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An Intelligent System for Monitoring and Predicting Water Quality

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Abstract: In this paper we present an intelligent system for monitoring and predicting water quality, whose main aim is to help the authorities in the "decision-making" process in the battle against the pollution of the aquatic environment, which is very vital for the public health and the economy of Northern Greece. Two sensor-telematic networks for collecting water quality measurements in real time (Andromeda, for sea waters, and Interrisk, for surface/fresh waters) were developed and deployed. Sensor readings (water temperature, pH, dissolved oxygen, conductance, turbidity, sea currents, and salinity) are transmitted to a main station for processing and storage. The intelligent system monitors sensor data, reasons, using fuzzy logic, about the current level of water suitability for various aquatic uses, such as swimming and piscicultures, and flags out appropriate alerts. Furthermore, the system employs Machine Learning and Adaptive Filtering techniques and algorithms which successfully predict measurements a day ahead, as well as techniques to incorporate the window of past values in order to be able to make a more precise prediction. The results showed that these algorithms can help make accurate predictions one day ahead and are better than the naive prediction that the value will be similar to today.

Keywords: Sensor Network; Pollution Monitoring; Aquatic Uses; Water quality; Pollution Prediction; Knowledge-Based System.

1. INTRODUCTION

The environment includes the atmosphere, the soil and the water. By the term "water", we mean in general the aquatic resources, either surface waters (e.g. seas, lakes, tanks, rivers) or underground aquatic volumes (Bing et al. [2002]). In the technologically advanced countries, particularly in the USA and the countries of Western Europe, the need for monitoring the parameters related with qualitative environmental characteristics and especially with the quality of water, has been recognized for a long time. To this aim, several programs of automatic measurement of qualitative characteristics and analysis of results have been installed and placed in operation. If the authorities or organizations involved in the management of aquatic resources were able to monitor the quantitative and qualitative parameters related to the aquatic environment, they would be able to draw conclusions about trends, to predict undesirable situations on time and, therefore, to take counter-measures in a timely fashion. Furthermore, they could enforce longer term actions, including strategic resource planning for regional growth and development.

Research groups around the world are dealing with issues concerning environmental pollution. Considering that prevention is the best way to fight pollution, this paper deals with an intelligent system for the permanent monitoring of the quality of water as well as atmospheric and meteorological data. Up to today the main goal of research was the collection of data in real time. It soon became obvious that there was a lack of dynamic systems that would have the capability of processing the data in conjunction with knowledge bases capable to support decision making systems, risk analysis and early warning. At the same time these systems should include prediction capabilities to predict the evolution of phenomena's as well as defining future steps.

In the scope of this work two sensor-telematic networks for collecting water quality measurements in real time (Andromeda, for sea waters, and Interisk, for surface/fresh waters) were developed and deployed. Sensor readings (water temperature, pH, dissolved oxygen, conductance, turbidity, sea currents, and salinity) are transmitted to a main station for processing and storage.

Having numerous data collected on-line, we were able to develop an intelligent system that not only monitors the environmental pollution through assessing the water quality for various aquatic uses, but also includes early warning techniques to predict upcoming natural disasters. This is achieved via an expert system that monitors water quality and pollution (Hatzikos et al. [2007]). The expert system monitors sensor data collected by Local Monitoring Stations (LMS) and reasons about the current level of water suitability for various aquatic uses, such as swimming and piscicultures. The aim of the expert system is to help the authorities in the "decision-making" process in the battle against the pollution of the aquatic environment, which is very vital for the public health and the economy of Northern Greece. The expert system determines, using fuzzy logic, when certain environmental parameters exceed certain "pollution" limits, which are specified either by the authorities or by environmental scientists, and flags out appropriate alerts.

Furthermore, the system employs Machine Learning (Hatzikos et al. [2008]) and Adaptive Filtering (Hatzikos et al. [2009]) techniques and algorithms which successfully predict measurements a day ahead, as well as techniques to incorporate the window of past values in order to be able to make a more precise prediction. More specifically, the data acquired by the system have been used to study the problem of water quality prediction, performing both exploratory and automatic analysis of the collected data with a variety of methods. The results showed that these algorithms can help make accurate predictions one day ahead and are better than the naive prediction that the value will be similar to today.

The rest of the paper is structured as follows: Section 2 briefly reviews relevant systems found in the literature. Section 3 presents the overall system architecture, as well as issues related to the hardware and the software involved in building the telematic sensor networks. Section 4 presents the expert system that monitors water pollution levels using fuzzy logic. Section 5 briefly overviews results obtained for predicting water quality measurements using various techniques, presenting adaptive filtering techniques in more detail. Finally, Section 6 concludes this paper, summarizing its major issues and presenting ground for future work.

2. RELATED WORK

There exist quite a few systems in the literature that monitor the environment, in general, or sea/fresh water, in specific, and alert the user about possible dangers or water suitability. Usually, such systems are strongly related to the local environment they monitor, since environmental monitoring is a very complex task that is strongly dependent on the geomorphologic features of the monitored area. To the best of our knowledge, our system is the first one for monitoring the aquatic environment of northern Greece. In this section we review few such environmental and/or water monitoring systems.

In Hendee [1998], an expert system for marine environmental monitoring is presented, through the SEAKEYS network, which is situated along 220 miles of the coral reef tract within the Florida Keys National Marine Sanctuary. This network monitors meteorological parameters (wind speed, wind gusts, air temperature, barometric pressure, relative humidity), along with oceanographic parameters (sea temperature, photosynthetically active radiation, salinity, fluorometry, optical density). Then, an expert system is employed to provide daily interpretations of near real-time acquired data for the benefit of scientists, fishermen and skin divers. These interpretations are designed to be automatically emailed to Sanctuary managers of the network. The initial set of interpretations included environmental conditions conducive to coral bleaching.

Another knowledge-based approach was in Saunders et al. [2005], to build a system whose main goal is to classify lake-water resources in five acid-sensitive regions of the United States. It consists of a network of Decision Support Systems (DSS), one for each region. It is based on a set of rules, which is knowledge acquired from human acid-base chemistry experts. The DSS allows federal land managers to conduct a preliminary assessment of the status of individual lakes prior to consulting an expert. The authors claim that the DSS accurately portrays the decision structure and assessment outcomes of domain experts while capturing interregional differences in acidification sensitivity and historic acid deposition loadings. It is robust with respect to missing water chemistry input data.

The case-based reasoning system, presented in Fdez-Riverola and Corchado [2003], specializes in forecasting the red tide phenomenon in a complex and dynamic environment in an unsupervised way. Red tides are sea water discolorations caused by dense concentrations of phytoplankton. The system is an autonomous Case-Based Reasoning (CBR) hybrid system that embeds various artificial intelligence tools, such as case-based reasoning, neural networks and fuzzy logic in order to achieve real time forecasting. It predicts the occurrence of red tides caused by the pseudo-nitzschia spp diatom dinoflagellate near the North West coast of the Iberian Peninsula. Its goal is to predict the pseudo-nitzschia spp concentration (cells/liter) one week in advance, based on the recorded measurements over the past two weeks. The Authors claim that their prototype forecasts with an acceptable degree of accuracy. The results obtained may be extrapolated to provide forecasts further ahead. However, the further ahead the forecast is made, the less accurate it may be.

In Cheng et al. [2003] an expert system is presented for assisting the improvement of water quality in a city, applied in the Yellow River Basin of China. The system can analyze relationships between industrial water pollution and economic activities of industrial enterprises of a city. The system includes a decision model at its core, which integrates another four closely related subsystems. According to the authors, the system could provide better decision support for environmental management.

Finally, in Lee et al. [1997] a fuzzy expert system is presented for the determination of Water Quality Classification for Stream (WQCS) from uncertain and imprecise ecological information. The system employs 30 rules, generated from a rule matrix of seven water quality grades, toxicity of water and rarity of cases. According to paper results, smoothly varying curves of WQCS determination from the fuzzy expert system represented real-world experience more realistically than stepwise curves from a conventional expert system.

The work related to water quality prediction includes a variety of linear and nonlinear modelling techniques. Among the various models used are the early Bayesian probability network models focusing both on their accuracy and the correct characterization of the processes (Reckhow [1999]), the predictive clustering approach using a single decision tree for simultaneous prediction of multiple physico-chemical properties of river water from its current biological properties (Blockeed et al. [1999]), the work of regression trees for predicting chemical parameters of river water quality from bioindicator data (Dzeroski et al. [2000]), and the unvaried time series models for determining the long-term and seasonal behaviour of important water quality parameters (Lehmann and Rode [2001]).

3. SYSTEM ARCHITECTURE

The general architecture of both the Andromeda and the Interrisk sensor networks is shown in Figure 1. Each network consists of LMSs that host sensor plunged into water and collect aquatic numeric data concerning sea or fresh water. Sensor readings are transmitted to a Main Station (MS) for processing and storage.

In the case of the Andromeda sea water network, the 3 LMSs are plunged into Thermaikos Gulf and the following hydrological parameters are measured: water temperature, pH, dissolved oxygen, conductance, turbidity, sea currents, and salinity. The transmission of data between the LMSs and the MS is done via radio modems. A more thorough description can be found in Hatzikos [2002].

The Interrisk network collects, from lakes Doirani and Kerkini and the Strimonas River, hydrological parameters for fresh water (water temperature, pH, dissolved oxygen, % oxygen, turbidity, conductivity, water depth), as well as, meteorological parameters (air temperature, air relative humidity, solar radiation, wind speed, wind direction, rainfall, evaporation). The communication of the LMSs with the MS is performed through mobile telephony (GSM technology) with the use of suitable GSM Modems.

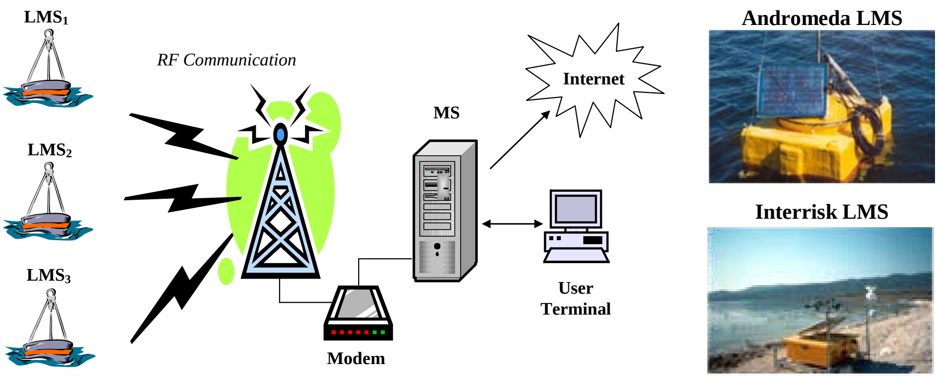

Figure 1. Architecture of the Sensor Networks.

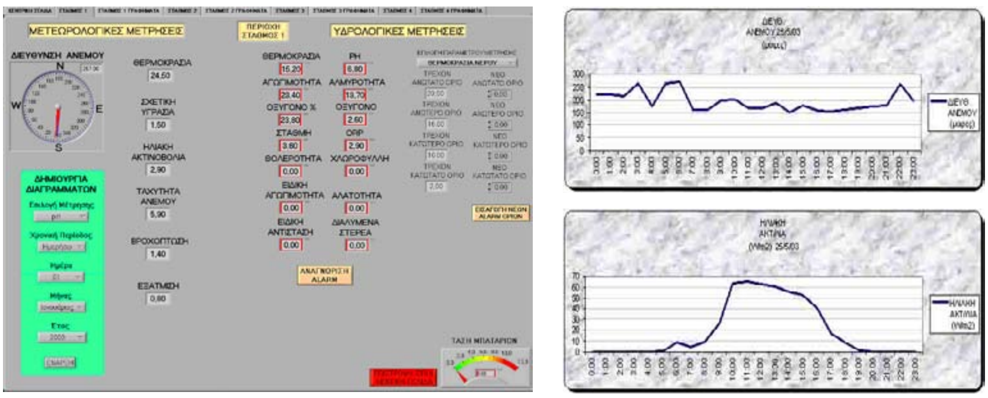

Figure 2. Sensor data visualization at the main station.

The Main Station (MS) is a workstation that collects sensor measurements from all the LMSs and visualizes the results in a SCADA environment. The MS initiates the communication with each of the LMSs in predetermined time intervals using a hand-shake technique. The MS also adjusts the frequency of measurements depending on the situation at hand, i.e. an emergency in the case of pollution. The LMS operates only during the rendezvous. In this way, less energy is consumed. Furthermore, the on-demand measurement policy achieves a higher level of flexibility.

The data collection from the sensors and its transmission to the MS is performed via the SCADA software. LabView is responsible for the data reception, visualization (Figure 2), long-term storage in databases and exporting them in various formats for further processing. Additionally, the administrator of the MS can set alarms in LabView (to be received by the user) when certain sensor measurements exceed some predefined limits.

4. MONITORING WATER QUALITY THROUGH A FUZZY EXPERT SYSTEM

As mentioned in the previous section, the check whether a sensor measurement exceeds certain pollution limits is performed in a rigid fashion, not allowing flexibility. To this end, the MS is equipped with a fuzzy expert system, implemented in MATLAB, which alleviates this by using fuzzy logic to check for violation of environmental parameter limits. The expert system is fed with data from the SCADA software and produces results about the water suitability regarding swimming, shell-culture and pisciculture, also alerting the user. Expert scientific knowledge is required for these issues to be resolved. If a human expert is not available at the corresponding operation centre, then the hydrological parameter values should be monitored automatically by a corresponding expert system, in order to draw conclusions about possible hazardous situations for the environment.

The scientific knowledge required for the expert system was elicited from the Greek environmental legislation for the Region of Central Macedonia. The desired and allowed values for the various measurements are set by the aforementioned law depending on the aquatic use: drinking water, swimming, shell cultivation, etc. This particular expert system deals with shell cultivation, swimming, Cyprinidae cultivation and Salmonidae cultivation.

All the above ranges are not crispy but fuzzily defined, in order to allow for fluctuations in sensor readings, due to either limited sensor accuracy or random fluctuations of physical conditions. Furthermore, fuzzy ranges can meet ascending or descending parameter trends, in the absence of proper trend analysis within the system. For example, if there is a descending trend for the pH that would turn it from normal to acidulous in a few hours, fuzzy ranges would cause an alert before the pH actually reaches the critical point. This means that authorities will be alerted in time to be prepared for action, when the actual critical situation arises. Notice that this approach might also cause false alarms due to random sensor reading fluctuations, but the alerting and mitigations strategies, i.e. importance and frequency of the alerts and proper measures to be taken, is not a part of the monitoring system.

A final justification for using fuzzy logic is that the latter can cater for the rigidness imposed by the legislation, which had to be formulated precisely, using crispy values. However, in practice such limits are never rigidly defined, since they are derived statistically. Notice that the overlapping of the fuzzy ranges are narrow, since the legislation cannot be highly disputed, meaning that measures against pollution and/or polluters cannot be taken if the actual crispy limits set by the law are not violated. Having large overlaps would cause more pollution alarms that would trigger authorities unnecessarily. In any case, the degree of overlapping was actually established through experimentation and it was tuned for smooth behaviour of the Fuzzy Inference System (FIS) transition function.

There is one FIS for each hydrological parameter. Each FIS has one input variable and four output variables, one per aquatic use. The use of multiple single-input-multiple-output (SIMO) FISs instead of one multiple-input-multiple-output (MIMO) FIS reduces the complexity of the transition function and is justified by the fact that the legislation correlates non-acceptable parameter values with a single water usage, i.e. it regards each variable as independent from the other ones.

The input variable is split in as many membership functions as needed to utilize the desired and allowed ranges for each aquatic use (Figure 3). The output variables affected by this particular measurement contain three membership functions: OK, CAUTION and DANGER. In each FIS, if the input falls within the desired range for a particular use, the respective output for this use is OK. In case the input is outside the desired range of values, but remains within the allowed range for a particular use, the corresponding output is CAUTION, otherwise it is DANGER. The rules for each FIS (Figure 4) were formulated by taking into account: a) the correlation between the input and the output variables, and b) the definitions of the membership functions. The system uses the Mamdani's min fuzzy inference method and the centroid defuzzification method.

Finally, overall conclusions are presented to the user. The system must be able to provide answers to questions like the following: "*Is the water suitable for swimming*?" Thus, the user reads on the screen a combination of the aquatic use, the alert type, and the precise measurements that were deemed abnormal (Figure 5).

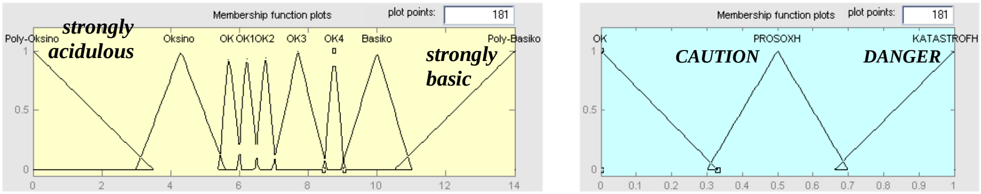

Figure 3. Membership functions of the input variable “pH” and the output variable “Shell”.

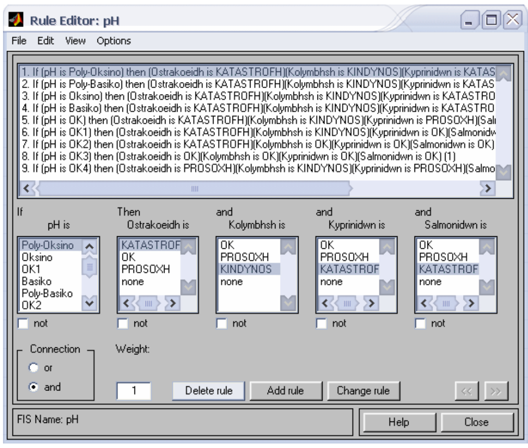

Figure 4. The set of rules of the pH FIS.

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<<<DATE / TIME:     25-Jul-2002 / 06:50>>>

SHELL CULTIVATION:
    DANGER: The allowed value ranges have been exceeded!
        Values that have exceeded the ALLOWED VALUE RANGE are:
        TEMPERATURE:   25.390    Code:  0.8613494
                 PH:   11.180    Code:  0.8485162
                %O2:   37.100    Code:  0.8691869
        Values that have exceeded the DESIRED VALUE RANGE are:
           SALINITY:    3.000    Code:  0.5000000

SWIMMING:
    DANGER: The allowed value ranges have been exceeded!
        Values that have exceeded the ALLOWED VALUE RANGE are:
                 PH:   11.180    Code:  0.8485162
        Values that have exceeded the DESIRED VALUE RANGE are:
                %O2:   37.100    Code:  0.5000000

CYPRINIDAE CULTIVATION:
    DANGER: The allowed value ranges have been exceeded!
        Values that have exceeded the ALLOWED VALUE RANGE are:
                 PH:   11.180    Code:  0.8485162
        Values that have exceeded the DESIRED VALUE RANGE are:
        TEMPERATURE:   25.390    Code:  0.5000000
       DISSOLVED O2:    0.080    Code:  0.5000000

SALMONIDAE CULTIVATION:
    DANGER: The allowed value ranges have been exceeded!
        Values that have exceeded the ALLOWED VALUE RANGE are:
                 PH:   11.180    Code:  0.8485162
        Values that have exceeded the DESIRED VALUE RANGE are:
        TEMPERATURE:   25.390    Code:  0.5000000
       DISSOLVED O2:    0.080    Code:  0.5000000
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Figure 5. Sample expert system output.

5. PREDICTING WATER QUALITY THROUGH ADAPTIVE FILTERING AND MACHINE LEARNING

Over the last decade monitoring water quality and other environmental variables has become considerably important, in an effort to predict their future behavior and prevent undesirable environmental situations, as well as, to enforce longer term actions for regional growth and development. The ability to predict the quality of water in an ecosystem one or more days ahead is very useful, giving the possibility to the authorities for the necessary precautionary actions in time.

In the MS of our sensor networks, we employ both Machine Learning and Adaptive Filtering techniques and algorithms in order to predict measurements a day ahead. In the case of Machine Learning, we also incorporate the window of past values in order to make a more precise prediction. The results showed (Hatzikos et al. [2008]) that the Machine Learning algorithms are able to predict more accurately several days ahead and the furthest ahead the prediction, the largest the window of past values should be incorporated in the model. However, in this paper we focus more on the results of the Adaptive Filtering techniques (Hatzikos et al. [2009]) which are more intuitive.

More specifically, we investigate the possibility to predict a number of water quality variables that are obtained by an under-water measurement set-up. Our interest is focused on one-day ahead predictions of certain water quality variables recorded by an under-water set of sensors, such as water temperature, pH, conductivity, salinity, amount of dissolved oxygen and turbidity. The measured data, forming time series, are stored in a database and a number of modeling methods could then be used to reveal any hidden information. Here we present results obtained for the water temperature, pH, amount of dissolved oxygen and turbidity, due to their higher importance in terms of commercial exploitation.

Adaptive Filtering is performed via a projection and a least squares algorithm. Their prediction ability is shown by comparing their performance against the delayed or naive prediction algorithm (Random Walk Model), which serves as a benchmark model in prediction tasks. The delayed prediction model states simply that the future value (tomorrow) of a variable will be equal to its current value (today), supporting in that way the unpredictability of the modeling object. However, due to the correlation and interaction between the water quality variables, it is interesting to investigate if there is an underlying mechanism that governs the data and thus will prove the predictability of these variables. The projection and least squares algorithms were chosen because they are widely used prediction algorithms and by applying both we can compare and contrast results The identification of such models is particularly useful for ecologists and environmentalists since they will be able to predict in advance the pollution levels in the sea water and thus to instruct all the necessary precaution actions.

The original data had a sampling time of 9 seconds. However, due to the fact that there were a large number of outliers in the data, and that the data did not vary too much on an hourly basis, it was decided that the data should be averaged over a period of one day. Figure 6 shows the autocorrelation sequences for temperature, pH, oxygen and turbidity, calculated from one-month data sets collected during July 2004. This figure demonstrates that temperature, oxygen and turbidity are correlated with past values, and therefore it is possible to use them in prediction. The autocorrelation sequence for pH, on the other hand, is very sharply peaked around time lag 0, which implies that it could be very difficult to construct one-day ahead predictions for this variable.

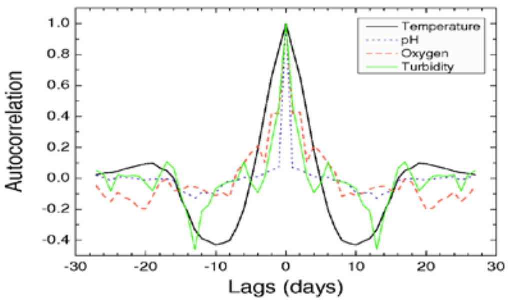

Figure 6. Autocorrelation sequences for temperature, pH, oxygen and turbidity.

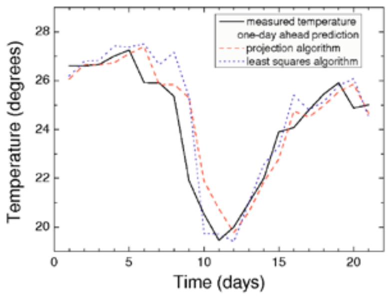

Figure 7. Temperature prediction.

In the following, we show the results we obtained for water temperature prediction, which are more encouraging. Results for the rest of the variables are obtained similarly and can be found in (Hatzikos et al. [2009]).

Initially, in the water temperature prediction, only the values of previous days were used. This was due to the fact that the water temperature is mainly influenced by external variables such as the amount of radiation from the sun, wind direction, etc. Based on the autocorrelation analysis, it was decided that the values of water temperature of the current day and two previous days should be used to predict the water temperature of the next day. The initial estimate was that in most cases the temperature tomorrow should be more or less equal to the temperature today. Before building the prediction model, the data was normalized to zero mean and unity variance. Figure 7 shows the measured and the predicted temperature by use of the Projection algorithm and of the Least squares algorithm.

The prediction of the projection algorithm is quite accurate, in particular after day 12. The algorithm converges in a way that shows that its prediction is based mostly on the current temperature, but corrects the value using previous temperatures as well. The prediction accuracy of the least squares algorithm is reasonable, although not as accurate as the projection algorithm. The algorithm converges in a way that shows that the prediction model uses the current temperature more heavily than the projection algorithm. The observation that the projection algorithm predicts more accurately after day 12 is due to the fact that the measured temperature shows a smoother trend after that day.

Table 1 shows the l_2-norm and l_∞-norm of the prediction error for the projection algorithm, the least squares algorithm and the “delayed prediction algorithm”. Prediction models from both the projection algorithm and least squares algorithm give better prediction accuracy, which is a remarkable result. Furthermore, the prediction model from the projection algorithm is the most accurate one.

Table 1. Prediction accuracy of temperature

Prediction method	l_2	l_∞
Projection algorithm	2.0	1.47
Least square algorithm	2.0	1.5
Delayed prediction algorithm	2.2	5.5

6. CONCLUSIONS AND FUTURE WORK

In this paper we have presented an intelligent system for monitoring and predicting water quality, whose main aim is to help the authorities in the "decision-making" process in the battle against the pollution of the aquatic environment, which is very vital for the public health and the economy of Northern Greece, and not only. The system is realized via two sensor-telematic networks for collecting water quality measurements in real time (Andromeda, for sea, and Interrisk, for fresh waters). Sensor readings are transmitted to a main station for processing and storage.

The intelligent system monitors sensor data, reasons, using fuzzy logic, about the current level of water suitability for various aquatic uses, such as swimming and piscicultures, and flags out appropriate alerts. Furthermore, the system employs Machine Learning and Adaptive Filtering techniques and algorithms which successfully predict measurements a day ahead, as well as techniques to incorporate the window of past values in order to be able to make a more precise prediction. The results showed that these algorithms can help make accurate predictions one day ahead and are better than the Naive prediction that the value will be similar to today.

The main advantage of the system and its architecture is its versatility by means of extensibility and mobility. Concerning the sensor network, new sensors for a variety of environmental readings (e.g. hydrological, meteorological, etc.) can be and have been easily added to the system. Furthermore, existing LMSs can be easily moved to different locations and new LMSs can be easily added, without disturbing the rest of the system. The communication between the LMSs and the MS can be and has been implemented with a variety of technologies, depending on the geomorphologic and socioeconomic features of the installation area. Another advantage of the flexibility of the system is that new methodologies and techniques both for predicting and monitoring can be used without disturbing the rest of the system.

The Andromeda network was working productively from 1998 until 2005, when it ceased working due to lack of Governmental funding. The monitoring system has been working 18 months during 2004-2005. During that period a large number of “pollution events" were recorded, for which the system responded issuing alerts properly, since the LMSs were installed near the port and the industrial area of Thessaloniki, where sea quality is very poor. However, only one severe event was recorded when all sensors indicated strongly a very large deterioration of water quality, which turned out to be due to a spill from a ship. Finally, there were also some false and/or missed alarms occurring on days when the maintenance of sensors was inadequate, or when litter was cluttering sensor readings, in both cases resulting in untrustworthy measurements.

One of the first future research priorities is to integrate the prediction algorithms employed in the MS with the fuzzy expert alerting system, so that the system will be able to issue early warnings based on predicted hydrological and/or meteorological parameters values. Furthermore, future study will explore the possibility to construct prediction models for the other variables on shorter time-scales than the one-day ahead prediction. We also intend to investigate various energy-preservation policies and the trade-off between prediction accuracy and data quality, which will allow us to deploy the water quality monitoring system in aquasystems with limited sunlight. Finally, one of our future aims is the use of model-based reasoning for self-diagnosing the sensors of the LMSs and for predicting spatial pollution propagation among LMSs.

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