An Intelligent Analytics System for Real-Time Catchment Regulation and Water Management

Ioan Petri, *Member, IEEE*, Baris Yuce, *Member, IEEE*, Alan Kwan, *Member, IEEE*, and Yacine Rezgui, *Member, IEEE*

***Abstract*—Regulation procedures and water management that incorporate projected hydrological changes with related uncertainties become extremely important in order to prevent degradation of water ecosystems. Ensuring real time water management and optimization becomes mandatory for resolving the constraints of water supply/demand and to comply with biodiversity requirements. We focus our research on water optimization and catchment regulation and present our solution that has been developed as part of the Innovate UK Radical project.[1] In our study, we use the Usk reservoir in South Wales with rich biodiversity and nationally significant fishery to optimize catchment flow and to conserve water with real-time catchment management information to support the decision makers. Our developed solution uses artificial intelligence techniques to deliver real-time decision support for water management and catchment regulation with reflection to biodiversity protection and reservation. We present an intelligent analytics system that uses real-time data from river stations enabling informed decisions and a more dynamic approach for managing water resources. The system utilizes a neuronal network engine to support river level prediction based on which a dependency modeling is developed for assessing the probability of risk in the Usk reservoir.**

***Index Terms*—Artificial neuronal network, dependency modeling, intelligent systems, river depth prediction, water analytics.**

I. Introduction

COMPUTER techniques have proven as efficacious instruments to help in addressing the emerging problems that the society and the environment solicits. Information and communications technology (ICT) networks and distributed systems can help in devising communication systems ensuring scalability, flexibility, efficiency, and security for computer systems to model real scenarios and to transpose into computer workflows. Such systems are becoming extremely beneficial especially when embedding artificial intelligence techniques with systems engineering mechanisms facilitating a holistic end-to-end communication system.

On the other hand, the growing interest on water research has been determined by various factors, such as climate change, urbanization, and population growth requiring new business and technology platforms to manage the increased level of diversity and complexity of water resources management. Such variability of both water supply and consumption also requires a more sophisticated and optimized decision making process. Therefore, regulation procedures for water management that incorporate projected hydrological changes with related uncertainties become extremely important in order to ensure water supply and demand and to prevent degradation of water ecosystems.

To address emerging requirements in water and energy savings, intelligent systems can provide the means to combine different innovative technologies and to integrate water distribution, real time sensor monitoring, and high power computing networks [1], [2]. Such systems can be used as a vehicle to (a) improve household, business and societal awareness, (b) induce changes in consumer behavior, (c) enable the introduction of innovative resource and demand management schemes, (d) pave the way to adaptive pricing incentives, and (e) develop and demonstrate widely applicable concepts for energy recovery from water use, enhancing the water-energy nexus [3]–[5].

A key method in the domain of water optimization is the river level prediction with associated requirements related to accuracy and decision data. As the rainfall identifies a complex process, accurate information can be essential for the planning and management of water resources and also crucial for reservoir operation and flooding prevention. River depth and rainfall represents a complex undertaking with regards to hydrology cycle which makes the modeling process demanding due to the complexity of the atmospheric processes that generate rainfall and the fluctuation over a wide range of scales both in space and time. Under these coordinates, accurate river depth and rainfall prediction represents a key challenge in the field of operational hydrology, despite the substantial progress achieved in weather forecasting in recent decades [6], [7].

The problem of prediction for water management and catchment regulation is evolving with various attempts to predict river

Manuscript received October 31, 2017; accepted December 6, 2017. Date of publication December 19, 2017; date of current version September 4, 2018. This work was supported by the Innovate UK Water Security Project: "Developing a Real Time Abstraction & Discharge Permitting Process for Catchment Regulation and Optimised Water Management" under Grant 504460. Paper no. TII-17-2559. *(Corresponding author: Ioan Petri.)*

I. Petri, Y. Rezgui, and A. Kwan are with the BRE Trust Centre on Sustainable Engineering, School of Engineering, Cardiff University, Cardiff CF24 3AB, U.K. (e-mail: petrii@cardiff.ac.uk; rezguiy@cardiff.ac.uk; kwan@cardiff.ac.uk).

B. Yuce is with the College of Engineering, Mathematics and Physical Sciences, Streatham Campus, University of Exeter, Exeter EX4 4QF, U.K. (e-mail: b.yuce@exeter.ac.uk).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2017.2782338

[1]Developing a Real Time Abstraction and Discharge Permitting Process for Catchment Regulation and Optimized Water Management.

level and rainfall accurately using various techniques. There are a number of limitations imposed by the nonlinear nature of these variables and prediction accuracy obtained by these techniques is still below the satisfactory level. In this context, artificial neural network (ANN) algorithms can support inductive approach in rainfall prediction ensuring nonlinearity, flexibility, and data driven learning in building models without any prior knowledge about catchment behavior and flow processes [8], [9].

Based on water observations data, water resources information systems have appeared as an answer to the need to accurately monitor, assess, and forecast the availability, condition, and use of water resources. Such water information systems impose new standards for information about climate and environmental data facilitating data to be easily exchanged among water authorities, meteorological bureaus, and other environmental stakeholders [10]. Our study aggregates inputs and commentary from various sources leading to the conclusion that a real time system for water analytics can support an efficient decision process and automated information exchange. Such a system can provide the means to enable efficient management of water resources based on real-time flow data integrated with decision models.

We have developed an intelligent system for water analytics and catchment regulation as a more integrated and real time approach to meet the challenges of water management. The key element of the system is the prediction engine which supports five days forecast for river depth, river flow, and rainfall. The data is further manipulated and analyzed to assess risk based on which users can take informed decision on the various actions that need to be considered in relation to regulating the catchment ecosystem. Our solution is based on requirements of thel South Wales Usk Reservoir and the evaluation is developed with real-time data collected from seven stations within the Usk reservoir.

The rest of the paper is organized as follows: in Section II, we present related studies from the field of water research; in Section III, we present requirements in relation to water management and catchment regulation; in Section IV, we present the methodology and the modeling process adopted in this study followed by the evaluation in Sections V, and VI. We conclude in Section IX.

II. Related Work

The Water analytics and Intelligent Sensing for Demand Optimised Management (WISDOM) project [11] aims at developing and testing an intelligent ICT system that enables "just in time" actuation and monitoring of the water value chain from water abstraction to discharge, in order to optimize the management of water resources. The project aims to adopt a semantic approach that captures and conceptualizes holistic water management processes, including the associated socio-technical dimensions (social networks interactions with physical systems). As part of the project the following modules have been developed:

1) (semi)automated control of the water system operation,
2) a computer-aided decision making for human intervention,
3) a data sharing among numerous components and tools, and
4) the integration of the water infrastructure functionalities, the interfacing with other smart energy infrastructures and building systems.

The WISDOM project considers a holistic view of water management systems and processes across the entire water value chain, from abstraction to discharge also related to the relative costs [12].

Another researching attempt on water optimization from Takahiro *et al.*, [13], manages to develop an ICT system for water management by modeling the water infrastructure and its optimal operation with electronic control. The expected benefits aim to maintain or renew the water infrastructure at the same quality of service under the challenging conditions of demand increase. The objective is to advance the development and implementation of a novel concept of adaptive water distribution networks with dynamically reconfigurable topology for optimized pressure control, leakage management, and improved system resilience. This research brings together concepts and techniques from ICT, cloud and big data technology, sensing technology and model predictive control and optimization for large scale water supply networks.

The UrbanWater project [14] integrates high quality and already proven solutions for data management and billing systems, with innovative models for forecasting water supply availability, predicting customers demand, and detecting leakages. This project also gathers real measured data from sensors connected to the water network infrastructure for developing spatial tools based on strong know-how from previous developments in the field of supporting distributors and authorities in decision-making. The project also looks at innovative solutions to empower customers and efficiently integrate them in the UrbanWater platform.

To resolve these issues and establish infrastructure for water that is safe and gives users easy access to water and confidence in its quality, Hitachi [15] has proposed the intelligent water system concept. This concept aims to perform comprehensive management of the water cycle at a regional or city level based on the ideas of harmony, sustainability, and self-reliance by adopting more intelligent individual technologies. Such technologies identify water recycling and other water treatment technologies, information technology, and monitoring and control technology, and water cycle traceability.

On the other hand, artificial neuronal networks have been intensively used for, rainfall-runoff modeling which is a required task for planning, operation, and control of any water resource project [16]. The problem of estimating river levels and how much of the rainfall effectively contributes to the runoff represents a scientific challenge for modelers as hydrological phenomena is extremely complex, highly nonlinear, and exhibit a high degree of spatial and temporal variability. Among many data-driven techniques, the ANNs can provide the means to model and predict events related to rainfall and river levels greatly supporting hydrological and hydraulic engineering community in achieving objectives related to water management and catchment regulation [17], [18].

Various solutions also have been explored in the filed of rainfall prediction and hydrology aiming to reduce the computational cost and high resolution requirements of such complex workflows. Such options range from parallel computing techniques that can reduce the overall computational time to fast models to replace computationally expensive model evaluations [21]. Support Vector Machine (SVM) techniques, have been also popular for the hydrological and hydraulic engineering community with encouraging results in handling the complexity with modeling and prediction [19], [20].

Our approach borrows concepts and techniques from these related approaches but provides a more holistic view of catchment management aiming to create a greater ability to conserve existing water resources through smarter management. We monitor the Usk reservoir with real time data collected from sensors and using artificial neuronal networks techniques we predict river depth within the stations. This intelligence is then embedded into a decision support system called i-Depend which based on a Bayesian dependency modeling can help users to assess risk and take informed decisions for regulating the water ecosystem.

III. Approach

A method for water management and regulation is the Supply and Demand (S and D) model which is currently being used as a tool for guaranteeing water across the UK at minimum cost. Such models are covering a wide range of factors related to water distribution but there are other environmental and societal factors more problematic to integrate within the same models. However, in the water management context there are multiple factors to consider, such as ecological protection where prediction is based on historical data and trends for applying strategies, rather than predicting what might happen several days ahead using real time data. In this study, we are also exploring ways whereby taking a more integrated approach to allow a more inclusive assessment of situations that could impact the "health" of the Usk river catchment (whether such impacts are environmental, societal, or financial) and which could make significant improvements in the way water is optimized.

We apply our analysis on the Usk Reservoir, an water ecosystem located in the upper Usk Valley, at 1050 feet (320 m) above sea level, in southern Wales. The reservoir is situated in part of the Brecon Beacons National Park sitting below the Black Mountain (range) and represents important landmark for walkers on the mountain range and a main water source for South Wales. We use the Usk reservoir and Usk river as an use-case with seven water stations and identify few possible areas of improvement with a more holistic and inclusive management approach. Based on a requirement capture process (meetings, interviews, panels formed of Usk reservoir members and water specialists in South Wales), we have determined the following aspects that need to be addressed in relation to water management and catchment regulation in the Usk reservoir.

1) *Simplifying Usk catchment management* where the benefit of real time data might help with decision making; this is becoming increasingly important to address the challenge of meeting increased demand as population grows with decreasing supplies from changes in climate.
2) *Have an ability to incorporate water quality as well as water quantity* decision making in a more automated way; e.g., looking at the actions and consequences of releasing treated water from waste water treatment plants at locations within a catchment or subcatchment.
3) *Incorporate analysis of environmental impacts* of water scarcity flooding to biodiversity and habitat protection directly into the catchment model.
4) *Include other environmental societal impacts* which are hard to quantify, but which are interdependent on catchment management.
5) *Reduce some of the data intensity* to make an informed decision.
6) *Making decision making more auditable and consistent* by removing some of the collective decision making which for a given set of circumstances over time would not necessarily have the same outcome depending upon which experts are reviewing data at the time.
7) *Having a more robust way of analyzing the impact of a decision* across all catchment stakeholders by having a wider ability to determine relationships of cause and effect and add influences based upon seemingly unrelated pieces of evidence, using a Bayesian Belief Network.
8) *Replacing water scarcity and flood predictions* based upon historical trends with predictions using current real time data; hence decisions would not necessarily be reliant on a predetermined plan or triggers but could allow responses based upon changing climate or data trends at that point in time.
9) *Having the ability to estimate water levels and flows and assess risk* along river catchment tributaries, even if telemetry is only available at one or few points along the main river.

These objectives can lead to a more comprehensive catchment management process and may be able to ensure sustainability and accuracy in the decision process as well as delivering reliable cost solutions. To address these aspects we have decided to adopt a prediction-based approach for river level forecasting followed by a risk dependency modeling to evaluate the level of risk associated with various environmental changes that may occur within the Usk reservoir. In this paper, we aim to develop an intelligent system for both water managers and regulators to control/(maintain) the quantity, quality, and sustainability of water resources and to decide (i) where to manage implying capability to monitor and to intervene responsively, or strategically, knowing in advance of the likely effects of intervening and (ii) when to regulate by ensuring the statutory requirements and objectives are in place, enforced and, achieved.

IV. Methodology

Our developed solution represents an intelligent analytics system with an artificial intelligence module used for predicting river levels and assess risk. Based on the architectural levels (illustrated in Fig. 1), we enable a water management workflow that facilitates users to conduct real-time river level prediction and risk assessment.

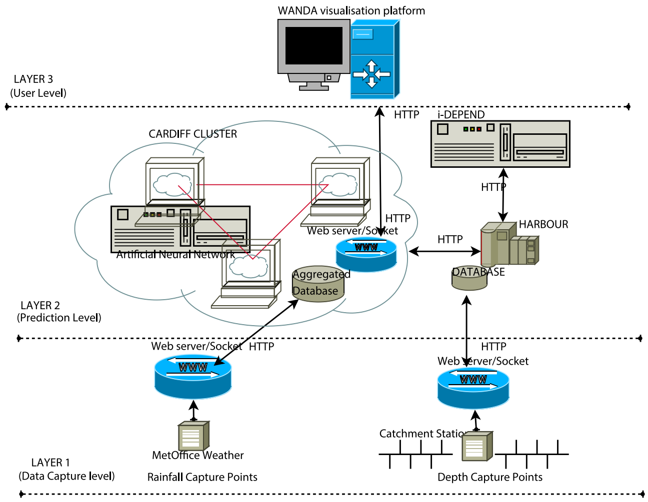


Fig. 1. System architecture.

A. Architectural Levels

We have developed an intelligent optimization engine for water analytics and catchment regulation formed by three different layers:

In the data capture layer, we aggregate data from seven stations within Usk reservoir. This data is provided on real-time basis and is provided on per day intervals. The stations we use for monitoring and data collection are: "Pont Ar Yscir," "Pont Hen Hafod," "Llandetty," "Millbrook," "Chainbridge," "Trostrey Weir," "Olway Inn." These stations are all part of the Usk reservoir alongside Usk river and have technical means to broadcast recorded river depth on daily basis. A secondary incoming data flow is the weather aggregation service fetching real-time rainfall data about the reservoir from the UK Met Office weather service.

The prediction layer is composed of three distinct modules: the Harbour module, the neuronal network module, and the i-Depend dependency modeling module.

1) The Harbour module controlled by Cambrensis (an industrial partner) is serving raw data to the artificial neuronal network module. Harbour uses a computer server which retrieves and stores river data from the seven stations within the reservoir. Harbour communicates via a HTTP connection with each individual station to collect river data on daily basis.
2) The artificial neuronal network (ANN) module predicts river depth, river flow and weather based on real-time data fetched from the river stations (The ANN module is presented in Section V-B).
3) At this level we also identify the i-Depend module which undertakes dependency modeling based on the results generated by the prediction module (the i-Depend module is presented in Section VII).

The workflow presenting the interaction between these modules is presented in Fig. 2. The infrastructure used to deploy the data aggregation process, prediction, and knowledge extraction is distributed over a cluster-based infrastructure hosted by the university (presented in Section IV-B) to increase efficiency and ensure functionality in use for the prediction process.

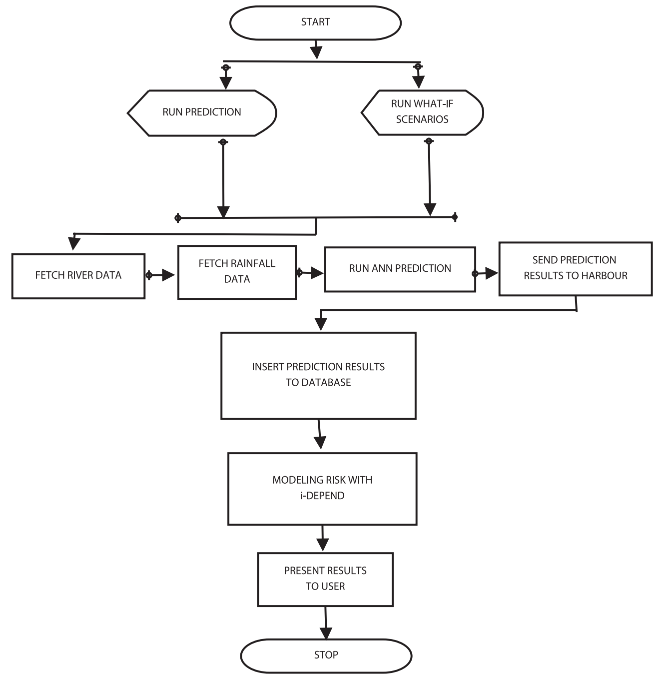


Fig. 2. System workflow.

The user layer represents a visual interface where the data manufactured by the prediction level is interpreted and displayed to the user. In the solution we provide, the user layer represents a web-platform where the information is tailored based on each user profile. We take into account that users may have various interests and roles in relation to water management and based on the interests/roles we enable specific data to be presented on the visual interface. We use this web interface also to assist users in the process of decision and to facilitate access to knowledge representation where a user can observe the status of the reservoir and make informed decisions.

B. Computing Infrastructure

We deploy our optimization system on a cluster based infrastructure with 12 dedicated cluster machines. Each machine has 12 CPU cores and 3.2 GHz CPU speed. Each physical machine uses a KVM (Kernel-based Virtual Machine) virtualization environment and runs Ubuntu Linux utilizing one 3.2 GHz core with 4 GB of RAM and 25 GB storage capacity. In our system each module works on a separate machine and uses the capability of the machines for their corresponding roles as follows: (i) in charge of computing the prediction tasks and (ii) to host the web-platform. Harbour and i-Depend are also hosted on a cloud based infrastructure.

V. System Modeling

We work with a set of water stations defined as, $S = \{s_1, s_2, s_3, ..., _s n\}$, $n = \overline{0, 6}$, where each s_i represents a station alongside the Usk river. Each station s_i has two main input parameters: d_i and r_i, $s_i \rightarrow [d_i, r_i]$, where d_i represents the

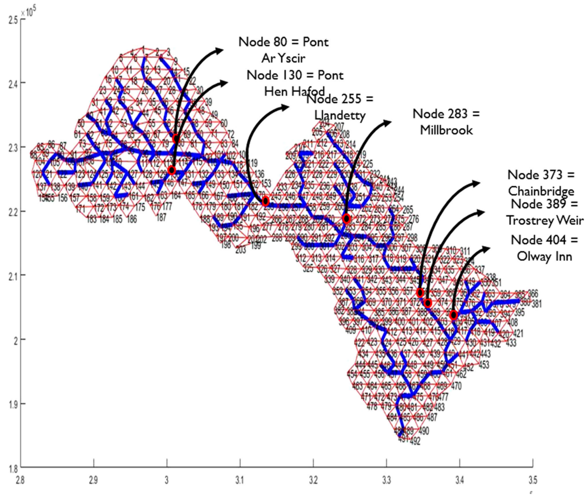


Fig. 3. Illustrating the Usk catchment reservoir model.

recorded river depth of station s_i and r_i represents the recorded rainfall at station s_i. Based on these river depth and rainfall input parameters, we apply artificial neuronal network algorithms to generate the output identified as: predicted river depth p_d, predicted river flow p_f, and predicted rainfall p_r.

A. Usk Reservoir Modeling

We model the Usk Reservoir as a node-to-node system $N = \{n_1, n_2, n_3, ..., n_m\}$, where each node n_i has a with fixed geographical position determined via GSP coordinates; longitude x_i, latitude y_i, and elevation (height) h_i. As illustrated in Fig. 3, the reservoir is a hexagonal grid where there are two types of points (nodes): (i) land points $L = \{l_1, l_2, l_3, ..., l_p\}$, $L \in N$ and (ii) river points $R = \{r_1, r_2, r_3, ..., r_s\}$, $R \in N$. We consider that each node can have a maximum six neighbors: $M = n_1, n_2, n_3, .., n_s, M \in N, s \leq 5$.

1) Technical Modeling and Algorithm: We create an artificial rain data where every day has an associated rain quantify following a linear rain pattern. We consider that both high lands nodes L and low lands (river) nodes R have the same rain record and every node has a 2 km^2 area associated. For all nodes in the reservoir grid, we calculate the following.

1) The incoming water quantity – how much water a node stores; where a node collects water from the 2 km^2 area.
2) The outgoing water quantity – based on a selection of the neighbors, we calculate the relative height for neighbors applying that 60% of water is stored in the node reservoir (we consider that a node has its own reservoir) and 40% of water is distributed to neighbors lower that the current node.
3) Reservoir node distribution – water is distributed as 10% ground water, 40% surface flow, and 60% as ground flow.

We consider that a river node $r_j \in R$ is a type of node that can have maximum one neighbor which is also a river node r_k from where it receives an amount of 80% of water flow. A master exit node (outlet) is the node with the lowest height in the reservoir. Low lands retain 25% of the incoming water, highlands retain

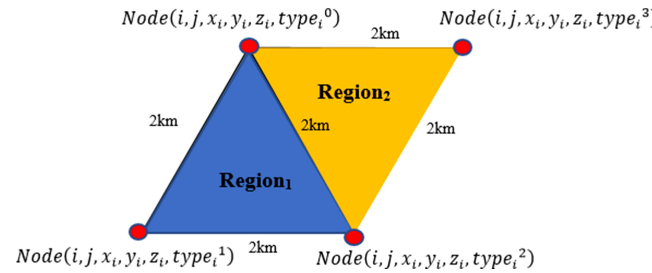


Fig. 4. Demonstration of the proposed triangulation method.

Algorithm 1: Usk Modeling Algorithm.

```
Set the total number of nodes;
Determine (x, y, z) nodes coordinates;
Set node can have six neighbors;
Set node area (2 km^2);
for all Nodes in catchment do
    Allocate volume of rain ;
    Determine relative heights;
    Determine water released to each neighbor;
    Determine water stored in node reservoir;
    if Node is highland then
        Node retains 40%;
    else
        Nodes retains 25%; (Node is lowland)
    end if
    Water released downhill;
    if Node is outlet (exit node) do
        Set no neighbors;
        Set node only to store;
    end if
end for
for all Neighbors of node do
    if Neighbor is lower joint then
        Release water only to next neighbor;
    end if
end for
for all River nodes do
    Release 80% water to next neighbor;
    Retain water 20%;
end for
```

40% of the incoming water. Highlands are the regions that have heights of greater than 250 m from ground. The modeling of the Usk river is generated based on finite difference methodology using a course map (≈1.73 km^2). During the modeling stage EdinaMap (developed by University of Edinburgh) is utilized to extract three-dimensional coordination information for both location and elevations. The entire river basin and nearby regions are mapped through this proposed triangulation-based mapping process as shown in Fig. 4. To represent the seven stations alongside the Usk river, we have selected seven reservoir nodes that are the closest nodes based on GPS location to the existing river stations. The steps we have followed for modeling the Usk reservoir is presented in Algorithm 1.

Algorithm1 is supported by the following list of equations:

$$\text{Equation}\quad 1: \mathrm{NodeWater}\,(\mathrm{i}, \mathrm{j}+1, \mathrm{x_i}, \mathrm{y_i}, \mathrm{z_i}, \mathrm{type}_\mathrm{i}^0)$$
$$= \text{Node Water}\,(i, j, x_i, y_i, z_i, \mathrm{type}_i^0)$$
$$+ \sum_{k=1}^{NN} \mathrm{NodeRelease}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^k)$$
$$+ \mathrm{NodeVolumeRainfall}\,(i, j+1) \tag{1}$$

$$\text{Equation}\quad 2: [\mathrm{type_i} = \text{river node}]$$
$$\mathrm{NodeRelease}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^0)$$
$$= 0.80 * \mathrm{NodeRelease}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_(i+1)^0) \tag{2}$$

$$\text{Equation}\quad 3: [\mathrm{type_i} = \text{highland}\,(\mathrm{z_i} > 250\,\text{meters})]$$
$$\mathrm{NodeRelease}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^k)$$
$$= \frac{(z_i - z_k)}{\sum_{i=1}^{N} N(z_i - z_k)} * (100 - 40) \tag{3}$$

$$\text{Equation}\quad 4: [\mathrm{type_i} = \text{highland}\,(\mathrm{z_i} < 250\,\text{meters})]$$
$$\mathrm{NodeRelease}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^k)$$
$$= \frac{(z_i - z_k)}{\sum_{i=1}^{N} N(z_i - z_k)} * (100 - 25) \tag{4}$$

$$\text{Equation}\quad 5: [\text{Rain Volume per node}]$$
$$\mathrm{NodeVolumeRainfall}\,(i, j+1)$$
$$= \frac{2000^2\sqrt{3}}{4} * \frac{\mathrm{DailyRainfall}\,(j+1)}{1000} \tag{5}$$

$$\text{Equation}\quad 6: [\text{Daily Volume decrease is } 20\%]$$
$$\mathrm{NodeWater}\,(i, j+2, x_i, y_i, z_i, \mathrm{type}_i^0) = 0.8*$$
$$* \mathrm{NodeWater}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^0). \tag{6}$$

For Fig. 4 and for all the equations, i denotes the node number, j is the current time, x_i, y_i, and z_i are the $x-$, $y-$, and z-axis value of the node i, type_i^k is the node type such as highland (if $k = 1$), lowland (if $k = 2$) or river node (if $k = 0$). NN is the total number of neighborhood nodes.

2) Model Postprocessing and Testing: The developed simulation model data is initially tested using a regular river pattern from the South-West regions. The simulation model generates the river volumetric flow for each node based on the existing rainfall, previous day's water volume and water flow from neighborhood nodes [based on elevation difference as presented in (1)–(6)]. However, this information cannot be used in real life, hence, this information is then postprocessed using the historical data for the years between 2000 and 2014 in a regression function under 95% confidence rates, and transformed into flow rate and depth information. This transformation is presented in Table I for nodes 80–404. The regression equation for depth conversion is presented in (7) and utilizes the today's and yesterday's volumetric flow and today's rainfall information, and the outputs are the today's flow rate and depth, respectively.

TABLE I
REGRESSION COEFFICIENT FOR THE VOLUMETRIC FLOW TO RIVER DEPTH

River node	Constant (a_0)	Coefficient for the today's rainfall (a_1)	Coefficient for the today's rainfall (a_2)	Coefficient for the today's rainfall (a_3)	Error rate (%) (2000–2014)
80	−0.0205	0.0128	$-8.3 * 10^7$	$9.9 * 10^7$	28.67
130	0.123	0.011	$-5.7 * 10^7$	$7.7 * 10^7$	10.36
255	0.285	0.034	$-1 * 10^6$	$1 * 10^6$	28.05
283	0.035	0.008	$-7.2 * 10^7$	$7.9 * 10^7$	15.70
373	0.224	0.045	$-2.48 * 10^7$	$2.50 * 10^6$	16.95
389	0.196	0.022	$-1.57 * 10^6$	$1.59 * 10^6$	16.51
404	−0.068	0.024	$-8.04 * 10^6$	$9.4 * 10^6$	29.43

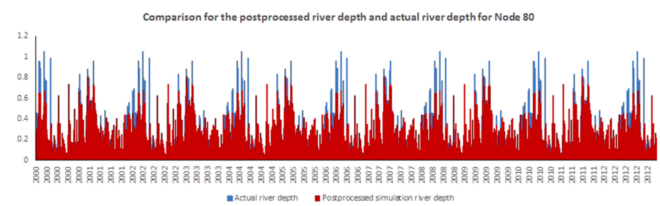


Fig. 5. River depth comparison between postprocessed river depth and actual depth.

$$\text{Equation}\quad 7: \mathrm{RiverNodeDepth}\,(\mathrm{i}, \mathrm{j}+1)$$
$$= a_0 + a_1 * \mathrm{DailyRainfall}\,(j+1) + a_2*$$
$$* \mathrm{NodeWater}\,(i, j+1, x_i, y_i, z_i, \mathrm{type}_i^0)$$
$$+ a_3 * \mathrm{NodeWater}\,(i, j, x_i, y_i, z_i, \mathrm{type}_i^0). \tag{7}$$

A comparison between simulated river depth and actual river depth for the river node 80 is presented in Fig. 5.

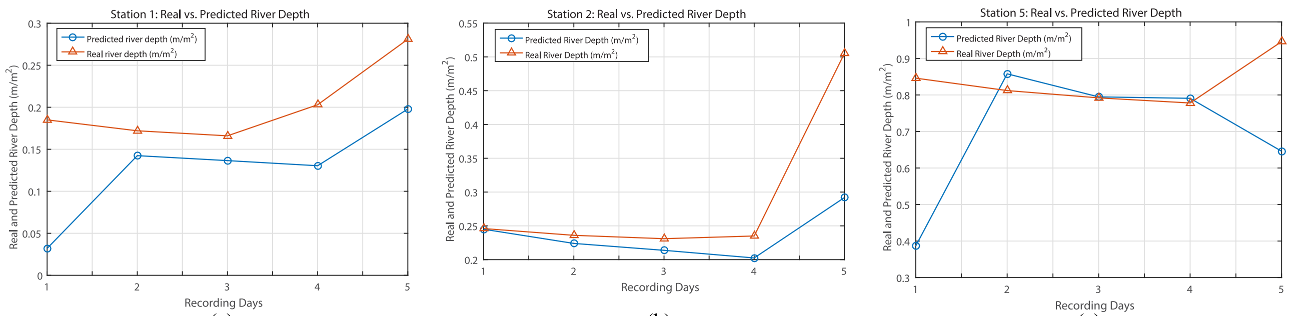
Based on this simulation model of the catchment, we have generated data to train the artificial neuronal network presented in Section V-B. The simulation model was used to generate daily river data and rain data for a period of 5 years which served as artificial training data for the neuronal network.

B. ANN-Based Optimization Module

Based on the modeling presented in Section V-A, we map an river level ANN-based prediction process as a function $f(a): I_a \to R_a$, where $I_a : [d_i, r_i]$ is a set representing the input of the ANN prediction (d_i is the river depth of node n_i, where node n_i is a station s_i from the reservoir), r_i represents the rainfall of node n_i and $R_a \to [p_d, p_f, p_r]$ is a set identifying the results (predicted output) of the ANN prediction (p_d is the predicted depth for n_i, p_f is the predicted flow for n_i, p_r is the predicted rainfall).

It is important to note that I_a identifies the input set of real data retrieved from the stations in the reservoir whereas R_a represents a set containing predicted river levels and rainfall for the stations in the reservoir.

With the large amount of training, the ANN module can replace the simulation module and provide optimized results in a shorter time interval. We use a calibrated Usk simulation model



(a) (b) (c)

Fig. 6. Real river depth and predicted river depth with three random stations. (a) Station 1: Pont Ar Yscir. (b) Station 2: Pont Hen Hafod. (c) Station 3: Llandetty.

to generate a large amount of data sets to train the corresponding ANN prediction engine. The trained ANN was then calibrated and used as cost function in an optimization program to help to achieve a certain accuracy target.

For training, we had the options to use historical data of parameters values recorded from the stations in Usk reservoir or artificial generated data obtained from the results of the Usk reservoir simulation (as presented in Section V-A). Due to inconsistencies determined in the real historical river and rain data for the Usk reservoir we have chosen to train our ANN with artificial historical data produced by our simulation module. The trained ANN has, therefore, the ability to predict future river levels and rainfall based on the current data readings from the reservoir.

Several ANN models have been tested to find the best configuration on both Visual Studio platform and MATLAB. For C++ based fast ANN (FANN) models we have used: (i) standard backpropagation—where the weights are updated after each training pattern and (ii) advanced batch training—not use the learning rate (default training algorithm). For MATLAB based ANN models we have used: (i) conjugate gradient backpropagation with Powell–Beale restarts and (ii) gradient descent backpropagation.

During the training process 80% of the data sets has been randomly selected and used. The rest of the data sets were utilized for the testing stage. The resulted ANN model developed based on the modeling presented in Section V-A has an accuracy of 93%. We have compared the neuronal network that we have developed with related forecasting algorithms, such as SVM [21] and time series [22]. According to our experiments, the lowest error has been found with the ANN as 6.32% whereas the error rate for SVM and time series were found to be of 12.91% and of 13.32%, respectively.

A comparison between ANN predicted river depth and real river depth (as recorded from stations) for three random stations within the reservoir is illustrated in Fig. 6. The proposed ANN model is based on the current river depth and rainfall information as fetched from stations. The collected data values can fluctuate from day to day, as the ANN's general purpose is to generalize the knowledge according to trained data. When any of the inputs exceed their regular patterns, the results of ANN can be different then real case as shown in the first day of the Fig. 5(c). However,

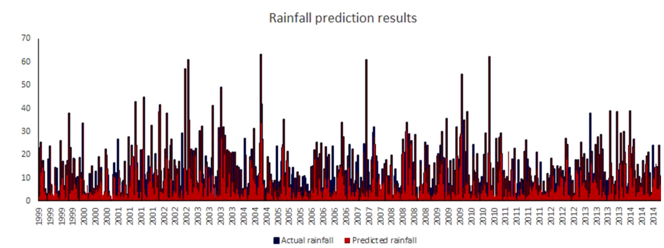


Fig. 7. Prediction results for rainfall.

in general ANN's performance on the historical data for the river depth is in average of 93%.

To develop this ANN model, the rainfall data between 1999 and 2014 for the river Usk is utilized and the prediction results are presented in Fig. 7. The proposed ANN utilizes the current rainfall information and date information (day, month, and year). According to ANN performance, the next day's rainfall information is predicted with an average performance of 89%.

VI. Evaluation Use-Case

In our analysis, we intend to predict the river depth, river flow, and rainfall for the seven stations alongside the Usk River. Employing the methodology presented in Sections V-A and V-B we conduct experiments for determining river depth[2] based on the data aggregated from the stations points. The objective of these experiments is to demonstrate that real-time river level prediction can be achieved and used into the process of decision making for water management.

A. Experiment 1: Catchment River Depth Prediction

The objective of this experiment is to predict the status of the Usk Reservoir in terms of river depth over a period of five days. In this experiment, we fetch real data from the seven stations within the Usk Reservoir and rainfall data from the Met Office UK weather service and determine what is the river depth for next five days within the reservoir.

[2]River flow is also part of our prediction module in a direct relationship with river depth but not displayed in our experiments.

River data fetched from Harbour

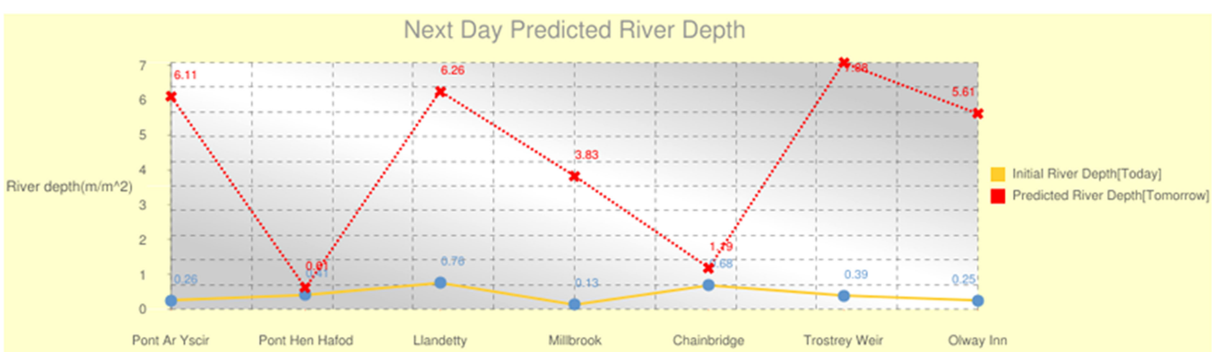
Time:	12:13:42
Date:	2017-01-10
Rainfall Per Day(mm/m^2):	31.0
River Depth Station "Pont Ar Yscir"(m/m^2):	0.26
River Depth Station "Pont Hen Hafod"(m/m^2):	0.408
River Depth Station "Llandetty"(m/m^2):	0.755
River Depth Station "Millbrook"(m/m^2):	0.131
River Depth Station "Chainbridge"(m/m^2):	0.682
River Depth Station "Trostrey Weir"(m/m^2):	0.394
River Depth Station "Olway Inn"(m/m^2):	0.252
Usk Reservoir (%)	50
Talybont Reservoir (%)	60
Llandegfedd Reservoir (%)	55

Submit

(a)

Type of parameter(mm/m^2)	Value
Initial Rainfall	31.0

Type of Parameter(m/m^2)	[Initial River Depth]	[Day 1 Prediction]	[Day 2 Prediction]	[Day 3 Prediction]	[Day 4 Prediction]	[Day 5 Prediction]
River Depth Station Pont Ar Yscir	0.26	6.1089	0.5523	0.1736	0.1833	0.2438
River Depth Station Pont Hen Hafod	0.408	0.6107	0.6542	0.3234	0.2747	0.2997
River Depth Station Llandetty	0.755	6.2587	2.3928	0.7108	0.5873	0.6916
River Depth Station Millbrook	0.131	3.8261	0.3336	0.1573	0.1531	0.2027
River Depth Station Chainbridge	0.682	1.1865	5.4420	3.5638	2.7568	2.3763
River Depth Station Trostrey Weir	0.394	7.0770	2.3800	1.6960	1.5445	1.4157
River Depth Station Olway Inn	0.252	5.6093	2.9953	2.1567	1.9466	1.8426



(b)

Fig. 8. What-If scenarios interface and results. (a) Prediction input phase. (b) Prediction output phase.

In Fig. 8, we present how the river depth evolves with the reservoir stations. Based on the input presented in Fig. 8(a), input collected from the stations based on real-time web service calls, we run a prediction process generating the output presented in Fig. 8(b). The graphical representation displays one day river depth prediction for seven river stations of the Usk reservoir.

We also provide the ability to simulate what-if scenarios based on heuristic data to determine the status of the entire reservoir when a particular weather phenomenon (scenario) occurs. With such instruments, we can determine what is the impact of each individual station river depth and rainfall on the overall status of the reservoir. This simulation can identify a range of cases from increased river levels with increase rainfalls to low river levels with low rainfalls.

Fig. 8 illustrates the input and the output of the simulation. Here the user can type various input scenarios with restrictions on the parameter ranges. By using this feature, the user can test different scenarios and measure the impact on the overall river depth as presented in Fig. 8(b).

B. Experiment 2: Station River Depth Prediction

The objective of this experiment is to adopt a more focused approach whereby the individual reservoir stations are positioned as central points in the prediction. We tailor the prediction results

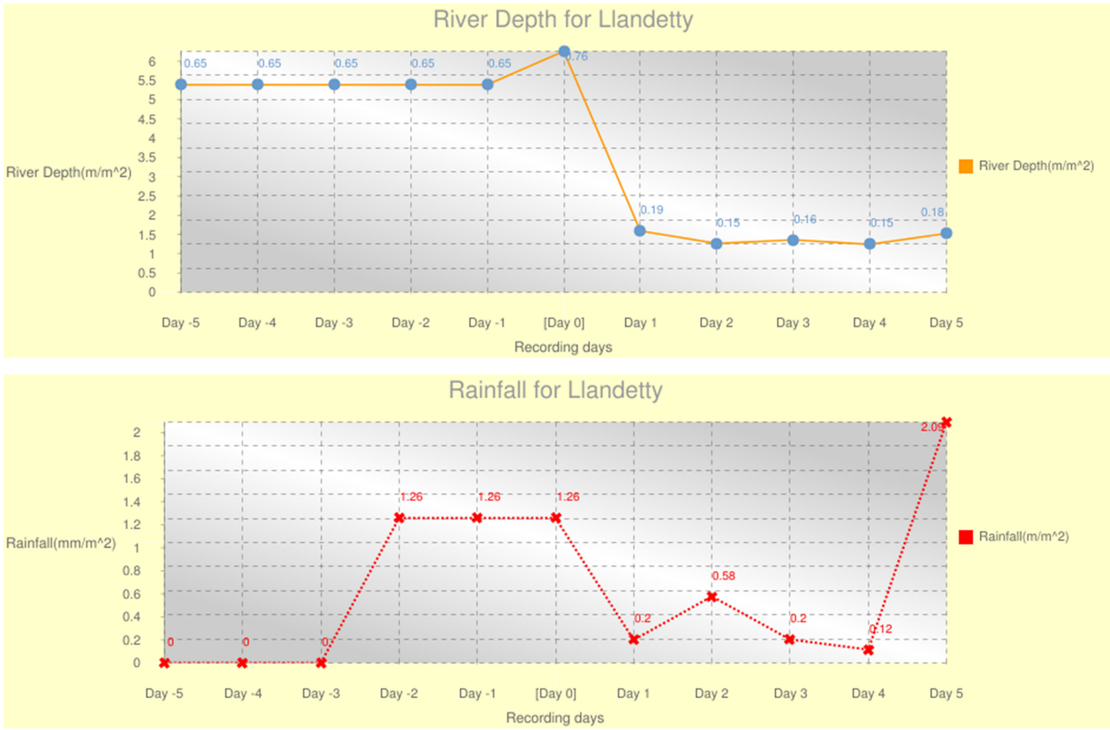


Fig. 9. Station based river depth prediction.

on per station basis and provide real-time river depth prediction for each individual station from the reservoir. Fig. 9 presents the initial (recorded) river depth in the last five days and the predicted river depth for the next five days. The initial river depth is a five days historical trend which the user can observe and compare with the upcoming predicted river depth. For the prediction, we use a five days prediction which can provide a clear view about how is the river level going to evolve. The interval we monitor is [Day -5, Days 5], where [Day 0] is today, [Day -5] represents five days ago, [Day 5] represents five days ahead.

In this experiment, we have chosen to add a rainfall variable for determining dependencies between rainfall and river depth. For historical trends, we use rainfall data as fetched from the UK Met Office weather service whereas for the rainfall prediction we utilize the neuronal network presented in Section V-B which generates a five days rainfall forecast per reservoir.

VII. i-Depend Decision Modeling

For extracting knowledge from the ANN prediction datasets, we use a modeling tool called i-Depend provided by one of our project partners. i-Depend is a dependency modeling tool that can help regulators identify intervention strategies and assess risk in order to improve the environmental compliance behavior of operators. i-Depend uses a Bayesian probabilistic approach [23] to measure the impact of one decision over another and is very useful for scenario analysis and for testing "what-if" type of questions. i-Depend enables the calculation of the probability of risk taking account of the different prediction outputs and what-if scenario analysis to determine probability of risk for water resources.

In i-Depend, each model is an "object" containing an xml model with entities that correspond to individual datasets. For each station we have created uniques datasets that store predicted data and real data. These datasets are hosted and exposed as endpoints into the i-Depend server. At every prediction run, the results of the prediction are pushed via a HTTP request into the datasets endpoints for i-Depend to interpret and determine probabilities. Each entity is configured on how to interpret the value from a dataset into a probability value based on predefined functional relationships (we use linear function). The model is able to generate probabilities based on: (i) today's real reading from the datasets (current river level) and (ii) a further five versions based on the next five days of prediction values from the datasets (forecast river level).

A. Risk Modeling for Usk Reservoir

In the Usk risk model, each entity has only two possible states—success shown in "GREEN" and failure shown in "RED" (as illustrated in Fig. 10). The widths of the color bands show the probabilities that each entity identifies in a state. States are always arranged in increasing order of desirability with the first state representing failure and the last state meaning success.

In the model, the main objective is to satisfy the river flow level within the Usk reservoir. The Usk model is formed of a set of entities (nodes) where each entity has associated states that occur with a certain probability. In the model, we have leaf nodes (i.e., stations in the reservoir) which are a special type of entities for which we predict trends using the ANN module. We also consider that between all entities we have relationships which show the dependency nature between these entities. In

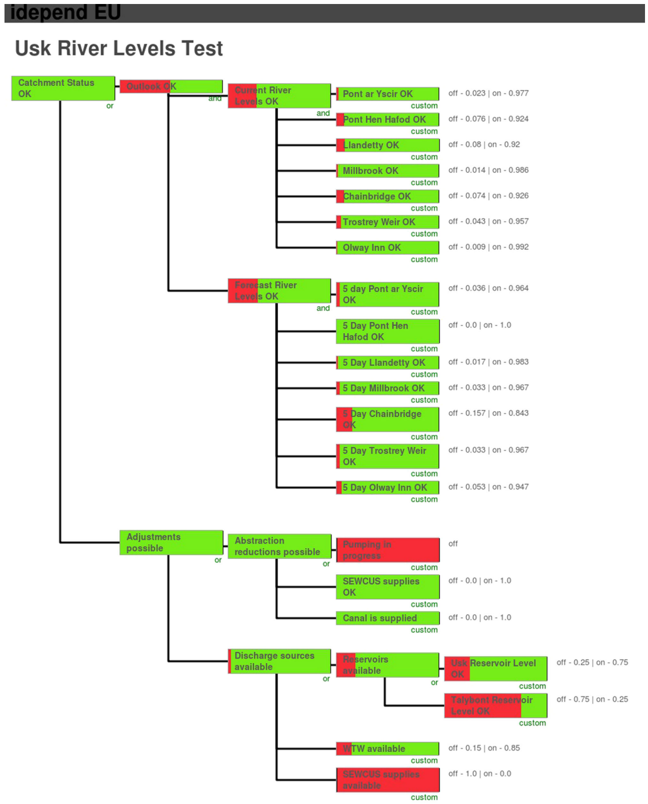


Fig. 10. Displaying Usk reservoir status.

our model, we use: probabilities for leaf nodes and entities relationships.

1) Leaf Nodes Probabilities: A leaf has predetermined probabilities specified for each state. For instance an entity can have two states called OFF and ON with probabilities of 25% (0.25) and 75% (0.75), respectively, meaning that during the forecast period (every day for a five days prediction) there is a 25% probability of failure for an entity and a 75% probability of success for the entity derived from the calculated risk probability (as explained in Section VII-B).

2) Entity Relationships: There are three kinds of relationships called AND-type, OR-type, and CUSTOM-type. The AND and OR types are indicated by small words above the links. The entity called "Current River Levels" is an AND-type and in order to be on an "OK" state it needs: "Pont Ar Yscir" AND "Pont Hen Hafod" AND "Llandetty" AND "Millbrook" AND "Chainbridge" AND "Trostrey Weir" AND "Olway Inn" entities to be in "OK" state (i.e., to be in their success state). The entity "Reservoirs Available" has an OR-type relationship. This means that the entity "Reservoirs Available" is on "OK" state if either the main "Usk Reservoir Level" OR the "Talybont Reservoir Level" are on "OK" state (i.e., have enough water). From the modeling we can assess that AND-type relationships are increasing risk while OR-type relationships greatly reduce it. The CUSTOM-type relationship refers to those states which are not AND or OR types.

TABLE II
LEAF NODES PREDICTED DATA AND INFERRED PROBABILITIES

Leafs entities	Predicted River Flow (l/m^3)	Fail(off)	Success(on)
Pont ar Yscir	0.87	2%	97%
Pont Hen Hafod	2.20	7%	92%
Llandetty	2.14	8%	92%
Millbrook	1.33	1%	99%
Chainbridge	2.28	7%	92%
Trostrey Weir	1.92	11%	89%
Olway Inn	1.33	3%	97%

B. Usk Data Model and Probability Modeling

The data resulted from the artificial network (i.e., river depth and river flow) is turned into risk probabilities. For each station we have an associated upper and lower bounds. The risk probabilities are determined based on the equation:

$$\text{Risk}_{\text{prob}} = (\text{predicted}_{\text{flow}})/(\text{stationflow}_{\text{upper}}) * \text{accuracy} \quad (8)$$

where, $\text{predicted}_{\text{flow}}$ represents the predicted river flow by using the Artificial Neuronal Network prediction, $\text{stationflow}_{\text{upper}}$ represents the fixed real river flow upper bound associated with each station (obtained from water management authorities) and accuracy represents the accuracy of the developed Artificial Neuronal Network (0.93). As illustrated in Table II, for Trostrey Weir station the upper bound 2000 ml/d and has an associated predicted river flow of 1.920 l/m^3 = 1920 ml/m^3. Based on (8), the calculated risk probability for Trostrey Weir station is 0.89(89%) = ((1920/2000)*0.93).

We apply the same method for determining probabilities associated with all the river stations each identifying unique upper/lower bounds. This approach, therefore, provides the ability to test water abstraction scenarios across the catchment and to determine when a factor of risk appears in relation to water supply and management.

The additional entities considered in the i-Depend risk modeling are:

1) reductions possible: (i) pumping [0.0–1.0], (ii) South East Wales Conjunctive Use System (SEWCUS) supplies [0.05–0.95] and (iii) Canal supplied [0.3–0.7];
2) source available: (i) reservoirs available to ensure: (i1) reservoir level Usk [0.2–0.8] (i2) reservoir level Talybont [0.4–0.6], (ii) WTW (Welsh water treatment) available flow [0.1–1.0], (iii) SEWCUS available [0.1–1.0];
3) current river levels—assessing the risk per day for individual stations;
4) forecast river levels—assessing the risk per five days for individual stations.

Based on the report generated with i-Depend, we can have a more accurate view on the overall status of the Usk reservoir (as illustrated in Fig. 10). The report can greatly assist users in the process of decision taking by providing per station information and also a dependency modeling for all the stations in the Usk reservoir.

Based on the reports generated with i-Depend, users/managers can decide to:

1) control the distribution of the available water using the appropriate taps that we can turn ON and OFF,
2) control abstraction to utilize excess flows,
3) control top up to maintain minimum flows,
4) control discharges to maintain minimum quality, and
5) control import/ export to meet long term strategy.

It is important to note that we use prediction inferred probabilities to assess risk in the Usk reservoir in determining the status of the seven stations and their impact of the Reservoir ("Outlook" subentities) combined with real data to determine possible adjustments for managing water resources ("Possible adjustments" subentities from Fig. 10). Such adjustments include: pumping, canal supply, and assessing the impact of the Usk reservoir status on other reservoirs.

VIII. Discussion

Our approach aimed at developing a system that can influence and inform abstractor behaviors in terms of where and when they abstract, encouraging sustainable and more efficient use of water resources. We believe that the impact of our research could be significant because our solution can represent a new product that: (i) does not directly compete with existing catchment hydrological models or engineering management software used by Water Companies or other organizations; and (ii) has an ability to offer a more holistic and inclusive way to test water scenarios on a real-time basis. Hence, our approach can assist with improving the current decision making process used by a number of organizations that activate in the field of water supply. Our model, therefore, complements existing models with the key benefit that all stakeholders can be accommodated and can assess how a decision made to satisfy water requirements to one stakeholder might impact on another. Our model also predicts river flow availability several days into the future, so that the impact and any water management decision can take into account of weather driven events. This allows a useful and more holistic insight for water supply and demand so that decision making can know in advance the river depth at a particular reservoir station. Fundamentally, our approach provides a way to conserve water (and redistribute it between catchments if necessary) by having a just-in-time way to manage water flow rather than let it flow out to sea.

At a wider scale, our approach serves to a number of objectives related to water management and regulation, such as to maintain much higher flows than the statutory minimum, resolve conflict and balance supply and demand with biodiversity protection to comply with the EU Water Framework Directive but also addresses the challenge with decreasing water supplies from changes in climate.

IX. Conclusion

Water optimization with intelligent systems represents a researching area intensively investigated both by industrial organizations and also by researching institutes. We provide a novel perspective on water optimization by looking at ecosystem implications and at possible use-cases that can derive with regards to water ecosystems. Our paper presents a prediction engine deployed over an intelligent ICT system to support water simulation and prediction. Our solution also provides useful insights into the domain of water optimization, facilitating users to take informed decisions based on real-time river depth prediction. We use a per-station approach where the input of the prediction is obtained from real-time station readings and demonstrate that prediction can provide the means to improve the status of a water ecosystem and ensure direct environment benefits.

The case study has focused on the River Usk which allows decision-making strategies and scenarios to be tested using a neural network model to predict river flow from rainfall rates. At a wider scale, possible areas of applicability range from water distribution to environment use-cases, such as salmon health population which we have in attention and plan further developments. As the Usk reservoir identifies a complex ecosystem we find that the output data and the knowledge representation can be also further interpreted by organizations and environment bodies to achieve specific objectives.

In this paper, we also propose a methodology to control water resources in a smarter way with a sophisticated level of computational power that improves the efficiency of the current process by integrating a range of disparate types of data. Such data is then analyzed to enable different scenarios to be tested, the consequences understood and a fair decision concluded considering the variety of stakeholders requiring water on a day-to-day basis. By this approach, we remove the sometimes-slow process of decision-making that often accompanies water resources management because of the complexity deriving from the huge amount of data to be assessed and the multiple organizations often involved.

References

[1] G. Kecskemeti, A. Kertesz, and Z. Nemeth, Eds, *Developing Interoperable and Federated Cloud Architecture*. Hershey, PA, USA: IGI Global, 2016, doi:10.4018/978-1-5225-0153-4.

[2] B. Yuce, H. Li, Y. Rezgui, I. Petri, B. Jayan, and C. Yang, "Utilizing artificial neural network to predict energy consumption and thermal comfort level: An indoor swimming pool case study," *Energy and Buildings*, vol. 80, pp 45–56, Sep. 2014. [Online]. Available: http://dx.doi.org/10.1016/j.enbuild.2014.04.052

[3] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (IoT): A vision, architectural elements, and future directions," *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, Sep. 2013.

[4] T. Robles *et al.*, "An internet of things-based model for smart water management," in *Proc. 2014 28th Int. Conf. Adv. Inf. Netw. Appl. Workshops*, Victoria, BC, USA, 2014, pp. 821–826, doi: 10.1109/WAINA.2014.129.

[5] I. Petri, T. Beach, Y. Rezgui, I. E. Wilson, H. Li, "Engaging construction stakeholders with sustainability through a knowledge harvesting platform," *Comput. Ind.*, vol. 65, no. 3, Apr. 2014, pp. 449–469, ISSN 0166-3615, http://dx.doi.org/10.1016/j.compind.2014.01.008

[6] P. Leahy, G. Kiely, and G. Corcoran, "Structural optimisation and input selection of an artificial neural network for river level prediction," *ELSEVIER J. Hydrol.*, vol. 355, pp. 192–201, 2008.

[7] Singh *et al.*, "Appropriate data normalization range for daily river flow forecasting using an artificial neural networks," in *Proc. Hydroinformat. Hydrol., Hydrogeol. Water Resour.*, International Association of Hydrological Sciences Publication, Oxfordshire, U.K., 2009, pp. 51–57.

[8] A. F. Atita *et al.*, "A comparison between neural network forecasting techniques case study: River flow forecasting," *IEEE Trans. Neural Networks*, vol. 10, no. 2, pp. 402–409, Mar. 1999.

[9] T.-L. Lee, "Predictions of tyhphoon storm surge in Taiwan using artificial neural networks," *ELSEVIER Adv. Eng. Software*, vol. 40, pp. 1200–1206, 2009.

[10] A. Sheth, C. Henson, and S. Sahoo, "Semantic Sensor Web," *IEEE Internet Comput.*, vol. 12, no. 4, pp. 78–83, Jul./Aug. 2008. http://knoesis.wright.edu/library/publications/SHS08-IC-Column-SSW.pdf

[11] Wisdom, EU FP7 Wisdon, 2014. Available at: http://www.wisdom-project.eu/, Last accessed: Sep. 2016.

[12] McCann, Julie A., *et al.*, "Optimized water demand management through intelligent sensing and analytics: The WISDOM Approach," in *Proc. Int. Conf. Hydroinformat.*, 2014. [Online]. Available: https://academicworks.cuny.edu/cc_conf_hic/456, Last accessed: Oct. 2016.

[13] K. Takahiro, S. Naofumi, T. Masatake, T. Shin, M. Sumio, and I. Stoianov, "Smart water management technology with intelligent sensing and ICT for the Integrated Water Systems," Special Issue on Solutions for Society – Creating a Safer and More Secure Society, Jan. 2015, pp. 103–106. [Online]. Available: http://in.nec.com/en_IN/images/140123.pdf, Last accessed: Oct. 2016.

[14] Wrbanwater, EU FP7 UrbanWater, 2015. Available at: http://urbanwater-ict.eu/, Last accessed: Sep. 2016.

[15] H. Tadokoro, M. Onishi, K. Kageyama, H. Kurisu, and S. Takahashi, "Smart water management and usage systems for society and environment, *Hitachi Rep.*, pp. 264–174, 2016.

[16] P. S. Dimitri, N. D. Khada, "Model trees as an alternative to neural networks in rainfall-runoff modelling," *Hydrological Sci. J.*, vol. 48, no. 3, pp. 399–411, 2003.

[17] V. Vapnik, *The Nature of Statistical Learning Theory*. New York, NY, USA: Springer-Verlag, 1995.

[18] B. Schlkopf, A. Smola, R. Williamson, and P. Bartlett, "New Support Vector Algorithms," *Neural Comput.*, vol. 12, pp. 1207–1245, 2000.

[19] Y. Liu and G. Pender, "Carlisle 2005 urban flood event simulation using cellular automata-based rapid flood spreading model," *Soft Comput.*, vol. 17, no. 1, pp. 29–37, 2013.

[20] W. C. Wang, K. W. Chau, C. T. Cheng, and L. Qiu, "A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series," *J. Hydrol.*, vol. 374, no. 3-4, pp. 294–306, 2009.

[21] J. Y. Lin, C. T. Cheng, and K. W. Chau, "Using support vector machines for long-term discharge prediction," *Hydrological Sci. J.*, vol. 51, no. 4 pp. 599–612, 2006.

[22] Connor, Jerome T., R. Douglas Martin, and Les E. Atlas, "Recurrent neural networks and robust time series prediction," *IEEE Trans. Neural Networks*, vol. 5, no. 2, pp. 240–254, Mar. 1994.

[23] David Slater, SIOPS—A system integration and operability study, Cambrensis, 2015. Available at: http://www.cambrensis.org/wp-content/uploads/2012/05/SIOPS1.1docx.pdf, Last accessed: Oct. 2016.

Ioan Petri (M'16) received the Ph.D. degree in cybernetics and statistics from Babeş-Bolyai University of Cluj-Napoca, Romania.

He is a Research Fellow with the School of Engineering at Cardiff University, Cardiff, U.K. He has worked in industry as a Software Developer with Cybercom Plenware. He is currently the member BRE Trust Centre for Sustainable Engineering working on cloud computing and data analytics with application in the engineering domain. He has worked on several EU and Innovated U.K. funded projects on software defined environments and workflow coordination including SCRIPT, SPORTE2, Clouds4Coordination, RADICAL, and BIM4VET. His research interests include cloud computing, edge computing, data analysis, resource management, and software defined networks.

Baris Yuce (M'16) received the graduated degree from the Department of Industrial Engineering at Sakarya University, Turkey, in 2005 and M.Sc. degree from Institute of Natural Science at Sakarya University, in 2007 and the Ph.D. degree from School of Engineering, Cardiff University, in 2012. He is a Lecturer with the College of Engineering, Mathematics and Physical Sciences, Streatham Campus, University of Exeter, Exeter, U.K. His research interests include intelligent systems, such as artificial neural network, fuzzy logic, multiagent systems and their applications on buildings, energy management systems, robotics, and supply chain management. He is also interested in optimization algorithms and their applications, in particular, swarm optimization algorithms, such as the bees algorithm, genetic algorithm, ant colony optimization, hill climbing, and simulated annealing. He has worked on several EU and (Building Research Establishment (BRE) funded projects on intelligent building management systems including SPORTE2, KnoholEM, and Estate Energy Optimization.

Alan Kwan (M'16) received the B.Eng. (Hons.) degree from Sheffield, in 1987, and Ph.D. from Cambridge, in 1991, he is working on deployable structures. He is a Professor of structural mechanics and member of the BRE Institute of Sustainable Engineering, School of Engineering. Since 2010, he has been active in the field of sustainability informatics, e.g., 4 out of 6 recent journal papers (average journal impact factor of 4.38) are all in this field.

Dr. Kwan is on the Editorial Board for three journals, and eleven international conferences. He has delivered two invited lectures at international conferences. He is a regular referee for about ten international journals, the UK research councils, and other journals.

Yacine Rezgui (M'16) received the M.Sc. degree from University Paris 6, Paris, France, in 1991, and the Ph.D. degree from Ecole Nationale des Ponts et chaussees, Paris, France, in 1994, both in construction informatics. He is a Professor of building systems and informatics, Cardiff University, Cardiff, U.K., and the Founding Director of the Building Research Establishment (BRE) Centre in Sustainable Engineering, sponsored by the BRE, U.K. He has authored or coauthored more than 40 research and development projects at a national (UK EPSRC and TSB) and international (European Framework Programs 5, 6, 7) level. He conducts research in informatics, including ontology engineering and artificial intelligence applied to the built environment.