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

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Abstract: Only a few scientific research studies referencing extremely low flow conditions have been conducted in Greece so far. Forecasting future low stream flow rate values is a crucial and decisive task when conducting drought and watershed management plans by designing construction plans dealing with water reservoirs and general hydraulic works capacity, by calculating hydrological and drought low flow indices, and by separating groundwater base flow and storm flow of storm hydrographs, etc. The 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 part of 2015. We compiled an Artificial Neural Network to simulate low stream flow rate data, acquired at a certain location of the entirely regulated, urban stream, which crosses the roads junction formed by Iokastis road and an Chrisostomou Smirnis road, Agios Loukas residential area, Kavala city, Eastern Macedonia & Thrace Prefecture, NE Greece, during part of July, August, and part of September 2015, until 12 September 2015, using a 3-inches conventional portable Parshall flume. The observed data were plotted against the predicted one and the results were demonstrated through interactive tables by providing us the ability to effectively evaluate the ANN model simulation procedure performance. Finally, we plotted the recorded against the simulated low stream flow rate data by compiling a log-log scale chart, which provides a better visualization of the discrepancy ratio statistical performance metrics and calculated further statistic values 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 25 July 2015 and 11 September 2015, which revealed that Dagum (4P) 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].

Another type of low flow analysis, specifically probability distribution analysis, was performed in the past by analyzing the observed data collected at another, with similar features, gauging station, located at the outlet of Perigiali Stream, Kavala City, NE Greece, NE Mediterranean Basin, between 14 May 2016 and 31 July 2016, which reveals 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 [3]. Furthermore, as far as the same gauging station, (Perigiali Stream watershed outlet), a similar type of analysis was elaborated considering, this time, the observed data collected at the same gauging station between 14 May 2016 and 29 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 [4,5]. The Monte-Carlo simulation method, as another type of low flow analysis, was employed to define, by generating multiple attempts, the anticipated value of a random (hydrological in the specific case) variable to the above mentioned gauging station, located at the outlet of Perigiali Stream, Kavala City, NE Greece, NE Mediterranean Basin, between 14 May 2016 and 31 July 2016 [6].

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 by respecting the San Juan River basin, Argentina, using meteorological data from Pachon meteorological station built at 1900 m of altitude and proved distinctively effective for fitting the observed stream flow data remarkably well [7]. In a scientific research article, an ANN model was developed and proved effective for simulating the daily high and low flows, in Mesochora catchment, (drained by the Acheloos River), central mountain region of Greece [8]. In another scientific research article, the performance of three different ANN schemes (a, b, and c) was tested in order to calculate bed load transport rate in gravel-bed rivers running within the Snake River Basin, U.S.A. [9]. In another scientific research article, an ANN model was developed and proved capable of stream flow modeling of Savitri catchment, India [10]. In another scientific research article, an ANN model was designed and performed adequately of stream flow modeling of Nestos River, NE Greece [11]. In another scientific research article, an ANN model, ($M_{13.10.1}$), was found to best fit and model the low stream flow data recorded at the outlet of Perigiali Stream, Kavala city, NE Greece, NE Mediterranean Basin [12].

In the present scientific research study, ANNs have been employed to design a forecasting model for the daily low flows of Iokastis Stream (at an intermediate point of the stream channel, within the urban area, of the homonymous watershed), Kavala city, Eastern Macedonia and Thrace Prefecture, NE Greece, NE Mediterranean Basin. Their selection is founded on the fact that they perform remarkably well (together within other sectors of scientific interests) in the field of hydrology. However, in some occasions, there are no available adequate information respecting all the variables contributing to the watershed system driving forces.

2. Study Area

The stream flow rate gauging station, which was established near the junction formed by Iokastis and Chrisostomou Smirnis roads, Agios Loukas residential sector, Kavala city, (NE Greece, NE Mediterranean Basin), a coastal city, located at the north of the Aegean Sea, across the Thassos Island, refers to an intermediate point of an absolutely channelized stream with bed, walls, and most of his top length is made from steel reinforced concrete. Thus, the major part of the stream's length and, consequently, its associated flow are invisible. It is 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 north exit of the city as well). More precisely, it is located at the specific co-ordinates 40°55′57.70″ N and 24°23′19.74″ E, Kavala city area, and operated continuously, which spans a time period from 25 July 2015 to 11 September 2015, as illustrated in Figure 1.

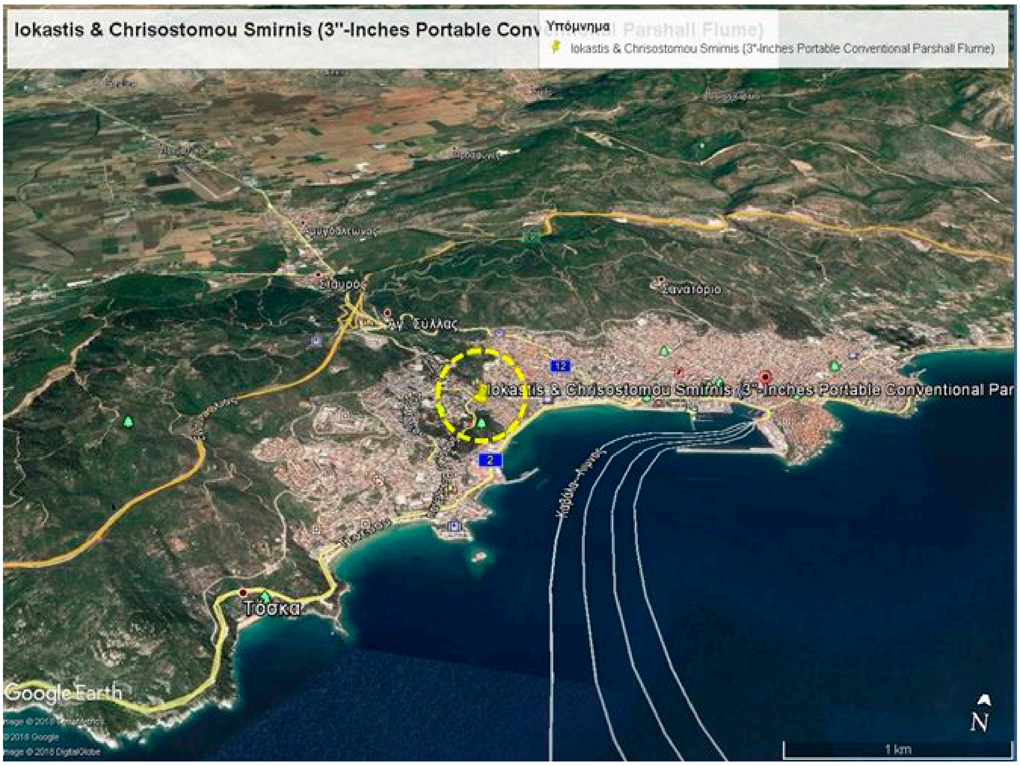

Figure 1. Parshall flume (conventional) gauging station, Iokastis Stream area, Kavala city, Greece.

3. Materials and Methods

We considered the stream flow data observed during a continuous period of 2015, more precisely, during part of July (from 25 July 2015), August 2015, and part of September 2015 (until 11 September 2015, when unfortunately, a sudden storm associated with heavy rainfall, caused a flash flood, which destroyed the apparatus).

The distinctively shallow waters, exacerbated by the extremely low water stream flow velocity occurring at the gauging station, make it impossible to perform the area-velocity method in order to calculate the stream flow rate (discharge) by using a current meter mounted on a wading rod due to the fact that there is no 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 (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 a small-sized flume, which, eventually, was our final selected option. More specifically, "3-inch U.S.G.S. Conventional Portable Parshall Flume" [13–24], made of pre-fabricated plastics, covered with a sprayed thin smooth polyester coating, which is identical to 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, which secures 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 and Thrace Prefecture–NE Greece–NE Mediterranean Basin private meteorological station (located at 40°56′25″ N–E24°24′01″ E, Altitude: 90 m).

Low stream flow rate values were forecasted by 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 on with a different number of neurons within both the input as well as the hidden layers. The superb model for daily forecasting (in the present study, $M_{17.10.1}$) is described within the first following subsection while the referenced statistical criteria are displayed within the second 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 ($M_{17.10.1}$)

A custom neural network (abbreviated as $M_{17.10.1}$) was employed in order to simulate all the 49 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, and Transfer Function: LOGSIG. It should also be stressed that epochs were selected equal to 1000. The input data for 49 site measurements were arranged as a time series with a length of 49 data. The selected custom neural network's architecture used for this simulation is depicted within Figure 2.

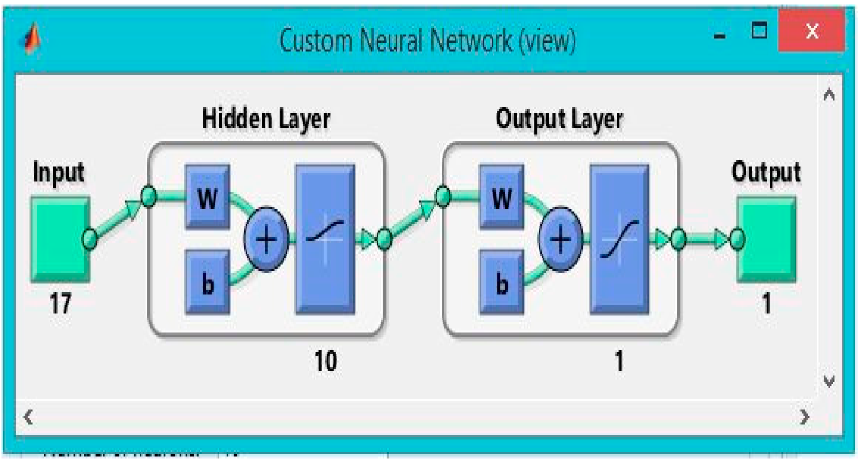

Figure 2. ANN ($M_{17.10.1}$) architecture plot of Iiokastis-Chrisostomou Smirnis Stream.

The input layer for this network consists of 17 neurons representing (for the same period ranging from 25 July 2015 to 11 September 2015) as following: 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 wind gusts velocity $U_{Wg}{}^{ave}$, maximum daily wind gusts velocity $U_{Wg}{}^{max}$, 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}, maximum daily air pressure P^{max}, mean daily discomfort index T^{di}, and mean daily dew point temperature T^{dp}. For this network, 10 neurons were selected for the hidden layer.

The validation performance of the ANN ($M_{17.10.1}$) is illustrated within Figure 3.

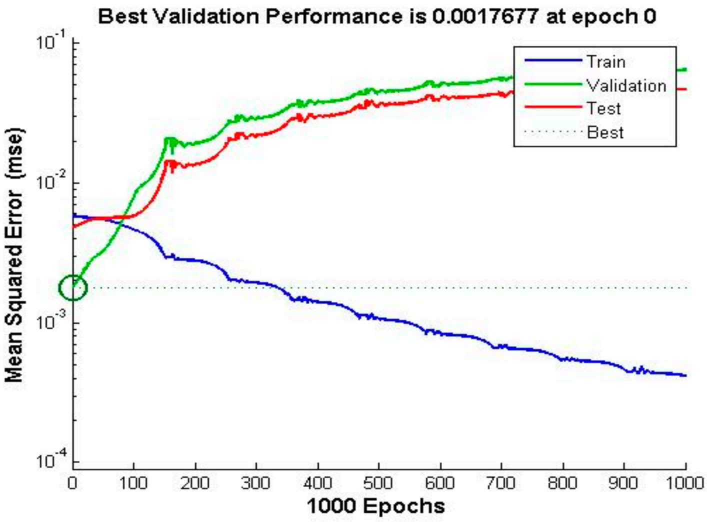

Figure 3. ANN ($M_{17.10.1}$) validation performance plot of Iokastis-Chrisostomou Smirnis Stream.

The training regression performance of the ANN ($M_{17.10.1}$) is illustrated within Figure 4.

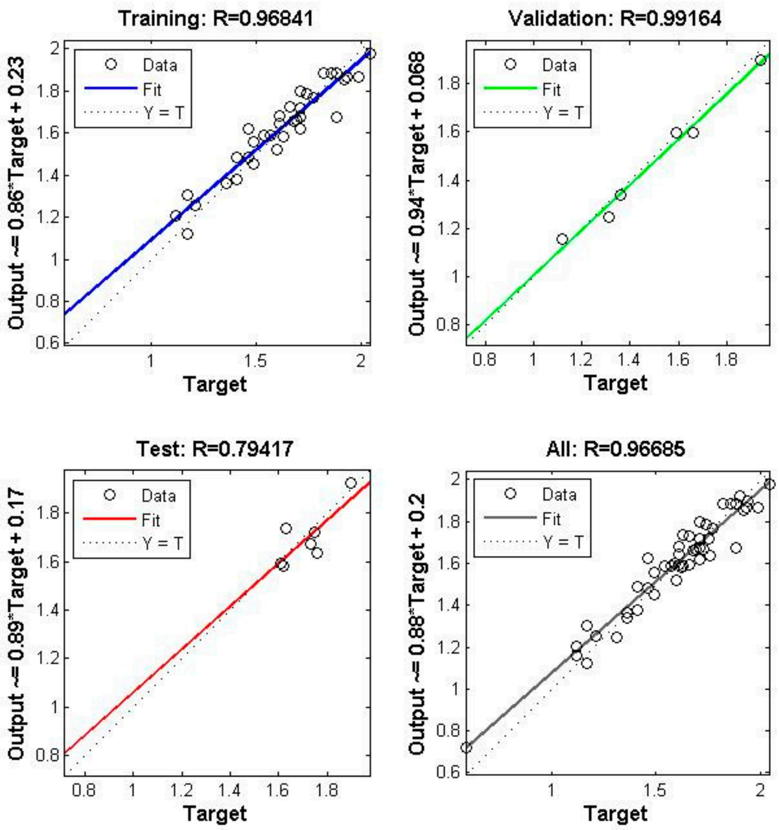

Figure 4. ANN ($M_{17.10.1}$) training regression performance plots of Perigiali-Chrisostomou Smirnis Stream.

4.2. Model Statistical Efficiency Criteria and Performance Metrics

The respective statistical criteria values concerning the Iokastis Stream regarding the selected artificial neural network ($M_{17.10.1}$) are depicted in Table 1 [25]. The relative error value depicted in 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 in Figure 5 represents the discrepancy ratio concerning Iokastis Stream with reference to the selected artificial neural network, depicting graphically, as far as the present study is concerned, the percentage of the computed low stream flow rate values lying between the double and half of the corresponding recorded values. At this point, it should be noted that both coordinate axes are in a logarithmic scale. Therefore, the equations y = x, y = 0.5x, and y = 2.0x are represented graphically by parallel straight lines [26].

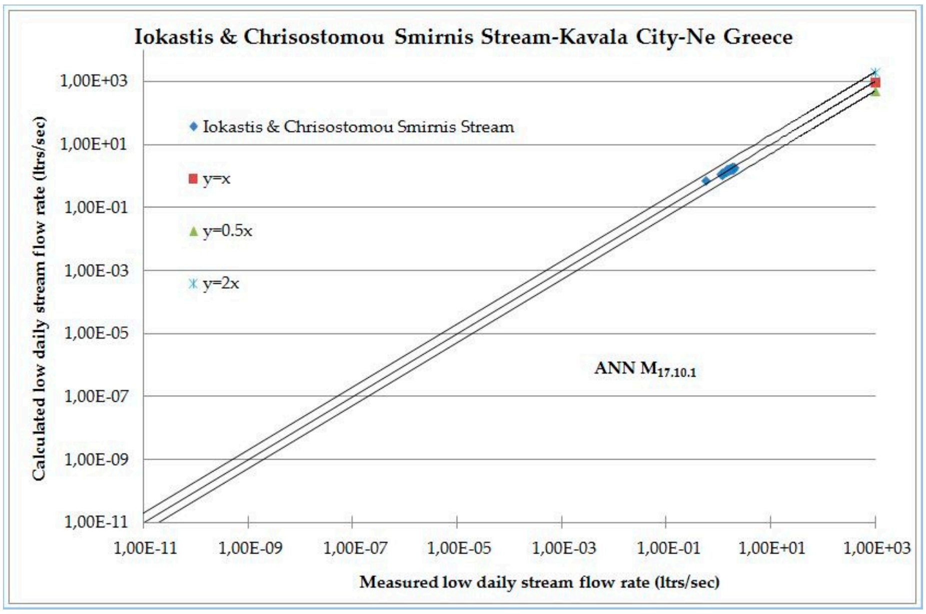

Figure 5. Discrepancy ratio plot of Perigiali Stream (ANN $M_{17.10.1}$).

Table 1. Statistical criteria values of Perigiali Stream (ANN $M_{17.10.1}$).

Number of Paired Values	RMSE (ltrs/s)	RE (%)	EC	r	r^2	Discrepancy Ratio
49	0.0718	−0.0054	0.9303	0.9664	0.9340	1.0000

In general, the obtained values of the statistical criteria RMSE, RE, and EC for Iokastis 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 (on demand).

5. Discussion–Conclusions–Further Research

Lots of models based on the 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 $M_{17.10.1}$) was employed in order to simulate all the 49 site-measured values of the observed low stream flow rate (as depicted within Table A1) with the certain architecture, using several meteorological parameters (exogenous variables of the runoff generating processes) as inputs, which prevails around the study area. This turned out, among others, to be the most appropriate way 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 Iokastis Stream, Kavala city, Greece, which suggests that the ANN modeling concept is able to efficiently simulate an 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 uncaged 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 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 the future, provided that a proper and adequate apparatus is available, we intend to monitor water quality parameters in order to perform statistical analysis and assessment [27,28] and apply stochastic models [29] to predict future respecting values, which are essential toward establishing a holistic Iokastis-Chrisostomou Smirnis Stream watershed management scheme.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

The dates of all measurements as well as both the site measured/recorded/observed as well as the calculated/forecasted/predicted/fitted stream flow rates of Perigiali Stream are presented in Table A1.

Table A1. Stream flow rate measurements of Iokastis (& Chrisostomou Smirnis Roads Junction) Stream.

No.	Date (dd-mm-yy)	Stream Flow Rate (m^3/s) Site-Measured	Stream Flow Rate (m^3/s) Calculated ($M_{17.10.1}$)
1	25-7-2015	0.5866	0.7177
2	26-7-2015	1.9370	1.8998
3	27-7-2015	1.1212	1.2052
4	28-7-2015	1.3574	1.3375
5	29-7-2015	1.6240	1.5830
6	30-7-2015	1.4066	1.4877
7	31-7-2015	1.7590	1.6366
8	1-8-2015	1.5730	1.5886
9	2-8-2015	1.7080	1.7965
10	3-8-2015	1.4890	1.4525
11	4-8-2015	1.6630	1.5945
12	5-8-2015	1.5350	1.5888
13	6-8-2015	1.7120	1.7173
14	7-8-2015	1.7510	1.7188
15	8-8-2015	1.8560	1.8871
16	9-8-2015	1.6770	1.6599
17	10-8-2015	1.5920	1.5971
18	11-8-2015	1.6040	1.5192
19	12-8-2015	1.7260	1.6711
20	13-8-2015	1.6330	1.7382
21	14-8-2015	1.8820	1.6746
22	15-8-2015	1.4920	1.5594
23	16-8-2015	1.3089	1.2469
24	17-8-2015	1.7675	1.7699
25	18-8-2015	1.2138	1.2538
26	19-8-2015	1.1671	1.3057
27	20-8-2015	1.1671	1.1211
28	21-8-2015	1.9170	1.8529
29	22-8-2015	1.6900	1.6653
30	23-8-2015	1.1212	1.1578
31	24-8-2015	1.7142	1.6205
32	25-8-2015	1.9865	1.8693
33	26-8-2015	1.6093	1.6805
34	27-8-2015	1.8759	1.8828
35	28-8-2015	1.8214	1.8834
36	29-8-2015	1.6093	1.6447
37	30-8-2015	1.6093	1.5918
38	31-8-2015	2.0426	1.9753
39	1-9-2015	1.9309	1.8669
40	2-9-2015	1.7142	1.6733
41	3-9-2015	1.6330	1.5862
42	4-9-2015	1.7440	1.7883
43	5-9-2015	1.8950	1.9231
44	6-9-2015	1.6620	1.7276
45	7-9-2015	1.3574	1.3640
46	8-9-2015	1.4563	1.6231
47	9-9-2015	1.3574	1.3377
48	10-9-2015	1.4563	1.4850
49	11-9-2015	1.4066	1.3784

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