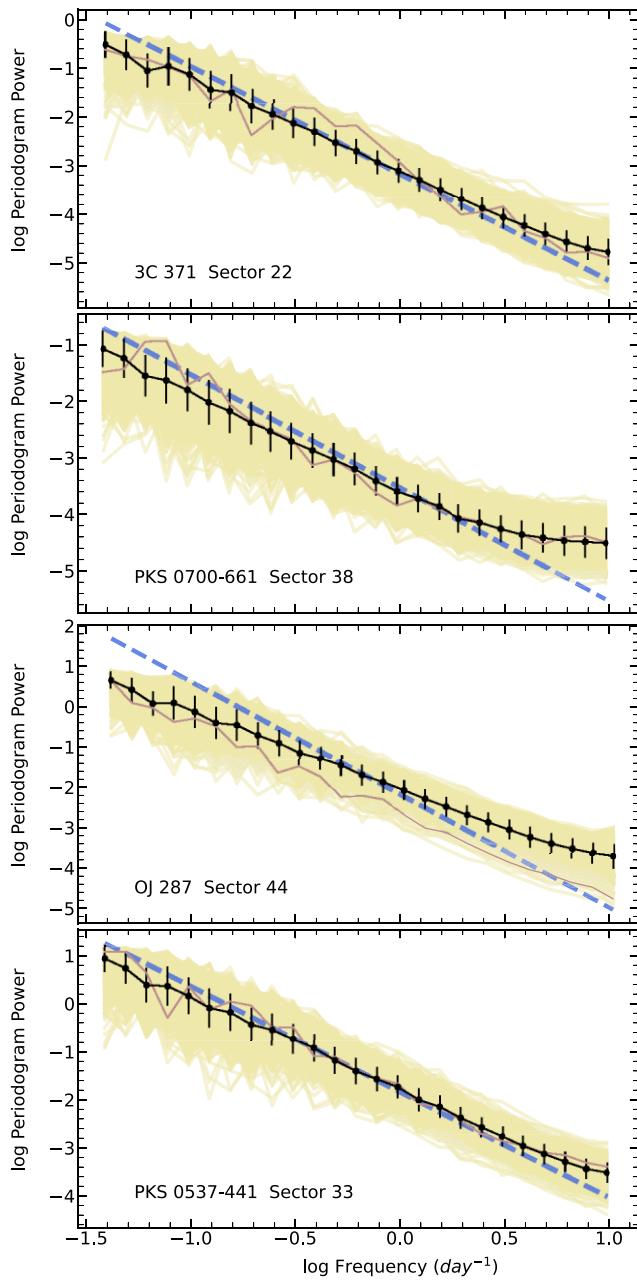


Figure 6. The best-fitting power-law models along with corresponding simulated light curve's PSD shown in relation with the observed PSD of few selected light curves. The black dotted line (with error bars) denotes the average PSD of the simulated light curves at the chosen power spectral index. The blue dashed line represents the power-law model. The pink line is the observed PSD. The yellow background is the enclosed space of 100 simulations at the chosen spectral index.

12.37 per cent. We investigated the nature of flux distribution of the optical flux of the sources by fitting the flux histogram with normal and lognormal PDFs, and performing statistical test. The lower AIC and BIC values for the normal PDF suggest that compared to the lognormal PDF, the normal PDF better represents the flux variability of the blazars. Furthermore, some of the sources reveal bimodal normal flux distribution, an indication of two dominant emission regions or states. We performed power spectral density analysis and estimated the power spectral slopes of the light curves. It is found

that the PSD is consistent with simple power-law model and the distribution of the slope indices is centred around 2.4.

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DATA AVAILABILITY

The paper includes data collected by the *TESS* mission, which are publicly available from the Mikulski Archive for Space Telescopes (MAST). Furthermore, the processed data will be shared on reasonable request to the corresponding author.

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⁶<http://www.astropy.org>

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APPENDIX A: LIGHT CURVES

This section provides some of the light curves of blazars shown in Table 2. These light curves contain SAP flux data that has not been quality flagged. The red crosses represent the outliers ignored during the analysis, based on 3 Sigma of 0.1 d bins.

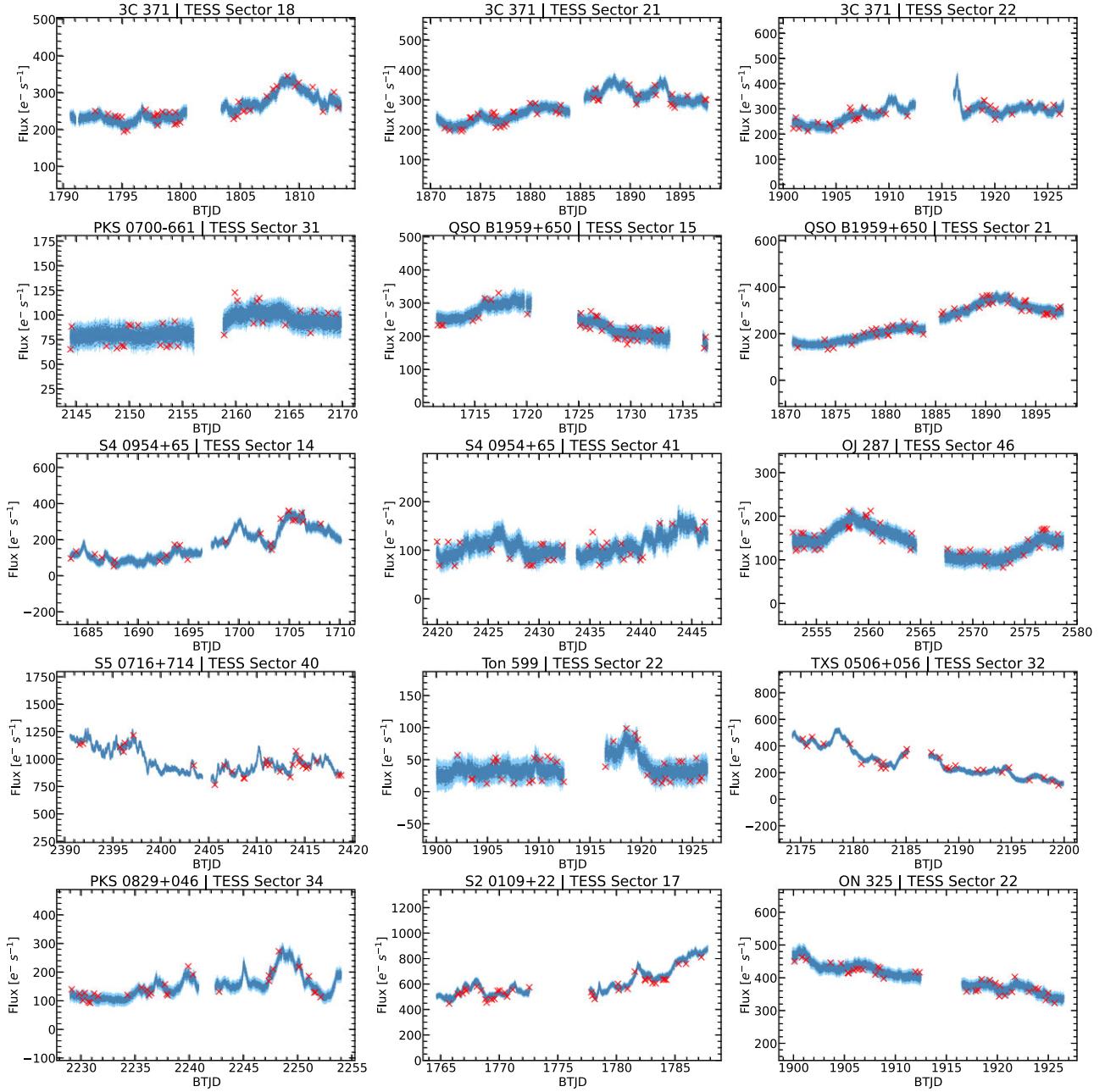


Figure A1. Some light curves from Table 2. The blue lines indicate the data that has not been flagged for quality issues while the red crosses indicate the outliers.

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