Groundwater level forecasting using an artificial neural network trained with particle swarm optimization

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1. Abstract

Artificial neural networks are an alternative method of groundwater modelling and can be used to predict the hydraulic head in wells. In the present work, the particle swarm optimization algorithm is used to train a feed forward multi-layer artificial neural network which simulates the hydraulic head change per day in a well.

Three different variations of the particle swarm optimization algorithm are considered, the classic algorithm with the improvement of inertia weight, PSO-TVAC and GLBest-PSO. Among the three variants, GLBest-PSO achieved the best performance with respect to training and testing errors. The neural network was trained and tested for performance with field data from an observation well in the area of Agia, Chania, Greece.

The trained neural network was also used for midterm prediction and in order to examine three climate change scenarios for the period 2010-2020.

2. Area of study

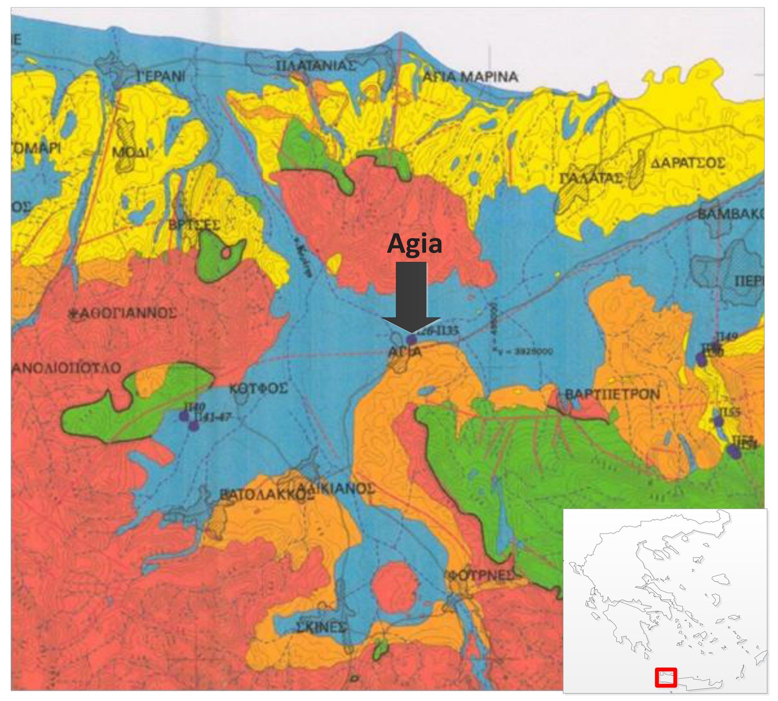

Figure 1: Map of the area of study in Agia, Crete, Greece

The ANN is used to simulate the water budget:

$$\Delta S = I - O + P - EPT \pm Q$$

where ΔS is the change in the aquifer's storage,
I/O the inflow to/outflow from the water basin,
P the precipitation,
EPT the evapotranspiration,
Q the pumping/recharge rate.

Available data for 678 days:
- Rainfall
  1. Alikianos station (S1)
  2. Samonas station (S2)
- Temperature
- Hydraulic head on a daily basis.

3. Methodology

3.1 Artificial neural network (ANN)

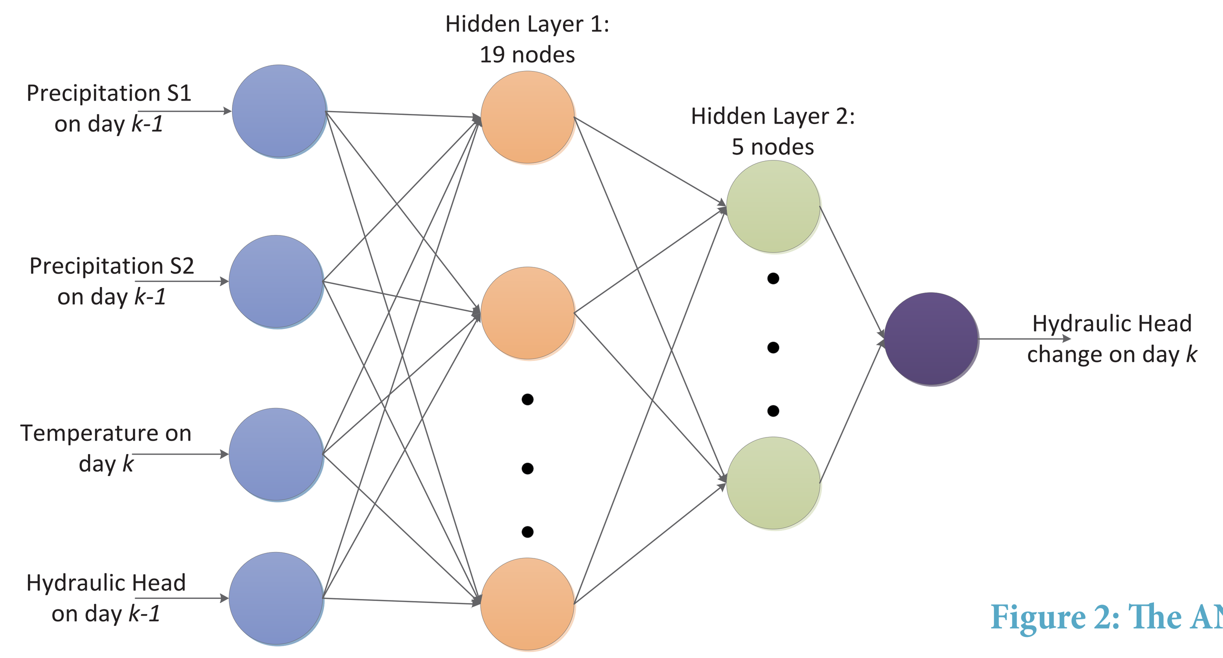

Figure 2: The ANN in use

3.2 Particle swarm optimization (PSO)

Particle swarm optimization is a new evolutionary algorithm (Eberhart and Kennedy, 1995) that can be used to find optimal solutions to numerical and qualitative problems. In every iteration of the algorithm, each particle updates its position according to Figure 3 and its velocity according to the following equation.

$$v_i(t) = wv_i \cdot (t-1) + c_1 \cdot r_1(t) \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2(t) \cdot (gbest - x_i(t))$$

Three velocity update equation variations were examined:

- The classic PSO with the inertia weight improvement (Shi and Eberhart, 1998):

$$v_i(t) = wv_i \cdot (t-1) + c_1 \cdot r_1(t) \cdot (pbest_i - x_i(t)) + c_2 \cdot r_2(t) \cdot (gbest - x_i(t))$$

- PSO-TVAC (Ratnaweera et al., 2004):

$$c_{1(iter)} = c_{1\max} - (c_{1\max} - c_{1\min}) \frac{iter}{iter_{\max}} iter$$

$$c_{2(iter)} = c_{2\min} - (c_{2\max} - c_{2\min}) \frac{iter}{iter_{\max}} iter$$

- GLBest-PSO (Arumugam et al., 2007):

$$v_i(t) = w_i v_i \cdot (t-1) + C \cdot r_1(t) \cdot (pbest_i + gbest - 2x_i(t))$$

$$w_i = 1.1 - \frac{gbest}{(pbest_i)_{average}} \qquad C = 1 + \frac{gbest}{pbest_i}$$

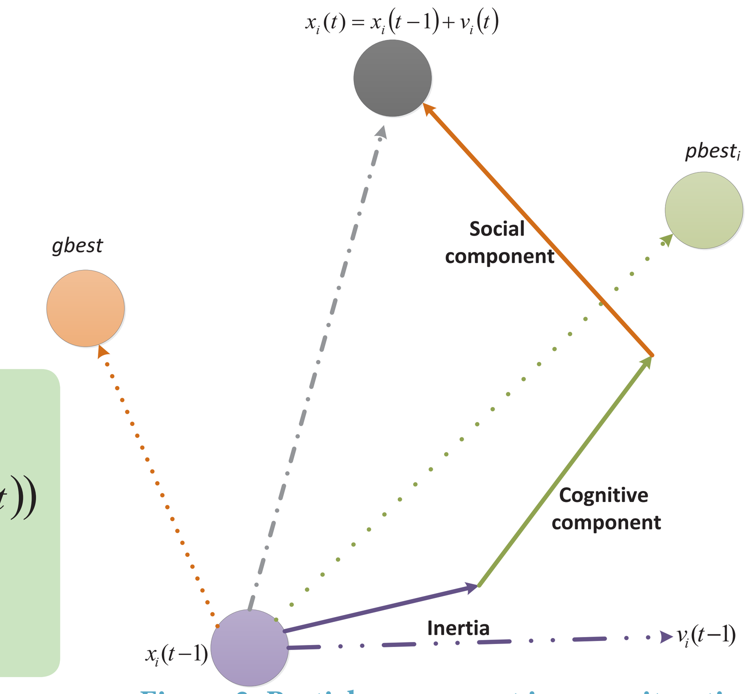

Figure 3: Particle movement in every iteration

4. Results

4.1 Choice of the appropriate variant

The three different variants were tested for 10000 iterations and for swarm size 20 (Table 1)

Table 1: Error results for every variant

	Classic PSO		PSO-TVAC		GLBest-PSO	
	E_{train} ($\times10^{-4}$)	E_{test} ($\times10^{-4}$)	E_{train} ($\times10^{-4}$)	E_{test} ($\times10^{-4}$)	E_{train} ($\times10^{-4}$)	E_{test} ($\times10^{-4}$)
	5.64	4.01	5.34	3.76	**4.06**	**3.50**
	5.23	3.66	5.71	4.26	**3.94**	**3.50**
	4.78	**3.45**	5.67	3.98	**3.91**	3.62
	4.76	**3.47**	5.67	4.14	**3.96**	3.97
	6.46	4.53	5.16	3.78	**3.85**	**3.45**
Mean value	**5.37**	**3.82**	**5.51**	**3.98**	**3.94**	**3.61**

GLBest-PSO has the best performance in most of the cases, so it is used for ensuing the simulation.

To determine the reliability of GLBest-PSO for different swarm sizes, the algorithm was tested for swarm size equal to 40, 50 and 60 and 40000 iterations (Table 2).

Table 2: Best result for GLBest-PSO

E_{train} ($\times10^{-4}$)	E_{test} ($\times10^{-4}$)	Swarm size
3.87	3.69	50
3.70	3.95	50
3.97	3.44	60
4.14	2.85	60

Compared with back-propagation:
- 9.3% improvement in training error (E_{train})
- 18% improvment in testing error (E_{test})

4.2 Simulation results

The results in terms of Hydraulic head change and Hydraulic head per day are shown in Fig. 4-5.

- The general trend of the system is captured by the ANN
- The model cannot describe precisely local and transient phenomena.

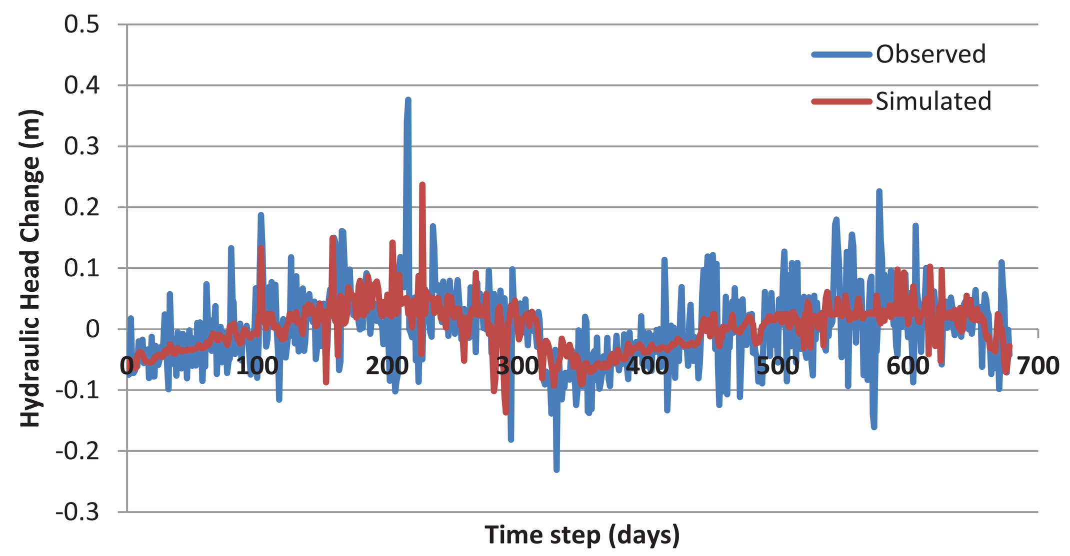

Figure 4: Observed and simulated hydraulic head change

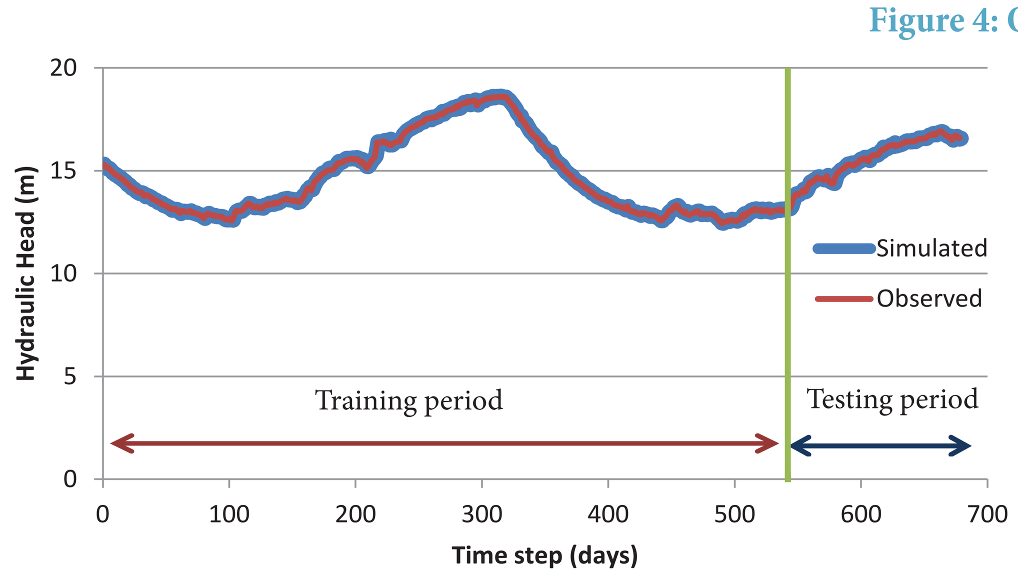

Figure 5: Observed and simulated hydraulic head

- Hydraulic head for day k:

$$h_k = h_{k-1} + dh_k$$

- Maximum value: 0.35 m
- Minimum value: 1.7×10^{-5} m
- Mean variance: 1.77×10^{-3} m

4.3 Midterm prediction

- Average difference: -0.08 m
- Maximum difference: -0.97(step 176)
- Accumulated error at the end of the simulation period: 0.05 m.

These values are considered relatively small and insignificant, and therefore, imply that the trained network is relatively accurate.

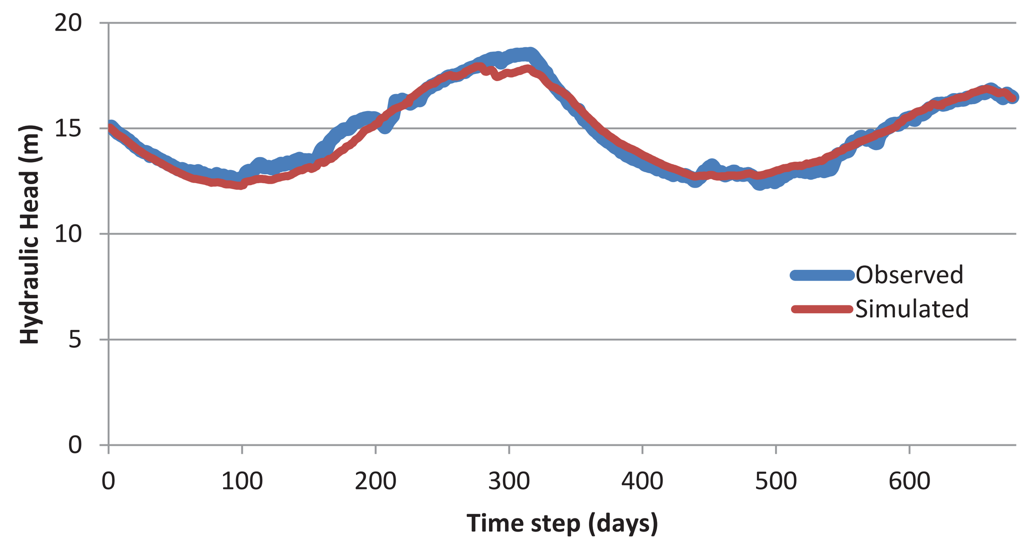

Figure 6: Midterm prediction

4.4 Climate change scenarios

Three climate change were examined based on the prediction of Tsanis et al. (2011), that a 12% (±25%) reduction in the mean precipitation and a 1.9°C (±0.8 °C) increase in the mean temperature is expected in Crete by the end of 2040. Climate change scenarios were tested for the period 2010-2020. The necessary timeseries were created using a stochastic weather generator LARS-WG.

1st scenario:
For S1: P=-2.598t+739.8
S2: P=-2.598t+587.4
T=+0.054°C per year

2nd scenario:
For S1: P=-1.19% per year
S2: P=-1.28% per year
T=+0.09°C per year

3rd scenario:
For S1: P=0.48% per year
S2: P=0.39% per year
T=+0.037°C per year

Table 3: Hydraulic head values (m) for the 3 scenarios examined

	Mean	Maximum	Minimum	Average Change
2008-2009	15.1	18.6	12.5	$1.77\cdot10^{-3}$
Scenario 1	15.7	19.9	11.7	$6.39\cdot10^{-4}$
Scenario 2	13	16.8	8.1	$-1.06\cdot10^{-3}$
Scenario 3	19.5	24.5	11.8	$1.88\cdot10^{-3}$

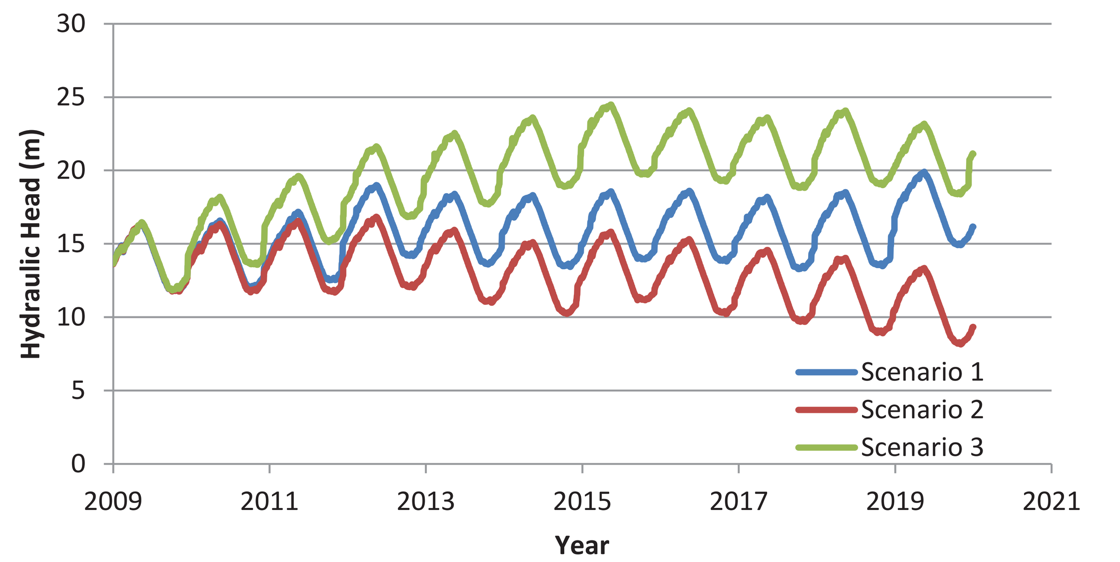

Figure 7: Climate change scenarios

5. Conclusions

1. Three different variations of the PSO algorithm were used and the most appropriate variation to train the specific neural network was GLBest-PSO.
2. The ANN was able to describe accurately the general trend in the hydraulic head change of the natural system, while it cannot simulate well local and transient phenomena, which cause abrupt changes in the hydraulic head.
3. When the hydraulic head change is converted to hydraulic head, using the observed hydraulic head of the previous day, the deviations of the simulated values from the observed, seem comparatively smaller.
4. In the case of midterm prediction, the ANN tends to underestimate the hydraulic head, but the error does not accumulate.
5. Three climate change scenarios were studied. Only the 2nd scenario (high decrease in precipitation) had a severe negative effect in the aquifer, while results for the other two scenarios varied from neutral to positive.

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