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MEASUREMENT AND PREDICTION OF KARSTIC SPRING FLOW RATES

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ABSTRACT

This paper deals with prediction of the response of karstic springs by means of artificial neural networks (ANNs). A feed-forward back propagation ANN with three layers has been developed, to predict flow rates of two karstic springs, located at Rouvas area, Crete, Greece, using rainfall data as input. While the number of neurons of the input and output layers was determined by choice of data and desired output respectively, the number of neurons of the hidden layer was decided by means of numerous tests. Data used in ANN training and testing include daily and monthly precipitation depths (from September, 2006 to December, 2010) and measured flow rates of the two springs (from April, 2007 to December, 2010). Results show that the trained artificial neural network performed well, although flow rate measurements were not very regular. Moreover, the possibility of estimating the flow rate of one spring, based on measurements of the other has been investigated. Again the ANN gave satisfactory results. All spring flow rate and rainfall measurements are presented as an appendix, to facilitate further scientific research in the area of ANN application to water resources management.

Keywords: karstic aquifer; karstic spring; artificial neural network; flow rate measurement

1. Introduction

Karstic aquifers are very important water resources for many areas of the world and it is estimated that 20 to 25% of the global population depends on them (Ford and Williams, 2007). Their efficient management is a very challenging task. The first problem that arises is proper flow simulation; application of the empirical Darcy law, used for flows through porous media, may not yield satisfactory results in karstic aquifers, due to the size and structure of void spaces, serving as water conduits.

When development of turbulent flow is anticipated, use of the Forchheimer formula leads, in principle, to more accurate results. This formula reads:

$$\mathrm{grad}h = cV + dV^2 \tag{1}$$

where h is the hydraulic head and V the Darcy velocity. Its combination with continuity equation is not that efficient, from the computational point of view, and for this reason its application is rather restricted (e.g. Moutsopoulos and Tsihrintzis, 2005; Mathias and Todman, 2010).

Moreover, in karstic (and fractured) aquifers different families of void spaces may exist, due to karstification and primary rock permeability. In such cases, dual porosity models might seem more appropriate. They have the drawback, though, of introducing additional flow parameters that are not easily defined (i.e. hydraulic conductivity for each medium and a constant for mass exchange between the two).

When rock karstification is intense, water actually flows through a network of natural conduits. In such cases models used to describe flows in pipe networks are more suitable. But knowledge of the network geometry is in most cases restricted, therefore some kind of macroscopic approach cannot be avoided (e.g. Jeannin, 2001). Moreover, in many cases flow due to the primary porosity of the host rock cannot be neglected (e.g. Liedl *et al.*, 2003). In such cases, combination of different flow models can be very useful (e.g. Rooij *et al.*, 2013). Use of Navier-Stokes equations has also been examined (Masciopinto and Palmiotta, 2013).

The last few years karstic aquifers have been simulated either as systems of reservoirs (e.g. Fleury *et al.*, 2009) or by means of artificial neural networks (ANNs), as discussed in the following section. In our study we have used an ANN to "simulate" a karstic aquifer, feeding two springs. The karstic system is located at the Rouvas area of the island of Crete, Greece, shown in Figure 1. Actually, our purpose was to forecast the spring flow rates, based on local rainfall data. The reason for using ANN is explained in the following section.

2. Artificial neural networks and their usefulness

Artificial Neural Networks (ANNs) are based on the idea that certain properties of biological neurons can be used for the creation of a simplified "brain", which imitates, to an extent, the learning and computational capacity of human brain. They are essentially grids of processing units, called neurons, which are arranged in layers (input, hidden and output layers). Each neuron produces an output value, based on input information received from other neurons. Each item of input information is weighted by a coefficient, called synaptic weight, which expresses the importance attributed to the particular source of input information. Neuron output depends on the weighted sum of inputs and a preselected activation function.

Approach to a problem by means of ANNs does not aim at mathematical description of natural phenomena, but at obtaining quantitative results for given data sets, based on "experience" from similar known cases. So, ANNs could be particularly useful when a) mathematical simulation of the physical phenomena is either impossible or too complicated and b) Parameters necessary for mathematical simulation (e.g. hydraulic conductivity, storativity) cannot be defined with acceptable accuracy. These situations arise quite often with karstic aquifers, rendering use of ANNs attractive. Moreover, surrogate models, such as artificial neural networks, are used quite often in conjunction with evolutionary optimization techniques, such as genetic algorithms, in order to reduce total computational volume, even when porous aquifers are involved (e.g. Nikolos *et al.*, 2008; Sreekanth and Datta, 2010). Combinations of ANNs with deterministic models have also been used (e.g. Lallahem and Mania, 2003; Jain and Srinivasulu, 2004; Chen and Adams, 2006).

ANNs have been already used extensively in water resources management problems (e.g. Kralisch *et al.*, 2003), modeling of rainfall-runoff relationship (e.g. Baratti *et al.,* 2003; Rajurkar *et al.*, 2004; Pan *et al.*, 2007), flood forecasting (e,g. Lekkas *et al.*, 2004), groundwater level forecasting (e.g. Daliakopoulos *et al.*, 2005; Trichakis *et al.,* 2011), groundwater pollution prediction (e.g. Sahoo *et al.*, 2005), determination of aquifer parameters (e.g. Zio, 1997; Samani *et al.*, 2007), prediction of reservoir inflow and level (e.g. Coulibaly *et al.*, 2005; Chang and Chang, 2006), etc. Regarding prediction of karstic spring discharge, encouraging results have been obtained, at least when there are abundant field data (e.g. Kurtulus and Razack, 2007; Hu *et al.,* 2008).

The most difficult stage in ANN application is selection of the most suitable structure for the examined problem, including number of layers, number of neurons of each layer, activation functions and connection weights. Experience from similar applications can serve as a guide, but the final choice is definitely case-specific.

Despite their usefulness, ANNs (or other surrogate models) may introduce some additional uncertainty. In such cases, use of ensembles of surrogate models has been recommended (Sreekanth and Datta, 2011).

3. The study area

Karstic systems are rather common in Greece (e.g. Novel *et al.*, 2007; Tsakiris *et al.*, 2009). As mentioned in section 1, this paper focuses on two karstic springs appearing at a distance of 800 m from each other, in the area of Gergeri (ex-Rouvas municipality), Crete, which is shown in Fig. 1. The two springs are called “Mai Vryssi” and “Pera Vryssi”. They are found at an elevation of 500 m asl approximately, while the average elevation of the area, which feeds the karstic system, is 950 m asl. A number of other springs appear in the same area, some of them in rough terrain.

Figure 1. Study area (Paleologos *et al.*, 2013)

3.1 Field data

To train and test the ANN, field data have been used, namely local daily precipitation and flow rates of the two karstic springs. These data cover a period larger than 3 years (daily rainfall from September, 2006 to December, 2010 and measured flow rates of the two springs from April 2007 to December 2010) and they have been collected by N. Darivianakis, mostly in the framework of his Ph.D. Thesis (Darivianakis, 2011).

A complete and reliable set of rainfall data (rainfall depth per day) was available from a rain gauge which is installed at the vicinity of Pera Vryssi, namely at a very suitable location for the purpose of this study.

The flow rates of the two springs have been measured in a very simple way, by means of a chronometer (accurate to one hundredth of a second) and a volumetric vessel. That vessel had a total volume of 18 lt. Each spring has two outlets. For each outlet, the time to fill the vessel up to the indication of 15 litres was counted three times. Then, the mean was used to calculate the flow rate of each outlet. Finally, the flow rate values of the two outlets were added to each other. While measured flow rate values are reliable, the measurement schedule has been rather irregular, rendering ANN application more challenging.

A table including all field data appears in Appendix, in order to facilitate testing of other ANNs. Dates of rain and/or spring flow rate measurements are shown in the first column. Precipitation depths (in mm) appear in the second column, while the third and fourth include flow rates of Mai Vryssi and Pera Vryssi, respectively (in Lit s^{-1}).

4. The investigated problems

Three problems have been investigated:

a. Simultaneous forecast of the flow rates of the two springs, based on precipitation data.

b. Forecast of the flow rate separately for each spring, based on precipitation data.

c. Forecast of the flow rate of one spring, based on the flow rate of the other and on precipitation data.

4.1 Selection of basic ANN features

As mentioned in section 2, selection of ANN is a case-specific task. We have opted for feed-forward, back-propagation ANN, based on literature for similar problems.

Back-propagation ANNs (e.g. Fausett, 1994) use supervised learning algorithms, namely they are provided both with input patterns and desired output patterns. After producing their own output, the ANNs calculate the discrepancy between estimated and expected output values, and adjust the synaptic weights in order to minimize it. The Root Mean Squared Error (RMSE) is used as discrepancy measure. Commonly used back propagation networks minimize RMSE by means of a gradient descent technique. In this work, we have used the Quickprop algorithm, which has been proposed by Fahlman (1988) and encompasses training speeding techniques. This choice was based mainly on previous positive experience of the authors with this algorithm, in cases with restricted field data (Fytianos and Katsifarakis, 2013). Moreover, the sigmoid function is used as activation function.

We have restricted our study to ANNs with three layers, namely with one hidden layer only, based again on literature for similar problems (e.g. Lallahem *et al.*, 2005; Kurtulus and Razack, 2007; Hu *et al.*, 2008) and on our anticipation (based on the geological features of the karstic area) that additional complexity, introduced by more hidden layers, will not be necessary.

Selection of a suitable ANN structure for a particular problem may not be unique. Using the larger part of the aforementioned rainfall and spring flow data Paleologos *et al.,* (2013) have come up with different ANN structures.

4.2 Selection of input data

To complete the construction of ANN for each of the aforementioned problems, we had to decide on: a) The combination of input data (and consequently the number of the neurons of the input layer) and b) the number of neurons of the hidden layer.

Decision on the input data was based on comparative inspection of precipitation and spring flow rate data and on soft information on the behavior of the two springs, provided by residents of the area, who call the “Pera Vryssi” spring short (namely responding earlier to rainfall and for a shorter period of time). Our aim was to arrive at practically useful predictions, namely to estimate spring flow rates at least few days in advance. Moreover, we aimed at checking whether a gross prediction, based on rainfall data of previous months, was meaningful. Having the above in mind, we conducted trials, using: a) Rainfall depths of the 5^{th} up to the 16^{th} day prior to the flow rate measurement date and b) Mean precipitation of the first up to the sixth month prior to the flow rate measurement date. After evaluation of these initial trials, we decided to include some, or all, of the following data:

1. Rainfall depth of the 5^{th} day prior to the flow rate measurement date
2. Rainfall depth of the 6^{th} day prior to the flow rate measurement date
3. Rainfall depth of the 7^{th} day prior to the flow rate measurement date
4. Rainfall depth of the 13^{th} day prior to the flow rate measurement date
5. Rainfall depth of the 14^{th} day prior to the flow rate measurement date
6. Rainfall depth of the 15^{th} day prior to the flow rate measurement date
7. Mean precipitation of the month prior to the flow rate measurement date

8. Mean precipitation of the 2nd month prior to the flow rate measurement date
9. Mean precipitation of the 3rd month prior to the flow rate measurement date
10. Mean precipitation of the 6th month prior to the flow rate measurement date.

Decision on the number of the neurons of the hidden layer was based on extensive trials. An outline of these trials appears in the next section, together with the results.

4.3. Trials and results

The first task was to construct an ANN that would forecast simultaneously the flow rate of both springs. Then, the output layer had two neurons, one for each flow rate. We divided the field data in two sets, one for training and one for testing, since their number is rather restricted (Hu *et al.*, 2008; Jain *et al.*, 2004). For training we used the 171 spring flow measurements of the first year, namely from April 16, 2007 to April 15 2008, during which measurements were more regular. The remaining 91 have been used for testing.

We have conducted a large number of trials, regarding both the input data and the number of neurons of the hidden layer. The best results were achieved when the rainfall depth of the 5th, 6th, 7th, 13th, 14th and 15th day, together with the mean precipitation of the 1st, 2nd and 3rd month prior to the flow rate measurement date were used. For this input combination, the dependence of the RMSE on the number of neurons of the hidden layer N_h is shown in Table 1.

Table 1. RMSE versus N_h (forecast of flow rate of both springs)

N_h	RMSE (Lit s^{-1})		
	Mai Vryssi	Pera Vryssi	Mean
1	0.875	1.243	1.059
2	0.786	1.081	0.933
3	0.804	1.002	0.903
4	0.830	1.192	1.011
5	0.838	1.036	0.937
10	0.797	1.060	0.929
12	0.829	0.966	0.898
14	0.816	1.010	0.913
18	0.815	0.981	0.898

As shown in Table 1 RMSE was always larger for Pera Vryssi. It seems that ANN tends to approximate better the larger of the 2 flow rates. Moreover, it attained its minimum value for 12 and 2 neurons for Pera Vryssi and Mai Vryssi, respectively. This somehow affirmed information from local residents, that the two springs exhibit different behavior.

Then we tried to develop an ANN separately for each spring. For Mai Vryssi best results (RMSE = 0.737 Lit s^{-1}) were achieved with the same input data and 4 neurons in the hidden layer. For Pera Vryssi best results (RMSE = 0.522 Lit s^{-1}) were achieved with 10 neurons in the hidden layer and all of the input data (namely when the mean precipitation of the 6th month prior to the date of measurement was added, too). Again, best results for May Vryssi have been achieved with substantially fewer neurons in the hidden layer, compared to Pera Vryssi. While ANNs are black box models, one could try to relate their structure to physical processes (e.g. Govindaraju, 2000; Jain *et al.*, 2004). In the case of Rouvas springs the aforementioned difference in the number of hidden layer neurons could be partially explained in the following way: As May Vryssi is fed by a comparatively larger area, local inhomogeneities are partially smoothed.

Calculated versus measured flow rates for Pera Vryssi appear in Fig. 2. Flow rate values (in Lit s^{-1}) appear on the y-axis, while the measurement number (starting from April 16, 2008) on the x-axis. It can be seen that the predicted values are generally smaller than the measured ones, but they follow a similar pattern. Visual inspection in this case verifies that the ANN performance is good.

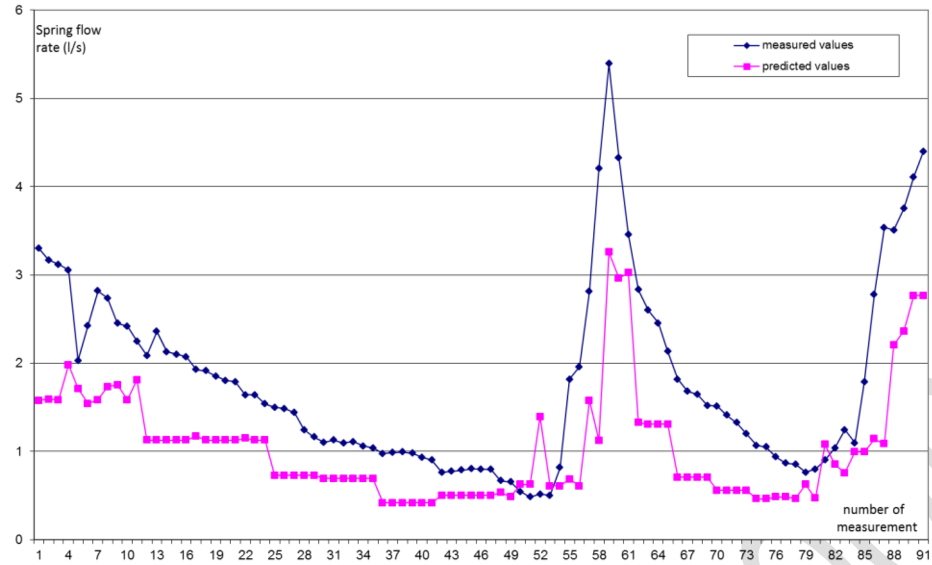

Figure 2. Calculated versus measured flow rates of Pera Vryssi

Moreover, since both springs have perennial flow, we checked whether some medium-term forecast is possible, using combinations of the aforementioned mean monthly precipitation values as input. Use of the mean precipitation of the first, second and third month prior to the date of measurement gave some acceptable results, namely RMSE = 0.746 Lit s^{-1} with 9 neurons in the hidden layer for Mai Vryssi and RMSE = 1.044 Lit s^{-1} with 6 neurons in the hidden layer for Pera Vryssi.

Then we checked whether we could use seasonal data for ANN training. This approach failed for Pera Vryssi but gave very good results for Mai Vryssi with regard to the RMSE criterion), although available data for training and testing are few, namely 31 for the training set (from spring, 2007) and 48 for the test set). With 12 neurons in the hidden layer and the complete set of input data RMSE is equal to 0.406 Lit s^{-1}. Calculated versus measured flow rates for the season of spring appear in Fig. 3. A rather large discrepancy appears in measurements 38 to 46, which correspond to spring 2009. Data inspection shows that rain was much heavier in early 2009 than in 2007. The aforementioned discrepancy could be attributed then to the fact that data for the training period come from one year's spring season only.

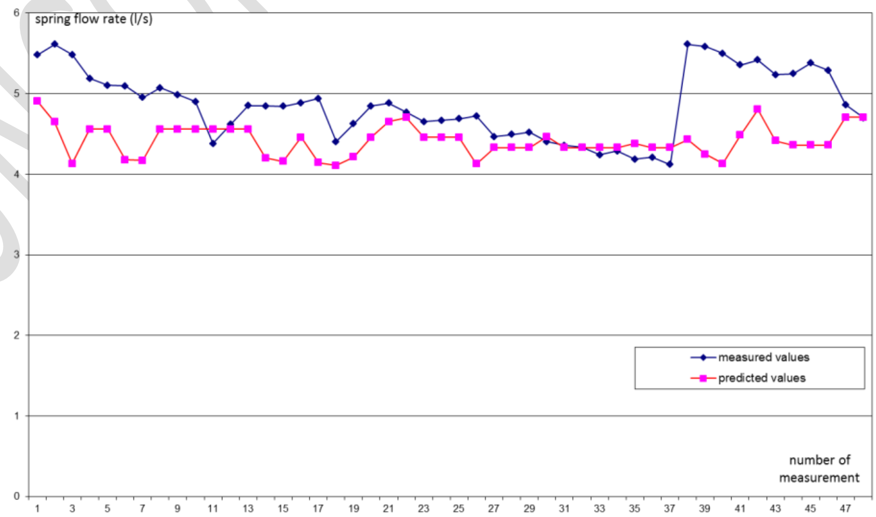

Figure 3. Mai Vryssi: Calculated versus measured flow rates for the season of spring

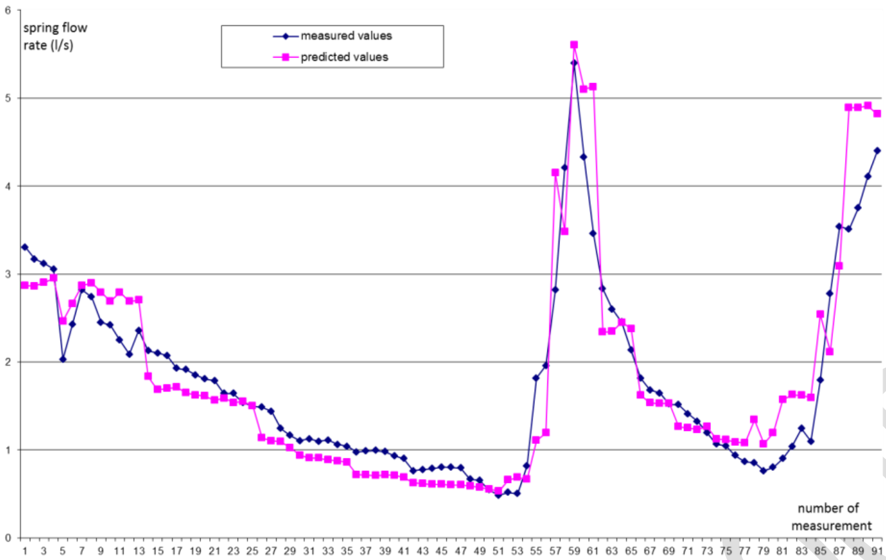

Figure 4. Calculated versus measured flow rates of Pera Vryssi (based on flow rates of Mai Vryssi and precipitation data)

Finally, we checked whether it was possible to forecast flow rate of one spring based on rainfall data and the flow rate of the other. This can be useful in practice, if access to certain springs is difficult. Despite our reservations, due to the different response of the two springs, we have achieved good results in forecasting the flow rate of Pera Vryssi, using as input the mean precipitation of the first, second, third and sixth month prior to the date of measurement, together with the flow rate of Mai Vryssi during the same day. As shown in Fig.4, calculated flow rate values follow the same pattern as the measured ones. The respective RMSE value is 0.447 Lit s^{-1} and has been achieved with 5 neurons in the hidden layer.

5. Conclusions

In our work we have tried to check ANN usefulness in providing predictions of karstic spring flow rates with restricted field data. For this reason, we have not used interpolation to artificially enrich the flow rate measurement set. Moreover, we have tried to get approximate, but comparatively early predictions, although karstic springs may respond rather quickly to rain events. Finally we have taken into account and we have evaluated soft information on spring behavior. The results that we have got led us to the following conclusions:

1) Artificial neural networks can serve for approximate prediction of karstic spring flow rates, even if the training data set is short. Moreover, they can offer useful results, even if flow rate measurements are not very regular.

2) Gross medium-term (e.g. one month) forecast could be achieved, at least for some perennial springs, as those studied in our paper.

2) Extensive trials are needed to achieve good results. In our paper we have presented a rather small part of the total volume of trials.

3) Different ANN structures can lead to comparable results. We have come to this conclusion, comparing our results with those presented in the literature, based on almost the same field data.

4) Visual inspection of calculated versus measured flow rate diagrams could be combined with the RMSE criterion, in order to achieve better evaluation of the ANN results.

5) Soft information on the behavior of springs could be useful in ANN construction. As an example, we have found out that the different behavior of the two springs, mentioned by residents of the area, was “verified” by the different structure of the ANNs that best fit the two springs.

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Appendix: Precipitation and spring flow rate data

date dd/mo/yr	Precipi-tation (mm)	Mai Vryssi flowrate (Lit s^{-1})	Pera Vryssi flowrate (Lit s^{-1})	date dd/mo/yr	Precipi-tation (mm)	Mai Vryssi flowrate (Lit s^{-1})	Pera Vryssi flowrate (Lit s^{-1})
20/09/2006	13,00			02/05/2008		4,725	2,359
23/09/2006	2,50			07/05/2008		4,468	2,128
10/10/2006	9,50			08/05/2008		4,495	2,101
11/10/2006	12,00			09/05/2008		4,522	2,074
12/10/2006	1,70			10/05/2008			
13/10/2006	5,00			11/05/2008	4,10		
15/10/2006	1,50			13/05/2008		4,403	1,928
17/10/2006	68,00			14/05/2008		4,360	1,912
18/10/2006	13,00			19/05/2008		4,336	1,853
01/11/2006	25,00			20/05/2008		4,243	1,805
02/11/2006	15,00			22/05/2008		4,287	1,788
03/11/2006	130,00			26/05/2008		4,188	1,641
05/11/2006	4,00			27/05/2008		4,211	1,642
12/11/2006	32,50			30/05/2008		4,121	1,538
14/11/2006	106,00			03/06/2008		4,052	1,499
23/11/2006	14,00			09/06/2008		3,961	1,485

24/11/2006	15,50			11/06/2008		3,925	1,439
27/11/2006	0,70			24/06/2008		3,716	1,244
06/12/2006	2,50			02/07/2008		3,643	1,164
13/12/2006	9,00			08/07/2008		3,493	1,105
19/12/2006	4,50			09/07/2008		3,491	1,127
27/12/2006	3,50			14/07/2008		3,415	1,098
03/01/2007	22,00			18/07/2008		3,401	1,112
05/01/2007	3,00			23/07/2008		3,331	1,061
13/01/2007	7,50			28/07/2008		3,255	1,039
14/01/2007	26,00			01/08/2008		3,231	0,977
20/01/2007	1,00			04/08/2008		3,224	0,988
03/02/2007	7,00			06/08/2008		3,164	0,993
05/02/2007	12,50			07/08/2008		3,216	0,979
06/02/2007	9,00			11/08/2008		3,198	0,935
12/02/2007	32,50			9/09/2008		2,801	0,764
15/02/2007	3,00			15/09/2008		2,761	0,776
17/02/2007	24,00			21/09/2008	16,00		
18/02/2007	22,50			22/09/2008		2,712	0,788
25/02/2007	36,00			23/09/2008	4,00	2,705	0,804
28/02/2007	14,50			24/09/2008		2,672	0,801
10/03/2007	10,00			25/09/2008		2,669	0,801
13/03/2007	14,00			29/09/2008	5,00	2,618	0,667
21/03/2007	20,50			03/10/2008	1,00		
22/03/2007	13,00			12/10/2008	3,50		
24/03/2007	6,50			15/10/2008	3,00		
25/03/2007	11,00			21/10/2008		2,411	1,250
11/04/2007	1,20			04/11/2008		2,353	0,546
16/04/2007		3,397	2,197	17/11/2008		2,230	0,484
17/04/2007	6,00	3,542	2,259	18/11/2008	8,00		
18/04/2007		3,542	2,284	23/11/2008	92,00		
19/04/2007		3,907	2,182	24/11/2008	19,00		
20/04/2007		3,921	2,160	25/11/2008	40,50		
24/04/2007		3,765	2,006	28/11/2008		2,842	0,517
25/04/2007		3,599	2,030	10/12/2008		2,475	0,504
26/04/2007		3,777	2,034	12/12/2008	4,50		
27/04/2007		3,832	2,029	14/12/2008	4,00		
30/04/2007		3,759	1,921	19/12/2008	3,00		
02/05/2007		3,556	1,877	20/12/2008	9,50		
04/05/2007		3,641	1,809	21/12/2008	6,00		
07/05/2007		3,561	1,747	22/12/2008	6,50		
08/05/2007		3,707	1,768	23/12/2008	89,50	2,387	0,818
09/05/2007		3,526	1,739	24/12/2008	11,50		
10/05/2007		3,494	1,699	27/12/2008	38,50		
11/05/2007		3,456	1,660	28/12/2008	63,00		
14/05/2007		3,439	1,597	29/12/2008	1,50		
15/05/2007		3,379	1,564	03/01/2009	37,50		
16/05/2007		3,408	1,578	04/01/2009	38,00		
17/05/2007		3,389	1,582	05/01/2009	12,00		
18/05/2007		3,355	1,588	06/01/2009	5,00		
19/05/2007	22,00	3,409	1,642	07/01/2009	10,00	5,349	2,816
20/05/2007	1,50			11/01/2009	5,00		
21/05/2007		3,379	1,537	14/01/2009		4,682	4,205
22/05/2007	1,70	3,357	1,519	16/01/2009	1,00		
23/05/2007	11,00	3,335	1,500	18/01/2009	20,00		

24/05/2007	1,50	3,401	1,488	23/01/2009	24,70		
25/05/2007	7,50	3,338	1,474	24/01/2009	21,00		
27/05/2007	3,40			25/01/2009	43,00		
28/05/2007	4,50			26/01/2009	34,50		
29/05/2007		3,276	1,416	28/01/2009	10,00		
30/05/2007		3,307	1,475	29/01/2009	25,00		
31/05/2007		3,267	1,417	30/01/2009	8,6	5,304	7,302
01/06/2007		3,233	1,412	07/02/2009	16,00		
05/06/2007	2,50	3,199	1,325	08/02/2009	7,00		
06/06/2007	1,50	3,250	1,320	10/02/2009	11,00	5,337	6,995
08/06/2007		3,253	1,318	11/02/2009	14,00		
13/06/2007		3,166	1,270	12/02/2009	32,00		
14/06/2007		3,169	1,257	13/02/2009	7,00		
15/06/2007		3,148	1,257	16/02/2009	9,00		
18/06/2007		3,150	1,230	18/02/2009	5,00	5,503	7,430
19/06/2007		3,109	1,199	19/02/2009	6,50		
21/06/2007		3,105	1,193	21/02/2009	3,00		
22/06/2007		3,112	1,186	24/02/2009	51,00		
26/06/2007		3,015	1,172	25/02/2009	13,00		
27/06/2007		3,078	1,158	26/02/2009	3,50		
28/06/2007		3,043	1,105	01/03/2009	6,5	5,613	9,091
02/07/2007		3,030	1,091	08/03/2009	12,00		
03/07/2007		3,023	1,058	09/03/2009	3,00		
06/07/2007		3,003	1,038	13/03/2009	14,00	5,586	8,750
09/07/2007		2,940	1,048	21/03/2009	3,00		
11/07/2007		2,927	1,048	23/03/2009	2,00		
12/07/2007		2,928	1,026	24/03/2009		5,500	5,394
13/07/2007		2,908	1,039	27/03/2009	12,00		
17/07/2007		2,856	0,976	05/04/2009	24,00		
20/07/2007		2,836	0,940	06/04/2009	11,00	5,355	4,328
23/07/2007		2,871	0,938	07/04/2009	7,00		
24/07/2007		2,842	0,945	08/04/2009	10,00		
25/07/2007		2,837	0,923	20/04/2009	0,80		
26/07/2007		2,821	0,918	22/04/2009	4,60		
30/07/2007		2,788	0,885	23/04/2009	0,20	5,419	3,458
31/07/2007		2,796	0,887	04/05/2009	21,10		
01/08/2007		2,777	0,930	07/05/2009		5,238	2,833
07/08/2007		2,720	0,870	14/05/2009		5,247	2,601
08/08/2007		2,747	0,868	18/05/2009	9,10		
27/08/2007		2,601	0,000	21/05/2009		5,381	2,453
29/08/2007		2,509	0,781	29/05/2009		5,289	2,132
31/08/2007		2,515	0,697	12/06/2009		5,249	1,817
04/09/2007		2,521	0,699	17/06/2009		5,066	1,680
05/09/2007		2,489	0,706	20/06/2009		5,048	1,647
06/09/2007		2,486	0,717	25/06/2009		5,057	1,520
10/09/2007		2,435	0,703	02/07/2009		5,063	1,514
13/09/2007		2,435	0,703	07/07/2009		5,012	1,412
17/09/2007		2,399	0,705	15/07/2009		4,963	1,327
20/09/2007		2,378	0,698	31/07/2009		5,059	1,198
21/09/2007		2,424	0,712	05/08/2009		4,888	1,067
25/09/2007		2,370	0,696	14/08/2009		4,850	1,049
27/09/2007		2,350	0,690	02/09/2009		4,736	0,937
28/09/2007		2,367	0,695	08/09/2009	2,10		
02/10/2007		2,328	0,684	10/09/2009	10,20		

03/10/2007		2,330	0,684	11/09/2009	50,40		
08/10/2007		2,291	0,673	14/09/2009	0,30		
10/10/2007		2,296	0,674	18/09/2009		4,705	0,865
11/10/2007		2,287	0,672	25/09/2009	0,50		
14/10/2007	1,00	2,259	0,631	05/10/2009	15,30	5,225	0,857
15/10/2007	31,00	2,232	0,589	14/10/2009	14,60		
16/10/2007	3,00	2,239	0,600	17/10/2009	0,80		
18/10/2007		2,247	0,629	18/10/2009	0,30		
21/10/2007	30,00			20/10/2009		4,503	0,763
22/10/2007	47,00	2,227	0,613	28/10/2009	0,20		
23/10/2007	43,00	2,272	0,671	29/10/2009	0,30		
24/10/2007	23,00	2,359	0,681	30/10/2009	20,30	4,854	0,801
25/10/2007	1,50	2,445	0,692	31/10/2009	2,70		
26/10/2007		2,491	0,643	01/11/2009	2,40		
29/10/2007		2,665	0,593	02/11/2009	5,60		
30/10/2007		2,672	0,593	03/11/2009	37,40		
01/11/2007		2,652	0,613	04/11/2009	13,80		
05/11/2007		2,572	0,625	08/11/2009	18,50		
06/11/2007	11,00	2,529	0,615	09/11/2009		4,700	0,902
08/11/2007	7,50			11/11/2009	16,30		
09/11/2007	1,70			12/11/2009	5,00	4,793	1,039
10/11/2007	15,00	2,442	0,633	20/11/2009		4,781	1,245
11/11/2007	2,00			01/12/2009		4,125	1,097
12/11/2007		2,354	0,651	02/12/2009	34,50		
13/11/2007	13,00	2,348	0,650	03/12/2009	18,10		
14/11/2007	8,30	2,318	0,665	04/12/2009	1,40		
15/11/2007	5,00			05/12/2009	29,10		
16/11/2007		2,312	0,698	06/12/2009	8,80		
18/11/2007	7,00			09/12/2009	2,10		
19/11/2007	7,00	2,339	0,706	10/12/2009	15,20		
20/11/2007	3,00	2,365	0,679	11/12/2009	23,30		
21/11/2007	1,50	2,362	0,678	12/12/2009	32,50		
23/11/2007		2,393	0,663	14/12/2009		5,355	1,790
27/11/2007		2,402	0,633	15/12/2009	0,60		
28/11/2007		2,402	0,633	16/12/2009	14,70		
30/11/2007		2,413	0,653	17/12/2009	4,00		
01/12/2007	2,50			18/12/2009	36,50		
03/12/2007		2,402	0,705	19/12/2009	0,80		
04/12/2007	1,70	2,415	0,709	20/12/2009	4,00		
05/12/2007	8,20	2,409	0,771	27/12/2009		4,865	2,779
06/12/2007	6,50	2,402	0,834	10/01/2010	1,00		
07/12/2007		2,422	0,778	11/01/2010	1,40		
09/12/2007	4,00	2,699	1,010	12/01/2010	25,30		
10/12/2007	37,30			13/01/2010	3,00		
11/12/2007	70,50	2,975	1,243	14/01/2010	51,30		
12/12/2007	34,00	3,584	1,355	16/01/2010	8,80		
13/12/2007	9,00	4,194	1,468	17/01/2010	23,20		
14/12/2007	2,50	4,860	1,480	18/01/2010	9,40		
15/12/2007	1,50			19/01/2010		4,884	3,538
17/12/2007	1,00	5,323	2,864	20/01/2010	3,20		
18/12/2007		5,105	3,265	21/01/2010	20,30		
19/12/2007		4,886	3,666	22/01/2010	60,10		
20/12/2007		4,711	3,598	29/01/2010	2,60		
21/12/2007		4,535	3,530	01/02/2010	1,90		

27/12/2007		3,469	2,807	02/02/2010	0,50	4,844	3,508
28/12/2007		3,362	2,734	03/02/2010	0,30		
29/12/2007				06/02/2010	1,90		
30/12/2007				07/02/2010	31,00		
31/12/2007				08/02/2010	17,00		
01/01/2008	14,50			11/02/2010	1,40		
02/01/2008		2,949	2,413	14/02/2010		4,852	3,752
03/01/2008		2,884	2,392	20/02/2010	12,80		
07/01/2008		2,698	2,229	21/02/2010	8,50		
08/01/2008		2,640	2,182	02/03/2010		4,864	4,108
09/01/2008	1,00	2,630	2,156	14/03/2010	0,30	4,701	4,396
10/01/2008		2,641	2,113	17/03/2010	2,10		
14/01/2008	3,00			18/03/2010	2,20		
15/01/2008	16,00	2,486	1,979	25/03/2010	0,20		
21/01/2008		2,370	1,844	11/04/2010	0,30		
22/01/2008		2,348	1,822	21/04/2010	0,50		
23/01/2008		2,345	1,821	22/04/2010	6,40		
24/01/2008	23,50	2,343	1,820	25/04/2010	0,30		
25/01/2008	38,50	2,372	1,852	01/06/2010	0,20		
29/01/2008		2,432	1,899	10/06/2010	11,50		
30/01/2008	28,00	2,493	1,946	13/06/2010	0,30		
01/02/2008		2,597	1,973	14/06/2010	12,80		
04/02/2008		2,731	2,143	16/06/2010	1,90		
07/02/2008	5,50	2,724	2,253	17/06/2010	9,00		
08/02/2008	8,00	2,842	2,461	19/06/2010	10,70		
09/02/2008	45,00	2,960	2,669	21/06/2010	0,80		
10/02/2008	13,00	3,077	2,878	26/06/2010	16,80		
11/02/2008	44,00	3,195	3,086	27/06/2010	11,00		
12/02/2008	0,50	3,676	3,300	28/06/2010	9,60	4,212	0,719
13/02/2008		4,213	3,593	02/07/2010	0,30		
14/02/2008		4,520	4,542	12/07/2010	32,90	4,480	1,694
17/02/2008	17,50	4,7	5,772	13/07/2010	7,70		
20/02/2008	13,00	4,880	7,001	15/07/2010	8,00		
25/02/2008		5,453	9,912	17/07/2010	0,30		
26/02/2008		5,559	9,925	19/07/2010		4,978	3,799
27/02/2008		5,664	9,937	24/07/2010	0,50		
03/03/2008		5,483	7,712	25/07/2010	10,70		
04/03/2008		5,614	7,358	09/08/2010	5,00		
05/03/2008		5,486	7,106	10/08/2010	10,00		
12/03/2008	14,50			11/08/2010	30,00		
13/03/2008		5,192	5,085	13/08/2010	8,70		
15/03/2008		5,104	4,765	15/08/2010	41,90	4,626	1,100
17/03/2008		5,097	4,481	16/08/2010	14,50		
18/03/2008		4,955	4,293	02/10/2010	0,20		
20/03/2008		5,075	4,104	11/10/2010	11,50		
22/03/2008		4,988	3,942	14/10/2010	0,30		
24/03/2008		4,901	3,779	15/10/2010	12,80		
27/03/2008		4,381	3,231	17/10/2010	1,90		
28/03/2008	5,50			18/10/2010	9,00		
29/03/2008	1,50	4,617	3,333	20/10/2010	10,70		
30/03/2008	7,00			22/10/2010	0,80		
31/03/2008		4,853	3,435	27/10/2010	16,80		
02/04/2008		4,848	3,303	28/10/2010	11,00		
03/04/2008	32,50			29/10/2010	9,60	4,212	0,719

04/04/2008	6,00	4,843	3,170	02/11/2010	0,30		
05/04/2008	12,50			12/11/2010	32,90	4,480	1,694
07/04/2008		4,886	3,120	13/11/2010	7,70		
09/04/2008		4,940	3,056	15/11/2010	8,00		
11/04/2008		4,403	2,031	17/11/2010	0,30		
13/04/2008		4,626	2,425	19/11/2010		4,978	3,799
15/04/2008		4,849	2,819	24/11/2010	0,50		
16/04/2008		4,884	2,737	25/11/2010	10,70		
18/04/2008		4,769	2,450	10/12/2010	5,00		
23/04/2008		4,654	2,418	11/12/2010	10,00		
27/04/2008	6,00			12/12/2010	30,00		
28/04/2008	10,00			14/12/2010	8,70		
29/04/2008		4,670	2,248	16/12/2010	41,90	4,626	1,100
30/04/2008		4,690	2,086				