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Research Article

Peaks Over Threshold Method Application on Airborne Particulate Matter (PM_{10}) and Sulphur Dioxide (SO_2) Pollution Detection in Specified Regions of İstanbul

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Abstract

In this study, we investigate the application of peak over threshold (POT) method on extreme events which usually appears with low frequently but high effects. Daily averages of PM_{10} and SO_2 pollutants are measured at 5 permanent monitoring stations in İstanbul (Beşiktaş, Yenibosna, Alibeyköy, Esenler, Aksaray). The SO_2 and PM_{10} concentration data are obtained from İstanbul Municipality through a period from January 2009 to December 2015. Daily averages of the concentrations are analyzed by using peaks over threshold methods of extreme value theory and then predicted for the largest concentrations for the following 12 months. We find that POT methods can provide useful information about the occurrence of limit exceedances of air pollution in Istanbul and these models can easily be used to make short term predictions about limit exceedances. As a consequence, we can say that predicting the air pollutant levels of SO_2 and PM_{10} will be beneficial for the decision makers which help them to develop advanced policies to control and prevent the air pollution.

Key words: POT; extreme Value Theory; istanbul air quality; PM_{10}; SO_2

1. Introduction

Rapid industrialization and high population increase are the important contributors of air pollution and this is one of the greatest environmental problems of Turkey. İstanbul, which is one of the megacities in the world, located in the Marmara Region of Turkey and having the population more than 15 million, is severely affected from the air pollution. According to Kuzu an Saral (2017)], the conventional air pollutants Particulate Matter (PM_{10}), Carbon Monoxide (CO) and Nitrogen Oxides (NO_x) gradually increased from fall to winter during 2015 in Istanbul and they emphasized that several air pollution episodes were observed during this period. Çapraz et al (2006) indicated the relationship between air pollution and mortality in İstanbul between 2007–2012, and they reported that Sulphur Oxide (SO_2) was associated with the lfargest relative risk for deaths from cardiovascular disease, respiratory disease and total mortality in Istanbul.

Since 1980, The Ministry of Health of Turkey has monitored the pollution levels of PM_{10} and SO_2 within the projects conducted at Refik Saydam Hygiene Institute of Turkey [3]. Istanbul Municipality (IM), Department of Environmental Protection & Development has currently been monitoring the air pollutants and publishing the daily air quality reports from the observed data of the ten monitoring stations. Six of the ten monitering stations (Aksaray, Alibeykoy, Besiktas, Esenler, Sariyer, and Yenibosna) are located at the European side, the rest four of them (Umraniye, Kadikoy, Kartal and Uskudar) are in the Anatolian side of Istanbul. We used the data from five monitoring stations (Alibeykoy, Esenler,Yenibosna, Aksaray and Besiktas) (Figure 1). We prefered to use these stations' data due the high population incrase, rapid industrialization and urbanization in this region (Bader et al. 2006; Begueria, 2005). The aim of this study is to forecast the short term predictions about limit exceedances of PM_{10} and SO_2 pollutants in İstanbul and to investigate the application of peak over threshold method on extreme events which usually appear with low frequently but high effects.

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Figure 1: Air Pollution Monitoring Stations

2. Theoretical Background

The prediction of extreme concentrations of air pollutant and the assessment of their contribution to atmospheric pollution are so vital issue for environmental concern. Presence of extreme concentrations these substances causes lots of different problem such as serious risk to people health, greenhouse effect and it can trigger other environmental damages as a consequence. Extreme value theory (EVT) provides the statistical framework to make inferences about the probability of very rare or extreme events and it is a robust technique to analyse the tail behavior of distributions. The EVT was firstly developed by Fisher and Tippett (1928) and formalized by Gnedenko (1943) and applied in hydrology (Chock and Sluchak1986), engineering, insurance sector (Coles, 2001), and in the environmental applications (Cox and Chu 1993; Embrechts et al. 1997).

There are two fundamental approaches for applying EVT as follows: the Block Maxima (BM) method and the Peak Over Threshold (POT) method. BM is widely suitable for applying the Generalized Extreme Value (GEV) distribution according to Fisher and Tippett (1928) and Gnedenko (1943) and the GEV distribution unites the Gumbel, Fréchet and Weibull distributions into a single family to allow a continuous range of possible shapes. Figure 2 indicates the difference between these two approaches. The GEV distribution has a cumulative distribution function, but these 3 distributions were unified under the name Generalized Extreme Value Theory.

$$F(x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\} \qquad \xi \neq 0$$

(1)

$$\exp\left\{-\left[\exp\left(\frac{x-\mu}{\sigma}\right)\right]\right\} \qquad \xi = 0$$

(2)

In the Equation (1) and (2), μ is the location, σ is scale,and ξ is the shape parameter. GEV has a three form as follow:

If $\xi > 0$, it suits well with Frechet distribution.

İf $\xi < 0$, it suits well with Weibull distribution

If $\xi = 0$, it suits well with Gumbel distribution

POT method analyzesthe distribution of Generalized Pareto Distribution (GPD) exceedances above a specific high threshold. The formulation of thismethod with the three parameters, $G_{\mu,\varepsilon,\varphi}$ is shown below;

$$G_{\mu,\varepsilon,\psi}(y) = \begin{cases} 1-e^{-z} & \varepsilon = 0 \\ 1-(1+\varepsilon z)^{-1/\varepsilon} & \varepsilon \neq 0 \end{cases} \qquad (3)$$

$$\begin{array}{ll} z \geq 0 & \varepsilon \geq 0 \\ 0 \leq z \leq -1/\varepsilon & \varepsilon < 0 \end{array} \tag{4}$$

The Generalized Pareto Distribution (GPD) was employed by Pickands and Balkema (1974) and the application of the distribution was performed by Hosking and Wallis (1987). Bader et al. (2016) stated that under suitable conditions, exceedances over a high threshold have been shown to follow the generalized GPD asymptotically.

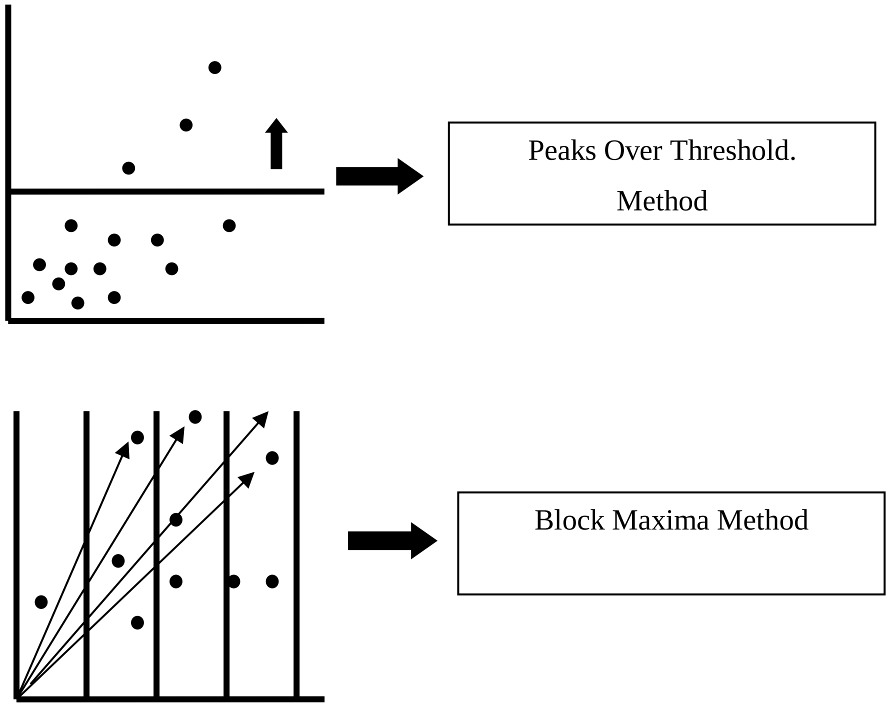

Figure 2: Differences between POT and BM

According to Ferreira and De Haan (2015) the POT method picks up all "relevant" high observations and the BM method on the one hand misses some of these high observations, and might retain some lower observations. BM method is also allowed to use only one data point in each taken block and this is depicted in Figure 2. As Bommier (2014) indicated that the second highest value in one block may be larger than the another block and POT method is a way to avoid this drawback, as the result the method uses the data more efficiently.

Numerous researchers used stastistical tests on air pollution episodes: Roberts (1979a) and Roberts (1979b) conducted the statistical tests on air pollution episodes and they reported the detailed review of EVT. They also demonstrated the extraordinary occurrences and explained that the trends should be removed in EVT applications. Surman et al. (1987) modeled the usefulness of EVT in the air pollution area for predicting violations of air quality standards. Smith (1989) also conducted study on EVT as a tool for detecting trend in ground level ozone concentration. Meanwhile, other researchers Cox and Chu (1993), Smith and Huang (1993), Smith and Shively (1995) have used EVT for forecasting the exceedances of high threshold ozone concentration. In Greece, it is noted that Abatzoglou et al. (1996) used EVT for projecting air pollution episodes in region of Athens. Gilleland and Nychka (2005) studied on ozone levels and they indicated EVT is a useful tool to monitor the ozone level. The application of EVT has also been studied by the following researchers: Horowitz (1980), Hosking et al. (1985), Chock (1985), Chock and Sluchak (1986), Smith, 1986 and Smith, 1989, Shively (1990), Jakeman et al. (1991), Sharma et al. (1999), Sfetsos et al. (2006) and Lu and Fang (2003).

It has been analyzed extreme values of daily air pollution data with distribution of monthly maxima and the distribution of maximum exceedances of a suitable threshold. For this purpose the generalized form of the extreme value distribution and the pareto distribution were used, respectively. EasyFit software is employed to conduct Q-Q plot and maximum likelihood estimation (MLE) analyses (Schittkowski, 2002) (Mehrania and Pakgohar,2014) respectively.

3. Methodology

The methodology of this study is sketched in Figure 3. The air pollution data were obtained from İstanbul Municipality, Department of Environmental Protection & Development, Directorate of Environmental Protection. Among them, daily average pollutant concentration data covers the time period from January 1, 2009 to December 31, 2015. The data were divided into two sets as follow: (i) the "development sample" from January 2009 to December 2014 and (ii) the "test sample" from January 2015 to December 2015 treating the latter as an unobserved data set in order to compare it with the predictions made using EVT with POT approaches.

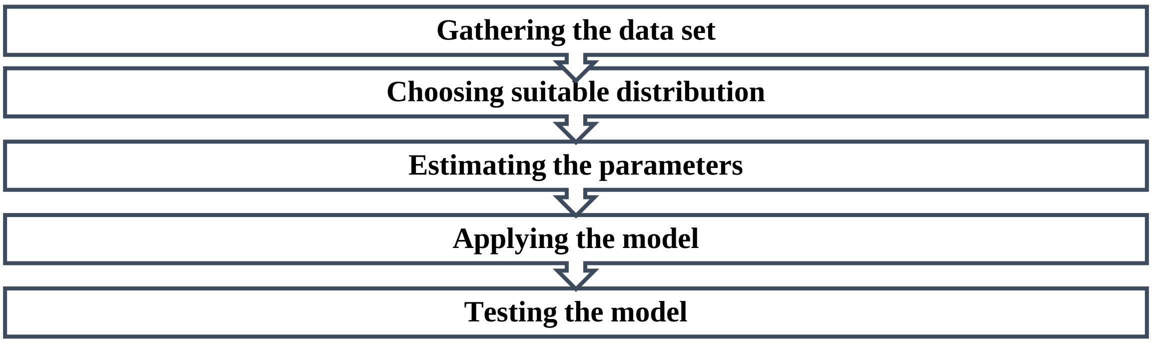

Figure 3: Applied methodology in the study.

Descriptive statistics are used to describe the basic features of the data set. In this study, we conduct decriptive statistics to provide simple summaries about the sample and the measures (Table 1). Some measures that are commonly used to describe a data set which are the measures of central tendency include the mean, while measures of variability include the standard deviation the minimum and maximum values of the variables.The values used for the descriptive statistics are the values which are used for obtaining the above the specific threshold “u”.

Table 1: Descriptive Statistics

Pollutant	Station	Sample size	Mean	Std. Deviation	Min.	Max
PM_{10}	Alibeyköy	179	111.24	23.7	85.2	214.9
	Beşiktaş	136	96,75	17,7	80,1	168
	Esenler	217	118,35	28,92	90,1	336.9
	Aksaray	203	116,45	24,92	90,1	226.1
	Yenibosna	148	152	42	110,2	329.6
SO_2	Alibeyköy	149	16.5	4.6	11.1	28.4
	Beşiktaş	161	13.23	5.26	9.1	41.5
	Esenler	465	10.18	4.99	5.4	31.3
	Aksaray	390	12.37	5.98	7.6	46.5
	Yenibosna	257	11.53	3.29	8.1	25.2

According to Gencay and Faruk (2004) in the extreme value theory and applications, the QQ-plot (quantile–quantile plot) is typically plotted against the exponential distribution to measure the fat-tailness of a distribution and if the data is from an exponential distribution, the points on the graph would lie along a positively sloped straight line. Moreover, if there is a concave presence, this would indicate a fat-tailed distribution, whereas a convex departure is an indication of a short-tailed distribution. QQ plots, together with simulations to provide an objective measure of goodness of fit, are used to show that these models fit the data well. As the result, Gencay and Faruk (2004) concluded that a visual inspection of the QQ-plots werealso helpful to determine a range for the threshold values. Based on the results reached by Gencay and Faruk (2004), the Figure 4 to Figure 13 shows that the Q-Q plot values for the exceedances of PM_{10} and SO_2 for the 5 stations are suitable for the prediction. The results also indicate that POT models can provide useful information about the occurrence of limit exceedances of air pollution and they can be used to make short term predictions about limit exceedances.

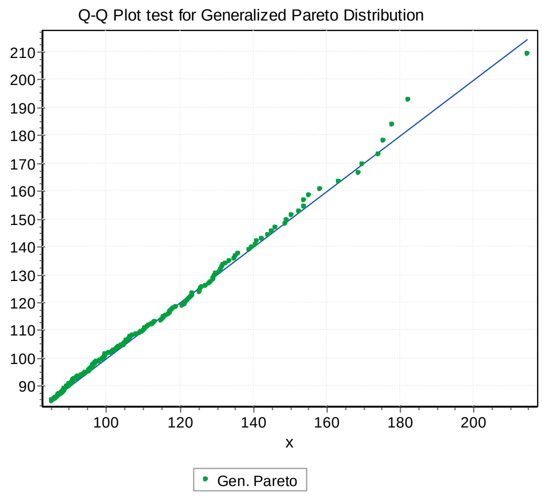

Figure 4: Q-Q plot for PM_{10}- Alibeyköy

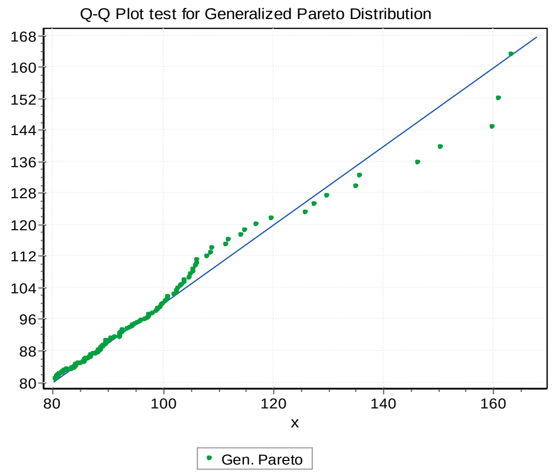

Figure 5: Q-Q plot for PM_{10}-Beşiktaş

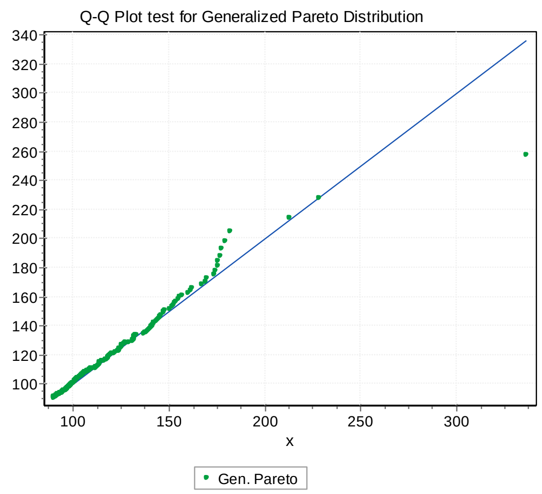

Figure 6: Q-Q plot for PM_{10} -Esenler

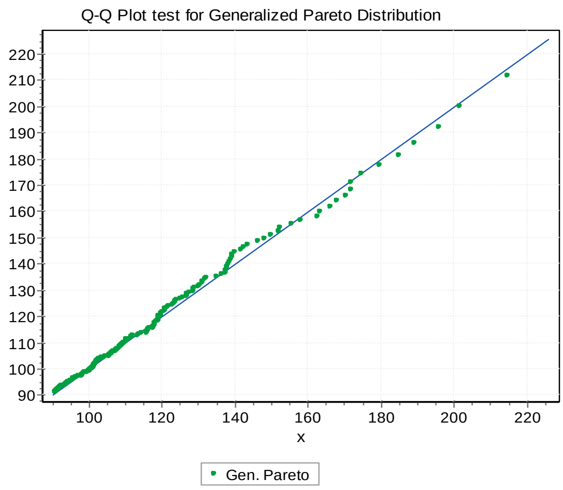

Figure 7: Q-Q plot for PM_{10} -Aksaray

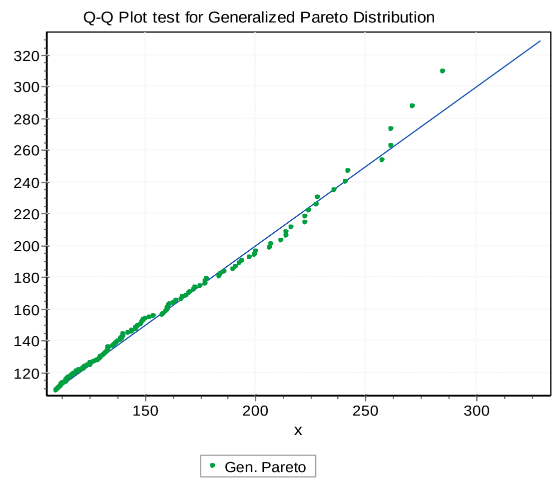

Figure 8: Q-Q plot for PM_{10} -Yenibosna

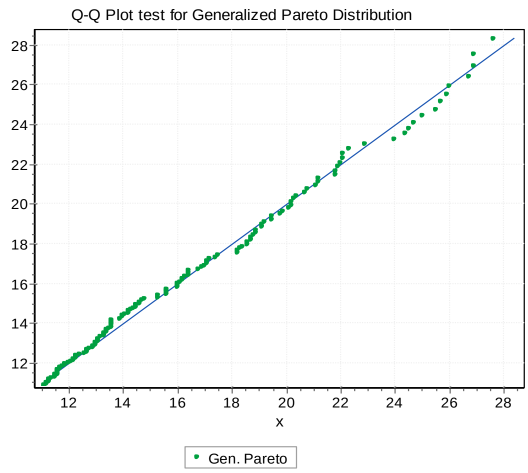

Figure 9: Q-Q plot for SO_2- Alibeyköy

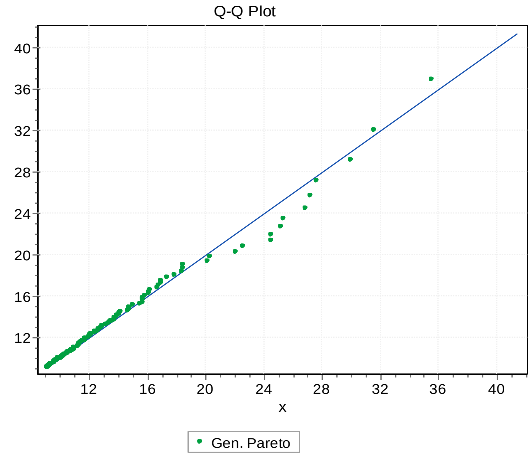

Figure 10: Q-Q plot for SO_2 -Beşiktaş

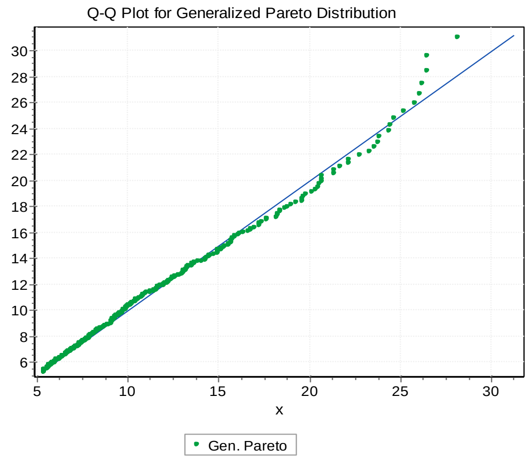

Figure 11 : Q-Q plot for SO_2-Esenler

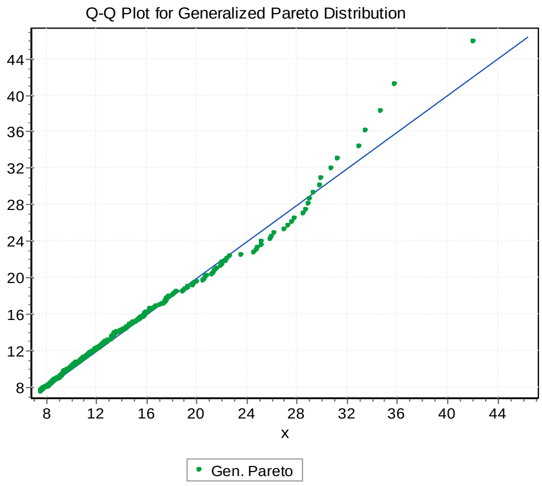

Figure 12: Q-Q plot for SO_2

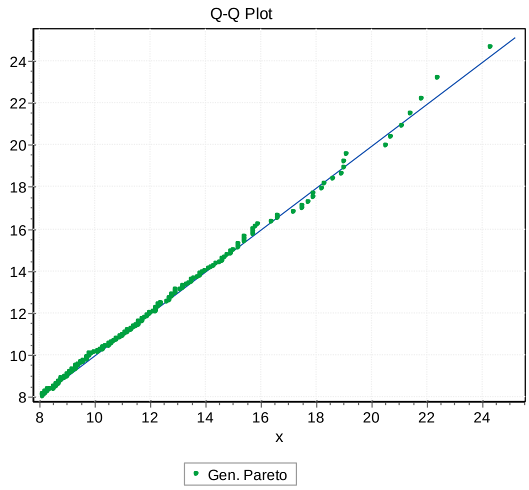

Figure 13: Q-Q plot for SO_2

We applied one of the main the iterative parameter estimation algorithm which is known as Maksimum Likelihood Estimation (MLE). This technique is usually preferred since they are asymptotically normal cases so it was used in this study for parameter estimation (Jae Myung, 2002). We analysed the extreme values of daily air pollution data with distribution of maximum exceedances of a suitable threshold. Selecting an appropriate threshold is a major problem for the POT method. As Coles (2001) indicated that too low a threshold is likely to violate the asymptotic basis of the model; leading to bias; and too high a threshold will generate too few excesses; leading to high variance. Here lies the idea is to pick as low a threshold as possible subject to the limit model providing a reasonable approximation (ISSE, 2009). GPD is a family of continuous probability distributions and this is specified by three parameters: location, scale, and shape which are presented in Table 2 for the whole stations.

In our study, Kolmogorov-Smirnov, Andersen-Darling were used in order to select the most appropriate distribution function for our data sets. As stated by Bader (2016) set of thresholds through the goodness-of-fit of the GPD for the exceedances were employed, and the lowest one, above which the data provides adequate fit to the GPD was selected. Then these values were checked with the Kolmogorov Smirnov and Anderson Darling tests, respectively (Table 3). The wrong selection of the threshold values will lead to obtain meaningless results related with the forecasting of the future predictions. Similarly indicated by Coles (2001), there is no theoretical approach lies behind of this selection.

Table 2: Threshold values and parameters

Pollutant	Station	μ(location par.)	σ(scale par.)	k (shape par.)
PM_{10}	Alibeyköy	84.41	30.3	-0.12
	Beşiktaş	80	14.75	0.09
	Esenler	90.18	28.52	-0.01
	Aksaray	90.56	26.8	-0.03
	Yenibosna	108.16	44.95	-0.011
SO_2	Alibeyköy	10.74	7.28	-0.25
	Beşiktaş	9.05	3.12	0.25
	Esenler	5.23	4.73	0.04
	Aksaray	7.53	4.74	0.12
	Yenibosna	7.06	3.7	-0.05

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Roberts (1979) and Sharma et al. (2012) reported that for data to be adequately represented by the theory of extremes, extraordinary occurrences and the trends should be removed. Linked with the Robert (1979) and Sharma et al. (2012)'s findings, in this study some extraordinary occurrences were removed and more effective predictions were occurred.

Table 3 presents the predicted and observed number of exceedances for January 2015 and December 2015 periods at 5 permanent monitoring stations in Istanbul. We found that some of the exceedances belong to monitoring stations' prediction are near to observed number of exceedances. By using these predictions one can make arrangements for the next term applications.

Table 3:Predicted and observed number of exceedances for 2015

			Number of exceedances in 2015	
		Over below values(mg/m^3)	Predicted	Observed
PM_{10}	Alibeyköy	**80$^+$**	12	10
	Beşiktaş	**85$^+$**	18	17
	Esenler	**120$^+$**	12	16
	Aksaray	**90$^+$**	14	13
	Yenibosna	**125$^+$**	18	20
SO_2	Alibeyköy	**5$^+$**	14	14
	Beşiktaş	**14$^+$**	11	10
	Esenler	**11$^+$**	16	17
	Aksaray	**12.5$^+$**	18	17
	Yenibosna	**12$^+$**	12	14

4. Discussions

There are two important issues which must be solved out when using the POT approaches. These are the selection of the threshold *u* and the minimum time span Δ*t* that will be required to assume the independence of for the events Coles (2001), Beguería (2005), Luceño et al., (2006). An important assumption of the classical EVT refers to the stationarity of the model, which implies that the model parameters do not change over time. This is related with the assumptions made by Coles (2001), Beguería (2005), Luceño et al., (2006). The usual way to make this assumption is known as declustering method illustrated by Coles (2001), and it is performed in this study.

Rieder (2014) concluded that selection of a threshold values involve a delicate trade-off between bias and variance and too high a threshold will reduce the number of exceedances . As the result, Rieder's (2014) finding concludes that the increase at the estimation variance and the reliability of the parameter estimates, whereas too low a threshold will induce a bias because the GPD will fit the exceedances poorly. Therefore, in this study, different threshold values produced with Q-Q plot test and thenconfirmed with Kolmogorov Smirnov and Anderson Darling Tests to make the accurate prediction.

The EVT concepts introduced a build on the assumption of independent identically distributed variables (Rieder, 2014). Added to that we know in practice most extreme values arise from a series of dependent observations. The prediction which could have made using BM, would be affected by the trend impact and the lack of the data might be appeared. As the reason, using of POT method in this study does make a sense. Furthermore, we noticed Kysely et al (2010) used POT approach in their study to estimate the extreme cases in climate change situations and they explained that POT approach is reasonable from the climatological point of view because high temperatures affect society and environment in an absolute rather than relative sense.

5. Conclusion

The presence of high concentrations of PM_{10} and SO_2 can be considered as one of the most important issues regarding with air quality. Forecasting the air pollutant capacity levels of PM_{10} and SO_2 and lovering their severity for the community health and the environment should be the main purpose of policy makers and the scientific community.

One of the main conclusions of this study is PM_{10} and SO_2 are the significant air pollution sources and they alter the air quality in Istanbul. The results also indicate that POT models can provide useful information about the occurrence of limit exceedances of air pollution and these models can easily be used to make short term predictions about limit exceedances.The results obtained with the theory presented in this study may be quite helpful for the future researchs which will be conducted in the dense populated locations in İstanbul. We also belive that the findings of this study can allow to develop advanced policies that aim to control the air pollution in Istanbul.

6. Acknowledgements

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