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Contents

Computational Intelligence in Hydroinformatics: A Review

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Abstract

Hydroinformatics is the field of study of the flow of information and its processing by knowledge as applied to the flow of fluids and their interaction with the aquatic environment. Many new modeling techniques have been entered in Hydroinformatics successfully. Among them, the application Computational Intelligence methods in Hydroinformatics is a relatively new area of research, even if some successful results have been already obtained. In this review we present a general overview of the applications of Computational Intelligence methods to Hydroinformatics and analyze some promising cases study concerning, namely, estimation of sanitary flows, rainfall prediction, unit hydrograph estimation, groundwater monitoring, flood waves propagation, and pump scheduling.

1 Introduction

Computational Intelligence or *Soft Computing* area includes neural networks [30, 8], fuzzy systems [34], chaos theory [2], evolutionary computation [27, 7], and some others tools linked to inductive learning from data[1] [16, 56].

In recent years the applications of Computational Intelligence methods have been gradually increased in many areas including Physics, Chemistry and Biology, in particular when complex phenomena must be modeled, as, in principle, Computational Intelligence methods are data-driven methods and require a limited knowledge of the phenomena.

One particular challenging application field for Computational Intelligence is Hydroinformatics, that is the application of Computer Science to Water Resources Management.

[1] Sometimes the term *Soft Computing* is ascribed to the attempts to integrate all those computing paradigms, under the claim that when utilized together, the strengths of each of those techniques can be exploited in a synergistic manner for the creation of 'smart' systems.

application	MLP	SOM	TLRN	PRNN	TDNN	FL	EC	HM
river flow *MP*	[4, 39]							
lake water levels *MP*	[11]							
rainfall-runoff *MP*	[40] [32] [9]			[40]	[40]		[9]	[9]
water tide *MP*								[15]
sanitary flows *MP*	[22]							
flood *MP*	[33] [31]		[31]			[49]	[33] [49]	[33] [49]
contaminations in ground water *MP*	[53]					[53]	[53]	[53]
water distribution network *MP*							[42]	[51]
wastewater treatment plant *PC*	[29]							
river discharges *DA*		[11]						
ecological *DA*		[11]						
regional flood *DA*	[28]	[49]						

Table 1: Some applications of Computational Intelligence tools (columns) reported in the recent Hydroinformatics literature (rows). The acronyms are explained in the text.

Hydroinformatics deals with the modeling and control of non-linear systems with too many freedom degrees and uncertainties [29]. For example, Hydroinformatics faces the modeling of rainfall, floods, river flows or the control of wastewater treatment plants. All of those problems involve non-linear and possibly chaotic systems with many freedom degrees and uncertainties [29].

In the past decades, many new modeling techniques have been entered in Hydroinformatics successfully. Among them, the application of Computational Intelligence methods is a relatively new area of research, even if some successful results have been already obtained, e.g. in rainfall-runoff modeling, in predictions of water levels, currents and waves using hydrological and meteorological data, in the optimization of operational parameters of wastewater treatment plants, in groundwater management, and in modeling of ecological and water quality processes.

While classical approaches fail in presence of non-linear systems with many freedom degrees, Computational Intelligence approach offers a more flexible, less assumption dependent and self-adaptive approach to modeling, and moreover shows:

- the potential for improved performance, faster model development and execution times and therefore reduced costs;
- the capability to plug sits components directly into conventional models;
- the ability to provide a measure of prediction certainty via bootstrapping techniques and on-line retraining to adapt to rapidly changing future events.

Some relevant applications of Computational Intelligence tools to Hydrology reported in the recent literature are:

- **Modeling/Prediction** (*MP*): Multilayer Perceptron (MLP) [4, 5, 12, 26, 28, 31, 32, 39, 40], Auto-Regressive Neural Network (ARNN) [12], Time Lagged Recurrent Network (TLRN) [31], Partial Recurrent Neural Network (PRNN) [40], Time Delay Neural Network (TDNN) [40], Fuzzy Logic (FL) [42, 49, 53], Evolutionary Computation (EC) [33, 49, 51, 53].
- **Data Analysis** (*DA*): Self Organizing Feature Maps (SOM) [11].
- **Process Control** (*PC*): Multilayer Perceptron (MLP) [29].
- **Classification** (*CL*): Multilayer Perceptron (MLP) [15].

In Tab. 1 we report some Computational Intelligence tools successfully used in recent papers in Hydroinformatics.

It is worth noting that some papers try to find new strategies for applying Computational Intelligence methods in hybrid modeling (*HM*) approaches [15]. We can notice for example, combinations of neural networks and finite difference modeling methods [26], individual feedfoward networks linked using fuzzy logic controlling model and optimized with evolutionary computation algorithms [49], MLPs and Fuzzy Systems used to set up Rule Bases for Expert Systems [53], and Evolution Strategies used to optimize MLPs [5, 53].

In the next Sect.s we shall present some cases study of application of Computational Intelligence methods to Hydroinformatics concerning, namely, estimation of sanitary flows (Sect. 2), rainfall prediction (Sect. 3), unit hydrograph estimation (Sect. 4), groundwater monitoring (Sect. 5), flood waves propagation (Sect. 6), and pump scheduling (Sect. 7). In Sect. 8 conclusions are drawn.

2 Estimation of Sanitary Flows

In [22] Dejebbar and Alila applied Multilayer Perceptrons to the prediction of current and future wastewater flows in order to support the operation, maintenance, and upgrading of municipal wastewater collection systems.

Existing methods are based on parametric approach and are very imprecise. Given the variability of wastewater flow generation, Multilayer Perceptrons can constitute a better alternative to establish relationships between tributary area characteristics and wastewater flow rates. The work by Dejebbar and Alila [22] concerns the development of a MLP model to estimate wastewater production given the sewerage area characteristics.

Dry weather flow measurements at 40 monitoring sites in the Fraser Sewerage Area (FSA) of the greater Vancouver Regional District, Vancouver, British Columbia, were used in the MLP training. The training data base concerned a total area that varies between 120 ha and 1700 ha, and a population varying between 3700 and 58000. The validation data set has been obtained from a geographically separated area with significantly different demographics, land use, and hydraulic characteristics. It represents 16 flow monitors with tributary areas varying from 100 ha to 4400 ha, and populations varying from 1300 to 120000. The validation data set extended beyond the range of the development data set, providing a check of the MLP ability to extrapolate results.

As a first step, weights, optimization and architecture selection of the neural network model were performed. The selected input variables are: total surface area, residential population, dwelling units, commercial areas, industrial areas, institutional areas, other non residential areas.

Both for the development and validations data, the MLP model estimated dry weather flows with an average error of less than 16%, that is better than the results obtained with traditional estimation methods. Larger errors have been noticed for small areas with a large industrial component.

Such model can minimize the need for flow monitoring, and can fill the gap between flow monitoring sites. It can be used to track the wastewater increase as the land use characteristics change, and to forecast future flows more accurately. Also it can be used to check the reasonableness of measured flows and is a useful estimation tool for wastewater quality related issues.

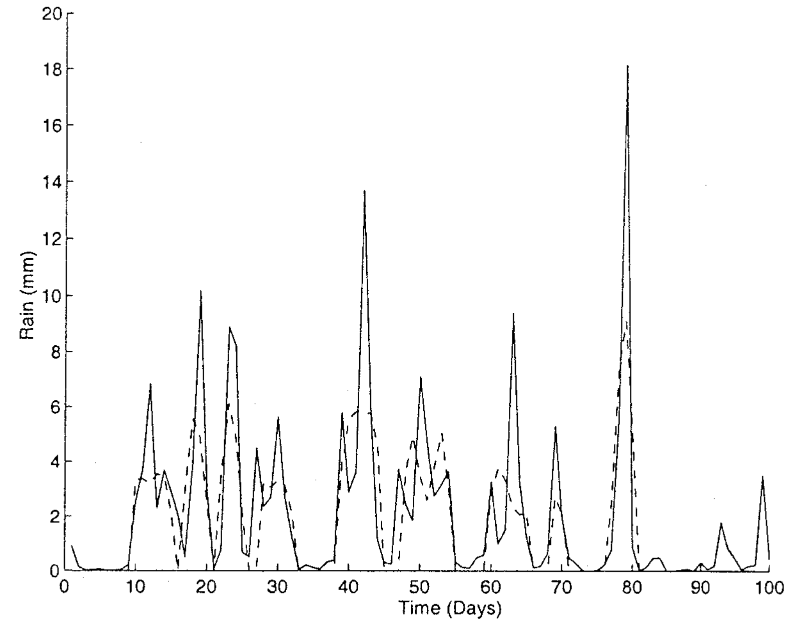

Figure 1: Mean Station: measured rainfall (continuous line) and 1 day ahead neural forecasting using SSA's components 1-76 (dashed line). Period 3/19/56 - 12/4/56.

3 Daily Rainfall Forecasting

In [44, 17, 18], Cicioni, Masulli, and Studer proposed a methodology for signal forecasting based on results and prescriptions related to the Takens-Mañé theorem [54, 41, 3] and its extension to the case of discontinuous signals prediction.

As an application, they faced the problem of forecasting of the rainfall intensities series collected by 135 stations distributed in the Tiber basin for a period of 10 years.

Classical regression techniques [13] are unable to obtain any suitable forecasting of the series of the hydrological variable, and also predictors based on neural or fuzzy systems give very poor results. The difficult of rainfall intensity forecasting can be ascribed mainly to the discontinuity of the hydrological variable, while Universal function approximation theorems for neural networks [20] and fuzzy systems [58] require the continuity of the function to be approximate.

In order to avoid the effect of the discontinues the authors applied to the hydrological series the Singular-Spectrum Analysis (SSA) [35, 45, 57, 38]. In SSA the state vector is a temporal window of the series of a given number of samples. A Principal Component Analysis [55] is performed in the space of state vectors, and the original temporal series can be decomposed in series components. The series components of the rainfall intensity are continuous and then we can use fuzzy or neural predictors for forecasting each of them.

A good property of SSA is that the original series can be recovered as the sum of all the individual series components. If we truncate this sum to an assigned number of component an estimation of the resulting reconstruction error is the sum of the eigenvalues corresponding the the remaining components.

In [18], the data analysis started by considering the virtual series of the Mean Station (MS), obtained by averaging all 135 rainfall intensity series. The application of the SSA to this signal produced an eigenvalue space that was separated in 10 sub-spaces (each of them representing a 10% of the reconstruction error) from where 10 signal components (waves) were obtained.

For each individual wave of the MS, the authors prepared a neural predictor based on a Multi-Layer Perceptron (MLP) [30] following the constructive approach described in [52, 44]. After the determination of the first minimum of the mutual information, the embedding dimension has been estimated, thorough the global false nearest neighbors technique. As a consequence, the selected MLP predictor has two hidden layers of 5 neurons, and an input layer of six neurons (equal to the embedding dimension of the signal).

The first waves, corresponding to the principal components of the SSA, are enough regular and easy to be predicted, while waves corresponding to sub-spaces with low eigenvalues are less regular and their predictions are unsatisfactory. For the first 6 waves, corresponding to the first 76 principal components, (i.e. 60% of the explained variance) the prediction results are of good quality (see Fig. 1). The sum of the prediction of the 6 waves at 1 and 2 days ahead give a signal well correlated with the original rainfall intensity of the MS.

In [18], the authors reported also good preliminary results of the application of the describe methodology to rainfall intensity series of individual stations using projections of the signal of the principal component space of the MS.

4 Unit hydrograph

One of the more effective means for the analysis of the formation of the outflows and their modulation, in correspondence of a section of a river basin, is given from the hydrograph, i.e., the diagram of the distribution of the flow in function of the time. The total outflow defined from the area of the hydrograph is equal to the effective rainfall to the river basin dependent from one rain of known duration and intensity.

The concept of the unit hydrograph was developed by Sherman in 1932 [50]. The unit hydrograph has many functions in hydrology, and it is used, e.g., in the characterization of the rainfall-runoff behavior of a catchment, in flood estimations, and, as an transfer-function, in existing conceptual models.

The First Differenced Transfer Function - Excess Rainfall and Unit Hydrograph by a Deconvolution Iterative Identification Technique (FDTF-ERUHDIT)

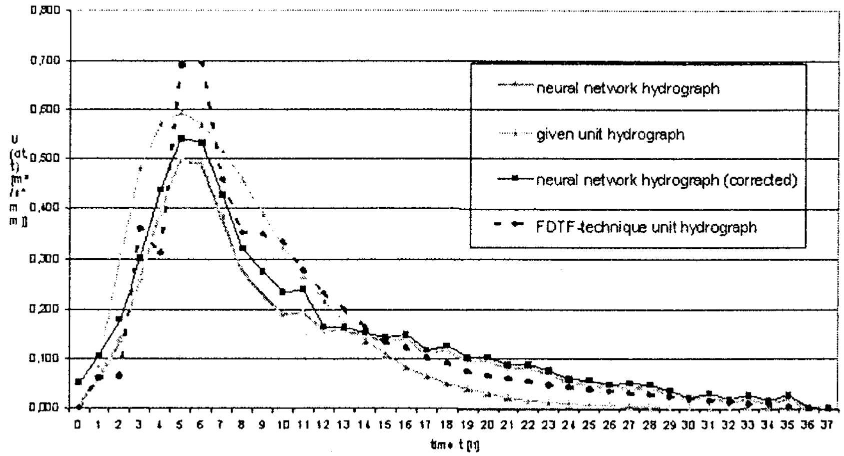

Figure 2: Computed hydrographs gauge *Bairawies* ($U(dt,t)[m^3/s^*mm]$ versus time $t[h]$). (Reprinted with permission from [6]).

derives numerically a unit hydrograph from rainfall and runoff records [24, 43]. The unit hydrograph is calculated in a iterative way by convolutions and deconvolutions. As the method uses measured rainfall and runoff records, it can estimate the effective rainfall and can cut off the base flow on its own. The user just has to give the size (area) of the catchment and the numbers of the ordinates of the expected unit hydrograph.

In [36], Lange proposed the derivation of shown the unit hydrograph using neural networks. By using the artificial neural network simulator SNNS (Stuttgart Neural Network Simulator) developed at University of Stuttgart [59], an optimal Multilayer Perceptron architecture was found after a great numbers of tests. The topology of the network with the best efficiency has 1 hidden layer. The input to the MLP are the measured rainfall data. The output represents the ordinates of the discharge at the gauge station. The number of hidden neurons is up to 15. The learning rule is the back-propagation algorithm [47] accelerated by using the flat-spot-elimination and the momentum-term (conjugated back-propagation method [14]).

After the training the neural network is able to produce a complete hydrograph depending on the given rainfall without simulation of any single physical process in the catchment. So the neural network is indeed a "black box" representing the catchment response.

In Fig. 2, a unit hydrograph of the catchment "Bairawies", is derived by using the neural network and the FDTF-technique. Both unit hydrographs are compared with the given unit hydrograph which was found in the documentation of the Bavarian state authority of water management. Both methods, the neural network and the FDTF-technique, are using the same input data so they can be compared likely. Data of rainfall and runoff from the year 1971 to 1981 for for this catchment were used. The time step of the measured data was five minutes for the rainfall data and fifteen minutes for the runoff data.

The FDTF-technique calculates a unit hydrograph directly. On the other hand the neural network presents the whole rainfall-runoff behavior of the catchment so the derivation of the unit hydrograph is just possible with a little trick. The trained network is able to calculate a hydrograph which is comparable with the unit hydrograph when the input value of the rainfall record is 1 mm. This methods works pretty well when the range of the training data is wide enough. That means that not only extreme events with high peak flows has to considered in the training set, but also events with low peak flows. This stands in contrast to the usual practice of unit hydrograph generation where just the largest events with spatially near-uniform rainfall are used. To receive a real unit hydrograph, the hydrograph of the neural network must be corrected to fulfill the condition of volume.

Compared with the given unit hydrograph the unit hydrograph of the neural network is in the first section to low and in the second part to high. The FDTF-technique produces a unit hydrograph which is similar to the neural network hydrograph except the maximum ordinate which is to high.

As reported in the paper by Lange [36], the derivation of a unit hydrograph by a neural network has some advantages than that using the FDTF-ERUHDIT approach. In particular, it needs less calculation time and, moreover, it is very robust concerning the training events. For example the calculation time of the catchment "Bairawies" was up to 15 hours on a regular PC with an Intel 200 Pentium Processor, while the calculation time of the training of the neural network costs about minutes.

The reduction of a neural network to a single hydrograph, i.e. the unit hydrograph , provides a tool which gives the user of neural network an idea about the quality of the events used in the training and how many events are necessary to describe the rainfall-runoff-relation in a perfect way. Another advantage is the possibility to use the unit hydrograph from the neural network in existing hydrologic procedure and models.

5 Groundwater monitoring

In [21], D'Agostino, Passarella and Vurro presented an approach to the optimization of networks of groundwater monitoring based on fuzzy geostatistics.

Recent literature reports a large number of methodologies for the design of monitoring networks and outline of sampling optimization procedures [1, 37]. Cokriging Estimation Variance (CEV) is a useful tool to determine the influence of the spatial configuration of monitoring networks on the estimations. CEV depends on the variograms [23]. Reduced and optimal configurations of a network based on the CEV suffers from the uncertainties caused by the variographer's choices on type and parameters of the variogram model when the

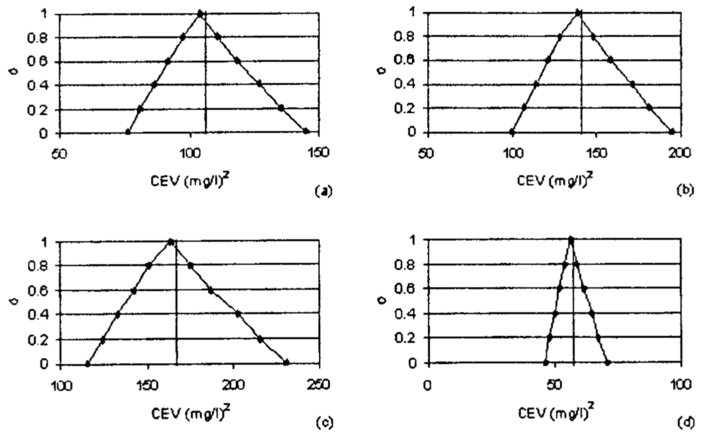

Figure 3: Membership functions of CEV and centroids in four critical points: (a) point n.2, (b) point n. 3, (c) point n. 8, (d) point n. 11. (Reprinted with permission from [46]).

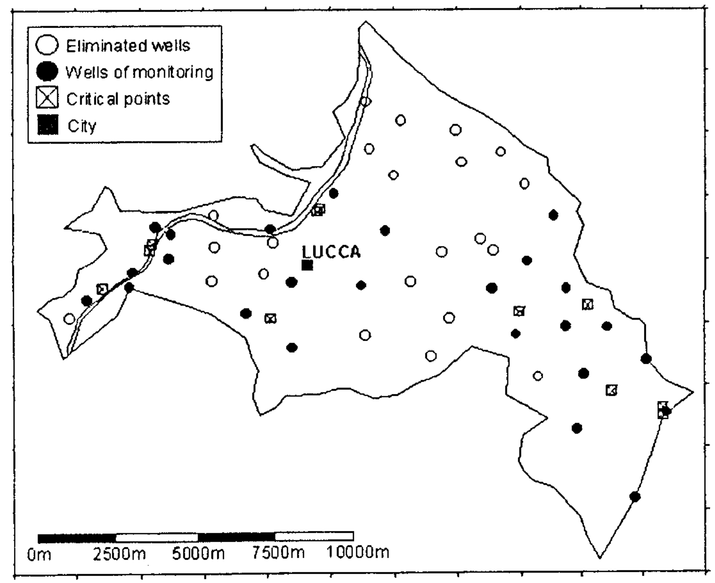

Figure 4: Reduced configuration (25 wells of monitoring) turning out from the case study. (Reprinted with permission from [46]).

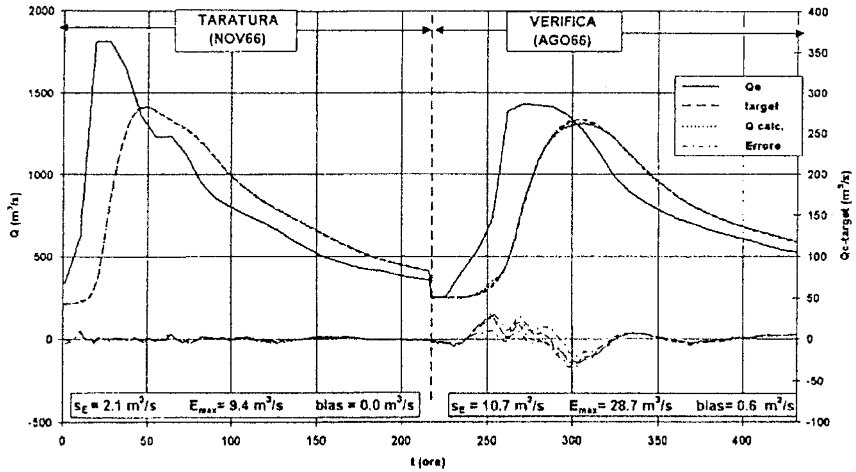

Figure 5: Comparison of the flood values estimated by the 46:4:1 MLP trained using the November wave and tested with the August wave (*novago.net*). (Reprinted with permission from [46]).

actual data are missing. Using a fuzzy approach to represent the uncertainties related to variogram parameters estimation, the variogram parameters can be described as fuzzy numbers and the parameter uncertainties by means of membership functions [10]. Using such fuzzy variograms [10], the cokriging method produces membership functions of both the estimation and the CEV. When an optimal network arrangement has to be defined, a defuzzification measure can be used. An application of the sequential research algorithm, based on the fuzzy CEVs, has been carried out in order to verify the methodology (see Fig.s 2, 3).

6 Flood waves propagation

The flood waves propagation is a typical non linear phenomenon of River Hydraulics. The propagation of the flood waves in the river hydraulics can be studied with hydraulic methods, conceptual models or black-box models.

In [25], Fiorillo presented a Multilayer Perceptron model for modeling the flood waves propagation trained using the Back-Propagation (BP) learning rule. They tested the effectiveness of the neural model in the determination of non linear transfer function between the relative waves of flood to the extreme sections of Adige river. For the training and verification, two events of flood (August 1996 and November of 1966) between the stations of "Marco" and "Boara Pisani", spaced about 180 km, have been in turn considered.

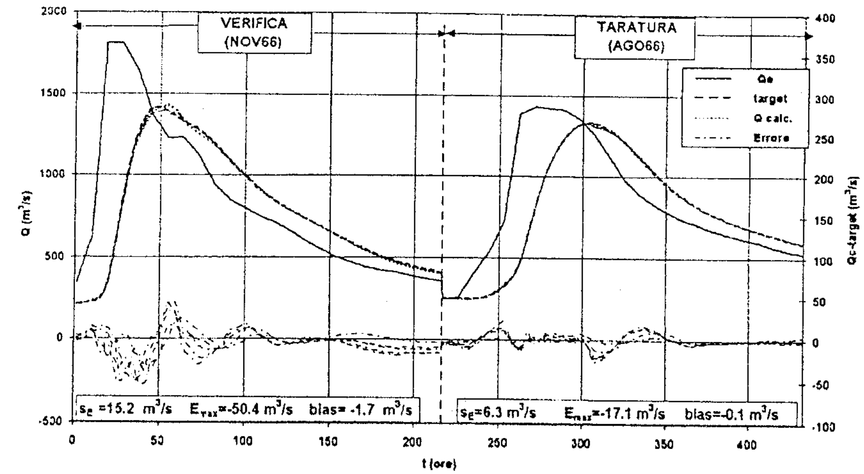

Figure 6: Comparison of the flood values estimated by the 46:4:1 MLP trained using the August wave and tested with the November wave (*agonov.net*). (Reprinted with permission from [46]).

The structure of the model of artificial neural network is based on the assumed functional dependence between input and output variables, on the basis of the propagation phenomenon, of the type $Q_t^{BP} = F(Q_t^m,\ Q_{t-1}^m, \dots, Q_{t-k}^m)$, in which Q_t^{BP} it is the outflow of gauge station "Boara Pisani" at time t, while $Q_t^m, Q_{t-1}^m, \dots, Q_{t-k}^m$ are the outflows of the gauge station "Marco" at the time t and previous hourly intervals. k has been fixed to 45 hours on the basis of the evaluation of the propagation time in the section, of the 10 – 40 order hours for variable outflow from 200 to 1800 m^3/s. The neural network is constituted by one input layer of 46 neurons, one hidden layer with 4 neurons and one output layer with one single neuron (i.e., 46:4:1). In the learning and test Q_t^{BP} target data have been corrected using the varying parameters Muskingum-Cunge model were used as target [19], taking into account the not linearity of the phenomenon.

As shown in Fig.s 5 and 6, the test with the floods not employed in training gave acceptable results, even if the task is difficult due to the hight diversity of the two waves of the mount section shown both in the overflow value and in the steepness of the growing part.

7 Pump Scheduling in Water Supply Systems

In [48], Schaetzen, Savic and Walters presented a method based on Evolution Programs for determining an optimal schedule of pumping on a 24-hour basis

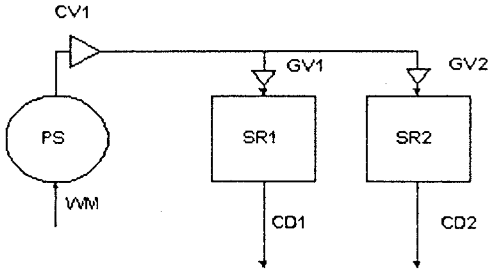

Figure 7: The model of the water network. (Reprinted with permission from [6]).

in a water supply system.

Pump scheduling is the process of choosing which of the available pumps within the system are to be used, the periods when they are to be run, and in the case of variable-speed pumps the pump speeds. The main objective of pump scheduling is to minimize operating costs whilst keeping within operating constraints.

A Genetic Algorithm (GA) [27] is applied in order to minimizing the total operating cost. Savings can be achieved by taking advantage of the lower unit cost of electricity at nights and weekends. An application of the method to the Sidmouth - Seaton water supply system in Devon (UK) is presented in the paper, showing that considerable savings are possible.

The required data for the GA are: The optimization period and the time interval, the demand plots during this optimization period, the initial minimum and maximum water levels of the reservoirs, the number of pumps comprising the pumping station, the different pump combinations and corresponding flows, the different valve combinations, and the electricity consumption for each pump combination and the pattern of the electricity tariffs used during this period.

A schematic representation of the Sidmouth - Seaton water network, as used in the optimization, is shown in Fig. 7. This simplified schematic is in direct correspondence to the proposed programming formulation of pump scheduling problems. The water supply network includes: two service reservoirs noted as SR1 and SR2, two lumped consumer demands noted as CD1 and CD2, one pumping station including three booster pumps noted as PS, two gate valves and one check valve noted as GV1, GV2 and CV1 respectively and a water main supplying the pumping station noted as WM.

The best GA-optimized pump schedule (Fig. 8) was determined in less than 8000 iterations. Tab. 2 compares the data resulting from the best chromosome found by the GA optimization process and the data which have been supplied by South West Water Services Ltd. (SWW). The hydraulic requirements of the GA-optimized pump scheduling are assumed to be satisfied.

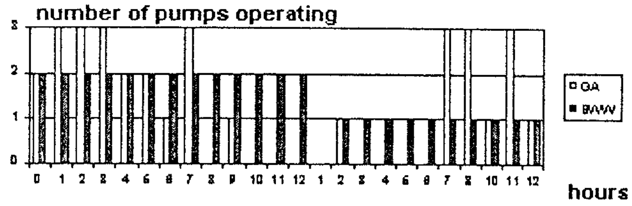

Figure 8: Comparison of Pump Schedules. (Reprinted with permission from [6]).

DATA DESCRIPTION	GA	SWW
Electricity Cost [£]	70.1	144.6
Total volume pumped [m^3]	5220	4964
Cumulative demand [m^3]	5159	

Table 2: Optimization results.

Comparing the GA-optimized pump scheduling with the original pump scheduling solution demonstrates theoretical savings of about 50% achieved by the GA optimization technique. The substantial theoretical savings are reduced when special operational costs are taken into account (i.e., costs associated with turning on or off pumps or valves).

As shown in the paper by Schaetzen and co-workers [48], Genetic Algorithms offer a valid way to achieve potential energy savings, and could be used in a wide range of water supply networks varying in size and complexity.

8 Conclusions

The information technology revolution of the last 30 years has altered the traditional planning, modeling and decision-making methodologies of the water-related sciences and technologies. Computer Science plays an essential role in the sustainable development of water resources and the responsible management of the aquatic environment. The general availability of sophisticated computers with ever-expanding capabilities has given rise to an increasing complexity in terms of computational ability in the storage, retrieval and manipulation of information flows.

Hydroinformatics is the field of study of the flow of information and its processing by knowledge as applied to the flow of fluids and their interaction with the aquatic environment. Many new modeling techniques have been entered in Hydroinformatics successfully. Among them, the application Computational Intelligence methods (such as neural networks, fuzzy systems, and evolutionary computation) in Hydroinformatics is a relatively new area of research, even if some successful results have been already obtained, e.g. in rainfall-runoff modeling, in predictions of water levels (or currents, or waves) from hydrological and meteorological inputs, in the optimization of operational parameters of wastewater treatment plants, in groundwater management, and in modeling of ecological or water quality processes.

In this review we have presented a general overview of the applications of Computational Intelligence methods to Hydroinformatics and we have analyzed some promising cases study concerning, namely, estimation of sanitary flows, rainfall prediction, unit hydrograph estimation, groundwater monitoring, flood waves propagation, and pump scheduling.

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