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Artificial Neural Network for Daily Low Stream Flow Rate Prediction of Perigiali Stream, Kavala City, NE Greece †

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† Presented at the 3rd EWaS International Conference on "Insights on the Water-Energy-Food Nexus", Lefkada Island, Greece, 27–30 June 2018.

Published: 20 August 2018

Abstract: Only a few scientific research studies with reference to extremely low stream flow conditions, have been conducted in Greece, so far. Forecasting future low stream flow rate values is a crucial and desicive task when conducting drought and watershed management plans, designing water reservoirs and general hydraulic works capacity, calculating hydrological and drought low flow indices, separating groundwater base flow and storm flow of storm hydrographs etc. Artificial Neural Network modeling simulation method generates artificial time series of simulated values of a random (hydrological in this specific case) variable. The present study produces artificial low stream flow time series of both a part of the past year (2016) as well as the present year (2017) considering the stream flow data observed during two different respecting interval period of the years 2016 and 2017. We compiled an Artificial Neural Network to simulate low stream flow rate data, acquired at a certain location of the partly regulated semi-urban stream which runs through the eastern exit of Kavala city, NE Greece, using a 3-inches U.S.G.S. modified portable Parshall flume, a 3-inches conventional portable Parshall flume, a 3-inches portable Montana (short Parshall) flume and a 90° V-notched triangular shaped sharp crested portable weir plate. The observed data were plotted against the predicted one and the results were demonstrated through interactive tables providing us the ability to effectively evaluate the ANN model simulation procedure performance. Finally, we plot the recorded against the simulated low stream flow rate data, compiling a log-log scale chart which provides a better visualization of the discrepancy ratio statistical performance metrics and calculate the derived model statistics featuring the comparison between the recorded and the forecasted low stream flow rate data.

Keywords: artificial neural network; discrepancy ratio; drought; low flow data; Parshall flume

1. Introduction

Low flow regimes in rivers and streams are of paramount importance to the ecological conditions of any land surface hydrological feature. Any shift in the flows pattern throughout any hydrological year, stemming, for instance, from either individual activities e.g., groundwater abstraction, precipitation shortage, riparian areas encroachment, stream channelizing due to urbanization etc., or a combination of them, may contribute to stream ecology changes that cannot be undone [1]. Low flow analysis and forecasting is also fundamental when building works along watercourses (e.g., dams, reservoirs, water deviation channels for irrigation purposes etc.) and for watercourse rehabilitation plans regarding which a knowledge of hydrological fluctuation is of fundamental importance in designing sustainable rehabilitation works.

Another type of low flow analysis, specifically probability distribution analysis, was performed in the past analyzing the observed data collected at the same gauging station between 14th of May 2016 and 31th of July 2016 revealing that Pearson type 6 (3P) demonstrated the highest final goodness of fit obtained score based, simultaneously, on all available (Anderson-Darling, Chi-Squared and Kolmogorov-Smirnov) goodness of fit criteria [2]. Furthermore, as far as the same gauging station, similar type of analysis was elaborated considering, this time, the observed data collected at the same gauging station both between 14th of May 2016 and 29th of August 2016 revealing that Wakeby type (5P) demonstrated the highest final goodness of fit obtained score based on the Kolmogorov-Smirnov goodness of fit criterion and employed to generate an artificial low flow time series for the same time interval [3,4].

Especially within the last decade, a great number of ANN models have been designed for stream flow and sediment transport rates simulation. In a scientific research article, an ANN model was employed to design a model for streamflow forecasting respecting San Juan River basin, Argentina, using meteorological data from Pachon meteorological station built at 1900 m of altitude and proved distinctively effective of fitting remarkably well the observed stream flow data [5]. In a scientific research article, an ANN model was developed and proved effective of simulating well the daily both high and low flows, in Mesochora catchment, (drained by the Acheloos River), central mountain region of Greece [6]. In another scientific research article, the performance of three different ANN Schemes (a–c) was tested in order to calculate bed load transport rate in gravel-bed rivers running within the Snake River Basin, USA [7]. In another scientific research article, an ANN model was developed and proved capable of stream flow modeling of Savitri catchment, India [8]. In another scientific research article, an ANN model was designed and performed adequately of stream flow modeling of Nestos River, NE Greece [9].

In the present scientific research study, ANNs have been employed to design a forecasting model for the daily low flows of Perigiali Stream (at the exit of the homonymous watershed), Kavala city, Eastern Macedonia & Thrace Prefecture, NE Greece. Their selection is founded on the fact that they perform remarkably well (together within other sectors of scientific interests) in the field of hydrology, although, in some occasions, there is not available adequate information respecting all the variables contributing to the watershed system driving forces.

2. Study Area

The stream flow rate gauging station established in Kavala city coastal area, is located at the north of the Aegean Sea, across the Thassos Island, and surrounded by the Lekani mountain series branches to the North and East and the Paggaion Mountain ramifications to the West, (established in the proximity of the city urban web center and at the eastern exit of the city as well), located at the specific co-ordinates 40°56′727″ N and 24°25′929″ E, Perigiali city area, and operated during specified time intervals, bridging a time interval period from 14 May 2016 to 7 October 2017, as illustrated in Figure 1. It should be noted that since it is located just a few decades of meters upstream the sea shore and simultaneously at the exit of the entire Perigiali area watershed, between the sea shore and the Old National Road connecting the eastern exit of the Kavala city to the Xanthi city, drained by the homonymous Perigiali area stream, the associated stream flow rate measurements provide profooundly valuable scientific information respecting the entire regime of the water resources, (incorporating headwaters and lower order streams to higher order streams and the main stream channel), of the Perigiali area watershed.

Figure 1. Parshall flumes and V-Notched weir gauging station, Perigiali Stream area, Kavala city, Greece.

3. Materials and Methods

We considered the stream flow data observed during two different center interval period of the years 2016 and 2017, more precisely, during part of May (from the 14th of May 2016), June, July and part of August 2016 (until the 30th of August 2016), part of December 2016 (from the 24th of December 2016), part of January 2017 (until the 5th of January 2017) as well as part of May (from the 24th of May 2017), June, July, August, September and part of October 2017, until the 7th of October 2017, without filling the consecutive data gaps for the rest, ungauged gaps, of the years 2016 and 2017, (see supplementary materials).

The distinctively shallow waters, exacerbated by the extremely low water stream flow velocity occurring at the gauging station, make impossible to perform the area-velocity method in order to calculate the stream flow rate (discharge), using a current meter mounted on a wading rod, due to the fact that there isn't adequate depth to submerge the current meter; Moreover, the pronounced low water stream flow velocity is not sufficient enough to trigger the operation of a current meter. Under those noticeable circumstances the only other remaining options, are the use of either a small-sized portable weir (all those its implementation brings difficulties due to the fact that weirs, in general, demand a relatively great head loss which is not available at areas in proximity to watersheds' outlets, where, in most cases, the natural slope of the channel bed is extremely low if not zero) plate or/and a small-sized flume or/and a set of small-sized weir and flumes which, eventually, was our final selected option, more specifically, a "3-inch U.S.G.S. Modified Portable Parshall Flume", "3-inch U.S.G.S. Conventional Portable Parshall Flume" and a "90° V-Notched Triangular-Shaped Sharp-Crested (Sharp-Edged) U.S.G.S. Portable Weir Plate" [10–20], made of sea plywood, covered with a sprayed thin smooth polyester coating, (identical to that usually the industry covers the outside surface of high-speed sea boats, in order to reduce the friction developing between the outside area of those sea boats and the sea water, thus securing that the friction developed between the bottom as well as the walls of the stream flow rate gauging apparatus is minimized/restricted to a minimum.

Meteorological data has been collected from Dexameni-Kavala city—Eastern Macedonia & Thrace Prefecture—Greece private meteorological station (located at 40°56′25″ N–E 24°24′01″ E, Altitude: 90 m).

Low stream flow rate values were forecasted employing MLFP that is an appropriate type of ANNs both for meteorological as well as for river stream flow rate predictions.

4. Results and Discussion

Employing MATLAB software, various different designs of MLFP were elaborated with different number of neurons within both the input as well as the hidden layers. The superb model for daily forecasting (in the present study, $M_{13.10.1}$) is described within the first following subsection whilst the referenced statistical criteria are displayed within the second following one. The three important identification characteristics of the model are as following: the number of neurons in input (i), hidden (j) and output (k) layers respectively.

4.1. Structure of Artificial Neural Network ($M_{13.10.1}$)

A custom neural network (abbreviated as $M_{13.10.1}$) was employed in order to simulate all the 246 site-measured values of the observed stream flow rate, (as depicted within Table A1), with the following architecture: Network Type: Feed-forward back propagation, Training Function: TRAINGDX, Adaption Learning Function: LEARNGDM, Performance Function: MSE, Number of Layers: 2, Number of Neurons: 10, Transfer Function: LOGSIG. It should also be stressed that epochs was selected equal to 1000. The input data for 246 site measurements were arranged as a time series with length of 246 data.

The selected custom neural network's architecture used for this simulation is depicted within Figure 2.

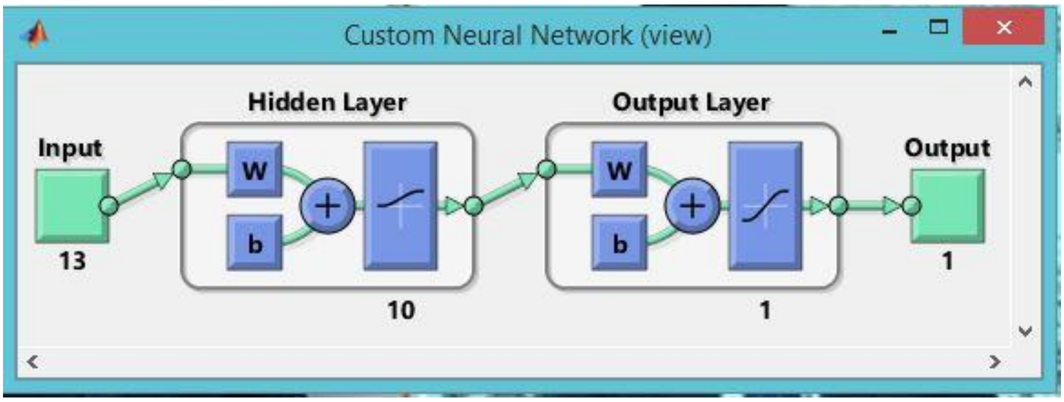

Figure 2. ANN ($M_{13.10.1}$) architecture plot of Perigiali Stream.

The input layer for this network consists of thirteen neurons representing total daily rainfall R, cumulative total daily rainfall R_C, mean daily wind velocity U_W^{ave}, maximum daily wind velocity U_W^{max}, mean daily air temperature T^{ave}, minimum daily air temperature T^{min}, maximum daily air temperature T^{max}, mean daily air humidity H^{ave}, minimum daily air humidity H^{min}, maximum daily humidity H^{max}, mean daily air pressure P^{ave}, minimum daily air pressure P^{min} and maximum daily pressure P^{max}. For this network 10 neurons were selected for the hidden layer.

The validation performance of the ANN ($M_{13.10.1}$) is illustrated within Figure 3.

The training regression performance of the ANN (M_{681}) is illustrated within Figure 4.

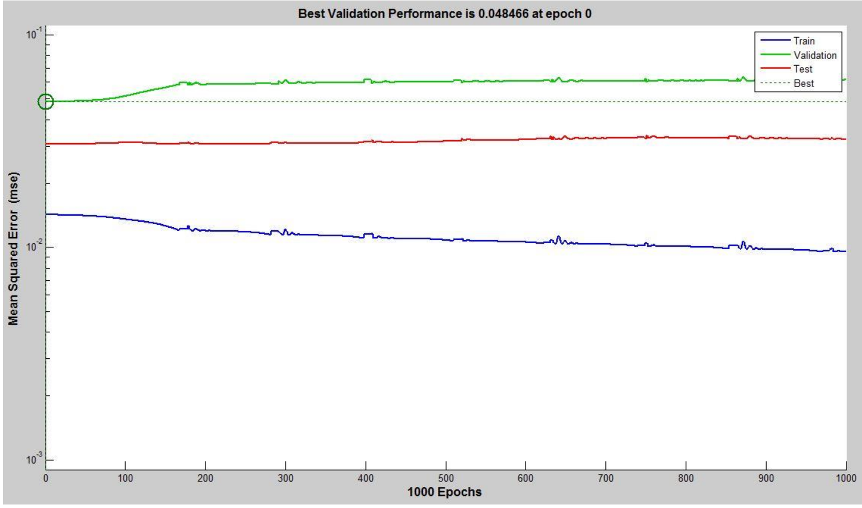

Figure 3. ANN ($M_{13.10.1}$) validation performance plot of Perigiali Stream.

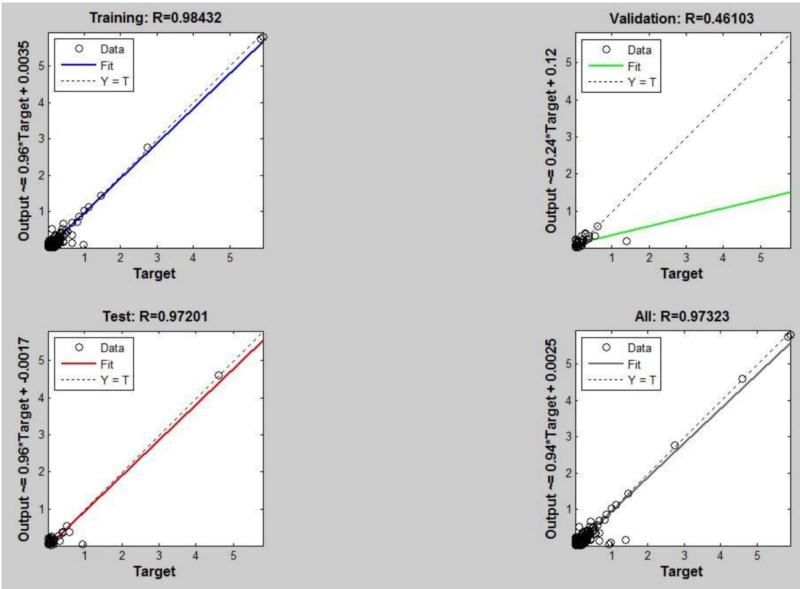

Figure 4. ANN ($M_{13.10.1}$) training regression performance plots of Perigiali Stream.

4.2. Model Statistical Efficiency Criteria and Performance Metrics

The respective statistical criteria values concerning Perigiali Stream regarding the selected artificial neural network ($M_{13.10.1}$) are depicted within Table 1 [21]. It is noted that the relative error value depicted within Table 1 represents the average value of the relative errors calculated for each pair of calculated and site measured low stream flow rate values.

The plot depicted within Figure 5 represents the discrepancy ratio concerning Perigiali Stream with reference to the selected artificial neural network, depicting graphically, more specifically, as far as the present study is concerned, the percentage of the computed low stream flow rate values lying between the double and the half of the corresponding recorded values. At this point, it should be noted that both coordinate axes are in logarithmic scale; therefore, the equations y = x, y = 0.5x and y = 2.0x are represented graphically by parallel straight lines [22].

In general, the obtained values of the statistical criteria RMSE, RE, EC for Perigiali Stream can be considered fairly satisfactory. Additionally, the degree of linear dependence between computed and observed low daily stream flow rate is very high.

The dates of all measurements as well as both the site measured as well as the calculated stream flow rates of Perigiali Stream are presented in Table A1.

Table 1. Statistical criteria values of Perigiali Stream (ANN $M_{13.10.1}$).

Number of Paired Values	RMSE (ltrs/s)	RE (%)	EC	r	r^2	Discrepancy Ratio
246	0.1479	−0.4080	0.9468	0.9732	0.9472	0.6789

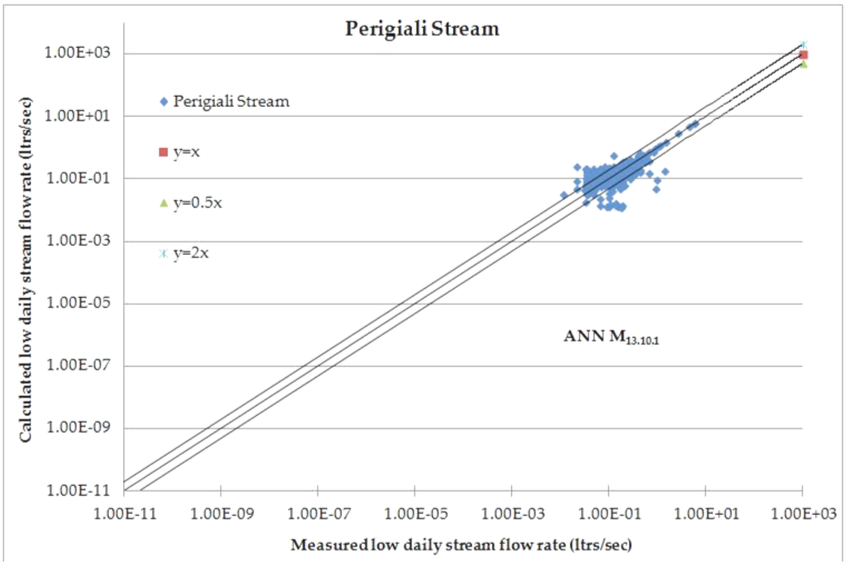

Figure 5. Discrepancy ratio plot of Perigiali Stream (ANN $M_{13.10.1}$).

5. Discussion-Conclusions-Further Research

Lots of models based on ANN procedure concept have been employed and proposed by researchers so far in order to model daily stream flow and sediment transport rate worldwide. In the present study, a custom neural network (abbreviated as $M_{13.10.1}$) was employed in order to simulate all the 246 site-measured values of the observed low stream flow rate, (as depicted within Table A1), with the certain architecture, using as inputs several meteorological parameters, (exogenous variables of the runoff generating processes), prevailing around the study area, and turned out, among others, to be the most appropriate to simulate the recorded daily low stream flow rate data. The resulted statistical efficiency criteria proved a strong relationship between those meteorological parameters involved and the daily stream flow rate of Perigiali Stream, Kavala city, Greece, suggesting that that ANN modeling concept is able to efficiently simulate observed daily low stream flow rate data which is essential for water resources management at a watershed level in terms of drought forecasting and management, water reservoir and water deviation works design, agricultural schemes planning at a regional level, filling gaps within low stream flow rate time series, low-flow indices calculation for environmental purposes, model implementation in ungaged catchments in order to generate artificial low stream flow rate data etc. Furthermore, the fact that the observed data represents short time intervals instead of an adequately long continuous time series can be definitely considered as a limitation underlining the need of more collected low stream flow rate recorded data in order to prove that our model can be regarded as an undoubtedly reliable one. In future, provided that proper and adequate apparatus is available, we intend to monitor water quality parameters in order to perform statistical analysis and assessment [23,24] and apply stochastic models [25] to predict future respecting values which are essential towards the establishment of a holistic Perigiali watershed management scheme.

Supplementary Materials: The following are available online at https://www.youtube.com/watch?v=Wu8KBj3qqXg, Video S1: Watershed Stream Flow Measurement-Stream Perigiali-2016.06.18-Kavala City-Greece, https://www.youtube.com/watch?v=-HbPZLNGplY&feature=youtu.be, Video S2: Watershed Stream Flow Measurement-Stream Perigiali-2017.07.27(a)-Kavala City-Greece (08:16:49 a.m.).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The dates of all measurements as well as both the site measured as well as the calculated stream flow rates of Perigiali Stream are presented in Table A1.

Table A1. Stream flow rate measurements of Perigiali Stream.

No.	Date	Stream Flow Rate (m^3/s) Site-Measured	Stream Flow Rate (m^3/s) Calculated ($M_{13.10.1}$)
1	14-5-2016	0.4370	0.3151
2	15-5-2016	0.5080	0.5156
3	16-5-2016	0.4030	0.5368
4	17-5-2016	0.4030	0.3824
5	18-5-2016	0.4720	0.4206
6	19-5-2016	0.5830	0.3695
7	20-5-2016	0.5080	0.5401
8	21-5-2016	2.7460	2.7714
9	22-5-2016	1.0110	1.0422
10	23-5-2016	0.8300	0.7277
11	24-5-2016	0.8740	0.8777
12	25-5-2016	0.6620	0.6884
13	26-5-2016	0.6620	0.3522
14	27-5-2016	0.3700	0.3328
15	28-5-2016	0.2488	0.1621
16	29-5-2016	0.3701	0.2290
17	30-5-2016	0.2775	0.2464
18	31-5-2016	0.3381	0.2399
19	1-6-2016	0.2488	0.1881
20	2-6-2016	0.1700	0.2775
21	3-6-2016	0.3701	0.4214
22	4-6-2016	0.5451	0.3349
23	5-6-2016	0.3381	0.2148
24	6-6-2016	0.5450	0.4573
25	7-6-2016	0.3072	0.3277
26	8-6-2016	0.1950	0.3244
27	9-6-2016	0.1238	0.5328
28	10-6-2016	0.1238	0.2220
29	11-6-2016	0.1950	0.1596
30	12-6-2016	0.1238	0.2532
31	13-6-2016	1.4650	1.4400
32	14-6-2016	0.6220	0.5874
33	15-6-2016	0.4371	0.6716
34	16-6-2016	0.3072	0.3144
35	17-6-2016	0.2213	0.2456
36	18-6-2016	0.3072	0.1447
37	19-6-2016	0.2775	0.0960
38	20-6-2016	0.1950	0.1450
39	21-6-2016	0.2775	0.1379
40	22-6-2016	0.0832	0.1844
41	23-6-2016	0.1028	0.0345
42	24-6-2016	0.0115	0.0324
43	25-6-2016	0.0344	0.1006
44	26-6-2016	0.1462	0.0823
45	27-6-2016	0.1462	0.2139

46	28-6-2016	0.2775	0.3824
47	29-6-2016	0.1700	0.2488
48	30-6-2016	0.0652	0.1717
49	1-7-2016	0.1700	0.1751
50	2-7-2016	0.1700	0.1731
51	3-7-2016	0.3701	0.2599
52	4-7-2016	0.2775	0.1681
53	5-7-2016	0.2775	0.1840
54	6-7-2016	0.0652	0.1986
55	7-7-2016	0.2213	0.2425
56	8-7-2016	0.0218	0.2421
57	9-7-2016	0.0832	0.2085
58	10-7-2016	0.1028	0.1696
59	11-7-2016	0.1028	0.0924
60	12-7-2016	0.1028	0.1883
61	13-7-2016	0.0489	0.1802
62	14-7-2016	0.1238	0.2023
63	15-7-2016	0.0652	0.1956
64	16-7-2016	0.2213	0.3563
65	17-7-2016	0.1462	0.1511
66	18-7-2016	0.0344	0.2032
67	19-7-2016	0.1950	0.2087
68	20-7-2016	0.1028	0.1845
69	21-7-2016	0.0344	0.1792
70	22-7-2016	0.3381	0.1551
71	23-7-2016	0.2213	0.1385
72	24-7-2016	0.1950	0.1859
73	25-7-2016	0.1238	0.1675
74	26-7-2016	0.0340	0.2132
75	27-7-2016	0.1028	0.1404
76	28-7-2016	0.0489	0.2120
77	29-7-2016	0.0832	0.1716
78	30-7-2016	0.1238	0.1539
79	31-7-2016	0.3701	0.2470
80	1-8-2016	0.0652	0.1286
81	2-8-2016	0.1950	0.1875
82	3-8-2016	0.1028	0.2106
83	4-8-2016	0.1462	0.1703
84	5-8-2016	0.2488	0.1431
85	6-8-2016	0.3381	0.1404
86	7-8-2016	0.1238	0.1855
87	8-8-2016	0.1950	0.1470
88	9-8-2016	0.3701	0.3080
89	10-8-2016	0.1950	0.0914
90	11-8-2016	0.3381	0.1474
91	12-8-2016	0.2488	0.1523
92	13-8-2016	0.1950	0.1698
93	14-8-2016	0.2488	0.1911
94	15-8-2016	0.2219	0.2268
95	16-8-2016	0.2775	0.2724
96	17-8-2016	0.4371	0.3402
97	18-8-2016	0.3701	0.3989

98	19-8-2016	0.4031	0.3530
99	20-8-2016	0.3072	0.3288
100	21-8-2016	0.1950	0.1659
101	22-8-2016	0.2213	0.1439
102	23-8-2016	0.4371	0.1598
103	24-8-2016	0.2775	0.1746
104	25-8-2016	0.2213	0.1580
105	26-8-2016	0.2775	0.3003
106	27-8-2016	0.2775	0.4087
107	28-8-2016	0.3072	0.2810
108	29-8-2016	0.4371	0.1957
109	30-8-2016	0.6616	0.1487
110	24-5-2017	0.1210	0.0630
111	25-5-2017	0.0820	0.2088
112	26-5-2017	5.9150	5.8006
113	27-5-2017	0.2130	0.3294
114	28-5-2017	0.0820	0.0721
115	29-5-2017	0.0650	0.1313
116	30-5-2017	0.1010	0.0732
117	31-5-2017	0.0490	0.0942
118	1-6-2017	0.0340	0.0577
119	2-6-2017	0.0650	0.0701
120	3-6-2017	0.0650	0.0926
121	4-6-2017	0.0820	0.1520
122	5-6-2017	0.0650	0.1203
123	6-6-2017	0.0820	0.1310
124	7-6-2017	0.0650	0.0775
125	8-6-2017	0.0820	0.0967
126	9-6-2017	0.1010	0.2323
127	10-6-2017	0.0820	0.0822
128	11-6-2017	5.8560	5.7520
129	12-6-2017	1.4010	0.1787
130	13-6-2017	0.0650	0.1244
131	14-6-2017	0.1010	0.0562
132	15-6-2017	0.0820	0.0934
133	16-6-2017	0.0820	0.1727
134	17-6-2017	0.1010	0.0953
135	18-6-2017	0.0820	0.2393
136	19-6-2017	0.0650	0.1153
137	20-6-2017	0.0650	0.2136
138	21-6-2017	0.0650	0.0858
139	22-6-2017	0.0650	0.1791
140	23-6-2017	0.0650	0.0815
141	24-6-2017	0.0490	0.0913
142	25-6-2017	0.0650	0.0944
143	26-6-2017	0.0490	0.1180
144	27-6-2017	0.0490	0.1054
145	28-6-2017	0.0490	0.0907
146	29-6-2017	0.0490	0.0868
147	30-6-2017	0.0490	0.0799
148	1-7-2017	0.0490	0.0761
149	2-7-2017	0.0490	0.0405

150	3-7-2017	0.0645	0.0220
151	4-7-2017	0.0486	0.0528
152	5-7-2017	0.0486	0.0771
153	6-7-2017	0.0486	0.1173
154	7-7-2017	0.0486	0.0557
155	8-7-2017	0.0486	0.0526
156	9-7-2017	0.0486	0.0943
157	10-7-2017	0.0344	0.0954
158	11-7-2017	0.0344	0.1002
159	12-7-2017	0.0645	0.1101
160	13-7-2017	0.0344	0.0953
161	14-7-2017	0.9872	0.0938
162	15-7-2017	0.1007	0.1689
163	16-7-2017	0.0819	0.0594
164	17-7-2017	0.1421	0.1343
165	18-7-2017	0.1208	0.0546
166	19-7-2017	0.1007	0.1309
167	20-7-2017	0.0819	0.1488
168	21-7-2017	0.0486	0.1666
169	22-7-2017	0.0645	0.0871
170	23-7-2017	0.0645	0.0853
171	24-7-2017	0.0645	0.0791
172	25-7-2017	0.0344	0.0470
173	26-7-2017	0.0486	0.0324
174	27-7-2017	0.0486	0.1451
175	28-7-2017	0.0486	0.0401
176	29-7-2017	0.0486	0.0833
177	30-7-2017	0.0486	0.0854
178	31-7-2017	0.0486	0.0917
179	1-8-2017	0.0344	0.1454
180	2-8-2017	0.0344	0.1289
181	3-8-2017	0.0344	0.0650
182	4-8-2017	0.0344	0.0745
183	5-8-2017	0.0344	0.0478
184	6-8-2017	0.0486	0.0646
185	7-8-2017	0.0344	0.0831
186	8-8-2017	0.0344	0.0593
187	9-8-2017	0.0344	0.0648
188	10-8-2017	0.0344	0.0761
189	11-8-2017	0.0344	0.0717
190	12-8-2017	0.0344	0.0536
191	13-8-2017	0.0344	0.0579
192	14-8-2017	0.0344	0.0325
193	15-8-2017	0.0344	0.0407
194	16-8-2017	0.0344	0.0666
195	17-8-2017	0.0344	0.0412
196	18-8-2017	0.0221	0.0871
197	19-8-2017	0.2060	0.0963
198	20-8-2017	0.1890	0.0784
199	21-8-2017	0.1670	0.0463
200	22-8-2017	0.0486	0.1150
201	23-8-2017	0.1210	0.0395

202	24-8-2017	0.0486	0.0695
203	25-8-2017	0.0486	0.0432
204	26-8-2017	0.2070	0.0584
205	27-8-2017	0.1690	0.0670
206	28-8-2017	0.0344	0.0642
207	29-8-2017	0.0486	0.0653
208	30-8-2017	0.1770	0.1272
209	31-8-2017	0.1710	0.0511
210	1-9-2017	0.0730	0.0719
211	2-9-2017	0.0470	0.0651
212	3-9-2017	0.1930	0.0619
213	4-9-2017	0.9439	0.0466
214	5-9-2017	0.0344	0.0558
215	6-9-2017	0.0360	0.0309
216	7-9-2017	0.0320	0.0423
217	8-9-2017	0.0430	0.1097
218	9-9-2017	0.1390	0.1766
219	10-9-2017	0.1370	0.1078
220	11-9-2017	0.0220	0.0488
221	12-9-2017	0.0344	0.0442
222	13-9-2017	0.1450	0.0686
223	14-9-2017	0.0344	0.1917
224	15-9-2017	0.1610	0.1379
225	16-9-2017	0.1490	0.0648
226	17-9-2017	0.0486	0.0852
227	18-9-2017	0.1080	0.0699
228	19-9-2017	0.0486	0.0667
229	20-9-2017	0.0344	0.0622
230	21-9-2017	0.0990	0.0127
231	22-9-2017	0.0714	0.0565
232	23-9-2017	0.1380	0.0165
233	24-9-2017	0.0996	0.0243
234	25-9-2017	0.0934	0.1726
235	26-9-2017	4.6003	4.6082
236	27-9-2017	0.1870	0.0140
237	28-9-2017	0.1510	0.0125
238	29-9-2017	0.1790	0.0118
239	30-9-2017	0.0330	0.0174
240	1-10-2017	0.1280	0.1406
241	2-10-2017	0.1420	0.0136
242	3-10-2017	0.0910	0.0124
243	4-10-2017	0.0650	0.0139
244	5-10-2017	0.1050	0.0147
245	6-10-2017	0.0590	0.0550
246	7-10-2017	1.1245	1.1225

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