Received: 18 December 2023 | Revised: 18 February 2024 | Accepted: 19 May 2024 | Published online: 29 May 2024

RESEARCH ARTICLE

Green and Low-Carbon Economy
2024, Vol. 2(4) 310–324
DOI: 10.47852/bonviewGLCE42022327

BON VIEW PUBLISHING

Electricity Demand, Forecasting the Peaks: Development and Implementation of C-EVA Method

Petros Theodorou[1,2,*] **and Demetris Theodoros Christopoulos**[3]

[1]*Athens University of Economics and Business, Greece*

[2]*Public Power Corporation SA, Greece*

[3]*Department of Economics, National and Kapodistrian University of Athens, Greece*

Abstract: Price spikes in electricity markets are very frequent, posing tremendous burden on household income and on manufacturing cost. Electricity demand (load) can be divided into two parts, energy (MWh) and peak (MW), and most of the time peak is responsible for the price spikes. Literature review while devoting most of the discussion to energy lags in the investigation of peak. In this research, a model for peak demand analysis and forecasting is developed. The model is based on a portfolio of cluster and extreme value analysis (C-EVA) methods using unit invariant knee, extremum distance estimator, and weighted scale load innovations for the optimal determination of clusters and the daily peaks divulgence. The C-EVA method consists of the clustering part for an optimal number of clusters determination and classification of day and month of peak and the part of EVA for computation of the statistical confidence interval for the load maxima. C-EVA, after using all the currently available load maxima, estimates statistically the expected worst-case scenario for peaks of loads. Load peaks will be determined by EVA based on an estimated bimodal distribution, while a signaling method will prompt the probability of extremes. The added value of the proposed method is that it does not reject the extreme values as most methodologies do. EVA for maxima and minima provides estimators for the highest and the lowest expected hourly load, while giving the confidence interval of the return level using an optimization method for the selection of a rolling time window, as the return period. It was found that distributed generation of renewables creates a camel effect on the load peaks which increases sharpness. The proposed methodology solved this issue while opening the ground for future research for the role of storage, batteries, as well as for virtual power plants as an integrated portfolio of renewables generation.

Keywords: electricity load, demand, extreme value analysis, cluster, camel effect, peak forecasting, energy markets

1. Introduction

Peak load forecasting is of high significance for electric utilities as their cost structure is inelastic, inflexible in relation to demand variations. This inflexibility is derived from the structure of fuel procurement which is (the highest operational cost) based on take or pay clauses and high investment cost (CAPEX). The uncertainty of future power delivery at a competitive price increases the need for an accurate profiling of demand and expectations. Accurate representation of demand expectations is a prerequisite for trading forward, for implementing efficient risk management and hedging programs, and for the market integration of renewable resources through the model of virtual power plant operation. The stochastic and intermittent nature of renewables increases the need to alleviate the extreme peak load (demand) through flexibility [1], as well as other demand-side actions. This is why there is increasing need for the virtual power plants (VPP) scheme, to realize flexibility through aggregation, optimization, and control of renewables as well as other resources that belong in different geographical areas. VPPs have the capability to standardize the aggregation of such dispersed renewable sources along with controllable loads, energy storage devices, and other distributed generation (DG). This aggregation is made within integrated portfolios through optimization and control. In order not to abstract from our main subject, the readers who need more information on VPPs and DG can read the works of Gao et al. [2], and Naraindath et al. [3].

Electricity load forecasting can be divided into two parts (a) energy and (b) peak forecasting. Energy forecasting is relatively simpler and of lower risk (repetitive seasonal patterns) compared to peak forecasting, especially if the availability of dispatching units is guaranteed in low LOLP (loss of load probability) situations (high reserves). Peak is the most important part of demand as it triggers price spikes of high magnitude within seconds. Spikes surpass significant parts of cost in a short time and generate high premiums. Peak forecasting methods can be used complementary to energy forecasting and provide more accurate signal for capacity addition (CAPEX needed). If capacity covers the peak, then inevitably volumetric load (integral) will be covered as well; by the minimum realized costs. Furthermore, apart from capacity additions, peak forecasting determines the

*Corresponding author: Petros Theodorou, Athens University of Economics and Business and Public Power Corporation SA, Greece. Email: theodorou@aueb.gr

appropriate level of reserves to minimize the loss of load probability and guarantee normal system operation. Peak forecasting is an essential input to energy forecasting, since in business practice, the long- and medium-term expansion forecasts energy as a function of peak. Finally, peak is of high risk since it is heavily affected by externalities that humans cannot easily predefine or affect. That is why most of the time reserves are kept at high levels producing high costs for the system. But even though the significance of peak forecasting is very high, most of research discussion devoted only on the energy part of forecasting, and very few studies have been focused on peak, which is why this work is very significant as it covers a gap in the literature.

The set of methods found in electricity demand forecasting literature mostly belongs in the fields of time series, AI and Neural Nets (AI&NN). AI&NN optimize various combinations of time series methods by using the criteria of error minimization of cost dispatching. Methods used include time series (e.g., parameterize functions), pattern recognition, quadratic estimation, weighted multimodel, or advanced informatics like expert systems, artificial and neural networks, fuzzy logic, and wavelets. Most of the studies focus on the identification of the factors that affect the load. Time series models assume regularity of consumption over longer periods, proclaiming that load exempts random behavior. In the actual market operation, the random behavior of load (mostly derived from peaks uncertainty) is largely hedged by reserves and dispatching merit orders which both significantly increase the cost of the system. This hedging cannot cease the gap and the importance of forecasting peak's uncertainty. Hedging with reserves and merit order cannot absorb the effects by all operating hours as well as the significant variation leveraged by the spillover (transfer) of uncertainty in the fuel procurement (significant cost penalties). Moreover, time series methods and NN heavily rely on historical data, which are distorted by the shortage of generation and the low reserve margin. In our sample, this has been the fact for 3 years 2005, 2007, and 2008. All those methods have the restriction that the dataset must comply on a number of design features which are described in detail by Bunn [4]. Those restrictions and the relevant "statistical handling" (seasonality, detrending, distributional properties, etc.) lead to overweight the average of load and exclude data that contain the risk and volatility, restricting the explanatory power of forecasting extreme values. Time series statistical tests ultimately result in dropout extreme values (with filtering techniques) and analyze values around the mean. Thus, nothing has been done so far to extract from raw load information regarding the extreme values.

Suggested methodology will focus on peaks and the extreme values of the univariate daily hourly loads, filling a research gap by adding the methods of cluster and extreme value analysis [5–7]. The developed model will extract all available information from the load as well as the inherited risk and volatility pertained in peaks and lows. The purpose of the proposed model is through the clustering of load values through the separation of high and low extremes to proceed through the extreme value analysis on the estimation of peaks magnitude and generate relevant alert signals. Clustering will aid the separation of the "normal components" from the random components that belong in the max or min extremes. Innovative methods will be applied to determine the optimum number of clusters and to aggregate hourly daily maxima.

The sections that follow are (a) the literature review, (b) the research methodology, (c) descriptive analytics, (d) cluster analysis, (e) extreme value analysis, and (f) daily extrema as spike alerts. Finally, conclusions will be drawn at the end.

2. Literature Review

Literature on load and peak forecasting can be clustered according to time, for example, short, medium, and long term. Another distinction can be made in the following categories: (a) the conditional modeling approach, generally based on macroeconomic variables like inflation, GDP, and Forex [8–12], (b) the system indicators of the electrical distribution and transmission system, such as the number of connections and machinery capacity [13–18], (c) the historical modeling approach [9, 19], and (d) hybrid models [20, 21]. Finally, literature can be clustered around the method used, a distinction used by Weron [22] in the disciplines of (a) time series analysis-statistics [8, 21, 23, 24], (b) informatics or computational intelligence, and (c) hybrid models [25–28].

The statistical techniques related to time series include pattern recognition, quadratic estimation, probabilistic modeling, and weighted multimodel forecasting [5, 29–31] of which most focused on the impact of weather [8, 9, 24, 32]. Regarding time series, the most used models for load forecasting are those of regression and autoregression. Regression methods used in load forecasting include linear, nonlinear, logistic, nonparametric, stepwise, and partial least squares [32–34]. Autoregression models (mostly univariate) include autoregressive moving average (ARMA), ARIMA with exogenous (ARMAX), autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), vector autoregression (VAR), Bayesian VAR, and GARCH [20, 35–37]. Furthermore, it is worth mentioning the studies of Saqib et al. [38], Candila et al. [39] and An et al. [40].

The computational intelligence models utilize in load forecasting expert systems, artificial intelligence [41, 42] neural networks [43–47], fuzzy logic and wavelets, and ICEEMDAN-GS-WT-LSTM-ISSA [15–17]. Usually, most of the computational intelligence models are used to calibrate parameters in time series. Santos et al. [48] used artificial neural network (ANN) with standard feedforward backpropagation algorithm for structuring the model as well as the hyperbolic tangent function for learning purposes. Hippert et al. [49] identify the increasing complexity in many forecasting methodologies on the population of factors that affect consumption. Amjady and Keynia [50] point to the low interpretive value of adding many factors and complexities, cancelled by the regularities already inherited in univariate time series. Models of cooperative ant colony optimization genetic algorithms are also utilized in load forecasting [35, 51] as well as Gray prediction models [52]. Genetic algorithms have also been utilized in conjunction with particle swarm optimization (PSO) [20, 53], as we will also present in the discussion about hybrid models.

Hybrid forecasting methods have been developed by mixing neural networks, evolutionary algorithms, and time series (autoregression) models [20, 21, 50]. Crone and Dhawan [54] evaluate the performance of multilayer perceptron in forecasting synthetic time series (with different forms of seasonal and trend components) in order to evaluate the sensitivity of various architectural choices, in neural networks forecasting. Multilayer perceptron is the most frequently used method in neural network time series for load forecasting [15, 35, 55]. Eventhough some studies refer to the higher performance of hierarchical models in relation to multilayer perceptron as concerns the peak load forecasting [56]. Support vector machine (SVM) models have been mixed with least square methods for better prediction [57, 58]. Abductory inductive mechanisms (AIM) and group method of data handling were also used for iterated multiphase polynomial regression. This portfolio of methods summarized that (AIM) forecasting performance is increased by applying regression models alone [59]. Support vector regression (SVR) models are combined with stimulated annealing and chaotic genetic algorithms for improved forecasting performance [60]. Furthermore, firefly-based memetic algorithm used to determine SVR parameters [61]. Load forecasting ability of ARMAX models has been enhanced by evolutionary algorithms and PSO [62]. PSO combined also with moving average models to determine the weights of the coefficients while minimizing mean absolute percentage error of the load forecasting function [63]. PS also combined with ant colony optimization for the enhancement of forecasting performance [64]. Ant colony optimization combined also with SVM for short-term load forecasting [65, 66]. The gravitational search algorithm was also used in conjunction with regression and Kohonen neural network [67]. Immune algorithm was utilized for the parameter selection of an SVR model [68, 69]. Appropriate parameter combination in SVR and SVM models was also enhanced by simulated annealing algorithms [16, 59, 68, 69].

From the above presentation, it can be concluded that nothing has been done with a focus on peak demand forecasting, leaving a gap in literature (which this study attempts to cover). Moreover, nothing is referred to about the portfolio of models suggested by the methodology of this study (cluster and extreme value analysis (C-EVA)).

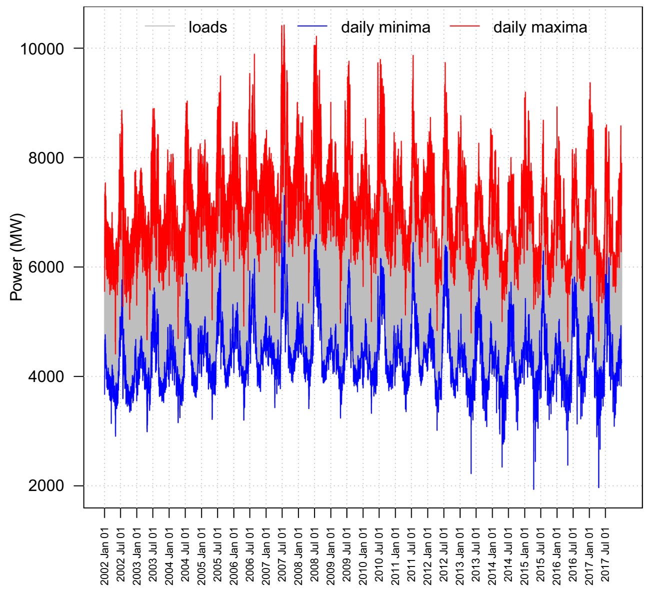
3. Research Methodology

As previously mentioned, after a brief description of the sample and relevant data analysis, we will proceed with descriptives regarding the density estimation and the probability density function to finalize the load duration curve and the DGE effect. The C-EVA method consists of two parts: the clustering and the EVA. The first part is used for determining the optimal number of clusters by classifying the month and day of the peak, while the second part involves computing the statistical confidence interval of the load maxima. By determining all the currently available load maxima, C-EVA statistically estimates the expected worst-case scenario for peak loads. The fundamental essentials of the EVA method can be found in Coles [70, 71]. The season, month, and day and hours where peaks mostly appear (historically) are estimated by using a first-time applied metric, the weighted scale load (WSL). The WSL was developed specifically for this research to identify the daily hours of high load and aggregate hourly daily maxima. WSL is calculated by dividing the mean by the standard deviation and considering the relevant frequency of occurrences (Equation (2)). The calculations are provided in Table 9. The innovative method of UIK point will also be utilized for the optimal cutting of clusters. Having determined (by use of optimal clustering) the time, month, and day the peaks mostly appear, we will proceed with the EVA to determine the bandwidth of MW in which the system might operate in the worst-case scenario. Alert metrics will be developed for peak signaling purposes. By combining the results of clustering and EVA will determine the magnitude of peaks. Estimators will be generated for peak alerts, and benchmarking of the estimators will also be provided. It is worth mentioning that the extremum distance estimator (EDE) method is a statistical estimator of the inflection point which computes the two slanted maxima from the chord that connects the initial and final point of a sigmoid curve (more analysis on the subject, mathematical formulations, definitions, explanatory figures, and examples can be found in https://doi.org/10.48550/arXiv.1206.5478). The unit invariant knee (UIK) method is an estimator of the "knee" or "elbow" point for a strict convex or concave curve whose estimate is made by the EDE method (more analysis on mathematical formulations, definitions, explanatory figures, and examples can be found in https://doi.org/10.2139/ssrn.3043076) [72, 73]. For the reader who need a deep dive into extreme value theory, information can be found in Coles [70, 71] and in Elsevier's heuristic and machine-learning monitoring of the topic (https://www.sciencedirect.com/topics/mathematics/extreme-value-theory).

4. Descriptive Analytics

The data used represent the net real load as an hourly average in MW per day from 2002 to 2017 of the Greek interconnected system. This dataset excludes pumping and distributed generator consumption, as well as all types of demand from decentralized producers located close to the load. The data matrix is given in Figure 1 (140256 h X 5844 days):

Figure 1
Hourly load



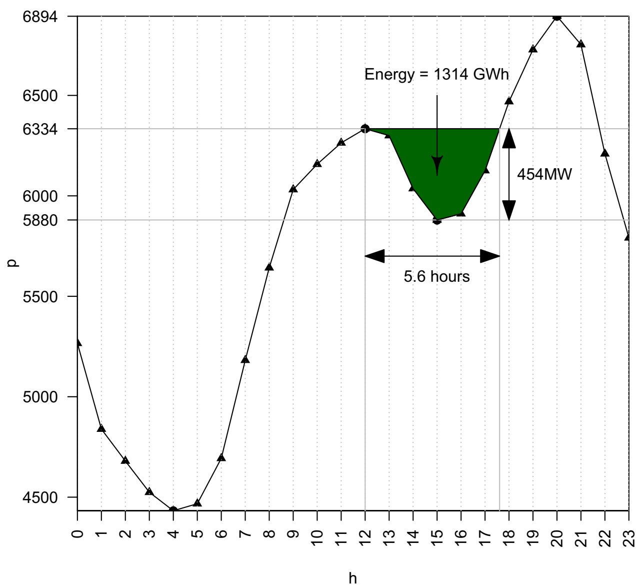
The database included the consumption of high-voltage consumers, mines, self-consumption of producers, consumption metered at substations in systems' borders (with distribution), as well as the system losses (metered over the Greek interconnected network). At this point must be mentioned that after 2004 energy demand at distributions' substations, decreased, due to the emergence of DG (photovoltaics connected in low and medium voltage). The same effect for the peak (of net load) started later around 2009 along with the macroeconomic crisis. This effect, termed as the DE effect (DGE), is the primary reason for the significant decrease in demand (metered at the limits borders of transmission with distribution). By the end of 2016, the installed photovoltaic capacity was approximately 2400 MW (2623 MW at the end of 2017, installed in the Greek interconnected system) of which the most in low and medium voltage (LMV). This capacity is expected to expand drastically in the coming years, along with the corresponding DGE effect. The historical effect of DGE on demand is also significant especially for the decade after 2006 when its contribution to total net energy demand rocketed from 393 to 4374 GWh an annual compound growth rate of approximately 28% (1105% for the whole period). Similarly, the compound effect on annual peak growth was 12% for a 7-year period (the significant part of the effect started 5 years later than that of energy) and up to 221% since the start of the period.

In Table 1, we observe both the demanded energy (volume) and peak. It can be noticed that in 2011, 2012, and 2015, the DGE effect was at its highest level. DGE covers a significant part of peak demand, which might be of the magnitude (sometimes larger) of a conventional CCGT capacity. In the diagram below, we can see that for the years 2002–2017, the DGE phenomenon starts at 12:00 and ends around 18:00, with an average capacity of 454 MW, measured as the distance from the previous change in concaveness (Figure 2).

Table 1
DGE

Year	DGE on energy GWh	DGE on peak MW
2006	393	0
2007	437	0
2008	635	0
2009	1054	47
2010	1216	78
2011	1423	237
2012	2322	703
2013	4214	397
2014	4462	171
2015	4714	618
2016	4734	151

Figure 2
Camel effect



In Figure 2, the camel effect is evident, signifying 2 local peaks affected by the net contribution of renewables, approximately 456 MW or 1314 GWh. The overall peak from the cumulative perspective is depicted below (duration curve in Figure 3):

Figure 3 presents a peak approximately 2912 MW higher than base load, which is up to 1913 MW. It can be noticed that the middle load spread with peak since 2013 has started to decrease, but the percentage of peaks since 2011 has increased drastically, pulling the middles upward as well. This evidences the sharpness of peak and its importance regarding the volumetric demand (Figure 4).

Figure 3
Load duration curve

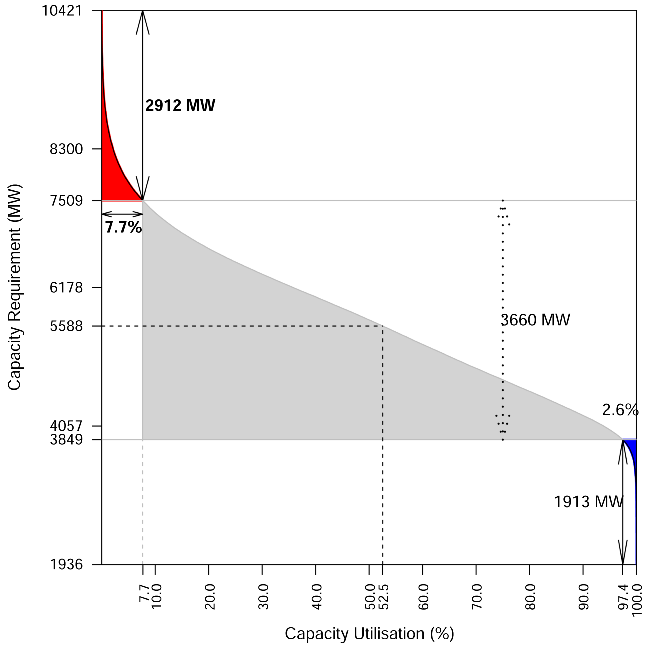
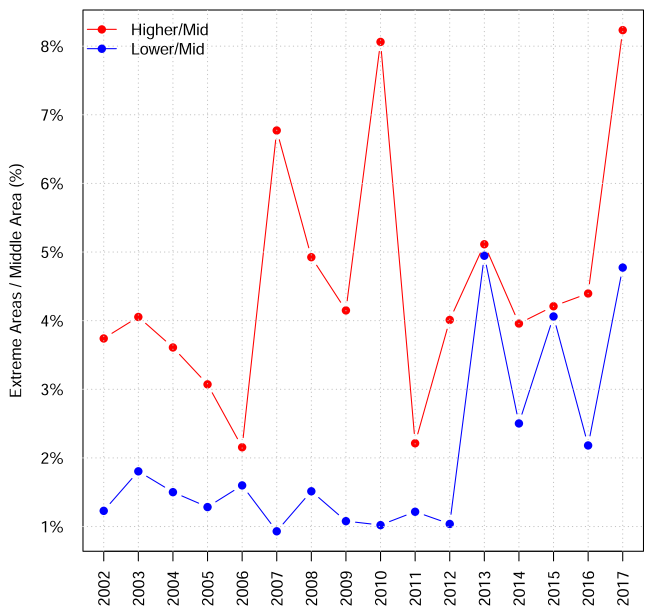


Figure 4
Load duration curve extreme areas/middle area (%)



At the end of 2016, a capacity of up to approximately 5 GW renewables was installed with wind and photovoltaics comprising the majority. Permissions suggest that this capacity could be increased up to 30 GW for the entire country. According to the Greek TSO (ADMIE) 10-year development study projections (May 2017), the installed renewables capacity is expected to approximately double, with a larger peak in the forefront and a compound growth rate of up to 7% p.a for the decade following the release of the study. The historical 5-year monthly average capacity factor up to 2016 (for all Rens) was approximately 33% with a 15% dispersion above and below the mean. With such high rates of renewables penetration, the DGE effect will certainly increase. The influence of DG and energy storage on the power system, specifically on the peak, is analyzed in the work of Ufa et al. [74]. Ufa et al. [74] represents this influence by the duck curve and the concept of peak saving, as well as leading/lagging power factor. The effect of energy storage and DG on the power system's uncertainty and volatility is presented in Pothireddy et al. [75]. The assessment of storage potential as a peaking capacity resource is provided in Frazier et al. [76] and Cole et al. [77]. For further depth and breadth on the influence of DG and energy storage, readers can explore relevant topics on ScienceDirect monitored by heuristic and machine-learning algorithms. (https://www.sciencedirect.com/topics/engineering/distributed-energy-resource and https://www.sciencedirect.com/topics/engineering/energy-storage-technology).

Finally, it should be noted that our dataset for the years 2005, 2007, and 2008 does not include load cuts that have been made. Estimates suggest up to 165 MW, 500 MW, and 150 MW, respectively. In Table 2, an estimation of the peak is provided under the assumption that load cuts have not been made:

Table 2
Estimated peaks with load cuts

Year	Load cuts MW	Estimated peak MW
2005	165	9651
2007	500	10911
2008	150	10367

Following the historical values given above, we conclude, in Table 3, that the average forward estimation of all scenarios taken by the TSO's for the load peak along with its dispersion around the mean. The estimations below include transmission losses and the generation of dispersed production (DGE effect). What can be observed is the drastic increase of risk over time, ending up at the capacity level of an average CCGT station (Figure 5). Thus, in the earlier timeframe, the risk inherited in the peak is at a magnitude of 30–100 MW and can be covered by a small turbine. However, at the end of the timeframe, the magnitude skyrockets to 400 MW, equivalent to a CCGT station (with a CAPEX of up to 200–250 M€). Therefore, in terms of capacity additions, and considering that depreciation is more than 20 years for such a size of CAPEX, it is very significant to have a concrete long-term view in order to avoid idle and sunk costs from many small installations (refer to Table 3).

Table 3
Yearly risk of DGE effect (MW)

Year	Average	Risk
2017	9869	30
2018	10076	65
2019	10260	110
2020	10593	145
2021	10700	190
2022	10773	235
2023	10842	278
2024	10910	325
2025	11520	375
2026	11603	430
2027	11690	470

Figure 5
Camel effect PDF estimations

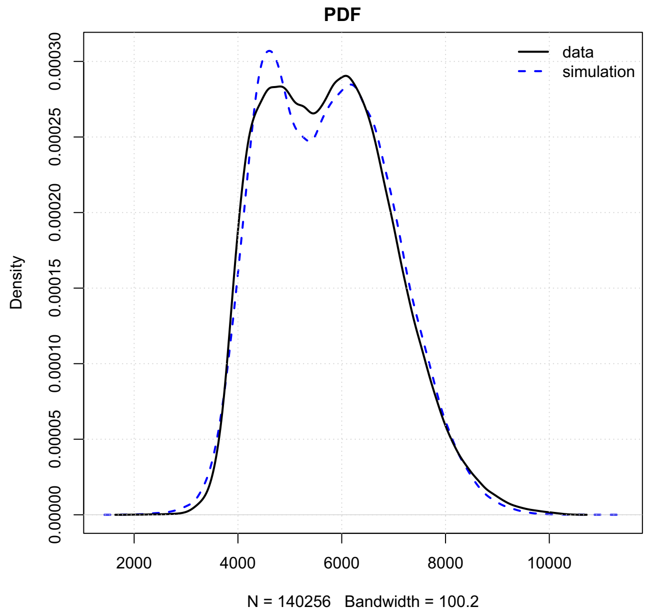


Table 4
Normal mixtures model for hourly loads (MW)

	Component1	Component2
λ	0.23	0.77
μ	4461.78	6117.13
σ	429.36	1077.89

It is noticed that every day two main local maxima and minima exist. This evidence obliges us to seek a two-mode distribution that will be used in extreme value analysis (Equation (1), Table 4). We come to the same conclusion by using the density plot below (Figures 2 and 5):

$$X \sim \sum_{i=1}^{2} \lambda_i N(\mu_i, \sigma_i) \tag{1}$$

5. Cluster Analysis

Finding the optimum number of clusters will be the first task of this method [78–80]. The procedure mostly found is a subjective determination of the number of clusters: $k = 1, \ldots n$ with $n > 10$ by calculation of the sum of squares where graphically the elbow point of the relevant convex curve is determined, values $k \geq 3$ are the candidate solutions. In this research, a robust and nonvisual method for choosing the elbow or knee point was suggested using procedure (UIK) based on EDE method developed by Christopoulos [81–83]. Extensive use in archetypal analysis cases [84] indicates better results for finding absolute values of SS second differences for UIK application, see Figure 6 where the same solution has been obtained for $k = 10, \ldots, 15$. Since the optimum number of cluster found by this method does not change if we vary the upper limit of k, it is reasonable to accept it as robust UIK method.

Following, we will proceed with cluster analysis for our 65424 hourly loads with 5 clusters. In Figure 7, we see the ranges, while in Tables 5 and 6, the description of clustering can be found in ascending order of central point. Clusters derived can be named as Minima, Midlower, Midupper, and Maxima.

From Tables 7 and 8 of daily minima and maxima, the frequencies can be obtained. Months of low load seem to be in April, May, October, March, while high loads appear in July, August, January, and December.

In order to reveal the daily hours of high load, a new index defined as WSL:

Definition 5.1. *Weighted Scaled Load (WSL) for an aggregated hourly daily maxima is the mean in standard deviations scaled by the relevant frequency of occurrences*

$$WSL = f\frac{\mu}{\varrho} \tag{2}$$

Figure 6
Robust UIK

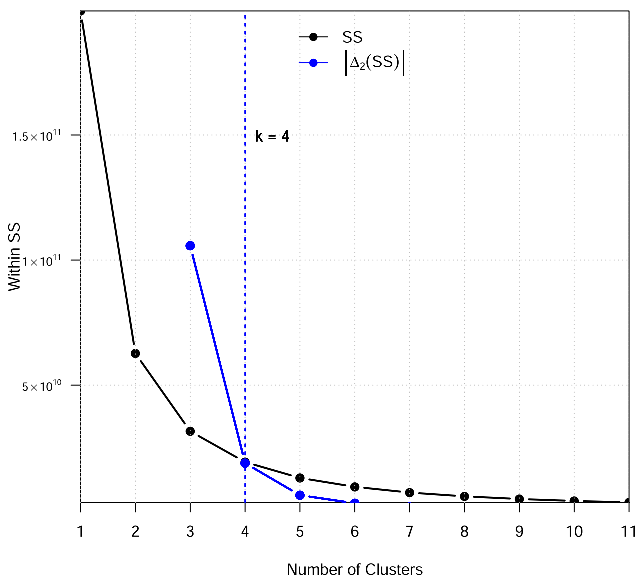


Figure 7
Range of clusters

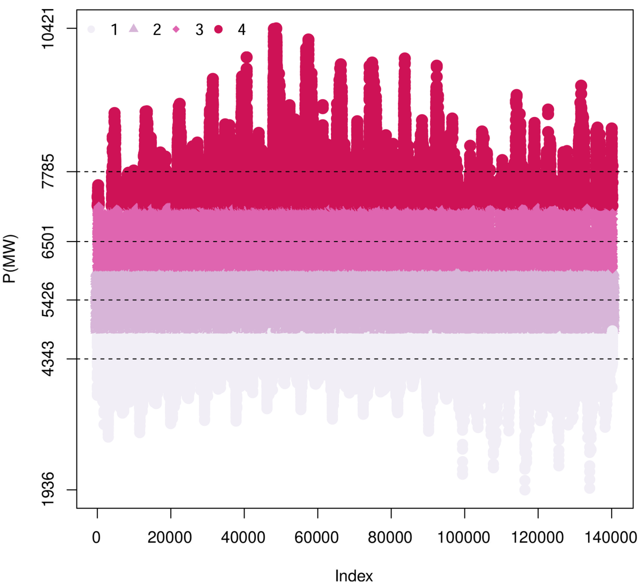


Table 5
Load clusters (MW)

	Center	Lower	Upper	Size	%
1	4343	1936	4884	39842	28.41
2	5426	4885	5963	41458	29.56
3	6501	5964	7142	41077	29.29
4	7785	7143	10421	17879	12.75

Table 6
Descriptive load clusters (MW)

	1	2	3	4
Min.	1936	4885	5964	7143
1st Qu.	4100	5152	6215	7355
Median	4379	5427	6478	7633
Mean	4343	5426	6501	7785
3rd Qu.	4633	5702	6771	8062
Max.	4884	5963	7142	10421

Table 7
Monthly cases of minima cluster

Month	Frequency
Jul	477
Aug	1220
Jan	2204
Feb	2414
Dec	2510
Jan	2988
Sep	3718
Nov	3790
Mar	4096
Oct	5143
May	5563
Apr	5719

Table 8
Monthly cases of maxima cluster

Month	Frequency
Apr	43
Oct	134
May	223
Mar	576
Nov	727
Sep	766
Feb	1693
Jun	1776
Dec	2171
Jan	2270
Aug	2875
Jul	4625

Based on Equation (2), Table 9 can be derived, where the criticality of hour 20:00 is noticed. Having determined the probable season, month, day and hour of peaks, the method proceeds to the extreme value analysis such as to determine the magnitude of peaks.

Table 9
Hourly maxima cluster

h	freq	mean	sd	WSL
0	154	7507.8	330.8	3494.7
1	36	7421.2	313	853.4
2	6	7598.7	202.3	225.4
3	5	7369.2	179.9	204.9
4	3	7312.3	87	252.1
5	3	7238.3	89.5	242.6
6	2	7284	32.5	447.9
7	21	7392.9	245.6	632.1
8	243	7517	344.7	5299.3
9	789	7700.1	470.6	12909.7
10	1001	7796.8	548.3	14235.3
11	1153	7888.1	610.8	14889.6
12	1281	7943.9	673.7	15104.8
13	1243	7983	725.8	13671.5
14	903	8004.6	741.6	9747.3
15	706	7942.8	701.3	7996.3
16	740	7816.3	619.4	9338.4
17	1104	7737.6	520.1	16425.1
18	1692	7775.1	478.4	27501.2
19	2063	7723.3	444.6	35836.2
20	2201	7671.4	413.4	40842.5
21	1530	7672.7	476.1	24656.5
22	640	7719.9	465.3	10619.3
23	360	7644	394.7	6971.8

6. Extreme Value Analysis

By collecting the daily minima and maxima, the generalized extreme value (GEV) distribution will be estimated whose PDF is given by Equation (3) and CDF in Equation (4), given that $x \geq \mu$.

$$f(x) = \begin{cases} \frac{1}{\sigma}\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}-1} \quad e^{-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}}, & \xi \neq 0 \\ \frac{1}{\sigma}e^{-\frac{x-\mu}{\sigma}} \quad e^{-e^{-\frac{x-\mu}{\sigma}}}, & \xi = 0 \end{cases} \tag{3}$$

$$F(x) = \begin{cases} e^{-\left(\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}}, & \xi \neq 0 \\ e^{-e^{-\frac{x-\mu}{\sigma}}}, & \xi = 0 \end{cases} \tag{4}$$

An interesting point with this family of distributions is the existence of a support interval, i.e., the range of definition, which is shown in Equation (5), where we see that cases with $\xi \neq 0$ are of special interest because they give upper and lower barriers.

$$S = \begin{cases} \left(-\infty, \mu - \frac{\sigma}{\xi}\right] & \xi < 0 \\ (-\infty, +\infty) & \xi = 0 \\ \left[\mu - \frac{\sigma}{\xi}, +\infty\right) & \xi > 0 \end{cases} \tag{5}$$

The estimation of parameters for maxima following Coles [70, 71] and using the relevant Original S functions written by Janet E. Hefernan with *R* port and *R* documentation provided by Heffernan et al. [85] is presented in Table 10, while for minima is given in Table 11, the support of the distribution included and is $\left(-\infty, \mu - \frac{\sigma}{\xi}\right)$, since $\xi < 0$ (Weibull type distribution) which is bounded.

Table 10
GEV for load maxima (MW)

	Lower 2.5%	Estimation	Upper 97.5%
μ	6711.61	6734.37	6757.13
σ	806.39	825.01	843.63
ξ	−0.17	−0.16	−0.14
support	11282.75	11958.3	12633.84

Table 11
GEV for load minima (MW)

	Lower 2.5%	Estimation	Upper 97.5%
μ	4128.62	4142.9	4157.19
σ	506.74	516.31	525.88
ξ	−0.12	−0.11	−0.1
support	8285.79	8915.43	9545.07

A plot of the overall diagnostics of estimations is given in Figure 8, where the goodness of fit is observed. For the effect of lower and upper points on the value of support, the next approximation from calculus follows:

$$f(\mu_0+\Delta\mu, \sigma_0+\Delta\sigma, \xi_0+\Delta\xi) \approx f(\mu_0, \sigma_0, \xi_0) + \frac{\partial f}{\partial \mu}\Delta\mu + \frac{\partial f}{\partial \sigma}\Delta\sigma + \frac{\partial f}{\partial \xi}\Delta\xi \tag{6}$$

for the function

$$f(\mu, \sigma, \xi) = \mu - \frac{\sigma}{\xi}.$$

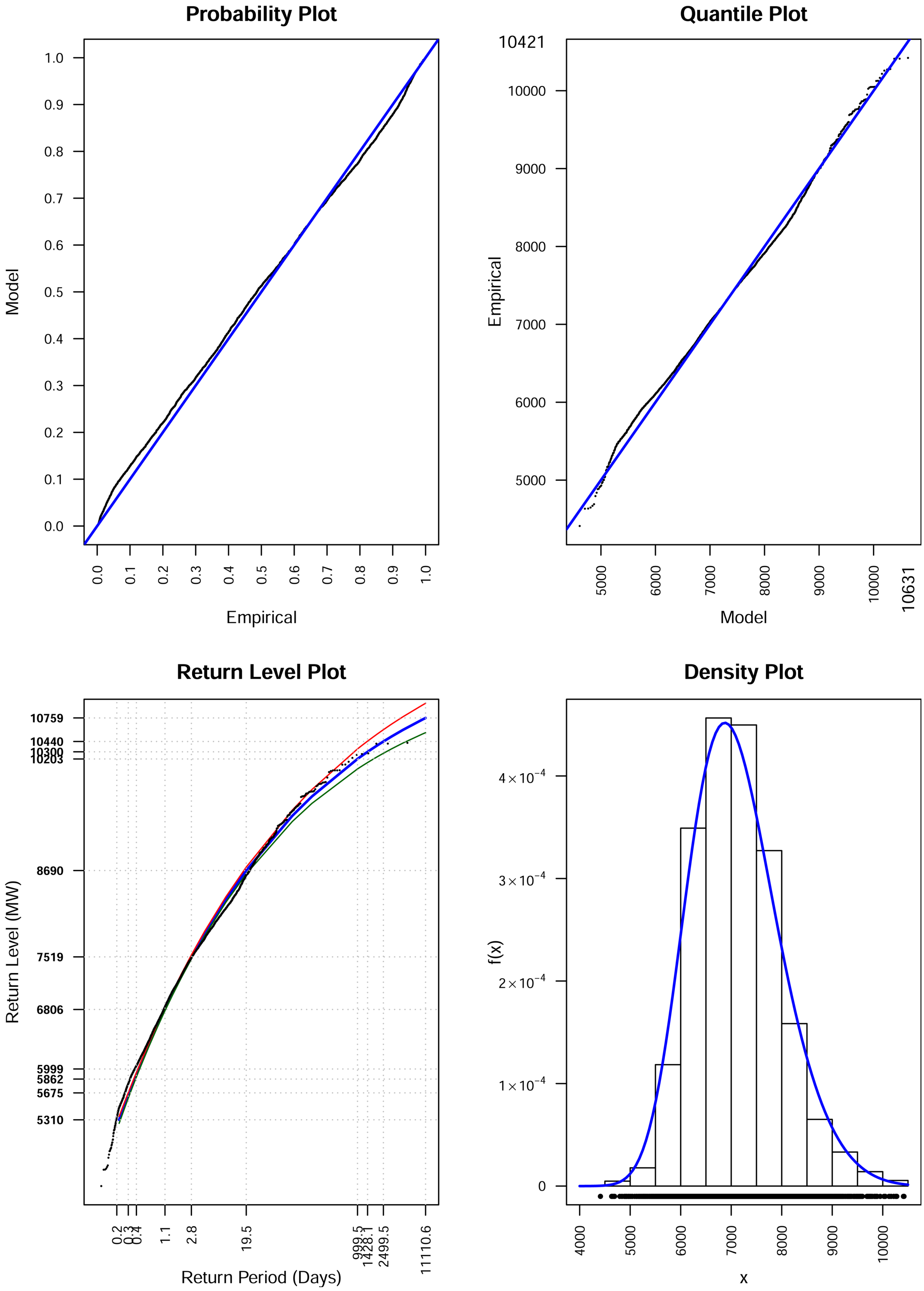
The central estimation for the worst-case scenario of daily hourly loads is approximately Min = 9 GW, Max = 12 GW and is the heaviest daily task expected from GEV analysis [86–95]. Next is a challenge to find the specific number of days for return level and current time by using an optimization method. Starting with the below definition that,

Definition 6.1. *A Return Period of T days for a specific load means that such a load appears with probability 1/T while the relevant Return Level RT is the corresponding quantile.*

$$F(R_T) = 1 - \frac{1}{T} \tag{7}$$

given F from Equation (4) thus is exactly

Figure 8
Diagnostics for GEV of daily maxima



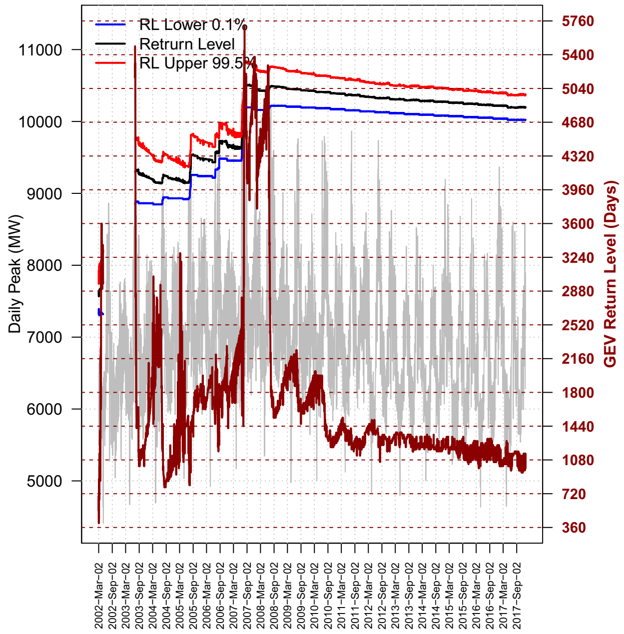
$$S = \begin{cases} \left(-\infty, \mu - \frac{\sigma}{\xi}\right] & \xi < 0 \\ (-\infty, +\infty) & \xi = 0 \\ \left[\mu - \frac{\sigma}{\xi}, +\infty\right) & \xi > 0 \end{cases}$$

$$R_T = \begin{cases} \mu - \frac{\sigma}{\xi} + \frac{\sigma}{\xi}\left(-ln\left(1 - \frac{1}{T}\right)\right)^{-\xi}, & \xi \neq 0 \\ \mu - \sigma\, ln\left(-ln\left(1 - \frac{1}{T}\right)\right), & \xi = 0 \end{cases} \tag{8}$$

Following, the temporal data range divided into many subintervals and compute the relevant return levels. Then we choose the upper 0.5% part of daily maxima until current time and find the minimum Euclidean distance for all proposed time windows. Finally, the one with the smallest distance is used to extract the return level. The results of this procedure are presented in Figure 9.

It is interesting to study the temporal evolution for the support of GEV in the case of maxima, see Figure 10, where a relatively stable pattern at the end of the time curve is observed, around the capacity of 12 MW.

Figure 9
Rolling return level for GEV of daily maxima

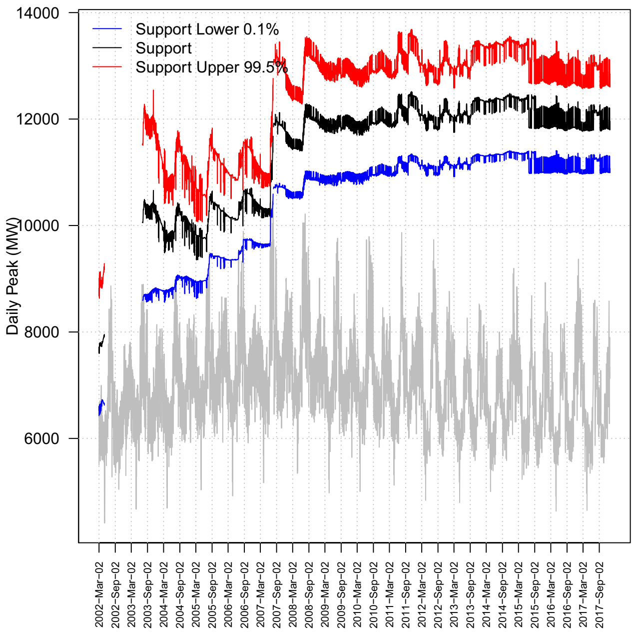


7. Daily Extrema as Spike Alerts

The development of the relevant alerts will be done by giving the below definitions:

Definition 7.1. *Load spike alert (LPA) is called a Boolean procedure that takes as input a set of past load data and returns TRUE or FALSE as an alert for the appearance of a spike on the next month.*

Figure 10
Rolling support for GEV of daily maxima



Our task is to use daily minimum (DN) and daily maximum (DX) as reliable predictors used by LPA. A plot of loads for the entire time range is given in Figure 11, with blue and red colors the relevant minima and maxima, while the LOWESS approximation of load (LA) is also plotted. Following Cleveland [96] in Figure 11, it can be concluded as given below:

1) When minima are much below the LA curve, then relevant maxima are not spikes
2) When minima reach the LA curve, then relevant maxima are spikes
3) When minima cross the LA curve from below, then relevant maxima are extreme spikes
4) When maxima cross from above the the LA, then extreme spikes follow

So, provided that we can transform our load data to deference's from LA approximation, then our conclusions can be reformulated by using zero axis as a reference. See Figure 12, where we have also marked the critical points (those that will lead to the highest spikes). Now that have found two estimators for dangerous maxima the bellow definitions can be developed:

Definition 7.2. *Daily Min Alert (DNA) is next function of past Daily Minima (DN) and value:*

$$DNA(DN) = \begin{cases} TRUE, & DN \geq LA(P) \\ FALSE, & DN < LA(P) \end{cases} \tag{9}$$

Definition 7.3. *Daily Max Alert (DXA) is next function of past Daily Maxima (DX) and value:*

$$DXA(DX) = \begin{cases} TRUE, & DX \leq LA(P) \\ FALSE, & DX > LA(P) \end{cases} \tag{10}$$

However, it would be interesting to investigate the predictions given by the two approaches just before the worst-case scenario, that of 2017, June and August. It is remarkable that we had next sequence of alerts in (see Figure 13) May 1 and 27 and June 14 and 26–29, and July 19–21 and 23–25 (Figure 14), and we remind that the highest system spike was on July 23, 13:30:00 at the level of 10421 MW. It is a remarkable observation that DXA is the first alert while DNA is just before or on the same day of the spike. Both indicators seem to work perfect.

Figure 11
Load extrema (MW)

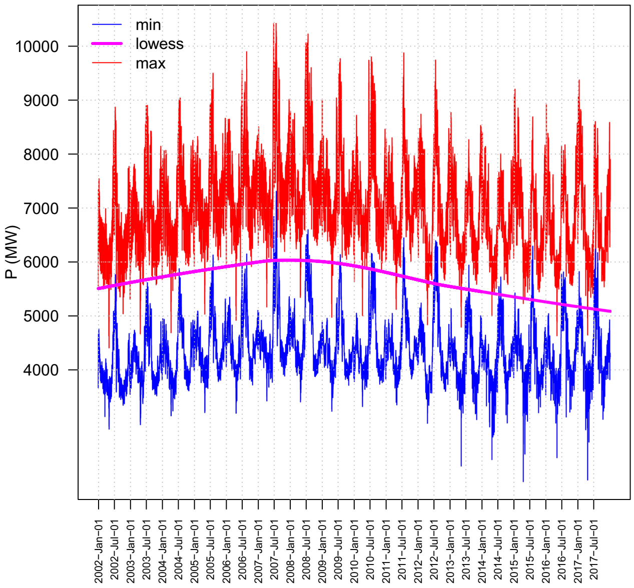


Figure 13
Daily max alerts

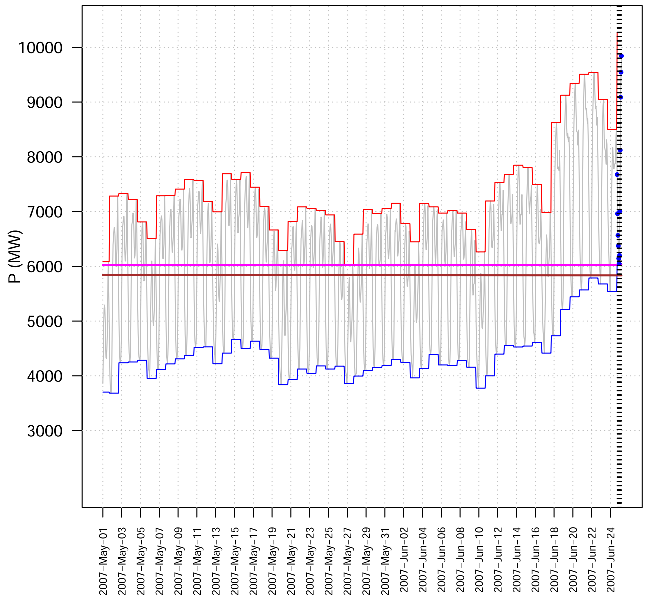


Figure 12
Load–LA (Load) (MW)

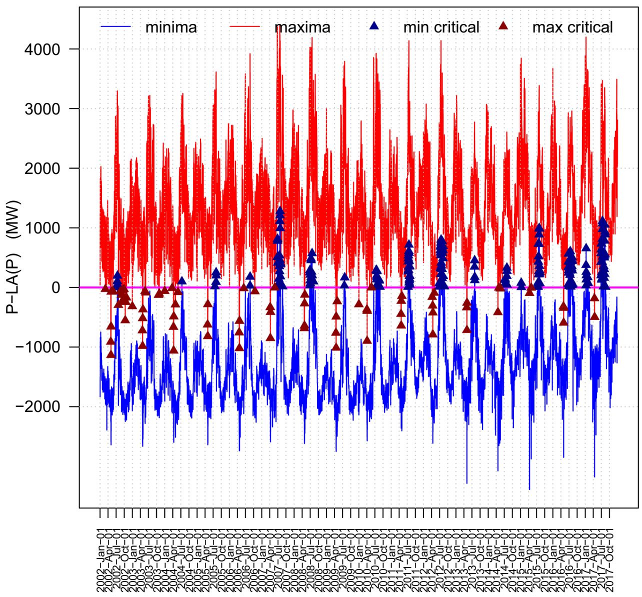
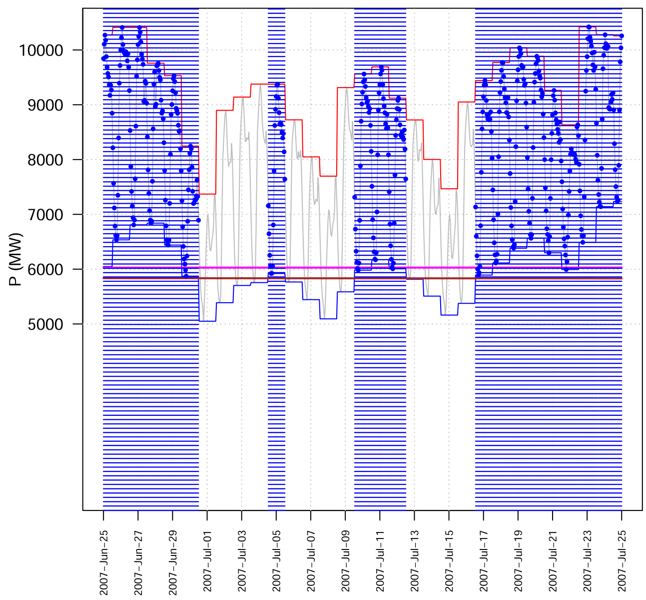


Figure 14
Daily min alerts



8. Conclusion

The purpose of this research was to develop an innovative methodology for forecasting the peak of electricity demand to fill a gap in literature, which is mainly devoted to the energy part of load (volume). A portfolio of models was developed under an algorithm utilizing advances of cluster and extreme value analysis [97–101]. The innovative methods of UIK & EDE were used for the optimal determination of clusters along with the WSL metric to reveal the daily peaks. It was found that DG of renewables generates a camel effect on peaks that increase sharpness. This finding opens the door for future research on the role of storage, batteries, as well as VPP as an integrated portfolio of renewable generation. The Camel effect was solved by the use of two normal distributions that simulated the observations, one component lying at the lower end around a mean value of ~4462 MW for 23% of cases, while the second component lies to the mid-upper with a mean of ~6177 MW (rest 77% of hours). The temporal evolution of peak was examined to conclude a relatively stable pattern producing daily extreme generalized spike alerts as estimators of daily maxima. A reliable upper limit for the highest expected hourly peak was found to be at ~11958 MW to support the distribution, while for the minima a value of ~1923 MW was found as a lower threshold. The rolling return period as an output from minimizing Euclidean distances from the upper 0.5% of daily maxima converged to a value of three years, while close to the historical high of year 2007 reached the value of 16 years. Thus, it can serve as an estimator of the upcoming peak. Two spike alerts have been found, the DNA that rises when Daily Minima exceeds LOWESS approximation and the DXA, which rises when Daily Maxima is below LOWESS. First alert acts as an index of increasing load, while the second is closer to the phenomenon of "hook contraction" before its expansion. The last effect is similar to the potential energy behavior of a classical mechanical system. The above results are very important for use by risk management, strategy and planning of renewables, as well as for their combination in the wholesale markets under the virtual power plant scheme.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The database that supports the findings of this study will be made available by the authors upon request only in a specific Excel format.

Author Contribution Statement

Petros Theodorou and **Demetris Theodoros Christopoulos:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Degefa, M. Z., Sperstad, I. B., & Sæle, H. (2021). Comprehensive classifications and characterizations of power system flexibility resources. *Electric Power Systems Research*, *194*, 107022. https://doi.org/10.1016/j.epsr.2021.107022

[2] Gao, H., Jin, T., Feng, C., Li, C., Chen, Q., & Kang, C. (2024). Review of virtual power plant operations: Resource coordination and multidimensional interaction. *Applied Energy*, *357*, 122284. https://doi.org/10.1016/j.apenergy.2023.122284

[3] Naraindath, N. R., Bansal, R. C., & Naidoo, R. M. (2023). Conceptual framework of microgrid and virtual power plants with renewable energy resources. In R. C. Bansal, J. J. Justo & F. A. Mwasilu (Eds.), *Modeling and control dynamics in microgrid systems with renewable energy resources* (pp. 19–44). Elsevier Science. https://doi.org/10.1016/B978-0-323-90989-1.00010-5

[4] Bunn, D. W. (1982). Short-term forecasting: A review of procedures in the electricity supply industry. *Journal of the Operational Research Society*, *33*(6), 533–545. https://doi.org/10.2307/2581037

[5] Hussein, A., & Awad, M. (2024). Time series forecasting of electricity consumption using hybrid model of recurrent neural networks and genetic algorithms. *Measurement: Energy*, *2*, 100004. https://doi.org/10.1016/j.meaene.2024.100004

[6] Michalakopoulos, V., Sarmas, E., Papias, I., Skaloumpakas, P., Marinakis, V., & Doukas, H. (2024). A machine learning-based framework for clustering residential electricity load profiles to enhance demand response programs. *Applied Energy*, *361*, 122943. https://doi.org/10.1016/j.apenergy.2024.122943

[7] Huang, Y., Yao, Z., & Xu, Q. (2024). Classification model of electricity consumption behavior based on sparse denoising autoencoder feature dimensionality reduction and spectral clustering. *International Journal of Electrical Power & Energy Systems*, *158*, 109960. https://doi.org/10.1016/j.ijepes.2024.109960

[8] Colelli, F. P., Wing, I. S., & De Cian, E. (2023). Intensive and extensive margins of the peak load: Measuring adaptation with mixed frequency panel data. *Energy Economics*, *126*, 106923. https://doi.org/10.1016/j.eneco.2023.106923

[9] Chen, H., Yan, H., Gong, K., & Yuan, X. C. (2021). How will climate change affect the peak electricity load? Evidence from China. *Journal of Cleaner Production*, *322*, 129080. https://doi.org/10.1016/j.jclepro.2021.129080

[10] Chen, H., Zhang, B., Geng, H., Wang, M. M., & Gao, H. (2022). Demand response during the peak load period in China: Potentials, benefits and implementation mechanism designs. *Computers & Industrial Engineering*, *168*, 108117. https://doi.org/10.1016/j.cie.2022.108117

[11] Alsaedi, Y. H., & Tularam, G. A. (2020). The relationship between electricity consumption, peak load and GDP in Saudi Arabia: A VAR analysis. *Mathematics and Computers in Simulation*, *175*, 164–178. https://doi.org/10.1016/j.matcom.2019.06.012

[12] Wu, Y., Waite, M., Conlon, T., & Modi, V. (2022). The role of electrification induced peak loads and gas infrastructure constraints on decarbonization pathways in New York State. *Energy Strategy Reviews*, *44*, 100985. https://doi.org/10.1016/j.esr.2022.100985

[13] Gilbert, C., Browell, J., & Stephen, B. (2023). Probabilistic load forecasting for the low voltage network: Forecast fusion and daily peaks. *Sustainable Energy, Grids and Networks*, *34*, 100998. https://doi.org/10.1016/j.segan.2023.100998
[14] Cerna, F. V., Coêlho, J. K., Fantesia, M. P., Naderi, E., Marzband, M., & Contreras, J. (2023). Load factor improvement of the electricity grid considering distributed energy resources operation and regulation of peak load. *Sustainable Cities and Society*, *98*, 104802. https://doi.org/10.1016/j.scs.2023.104802
[15] Jasiński, T. (2022). A new approach to modeling cycles with summer and winter demand peaks as input variables for deep neural networks. *Renewable and Sustainable Energy Reviews*, *159*, 112217. https://doi.org/10.1016/j.rser.2022.112217
[16] Tan, M., Liao, C., Chen, J., Cao, Y., Wang, R., & Su, Y. (2023). A multi-task learning method for multi-energy load forecasting based on synthesis correlation analysis and load participation factor. *Applied Energy*, *343*, 121177. https://doi.org/10.1016/j.apenergy.2023.121177
[17] Qiao, W., Fu, Z., Du, M., Nan, W., & Liu, E. (2023). Seasonal peak load prediction of underground gas storage using a novel two-stage model combining improved complete ensemble empirical mode decomposition and long short-term memory with a sparrow search algorithm. *Energy*, *274*, 127376. https://doi.org/10.1016/j.energy.2023.127376
[18] Naghikhani, A., & Hosseini, S. M. H. (2022). Optimal thermal and power planning considering economic and environmental issues in peak load management. *Energy*, *239*, 121955. https://doi.org/10.1016/j.energy.2021.121955
[19] Mirasgedis, S., Sarafidis, Y., Georgopoulou, E., Lalas, D. P., Moschovits, M., Karagiannis, F., & Papakonstantinou, D. (2006). Models for mid-term electricity demand forecasting incorporating weather influences. *Energy*, *31*(2–3), 208–227. https://doi.org/10.1016/j.energy.2005.02.016
[20] Kazemzadeh, M. R., Amjadian, A., & Amraee, T. (2020). A hybrid data mining driven algorithm for long term electric peak load and energy demand forecasting. *Energy*, *204*, 117948. https://doi.org/10.1016/j.energy.2020.117948
[21] Huang, Y., Hasan, N., Deng, C., & Bao, Y. (2022). Multivariate empirical mode decomposition based hybrid model for day-ahead peak load forecasting. *Energy*, *239*, 122245. https://doi.org/10.1016/j.energy.2021.122245
[22] Weron, R. (2007). *Modeling and forecasting electricity loads and prices: A statistical approach*. USA: Wiley.
[23] Sudta, P., & Singh, J. G. (2024). An approach to prosumer modeling and financial assessment with load clustering algorithm in an active power distribution network. *Sustainable Energy, Grids and Networks*, *38*, 101249. https://doi.org/10.1016/j.segan.2023.101249
[24] Miller, J. I., & Nam, K. (2022). Modeling peak electricity demand: A semiparametric approach using weather-driven cross-temperature response functions. *Energy Economics*, *114*, 106291. https://doi.org/10.1016/j.eneco.2022.106291
[25] Ghimire, S., Deo, R. C., Casillas-Pérez, D., Salcedo-Sanz, S., Pourmousavi, S. A., & Acharya, U. R. (2024). Probabilistic-based electricity demand forecasting with hyrid convolutional neural network-extreme learning machine model. *Engineering Applications of Artificial Intelligence*, *132*, 107918. https://doi.org/10.1016/j.engappai.2024.107918
[26] Ghimire, S., Deo, R. C., Casillas-Pérez, D., & Salcedo-Sanz, S. (2024). Electricity demand error corrections with attention bi-directional neural networks. *Energy*, *291*, 129938. https://doi.org/10.1016/j.energy.2023.129938
[27] Cao, Z., Wang, J., & Xia, Y. (2024). Combined electricity load-forecasting system based on weighted fuzzy time series and deep neural networks. *Engineering Applications of Artificial Intelligence*, *132*, 108375. https://doi.org/10.1016/j.engappai.2024.108375
[28] Gomez, W., Wang, F. K., & Lo, S. C. (2024). A hybrid approach based machine learning models in electricity markets. *Energy*, *289*, 129988. https://doi.org/10.1016/j.energy.2023.129988
[29] Zeng, H., Shao, B., Dai, H., Yan, Y., & Tian, N. (2023). Prediction of fluctuation loads based on GARCH family-CatBoost-CNNLSTM. *Energy*, *263*, 126125. https://doi.org/10.1016/j.energy.2022.126125
[30] Trull, O., García-Díaz, J. C., & Peiró-Signes, A. (2024). msf, a forecasting library to predict short-term electricity demand based on multiple seasonal time series. *Journal of Computational Science*, *78*, 102280. https://doi.org/10.1016/j.jocs.2024.102280
[31] Saranj, A., & Zolfaghari, M. (2022). The electricity consumption forecast: Adopting a hybrid approach by deep learning and ARIMAX-GARCH models. *Energy Reports*, *8*, 7657–7679. https://doi.org/10.1016/j.egyr.2022.06.007
[32] Skiles, M. J., Rhodes, J. D., & Webber, M. E. (2023). Perspectives on peak demand: How is ERCOT peak electric load evolving in the context of changing weather and heating electrification? *The Electricity Journal*, *36*(2–3), 107254. https://doi.org/10.1016/j.tej.2023.107254
[33] Flygare, C., Wallberg, A., Jonasson, E., Castellucci, V., & Waters, R. (2024). Correlation as a method to assess electricity users' contributions to grid peak loads: A case study. *Energy*, *288*, 129805. https://doi.org/10.1016/j.energy.2023.129805
[34] Dai, S., Meng, F., Dai, H., Wang, Q., & Chen, X. (2021). Electrical peak demand forecasting – A review. *arXiv Preprint: 2108.01393*. https://doi.org/10.48550/arXiv.2108.01393
[35] Chaturvedi, S., Rajasekar, E., Natarajan, S., & McCullen, N. (2022). A comparative assessment of SARIMA, LSTM RNN and Fb Prophet models to forecast total and peak monthly energy demand for India. *Energy Policy*, *168*, 113097. https://doi.org/10.1016/j.enpol.2022.113097
[36] Amara-Ouali, Y., Fasiolo, M., Goude, Y., & Yan, H. (2023). Daily peak electrical load forecasting with a multi-resolution approach. *International Journal of Forecasting*, *39*(3), 1272–1286. https://doi.org/10.1016/j.ijforecast.2022.06.001
[37] Brännlund, R., & Vesterberg, M. (2021). Peak and off-peak demand for electricity: Is there a potential for load shifting? *Energy Economics*, *102*, 105466. https://doi.org/10.1016/j.eneco.2021.105466
[38] Saqib, A., Chan, T. H., Mikhaylov, A., & Lean, H. H. (2021). Are the responses of sectoral energy imports asymmetric to exchange rate volatilities in Pakistan? Evidence from recent foreign exchange regime. *Frontiers in Energy Research*, *9*, 614463. https://doi.org/10.3389/fenrg.2021.614463
[39] Candila, V., Maximov, D., Mikhaylov, A., Moiseev, N., Senjyu, T., & Tryndina, N. (2021). On the relationship between oil and exchange rates of oil-exporting and oil-importing countries: From the great recession period to the Covid-19 era. *Energies*, *14*(23), 8046. https://doi.org/10.3390/en14238046
[40] An, J., Mikhaylov, A., & Jung, S. U. (2020). The strategy of South Korea in the global oil market. *Energies*, *13*(10), 2491. https://doi.org/10.3390/en13102491

[41] Mateo-Barcos, S., Ribó-Pérez, D., Rodríguez-García, J., & Alcázar-Ortega, M. (2024). Forecasting electricity demand of municipalities through artificial neural networks and metered supply point classification. *Energy Reports*, *11*, 3533–3549. https://doi.org/10.1016/j.egyr.2024.03.023
[42] Behm, C., Nolting, L., & Praktiknjo, A. (2020). How to model European electricity load profiles using artificial neural networks. *Applied Energy*, *277*, 115564. https://doi.org/10.1016/j.apenergy.2020.115564
[43] Xu, H., Hu, F., Liang, X., Zhao, G., & Abugunmi, M. (2024). A framework for electricity load forecasting based on attention mechanism time series depthwise separable convolutional neural network. *Energy*, *299*, 131258. https://doi.org/10.1016/j.energy.2024.131258
[44] Shen, H., Zhang, H., Xu, Y., Chen, H., Zhang, Z., Li, W., . . . , & Zhu, Y. (2024). Two stage robust economic dispatching of microgrid considering uncertainty of wind, solar and electricity load along with carbon emission predicted by neural network model. *Energy*, *300*, 131571. https://doi.org/10.1016/j.energy.2024.131571
[45] Li, B., & Khayatnezhad, M. (2024). Modified artificial neural network based on developed snake optimization algorithm for short-term price prediction. *Heliyon*, *10*(5), e26335. https://doi.org/10.1016/j.heliyon.2024.e26335
[46] Liu, S., Chen, H., Liu, P., Qin, F., & Fars, A. (2023). A novel electricity load forecasting based on probabilistic least absolute shrinkage and selection operator-Quantile regression neural network. *International Journal of Hydrogen Energy*, *48*(88), 34486–34500. https://doi.org/10.1016/j.ijhydene.2023.04.091
[47] Li, X., Wang, Z., Yang, C., & Bozkurt, A. (2024). An advanced framework for net electricity consumption prediction: Incorporating novel machine learning models and optimization algorithms. *Energy*, *296*, 131259. https://doi.org/10.1016/j.energy.2024.131259
[48] Santos, P. J., Martins, A. G., & Pires, A. J. (2007). Designing the input vector to ANN-based models for short-term load forecast in electricity distribution systems. *International Journal of Electrical Power & Energy Systems*, *29*(4), 338–347. https://doi.org/10.1016/j.ijepes.2006.09.002
[49] Hippert, H. S., Pedreira, C. E., & Souza, R. C. (2001). Neural networks for short-term load forecasting: A review and evaluation. *IEEE Transactions on Power Systems*, *16*(1), 44–55. https://doi.org/10.1109/59.910780
[50] Amjady, N., & Keynia, F. (2008). Mid-term load forecasting of power systems by a new prediction method. *Energy Conversion and Management*, *49*(10), 2678–2687. https://doi.org/10.1016/j.enconman.2008.04.008
[51] Ghanbari, A., Kazemi, S. M. R., Mehmanpazir, F., & Nakhostin, M. M. (2013). A cooperative ant colony optimization-genetic algorithm approach for construction of energy demand forecasting knowledge-based expert systems. *Knowledge-Based Systems*, *39*, 194–206. https://doi.org/10.1016/j.knosys.2012.10.017
[52] Akay, D., & Atak, M. (2007). Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energy*, *32*(9), 1670–1675. https://doi.org/10.1016/j.energy.2006.11.014
[53] Assareh, E., Behrang, M. A., & Ghanbarzdeh, A. (2012). Forecasting energy demand in Iran using genetic algorithm (GA) and particle swarm optimization (PSO) methods. *Energy Sources, Part B: Economics, Planning, and Policy*, *7*(4), 411–422. https://doi.org/10.1080/15567240903394265
[54] Crone, S. F., & Dhawan, R. (2007). Forecasting seasonal time series with neural networks: A sensitivity analysis of architecture parameters. In *International Joint Conference on Neural Networks*, 2099–2104. https://doi.org/10.1109/IJCNN.2007.4371282
[55] Rubasinghe, O., Zhang, T., Zhang, X., Choi, S. S., Chau, T. K., Chow, Y., ..., & Iu, H. H. C. (2023). Highly accurate peak and valley prediction short-term net load forecasting approach based on decomposition for power systems with high PV penetration. *Applied Energy*, *333*, 120641. https://doi.org/10.1016/j.apenergy.2023.120641
[56] Carpinteiro, O. A. S., Leme, R. C., de Souza, A. C. Z., Pinheiro, C. A. M., & Moreira, E. M. (2007). Long-term load forecasting via a hierarchical neural model with time integrators. *Electric Power Systems Research*, *77*(3–4), 371–378. https://doi.org/10.1016/j.epsr.2006.03.014
[57] Yuan, X., Chen, C., Yuan, Y., Huang, Y., & Tan, Q. (2015). Short-term wind power prediction based on LSSVM–GSA model. *Energy Conversion and Management*, *101*, 393–401. https://doi.org/10.1016/j.enconman.2015.05.065
[58] Ju, F. Y., & Hong, W. C. (2013). Application of seasonal SVR with chaotic gravitational search algorithm in electricity forecasting. *Applied Mathematical Modelling*, *37*(23), 9643–9651. https://doi.org/10.1016/j.apm.2013.05.016
[59] Abdel-Aal, R. E. (2008). Univariate modeling and forecasting of monthly energy demand time series using abductive and neural networks. *Computers & Industrial Engineering*, *54*(4), 903–917. https://doi.org/10.1016/j.cie.2007.10.020
[60] Zhang, W. Y., Hong, W. C., Dong, Y., Tsai, G., Sung, J. T., & Fan, G. F. (2012). Application of SVR with chaotic GASA algorithm in cyclic electric load forecasting. *Energy*, *45*(1), 850–858. https://doi.org/10.1016/j.energy.2012.07.006
[61] Hu, Z., Bao, Y., & Xiong, T. (2013). Electricity load forecasting using support vector regression with memetic algorithms. *The Scientific World Journal*, *2013*(1), 292575. https://doi.org/10.1155/2013/292575
[62] Wang, B., Tai, N. L., Zhai, H. Q., Ye, J., Zhu, J. D., & Qi, L. B. (2008). A new ARMAX model based on evolutionary algorithm and particle swarm optimization for short-term load forecasting. *Electric Power Systems Research*, *78*(10), 1679–1685. https://doi.org/10.1016/j.epsr.2008.02.009
[63] Zhu, S., Wang, J., Zhao, W., & Wang, J. (2011). A seasonal hybrid procedure for electricity demand forecasting in China. *Applied Energy*, *88*(11), 3807–3815. https://doi.org/10.1016/j.apenergy.2011.05.005
[64] Kıran, M. S., Özceylan, E., Gündüz, M., & Paksoy, T. (2012). A novel hybrid approach based on particle swarm optimization and ant colony algorithm to forecast energy demand of Turkey. *Energy Conversion and Management*, *53*(1), 75–83. https://doi.org/10.1016/j.enconman.2011.08.004
[65] Zhu, K., Li, Y., Mao, W., Li, F., & Yan, J. (2022). LSTM enhanced by dual-attention-based encoder-decoder for daily peak load forecasting. *Electric Power Systems Research*, *208*, 107860. https://doi.org/10.1016/j.epsr.2022.107860
[66] Niu, D., Wang, Y., & Wu, D. D. (2010). Power load forecasting using support vector machine and ant colony optimization. *Expert Systems with Applications*, *37*(3), 2531–2539. https://doi.org/10.1016/j.eswa.2009.08.019
[67] Gavrilas, M., Ivanov, O., & Gavrilas, G. (2014). Electricity load forecasting based on a mixed statistical-neural-computational intelligence approach. In *12th Symposium on Neural Network Applications in Electrical*

Engineering, 61–66. https://doi.org/10.1109/NEUREL.2014.7011461

[68] Hong, W. C. (2009). Chaotic particle swarm optimization algorithm in a support vector regression electric load forecasting model. *Energy Conversion and Management*, *50*(1), 105–117. https://doi.org/10.1016/j.enconman.2008.08.031

[69] Hong, W. C. (2009). Electric load forecasting by support vector model. *Applied Mathematical Modelling*, *33*(5), 2444–2454. https://doi.org/10.1016/j.apm.2008.07.010

[70] Coles, S. (2001). Classical extreme value theory and models. In S. Coles (Ed.), *An introduction to statistical modeling of extreme values* (pp. 45–73). Springer. https://doi.org/10.1007/978-1-4471-3675-0_3

[71] Coles, S. (2001). Threshold models. In S. Coles (Ed.), *An introduction to statistical modeling of extreme values* (pp. 74–91). Springer.

[72] Benaglia, T., Chauveau, D., Hunter, D. R., & Young, D. S. (2010). mixtools: An R package for analyzing finite mixture models. *Journal of Statistical Software*, *32*(6), 1–29. https://doi.org/10.18637/jss.v032.i06

[73] Gilleland, E., & Katz, R. W. (2016). extRemes 2.0: An extreme value analysis package in R. *Journal of Statistical Software*, *72*(8), 1–39. https://doi.org/10.18637/jss.v072.i08

[74] Ufa, R. A., Malkova, Y. Y., Rudnik, V. E., Andreev, M. V., & Borisov, V. A. (2022). A review on distributed generation impacts on electric power system. *International Journal of Hydrogen Energy*, *47*(47), 20347–20361. https://doi.org/10.1016/j.ijhydene.2022.04.142

[75] Pothireddy, K. M. R., Vuddanti, S., & Salkuti, S. R. (2021). Impact of demand response on optimal sizing of distributed generation and customer tariff. *Energies*, *15*(1), 190. https://doi.org/10.3390/en15010190

[76] Frazier, A. W., Cole, W., Denholm, P., Greer, D., & Gagnon, P. (2020). Assessing the potential of battery storage as a peaking capacity resource in the United States. *Applied Energy*, *275*, 115385. https://doi.org/10.1016/j.apenergy.2020.115385

[77] Cole, W., Denholm, P., Carag, V., & Frazier, W. (2023). The peaking potential of long-duration energy storage in the United States power system. *Journal of Energy Storage*, *62*, 106932. https://doi.org/10.1016/j.est.2023.106932

[78] Rodríguez-Gómez, F., del Campo-Ávila, J., & Mora-López, L. (2024). A novel clustering based method for characterizing household electricity consumption profiles. *Engineering Applications of Artificial Intelligence*, *129*, 107653. https://doi.org/10.1016/j.engappai.2023.107653

[79] Pullinger, M., Zapata-Webborn, E., Kilgour, J., Elam, S., Few, J., Goddard, N., . . . , & Webb, L. (2024). Capturing variation in daily energy demand profiles over time with cluster analysis in British homes (September 2019–August 2022). *Applied Energy*, *360*, 122683. https://doi.org/10.1016/j.apenergy.2024.122683

[80] Li, Z., Alonso, A. M., Elías, A., & Morales, J. M. (2024). Clustering and forecasting of day-ahead electricity supply curves using a market-based distance. *International Journal of Electrical Power & Energy Systems*, *158*, 109977. https://doi.org/10.1016/j.ijepes.2024.109977

[81] Christopoulos, D. T. (2012). Developing methods for identifying the inflection point of a convex/concave curve. *arXiv Preprint: 1206.5478*. https://doi.org/10.48550/arXiv.1206.5478

[82] Christopoulos, D. T. (2014). Reliable computations of knee point for a curve and introduction of a unit invariant estimation. *Project: Basic Characteristics of Planar Noisy Curves*. https://doi.org/10.13140/2.1.3111.5844

[83] Christopoulos, D. T. (2016). Introducing Unit Invariant Knee (UIK) as an objective choice for elbow point in multivariate data analysis techniques. *SSRN: 3043076*. https://dx.doi.org/10.2139/ssrn.3043076

[84] Cutler, A., & Breiman, L. (1994). Archetypal analysis. *Technometrics*, *36*(4), 338–347. https://doi.org/10.1080/00401706.1994.10485840

[85] Heffernan, J. E., Stephenson, A. G., & Gilleland, E. (2016). *ismev: An introduction to statistical modeling of extreme values*. Retrieved from: https://doi.org/10.32614/CRAN.package.ismev

[86] Habeeb, S. B., Abdullah, F. K., Shalan, R. N., Hassan, A. S., Almetwally, E. M., Alghamdi, F. M., . . . , & Hossain, M. M. (2024). Comparison of some Bayesian estimation methods for type-I generalized extreme value distribution with simulation. *Alexandria Engineering Journal*, *98*, 356–363. https://doi.org/10.1016/j.aej.2024.04.042

[87] De Luca, D. L., & Napolitano, F. (2023). A user-friendly software for modelling extreme values: EXTRASTAR (EXTRemes Abacus for STAtistical Regionalization). *Environmental Modelling & Software*, *161*, 105622. https://doi.org/10.1016/j.envsoft.2023.105622

[88] Ueki, T. (2023). Generalized extreme value analysis of criticality tallies in Monte Carlo calculation. *Progress in Nuclear Energy*, *159*, 104630. https://doi.org/10.1016/j.pnucene.2023.104630

[89] Ueki, T. (2024). Generalized extreme value analysis of efficient evaluation of extreme values in random media criticality calculations. *Progress in Nuclear Energy*, *173*, 105236. https://doi.org/10.1016/j.pnucene.2024.105236

[90] Lu, X., He, P., Zhang, Z., Apergis, N., & Roubaud, D. (2024). Extreme co-movements between decomposed oil price shocks and sustainable investments. *Energy Economics*, *134*, 107580. https://doi.org/10.1016/j.eneco.2024.107580

[91] He, S., Li, Z., & Liu, X. (2023). An improved GEV boosting method for imbalanced data classification with application to short-term rainfall prediction. *Journal of Hydrology*, *617*, 128882. https://doi.org/10.1016/j.jhydrol.2022.128882

[92] Hu, K., Wang, R., Xu, J., Constantinescu, C., Chen, Y., & Ling, C. (2024). Extreme analysis of typhoons disaster in mainland China with insurance management. *International Journal of Disaster Risk Reduction*, *106*, 104411. https://doi.org/10.1016/j.ijdrr.2024.104411

[93] Bakhshi, A. K., & Ahmed, M. M. (2022). Bayesian extreme value analysis of kinematic-based surrogate measure of safety to detect crash-prone conditions in connected vehicles environment: A driving simulator experiment. *Transportation Research Part C: Emerging Technologies*, *136*, 103539. https://doi.org/10.1016/j.trc.2021.103539

[94] Rafiu, H. A., Adesina, O. S., & Adekeye, K. S. (2024). Modelling the response rate of Apache web server using extreme value theory. *Scientific African*, *23*, e02086. https://doi.org/10.1016/j.sciaf.2024.e02086

[95] Falkensteiner, M. A., Schellander, H., Ehrensperger, G., & Hell, T. (2023). Accounting for seasonality in the metastatistical extreme value distribution. *Weather and Climate Extremes*, *42*, 100601. https://doi.org/10.1016/j.wace.2023.100601

[96] Cleveland, W. S. (1981). LOWESS: A program for smoothing scatterplots by robust locally weighted regression. *The American Statistician*, *35*(1), 54. https://doi.org/10.2307/2683591

[97] Ardakani, O. M. (2024). Bayesian extreme value models: Asymptotic behavior, hierarchical convergence, and predictive robustness. *Econometrics and Statistics*. https://doi.org/10.1016/j.ecosta.2024.04.002

[98] Candia, C., & Herrera, R. (2024). An empirical review of dynamic extreme value models for forecasting value at risk, expected shortfall and expectile. *Journal of Empirical Finance*, *77*, 101488. https://doi.org/10.1016/j.jempfin.2024.101488

[99] Ankunda, A., Ali, Y., & Mohanty, M. (2024). Pedestrian crash risk analysis using extreme value models: New insights and evidence. *Accident Analysis & Prevention*, *203*, 107633. https://doi.org/10.1016/j.aap.2024.107633

[100] Potisomporn, P., Adcock, T. A. A., & Vogel, C. R. (2024). Extreme value analysis of wind droughts in Great Britain. *Renewable Energy*, *221*, 119847. https://doi.org/10.1016/j.renene.2023.119847

[101] Weng, Y. Y., Zhang, X. Y., Lu, Z. H., & Zhao, Y. G. (2024). A conditional extreme value distribution method for dynamic reliability analysis of stochastic structures. *Structural Safety*, *106*, 102398. https://doi.org/10.1016/j.strusafe.2023.102398

How to Cite: Theodorou, P., & Christopoulos, D. T. (2024). Electricity Demand, Forecasting the Peaks: Development and Implementation of C-EVA Method. *Green and Low-Carbon Economy*, *2*(4), 310–324. https://doi.org/10.47852/bonviewGLCE42022327