



# Intelligent Urban Water Infrastructure Management

*Dragan A. Savić\*, Josef Bicik, Mark S. Morley, Andrew Duncan,  
Zoran Kapelan, Slobodan Djordjević and Edward C. Keedwell*

**Abstract** | Urban population growth together with other pressures, such as climate change, create enormous challenges to provision of urban infrastructure services, including gas, electricity, transport, water, etc. Smart-grid technology is viewed as the way forward to ensure that infrastructure networks are flexible, accessible, reliable and economical. “Intelligent water networks” take advantage of the latest information and communication technologies to gather and act on information to minimise waste and deliver more sustainable water services. The effective management of water distribution, urban drainage and sewerage infrastructure is likely to require increasingly sophisticated computational techniques to keep pace with the level of data that is collected from measurement instruments in the field. This paper describes two examples of intelligent systems developed to utilise this increasingly available real-time sensed information in the urban water environment. The first deals with the failure-management decision-support system for water distribution networks, NEPTUNE, that takes advantage of intelligent computational methods and tools applied to near real-time logger data providing pressures, flows and tank levels at selected points throughout the system. The second, called RAPIDS, deals with urban drainage systems and the utilisation of rainfall data to predict flooding of urban areas in near real-time. The two systems have the potential to provide early warning and scenario testing for decision makers within reasonable time, this being a key requirement of such systems. Computational methods that require hours or days to run will not be able to keep pace with fast-changing situations such as pipe bursts or manhole flooding and thus the systems developed are able to react in close to real time.

**Keywords:** *urban water, infrastructure, intelligent/smart systems, decision support, real-time, sensor.*

## 1 Introduction

Today, half of the world’s population lives in cities and, by 2030, this will grow to nearly 60%.<sup>1</sup> The trends in urban population growth together with other pressures, such as climate change, create enormous challenges to provision of urban infrastructure services, including gas, electricity, transport, water, etc. Urban water services are delivered by complex and interconnected water infrastructure and its management involves consideration of sustainable use of water resources, pollution control, stormwater

and wastewater network management and flood control and prevention. Expanding, renewing and strengthening the physical infrastructure could help relieve the pressures of urban population growth and global climate change, although at extremely high costs. Therefore, there is a critical and urgent need to investigate and implement efforts toward improved use of the existing urban water infrastructure by employing ‘intelligent’ management techniques. This, in turn, will help delay the large investments required for a foreseeable future.

*Centre for Water Systems,  
University of Exeter,  
UK.*

*\*d.savic@exeter.ac.uk*

“Intelligent grid” and/or “smart grid” are terms that have their origin in the electricity industry. They refer to an electrical grid that uses information and communications technology (ICT) to automate processes that improve the efficiency, reliability, economics and sustainability of the production and distribution of electricity. This concept of smart-grid technology is being adopted in many countries around the world as the way forward to ensure that electricity networks are flexible, accessible, reliable and economical.<sup>2</sup> The intelligent grid concept will also benefit from the rapid increase in the amount of data (i.e., “big data”) becoming available through proliferation of sensors, mobile communications, social media, etc. However, without intelligent computational methods, grid managers and decision makers will find it increasingly difficult to make sense of the large amount of data being made available in near real-time.

In a similar vein to the smart electricity grid, “intelligent water networks” or “intelligent water infrastructure”, which take advantage of the latest ICT to gather and act on information in an automated fashion, could allow the minimisation of waste and delivery of more sustainable water services. This paper introduces two examples of intelligent systems developed to utilise increasingly available real-time sensor information in the urban water environment. The first deals with the failure-management decision-support system for water distribution networks that takes advantage of intelligent computational methods and tools applied to near real-time logger data providing pressure, flows and tank levels at selected points throughout the system. The second deals with urban drainage systems and utilisation of rainfall data to predict flooding of urban areas in near real-time.

## 2 Real-Time Failure Management in Water Distribution Systems

Water utilities around the world are obliged by law to supply water in sufficient quality and quantity to the consumers. However, due to their ageing assets utilities are under increasing pressure to improve the management of their infrastructure and optimise operational and capital expenditure. The performance of water utilities in the UK is monitored by the Economic Regulator, OFWAT, which seeks to ensure that performance is achieved in an efficient way, thus protecting the interest of the consumers. Since economic regulation of the UK water sector began in the late 1980s, OFWAT has facilitated over £98bn of private investment and delivered safe drinking water, a much improved environment and improved customer service.<sup>3</sup> Water utilities have made progress in reducing

leaks, and leakage is now around 35% lower than its 1994–95 high, but still amounts to 3.4bn litres of water every day, almost a quarter of the entire supply. Leaks and interruptions to water supply often occur due to partial or complete failure of various water distribution system (WDS) elements (e.g., pipes and pumps) or due to accidental damage caused by third-parties (e.g., by digging roads). The scale of the impact of such failures can vary significantly beginning with inconvenience caused to the consumers that are cut off from the water supply or receiving water under sub-standard pressure leading up to water quality problems caused by discoloration or contaminant intrusion.<sup>4,5</sup> Monitoring and repairing failed infrastructure elements involves considerable costs. Therefore, early detection, location and repair of such failures in WDS are of primary interest to water utilities aiming to protect the continuity of water supply and mitigate the impact on the customers.

The wide availability of pressure and flow data has triggered research in early warning systems.<sup>6,7</sup> However, even with the latest developments in sensing technologies and promising results of various anomaly detection methodologies, diagnosing and locating problems in a District Metered Area (DMA) due to a pipe burst still remains a challenging task due to inherent uncertainties (e.g., stochastic nature of water consumption and lack of field data). The Neptune Project<sup>8</sup> developed and tested new methodologies supporting near real-time decision making for operators of WDS dealing with a variety of anomalies (pressure and flow) with primary focus on pipe bursts. These methods require considerable information inflow, hence a prototype Decision Support System (DSS) was developed to analyze, process and present data efficiently, allowing the operator to reach timely, informed decisions.

### 2.1 DSS for real-time anomaly management in WDS

The DSS is based on a risk approach, which considers both failures and interventions,<sup>9,10</sup> to assist the operator in evaluating the likelihood of occurrence and impact of undesired events and in prioritizing necessary actions for mitigating the impact of the event.<sup>11</sup> The key issues identified in the Neptune project can be summarised as follows: (1) the true nature of a failure in WDS is typically unknown until investigated and confirmed by a field technician, (2) the risk associated with a failure situation is a dynamic metric which evolves with time as new information from the field becomes available, (3) a new set of performance indicators needs to be established to assess the operational impact of failures, and (4) the computational complexity of

the underlying algorithms has to respect the near real-time environment where the methodology is going to be applied.

The primary source of information for the DSS is near real-time logger data reporting pressures, flows and tank levels at selected points throughout the system. This is based principally on flow and pressure monitoring at the entry to DMAs along with selected pressure monitoring points elsewhere within the DMA with data transmitted every 30 minutes, principally over the GPRS cellular communication network.

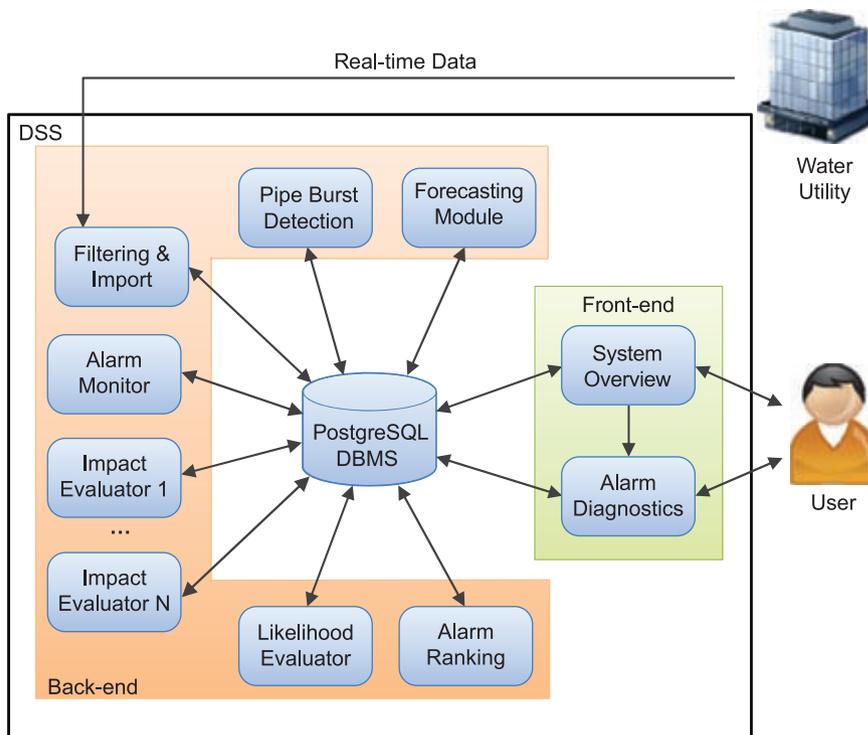
The DSS was designed in a modular fashion to maximise its extensibility. Figure 1 provides a high-level overview of an architecture for a real-time DSS for operational management of WDS under abnormal conditions. Off-line modules utilised by the DSS for one-off data import or model calibration are not included in the figure. A loose form of coupling between individual modules (i.e., mostly via a common database) was chosen to facilitate their integration within the DSS. All inter-process communication is achieved indirectly by polling information stored in a Database Management System (DBMS) or alternatively through Hypertext Transfer Protocol (HTTP) requests (e.g., the interaction between the “System Overview” and the “Alarm Diagnostics” UI modules of the DSS front-end).

A Database Management System (DBMS) is employed by the DSS to provide concurrent access to data utilised by a number of processes that form the DSS as shown in Figure 1. The PostgreSQL<sup>12</sup> Object-Relational DBMS, together with its spatial extension PostGIS<sup>13</sup> was chosen as a platform in this work. This combination allows easy storage and retrieval of relational as well as spatial data.

The back-end part of the DSS comprises a number of non-interactive background modules that are primarily responsible for:

- Import of ‘near’ real-time data received from a water utility into a DBMS and its filtering
- Data-driven detection of pipe bursts (Pipe Burst Detection)
- Monitoring of newly received alarms (Alarm Monitor)
- Forecasting of water consumption over the next 24 hours (Forecasting Module)
- Distributed evaluation of the impact of a failure (Impact Evaluator)
- Evaluation of the likelihood of pipe failure within a DMA (Likelihood Evaluator)
- Prioritisation of alarms (Alarm Ranking)

**2.1.1 Alarm Monitor:** The Alarm Monitor periodically checks the contents of the “source alarm” table in the Database (DB) for new (fresh) alarms.



**Figure 1:** An overview of a risk-based DSS for WDS management.

In case an alarm was generated by the Pipe Burst Detection module the Alarm Monitor performs the necessary initialisation steps (e.g., forecasting water demands, setting model boundary conditions, etc.) before the risk assessment can be started.

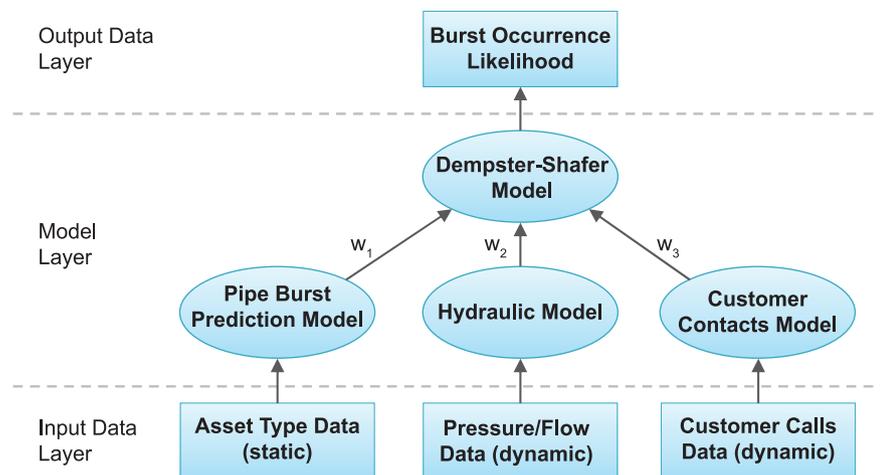
**2.1.2 Likelihood evaluator:** The Likelihood evaluator is a process responsible for determining the likelihood of occurrence of a burst in every pipe within a DMA where an alarm was generated. The evaluator combines the outputs from several sources of information (models) to assess the likelihood of a particular pipe burst being associated with the active alarm. The Dempster-Shafer theory of evidence<sup>14</sup> has been applied to combine the evidence from those sources of information, as shown in Figure 2.

A pipe burst prediction model, hydraulic model and a customer contacts model were developed to provide an indication of the likelihood of a burst occurrence in different parts of a DMA. The method explicitly considers the epistemic uncertainty (i.e., the lack of knowledge) in the outputs from the models and is capable of adjusting their credibility (i.e., weights  $w_1$ ,  $w_2$ , and  $w_3$ ) based on their historical performance. The approach is effective in narrowing down the area which needs to be investigated.<sup>10</sup> Due to the generic character of the methodology the outputs of additional models (e.g., based on the information of third parties working in the system) might be easily incorporated.

**2.1.3 Impact Evaluator:** Similarly to the Likelihood Evaluator described above, the process also monitors the alarms table for newly generated

alarms. If a new alarm, which requires impact assessment, is recognised, the process attempts to load an EPANET<sup>15</sup> hydraulic model of the whole WDS, which was generated by the Alarm Monitor including boundary conditions based on forecasted demands for all potential pipe bursts associated with the alarm. The Impact Evaluator can be launched on a number of computers simultaneously to distribute the load (i.e., each node evaluates the impact of only a part of potential pipe bursts).

Bicik et al.<sup>9</sup> presented a set of performance indicators suitable for assessment of impact of failures in WDS from operational perspective. It has been suggested that in order to capture the consequences of a pipe failure more realistically the impact on different stakeholders (i.e., the water utility and the customers) needs to be taken into account. The following set of impact factors triggered by a pipe burst has been proposed: lost water, low pressure, supply interruption, discolouration, damage to third parties and energy losses. The effects (e.g., revenue losses, inconvenience, etc.) of each of the above mentioned impact factors on the stakeholders have been further classified into one of the following categories: economic, social and environmental. It is argued that in order to evaluate the performance of the WDS under failure conditions it is vital to use a pressure-driven hydraulic solver<sup>16,17</sup> coupled with a Geographic Information System (GIS) in order to consider the sensitivity of different types of customers (i.e., residential, commercial, industrial and critical) to the reduced level of service. Although pipe bursts with small outflow are unlikely to cause significant impacts in terms of low pressure, they might still trigger discolouration problems.<sup>4</sup> It is thus



**Figure 2:** An information fusion concept to estimate the most likely location of a failure.

important to include such measure in the set of operational impact indicators.

The proposed performance indicators form a consequence vector comprising more than fifty values, which can be explored by WDS operators. The indicators capture not only the scale of the impact, but also its duration (which is one of the key measures), i.e., the DG3-Supply Interruptions indicator reporting on the number of properties affected, as used by OFWAT. It is obvious that the amount of information might be overwhelming for a human operator and the focus was to: (i) identify the most vital performance indicators, and (ii) aggregate them together according to the preferences of the decision maker (i.e., using the Multi-attribute Value Theory).<sup>18</sup>

**2.1.4 Alarm Ranking:** The Alarm Ranking process concludes the risk-based methodology by performing impact aggregation and alarm prioritisation. Similarly to the Likelihood and Impact Evaluators, the process also monitors the alarms table in the PostgreSQL DBMS (as shown in Figure 1). Once an alarm that underwent the complete risk analysis (i.e., the likelihood and impact of all potential pipe bursts were evaluated) is found, then the ranking process is initiated. At first, all active alarms that need to be re-prioritised are loaded. Next, the process retrieves all potential incidents, including their non-aggregated consequence vectors at a given risk horizon (i.e.,

24 hours), associated with those alarms. As various impact factors (i.e., components of the consequence vector discussed above) have different units and scales it is necessary to normalize them to a common range from 0.0 to 1.0 across all active alarms. Once the aggregated impacts of all potential incidents are re-computed (i.e., using the Multi-attribute Value Theory by applying weights reflecting the relative significance of particular impact factors), the actual alarm ranking can commence. The ranking of an alarm is determined by its relative overall risk (obtained by aggregating risks of all potential pipe bursts of an alarm) compared to other active alarms. The ranking then only suggests that a particular alarm is deemed to be more or less significant than another one rather than providing an absolute measure of alarm severity.

**2.1.5 The front-end:** The processes that form part of the front-end are responsible for presenting the outcomes of the risk-analysis as well as additional relevant information to the end user (i.e., a control room operator) of the DSS. At any time, an overview of the real-time state of the entire WDS is available to the operator through a prioritised list of all alarms (i.e., detected anomalies) as well as through using a GIS interface. Detailed results of the risk analysis are then made available to the end user through the “Alarm Diagnostics” user interface (Figure 3).

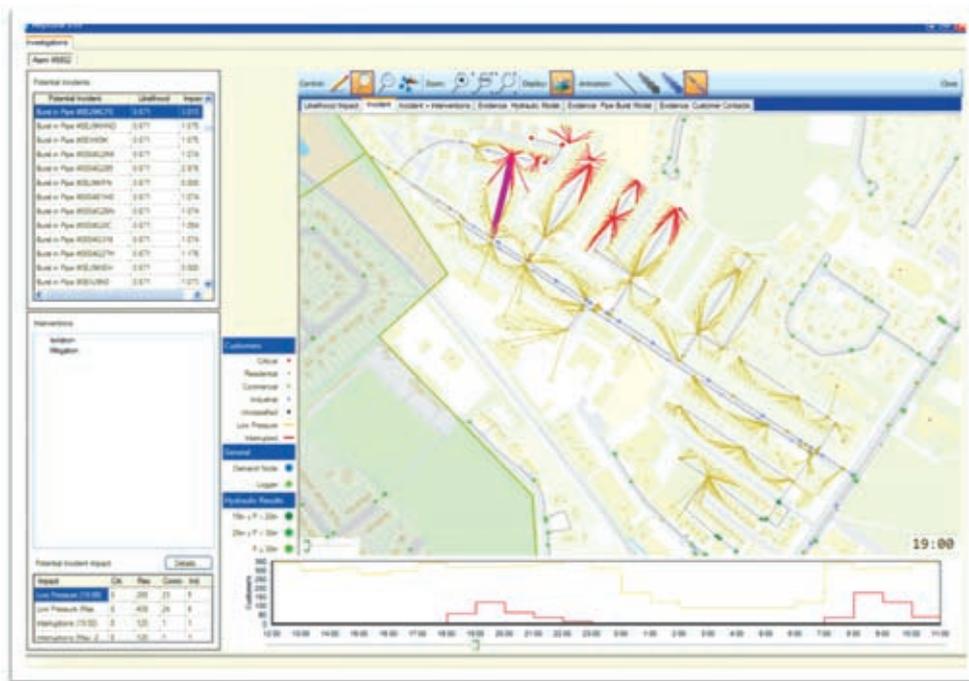


Figure 3: Neptune DSS Alarm Diagnostics user interface.

The DSS user interface permits the Operator to investigate, in detail, the outputs of the alarm-ranking procedure allowing the assessment of the likelihood of a burst having occurred in a particular pipe.

Having selected a pipe as a potential incident, the graphical displays of the DSS can be used to assess the risk of resultant discolouration in each pipe in the network, visually identify each property that is affected by insufficient pressure or no water and to allow the change in these impacts through time. An animated visualization is also presented representing a comparison of the normal flows through the network versus those experienced as a result of the incident. This visualization highlights pipes in which the flow has been substantially increased or reversed permitting the rapid identification of areas remote to the incident location which may consequently be affected by discolouration issues.

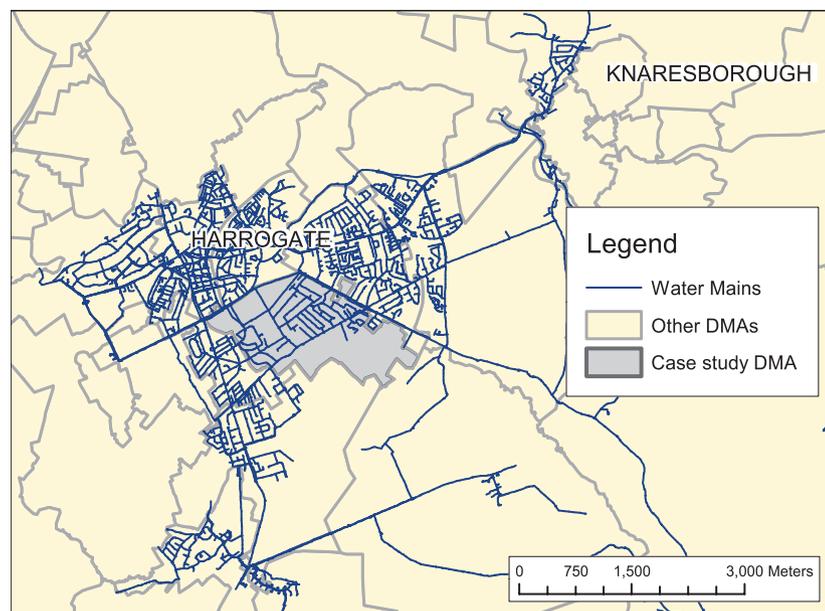
Following the confirmation of the location of an incident on the ground, the DSS further supports the operator by identifying the optimum isolation strategy to undertake as well as reconfiguring DMA boundary valves to restore supply to otherwise isolated zones, minimizing the impact on customers.

## 2.2 Case study

The above DSS has been applied on a case study in a highly looped urban DMA located in the city of Harrogate in North Yorkshire, UK (highlighted in grey in Figure 4). The studied DMA contained over 19 km of mains, supplying almost 1,600

properties (over 95% residential customers). The average minimum and maximum pressures were 30 m (8:00 AM) and 53 m (4:00 AM) respectively. The minimum night flow was  $6 \text{ l s}^{-1}$  and the overall daily water consumption was almost  $10^6$  litres per day (1 Ml/d). The DMA contained 450 pipe segments that were considered in the risk analysis (i.e., likelihood and impact evaluation).

**2.2.1 Likelihood evaluation:** The use of the hydraulic model (EPANET) as a source of evidence to support the location of a pipe burst within WDS relies on a number of appropriately located pressure and/or flow monitoring points. Additionally, it takes into account the timing and magnitude of the burst that needs to be large enough to cause head-loss that creates measureable drops in pressure at the location of pressure loggers in the vicinity of the burst pipe. 13 pressure monitoring sensors were deployed in the studied DMA at strategic locations (see Figure 5). No pipe burst has occurred since the loggers were placed and, therefore, it was necessary to simulate a burst based on a real, but past historical event with a detected burst flow magnitude of  $5 \text{ l s}^{-1}$  (i.e., 25% of peak DMA inflow). For the purpose of locating the burst using the hydraulic model, artificial reference pressure measurements at pressure monitoring points were obtained by simulating the burst at the real location (i.e., based on pipe repair records). Consequently uniformly distributed noise in the range of  $\pm 10\%$  and  $\pm 1\%$  has been added to nodal demands and the reference pressure measurements respectively to emulate more



**Figure 4:** An overview of the case study area.

realistic conditions. As shown in Figure 5 the historical burst was later reported by several customers mostly located in the proximity of the burst pipe (which does not always have to be the case).

The likelihood of burst occurrence in every pipe in the DMA has been obtained by combining the evidence provided by three information sources: the pipe burst prediction model, the hydraulic model and customer contacts. Even without considering the customer calls (see Figure 5) the two remaining information sources would identify the correct part of the DMA to allow proactive investigation. However, the result would not be as specific as in the case when the customer contacts were taken into the account.

**2.2.2 Impact evaluation:** For the purpose of the impact assessment burst pipes were modelled using EPANET as emitters with outflow described by the following equation:  $Q = C \times P^{N1}$  where  $Q$  is the flow rate,  $C$  is the discharge coefficient,  $P$  is the pressure and  $N1$  is the pressure exponent. The value of  $N1 = 0.5$  was assumed and the discharge coefficient was calculated by running a steady state simulation at the time of burst detection (i.e., midnight in this case) with an additional burst flow of  $5 \text{ ls}^{-1}$  to obtain the pressure at the burst location.

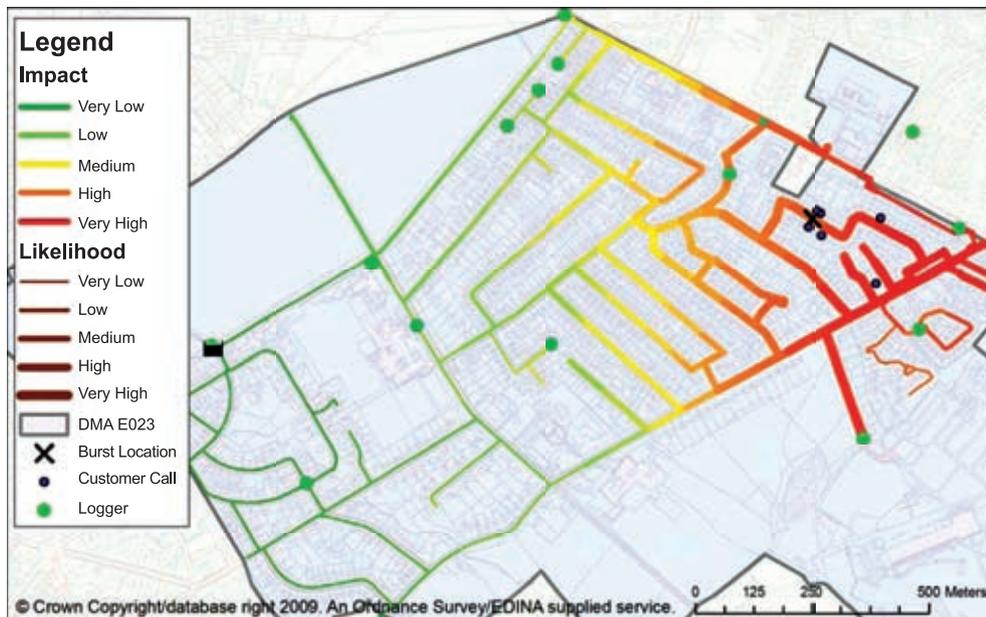
To evaluate the impact of a failure of any pipe in the DMA 450 pressure driven EPS simulations with a 1-hour time step were performed. This was followed by running a discolouration model<sup>19</sup> and by calculating various other performance indicators

(e.g., cost of lost water, duration of low pressure impact, etc.) for each of the pipes. As pointed out by Bicik et al.,<sup>20</sup> the impact of significant failures needs to be evaluated at system level since it is likely to affect other parts of the network (e.g., other DMAs downstream or trigger discolouration in the upstream parts of the system). Therefore, unlike for the burst diagnostics, where a small model of a DMA was used, the impact was evaluated on a large all-pipe model comprising more than 9,000 pipes and over 8,700 demand nodes.

**2.2.3 Results and discussion:** The risk metric comprising likelihood and impact measures, which were computed by the individual components as described above, is presented using a GIS in the form of a risk map shown in Figure 5.

The likelihood that a particular pipe burst is visualised using different line width, where thin and thick lines correspond to the least and the most likely burst locations, respectively. In a similar fashion the impact is displayed using different colours where green corresponds to very low impact and red represents very high impact. In the real case scenario the operator would also benefit from additional information layers which could not have been presented here.

Figure 5 shows the risks associated with a burst of every of the 450 pipes in the DMA in a non-aggregated form. This allows maintaining the information about pipe bursts that are less likely causing the detected abnormal flow than others, but, on the other hand, a burst at those locations



**Figure 5:** A risk map showing the pipe burst likelihood and its impact in different parts of a DMA.

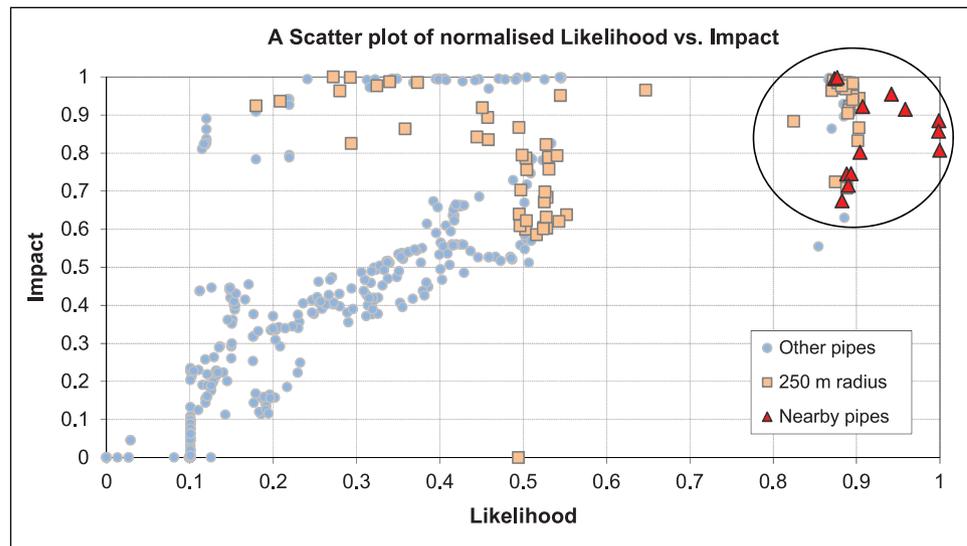
would have much more severe consequences. Such information would be lost if the likelihood was simply multiplied by the impact as it is commonly advocated.

**2.2.4 Risk-based decision making:** Figure 6 plots the same results as shown in Figure 5 in the form of a scatter plot (i.e., every element in the figure corresponds to the risk of failure of a single pipe). The figure provides an additional insight into the distribution of risk (i.e., the most critical points are located in the upper-right corner).

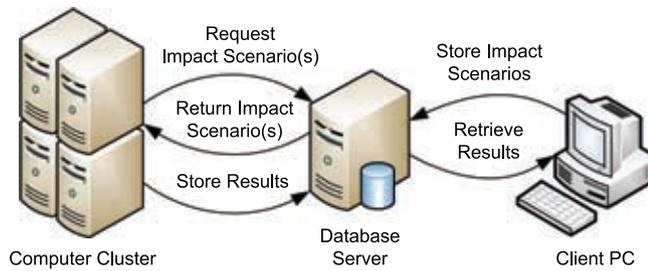
Given the risk distribution shown above, the decision maker would probably decide to put higher importance to the likelihood component of the risk since a relatively small number of pipes formed a cluster (see the points within the circle in Figure 6) with high likelihood of being the cause of the problem. In this case the decision-maker would also know that the likely pipes under investigation fell into the category of the critical ones as they have relatively high impact (e.g., compared to the majority of other pipes that have the normalised impact lower than 0.6). Therefore, even in the case that the diagnostics component providing the likelihood failed to identify the correct location, the region where the consequences of a burst would be significant is investigated. It should be noted that the closeness of the points in Figure 6 does not indicate geographical proximity of candidate pipes. Therefore, suitable visualisation techniques that allow easy exploration of the risk maps and the scatter plots need to be investigated in the future.

**2.2.5 Computational performance:** The primary focus of the methodology presented in this paper is to support near real-time decision making. Evaluating the impact of all potential pipe bursts within a DMA on the rest of the system requires a large number of runs of a hydraulic solver. Therefore, it is computationally demanding as those runs cannot be performed off-line. This is a consequence of the need to consider the current state of the system based on the information from: (i) pressure and flow monitoring devices, and (ii) demand forecast (as it is necessary to project the effects of the pipe bursts into the future, i.e., the next 24 hours). Even with the high-performance personal computers impact evaluation of a single failure is time consuming, which prevents its application in the near real-time domain. To increase the speed of impact evaluation a database-centric distributed architecture has been implemented (see Figure 7).

The system builds upon the strong transaction processing capabilities of modern DBMS, such as PostgreSQL. The RDBMS serves as a mediator between a client application and a computer cluster comprising of several nodes. The distributed impact evaluation is done in the following steps: (1) the client application inserts a set of impact scenarios into the database (2) each of the processes running on the computing nodes in the cluster periodically attempts to retrieve new scenario(s) from the database (3) if a new failure scenario(s) are retrieved from the database, their impact is evaluated and (4) the results are stored back into the database (5) the client application retrieves the results of evaluated scenarios.



**Figure 6:** A scatter plot capturing the non-aggregated risks of a pipe burst at various locations in a DMA.



**Figure 7:** A database-centric distributed architecture for pipe burst impact evaluation.

The above presented architecture has shown as suitable for given application since the time required to retrieve failure scenarios and to store the results was negligible compared with the time needed to evaluate the impact. Implementation of such distributed application was conceptually simple and the solution was scalable. The results for the case study presented in this paper have been obtained using the distributed impact evaluator which was concurrently running on 14 computing nodes. The full impact evaluation of the above DMA took approximately 5 minutes, which is acceptable given the fact that new data from the network is currently received every 30 minutes. However, this performance could still cause needless delay in the investigation.

The impact evaluation has been done deterministically neglecting the uncertainty in the nodal demands and in the estimated burst flow. The use of sampling methods<sup>21</sup> (e.g., Monte Carlo or Latin Hypercube simulation)<sup>22</sup> to account for this type of uncertainty in the near real-time environment would require the use of many more computing nodes that might be on-demand allocated in the cloud. As part of the future work it is envisaged that grouping of pipes with similar failure impacts could be used to reduce the computational burden.

### 3 Early Warning System for Urban Flood Management

Urban drainage comprises all surfaces and drainage elements (both underground and above-ground), which collect and transport rainwater. In recent years these systems have been under increased load due to an increase in the number of flood events and flood risk warnings in many urban areas. This is caused mainly by more extreme weather events, increasing urbanisation and deterioration of ageing infrastructure. As the complete redesign and construction of urban drainage networks to prevent flooding in each and every case would be prohibitively expensive, modelling is used to provide predictions of location,

severity and risk of flooding. In order to be operationally useful, models need to provide at least a 2-hour lead-time.<sup>23,24</sup>

Hydraulic modelling has commonly been used to assess the response of urban drainage systems to rainfall events. However, for large networks and/or when repetitive simulation runs are needed (i.e., for flood risk assessment), these can be slow and computationally expensive. We present a faster surrogate method based on Artificial Neural Networks (ANN) that permits modelling of very large networks in real-time, without unacceptable degradation of accuracy.

#### 3.1 Artificial neural networks for urban flood modelling

As part of University of Exeter's research under the Flood Risk Management Research Consortium Phase<sup>25,26</sup> Project and the UK Water Industry Research<sup>24</sup> (UKWIR, 2012) follow-on case studies, 'RADar Pluvial flooding Identification for Drainage System' (RAPIDS) was developed using ANNs to predict flooding in sewer systems.<sup>27,28</sup> This work assesses the opportunities of using data-driven ANN models for rapid prediction of flooding and Combined Sewer Overflow (CSO) spills. This is seen as a possible opportunity for being able to take action that will provide water utilities with the ability to improve their level of service and compliance with regulation as well as mitigate risks to their customers and general public.

The predictive ability of RAPIDS is limited by the "time of entry" for any given node in the sewer network, with the possibility of flooding commencing from this time onwards, following the start of precipitation. With the exception of the most downstream nodes in the very largest drainage networks, this would normally be very short, i.e., of the order of minutes, rather than hours, thus requiring prediction of rainfall to achieve the required operational lead-times. This type of modelling, commonly known as rainfall nowcasting, is commonly obtained from radar rainfall images.<sup>29,30</sup> Although work has been carried out

with the UK Met Office Nimrod 1 km composite radar images (with 5-minute temporal resolution) and Environment Agency telemetered raingauge network (with 15-minute temporal resolution),<sup>24</sup> in this study we present results based on synthetic design rainfall events using a range of return periods and durations.

Due to the lack of measured data of urban flooding events, the InfoWorks CS model<sup>31</sup> is used as a surrogate for providing ‘real’ information on urban drainage system performance at manholes, CSOs and outfalls. ANN models are then developed to predict performance at these key points of interest for any rainfall loading condition and these predictions are compared to InfoWorks CS results, which are treated as ‘ground truth’ for the purposes of the study.

**3.1.1 The ANN model:** The ANN model is based on a 2-layer, feedforward Multi-Layer Perceptron (MLP).<sup>32,33</sup> This is now an established machine-learning technique applied to many fields. In the case of supervised learning, it relies on the discovery of a multi-dimensional non-linear relationship between the desired model target outputs and a set of predictor factors applied as input signals to the model. In applications such as urban flooding, the inputs and targets take the form of time-series signals, sampled at a regular time interval (‘timestep’). The modelled relationship is discovered during a ‘training’ phase based on a number of events from the previous history of the system. Having learnt this generalised relationship, the trained model is then ready for use on new events including those occurring in real-time. Although training can require significant computational time, the resulting trained ANN model is able to provide flooding responses to rainfall in a fraction of the time require by traditional mathematical

models. The fundamental building block of the ANN is the neuron, which has a number of analogue inputs and one output and implements the transfer function:

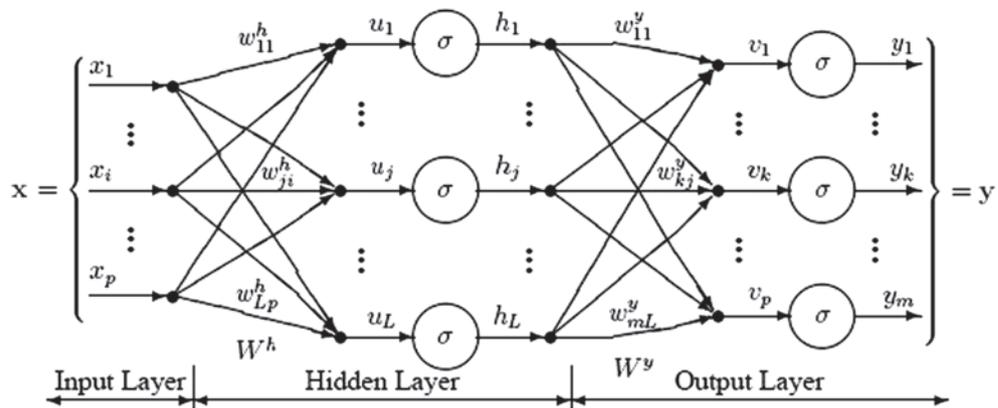
$$y = f(x) = \kappa \left( \left( \sum_i w_i g_i(x) \right) + b \right) \quad (1)$$

where:  $x$  is the input,  $g_i(x)$  is some function of  $x$ , implemented by the previous neuron towards the input of the network,  $w_i$  is a weight associated with input  $i$ ,  $b$  is a bias level and  $\kappa$  is an activation function applied to the output of the neuron. This might typically implement the hyperbolic tangent ( $\tanh$ ), a threshold switch or a linear function. The activation function is selected based on the type of data being processed and so selection is problem specific for output neurons (e.g., a threshold switch will output an all-or-nothing response whereas the linear and hyperbolic tangent functions will output floating point values).

Figure 8 illustrates 3-layered feed-forward ANN, which is fully-connected within each layer. Note that the input layer simply distributes inputs to all neurons in the hidden layer and there are only 2 layers of neurons.

In the ANN used, the number of output neurons is given by the number of key nodes in the sewer network to be modelled.\* The hidden layer neurons use a  $\tanh$  (i.e., non-linear) activation function, in order to enable modelling of the non-linear processes relating inputs to out-

\*Note that because this is not a physical model, there is no need to model every sewerage node; it is sufficient to model only those nodes identified from the target data as having a probability of flooding above some threshold value. This results in considerable computational cost saving and hence speed improvement when compared to physically-based hydrodynamic models.



**Figure 8:** Architecture of Multilayer Perceptron (ANN).  
Source: <http://www.dtrek.com/mlfn.htm>

puts. Because the production of hydrographs involves regression rather than classification, the output neurons use a linear activation function. The number of neurons in the hidden layer and number of input nodes are varied to establish an optimum. Batch-mode supervised training is used, in which expected target data are known for a given set of input data. At each epoch (step) in the training process, the entire training dataset of input samples is presented to the ANN. Target data (output from the InfoWorks CS model) are compared to the output generated by ANN and errors back-propagated towards the input, adjusting ANN weights and biases so as to reduce the output error. Error optimisation strategies include Scaled-Conjugate-Gradients (SCG), Levenberg-Marquardt (LM) and Quasi-Newton (QN),<sup>34–36</sup> which are gradient-based approaches.

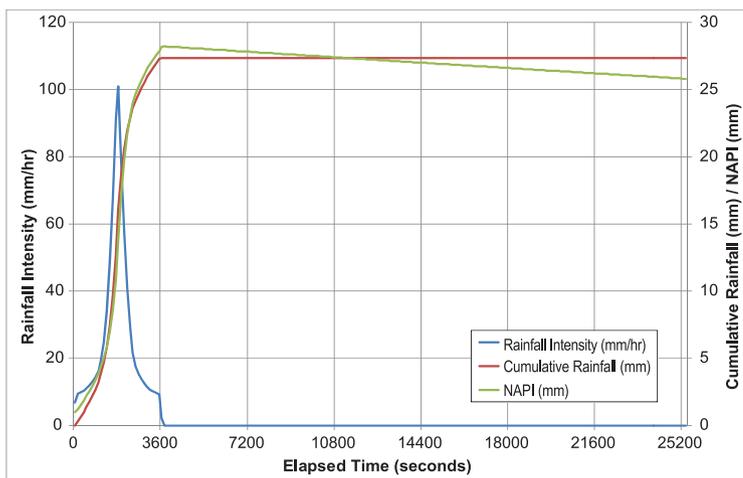
A moving time-window “time-lagged” approach<sup>37,38</sup> is implemented whereby a number of time-series traces (e.g., rainfall intensity, cumulative rainfall, etc.) are provided as inputs to the ANN. In the study presented here there were four input time-series including elapsed event time (seconds), rainfall intensity (mm/hour), cumulative rainfall (mm) and the New Antecedent Precipitation Index (NAPI) value (metres).<sup>39</sup> The number of input nodes is therefore four times the number of timesteps in the input time-window (e.g., for a 3-minute time step and 30-minute input time window, 40 input nodes would be used).

Output target signals for training and evaluation of ANN performance are provided from the flood-level hydrographs generated by InfoWorks CS<sup>31</sup> hydrodynamic simulator outputs for each output type (depth/flow/volume). The trained

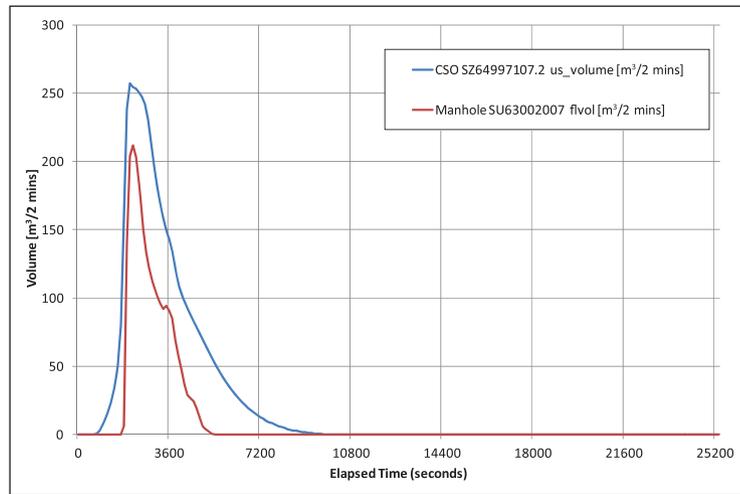
ANN is thus intended to approximate the same hydrographs. The target signals selected are the flood depths, flow rates or volumes per timestep at each manhole for a timestep advance that corresponds to the desired prediction lead-time (i.e., up to “time of entry” for the node). Event profile data arrays of the four input-signals and corresponding flood hydrographs are prepared for use as the time-series inputs and targets for the ANN as illustrated in Figure 9 and Figure 10. ANN input data are normalised as standard practice. For ‘proof-of-concept’ demonstration involved in stage 1 of the UKWIR<sup>24</sup> project, design rainfall profiles were used. Figure 9 and Figure 10 correspond to Event 14 in Table 1.

**3.1.2 The ANN procedure:** The staged approach to building the ANN model in this study is described next. It starts with obtaining rainfall data values for the rainfall events used for evaluating the system performance of the specific locations selected. These are in the form of rainfall intensity values at specific (short) intervals applied uniformly across the models.

InfoWorks drainage models were then used to provide predictions of the performance for a range of locations across the networks. The performance measurements considered were: (a) manhole flood volumes, i.e., the volume of water ejected from the manhole onto the street, (b) CSO spill volumes, i.e., the volume of water bypassing the water treatment plant and being released untreated into the receiving waters, (c) manhole surcharged depths, i.e., for the manholes that do not flood the street, but could flood basements in buildings and cause damage, and (d) outfall flow rate hydrographs.



**Figure 9:** ANN Input time-series signals for 50-year return period 1-hour duration rainfall event for Portsmouth catchment.



**Figure 10:** ANN Target time-series volume hydrographs for 2-nodes for 50-year return period 1-hour duration rainfall event for Portsmouth catchment.

The ANN model aims to replicate the results for each of these categories for their respective locations. Up to 100 node locations in each category could be selected.<sup>†</sup> In practice about 20 nodes were used.

The next step of the procedure was to divide the input data into training and test sets. A rule of thumb is that roughly 75–80% of data should be used for training the ANN model and 20–25% to test its predictive capability. To get the best results in the testing, the training events must be representative of the dataset as a whole. It is therefore important that representative training events are used to obtain good model predictions. The “test” events are not included when training the network so that they can be used as method for evaluating the ANN model’s ability to make predictions for all relevant rainfall events.

For this study, a matrix of 16 design rainfall events (4 return periods (RP) × 4 rainfall durations) was used for each of the 3 case-study catchments. For each event in turn, the input and output information is normalised and input signals are applied within a moving time window of a defined number of timesteps, to inputs of ANN. The corresponding training event InfoWorks hydrographs were used for the selected sewer node locations to be modelled, as target signals for training each ANN output. The training optimisation is stopped when an acceptable level of

<sup>†</sup>This limitation is due to available workspace memory during ANN training, when using SCG/Quasi-Newton optimisation. It could be overcome by using (for example) Evolutionary Algorithms (EA) for ANN training. These do not employ inversion of Hessian matrices; so are much more economical on memory use.

**Table 1:** Matrix of design rainfall events for Portsmouth.

Event no	Event type	Return period	Duration	Event use	Event ID
Design/real	rrr (years)	d.dd (hours)	Trg/Tst	Format rrrddd	
1	Design	1	0.5	Trg	001050
2	Design	1	1	Tst	001100
3	Design	1	2	Trg	001200
4	Design	1	4	Trg	001400
5	Design	5	0.5	Trg	005050
6	Design	5	1	Trg	005100
7	Design	5	2	Tst	005200
8	Design	5	4	Trg	005400
9	Design	20	0.5	Trg	020050
10	Design	20	1	Tst	020100
11	Design	20	2	Trg	020200
12	Design	20	4	Trg	020400
13	Design	50	0.5	Trg	050050
14	Design	50	1	Trg	050100
15	Design	50	2	Tst	050200
16	Design	50	4	Trg	050400

an error metric is reached, or when the error on a validation event (part of the training set, not used for optimisation) starts to increase again, or when a maximum number of training epochs is reached.

Table 1 illustrates; of the 16 events, 12 were used for ANN training and 4 were reserved (as shown) for test evaluation of the ANN after completion of training.

Once the ANN model is trained, the ANN is tested by propagating input data from the reserved 'test' set of events through the network and calculating the resulting errors from comparison with InfoWorks CS.

### 3.2 Case study

The above ANN methodology has been applied to three catchments in the UK,<sup>24</sup> with results on one of them, Dorchester, presented here. The Dorchester Sewer Model consisted of 1,391 nodes and was heavily modified to make it more suitable for the purposes of this study, i.e., to maximise the effects of delayed runoff and infiltration. The rainfall input to ANN was synthetic, single peak design storms. A matrix of design storm events was created in line with standard UK procedures. Table 1 illustrates.

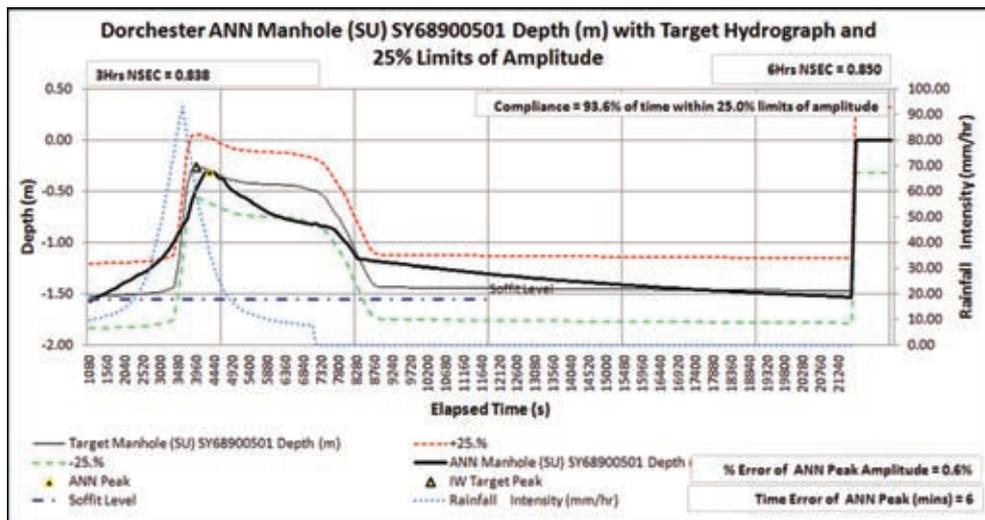
For 'flooding' manholes the target data were depth and flood volumes while for 'surcharged' manholes only the depth data was considered. For the CSOs the data used comprised depth at the CSO (relative to spill level) and volume on the spill link, while for the outfalls only the flow data was used. Twenty manholes that flooded on smaller and larger events were identified, as were 20 manholes that surcharged, 10 CSOs that spilled and 5 outfalls. The manholes were also chosen from different geographical locations, distributed across the network in order to include both runoff types used, and the infiltration module.

**3.2.1 Performance metrics:** A variety of statistical analyses were applied to the ANN output hydrographs in order to assess the ability of ANN

to match the output hydrographs from the InfoWorks Model. The Nash-Sutcliffe Efficiency Coefficient (NSEC) was identified as the most useful measure of the closeness of the 'fit' between two hydrographs. A value for the NSEC of 1 represents a perfect match between the InfoWorks output hydrograph and the ANN output hydrograph. Moriassi et al. defines an acceptable NSEC value as 0.5;<sup>40</sup> however, for this study a value above 0.85 had been outlined as "Excellent", though some degree of qualitative evaluation is recommended. A tolerance band was applied to the NSEC hydrograph to help evaluate the ANN performance.

The NSEC results considered start at 18 minutes (1080 seconds) after the start of the rainfall event with the analysis undertaken over the following 3 hours and 6 hours. As all the storms were relatively short and the main interest was to identify how well the peak values matched, it was considered more appropriate to report on the 3 hour analysis period.

Five metrics were used to measure the goodness-of-fit produced by the ANN for each modelled node. These are: (a) the NSEC over initial flooding period (3 hours here); (b) the NSEC over entire event (6 hours here); (c) the amplitude error between the ANN and the InfoWorks Target peak; (d) the timing error between the ANN and the InfoWorks Target peak; and (e) the percentage of time when the relationship between the ANN model and the InfoWorks model are within a  $\pm 25\%$  tolerance band of a 'perfect' fit. An example of the NSEC results for a 50-year RP, 2-hour duration event is given in Figure 11.



**Figure 11:** Example ANN output and target hydrographs for a 50-year RP, 1-hour duration design rainfall event, for a single sewerage node.

Further measures assess ANN performance over the collection of nodes for the model. These include box-and-whisker plots of the range of NSEC for the 3-hour analysis period and ‘confusion matrix’. This analyses just the peak amplitudes of the ANN output hydrographs in comparison with their targets and shows how many counts the ANN correctly predicts surcharge and how many counts it correctly predicts flooding according to 3 depth categories (A = below soffit; B = between soffit and basement flood level; C = above basement flood level). Figure 12 illustrates this.

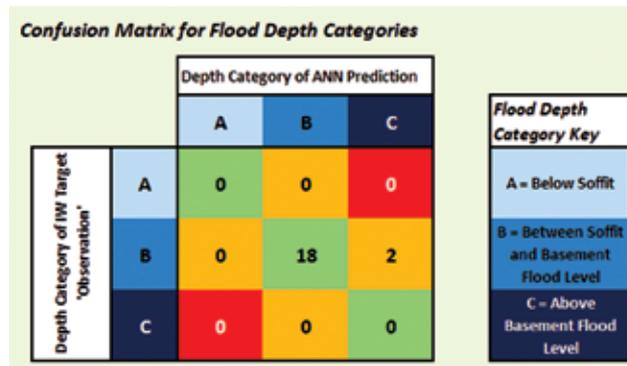
For the event shown, the accuracy band score is thus Pass (green) = 18/20 = 90%; Caution (amber) = 2/20 = 10%; Fail (red) = 0/20 = 0%. All percentages thus have +/-5% resolution.

Figure 13 (a) shows median Nash-Sutcliffe scores approx 0.8 over the 20 nodes in this ANN model, and (b) shows the spread of peak amplitude errors as percentages of peak target amplitudes.

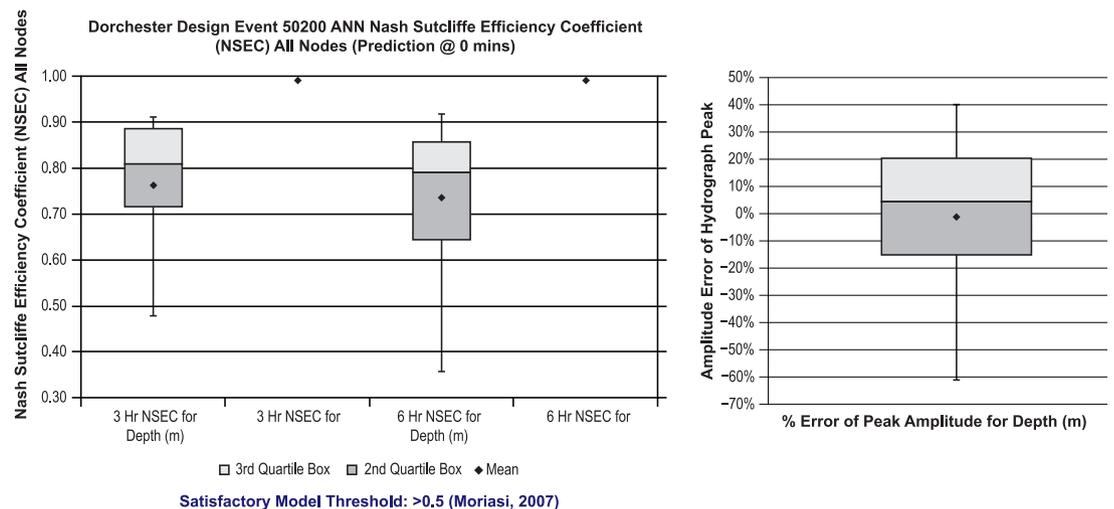
Focus is given to the peak of the hydrographs, since this is the factor that determines impacts from urban flooding.

**3.2.2 Results and discussion:** Figure 14 is a scattergram of NSEC scores for both 3 and 6 hour time periods, over all 20 nodes for all 4 test events shown in Table 1. It shows a total of 160 scores of which all apart from 13 (i.e., 92%) attain above the “good model” threshold as suggested by Moriasi.<sup>40</sup>

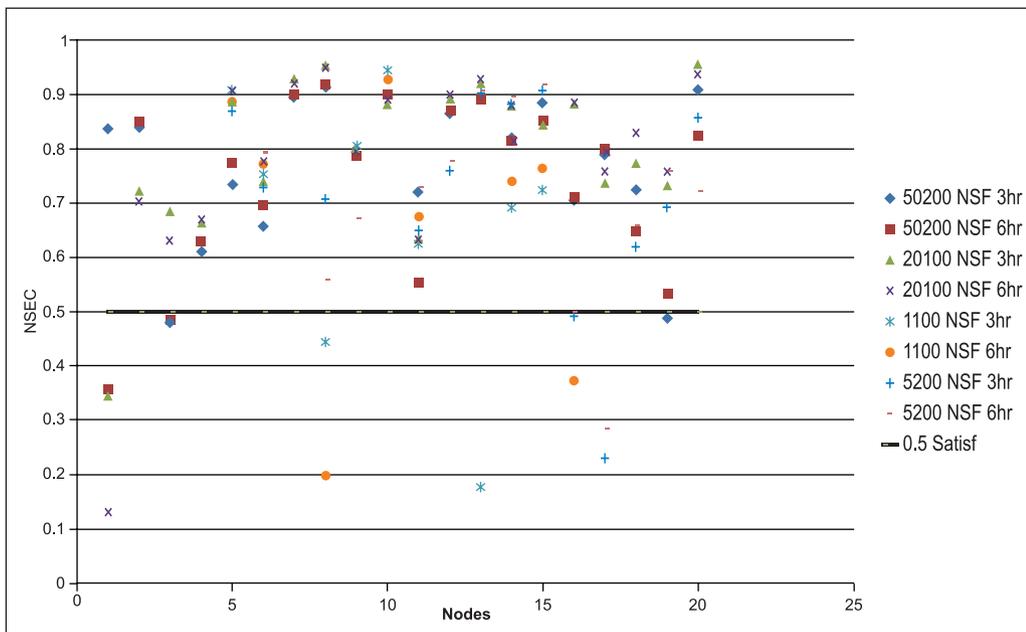
Overall, the results obtained have given a substantial degree of confidence that ANN models could, if trained adequately, provide a reasonably reliable prediction of flooding and/or CSO spills. The closeness of fit between the respective hydrographs gave varying results. The flooding (or spill) confusion matrices showed that the pass/fail test was in the range 33% to 93% and in Stage 2 (zero NAPI) the range was 40% to 76% and with time-varying NAPI was 33% to 79%.



**Figure 12:** Example Dorchester catchment confusion matrix for total of 20-nodes, for depth category of peak for a 50-year RP, 1-hour duration design rainfall event.



**Figure 13:** (a) Dorchester catchment NSEC-spread; (b) Spread of % peak amplitude error for a 50-year RP, 1-hour duration design rainfall event (for total of 20-nodes).



**Figure 14:** Dorchester summary of NSEC scores for surcharge manhole water levels for all 4 test events.  
Source: Richard Allitt Associates.

These are obviously a comparatively crude indication because they take no account of the number of manholes flooding or CSOs spilling. However, they do give an indication of the confidence which could potentially be given to ANN predictions.

From this study it is concluded that ANN technology has the capability to satisfactorily predict manhole flooding or CSO spills. However, this study has only used input signals which are isolated from the hydraulic performance of the sewer system and in particular any downstream influences causing backing up or reverse flow. Some of the measurement points were at locations where the InfoWorks modelling had indicated that reverse flows could occur but there was no input signal for this phenomenon. It is possible that ANN models may struggle to be reliable for all rainfall events, and careful attention to training should take account of these situations.

#### 4 Conclusions

Water utilities around the world already monitor and evaluate large amounts of data regarding the operations and performance of their physical infrastructure. Supervisory Control and Data Acquisitions (SCADA) systems continuously collect and provide data and information to the control room personnel. Furthermore, the water industry has invested heavily in a variety of asset management tools that store large amounts of data to assist with the maintenance, repair and replacement of system components and equipment. On the customer

side, the industry is also making progress with Automated Meter Reading (AMR) and considering smart metering to reduce water losses at customer premises and implement customer-facing behavioural change programmes.<sup>41</sup>

The effective management of water distribution, urban drainage and sewerage networks is likely to require increasingly sophisticated computational techniques to keep pace with the level of data that is generated from measurement instruments in the field. The sheer volume and speed of acquisition of this data means that decision makers will find it increasingly difficult to make sense of events as they are occurring within the network. The solution proposed here is the use of *intelligent computational methods* to help the decision maker and to present knowledge based on past experience with the network to propose solutions from which the decision maker can choose. The two systems described above have the potential to provide early warning and scenario testing for decision makers within reasonable time, this being a key requirement of such systems. Computational methods that require hours or days to run will not be able to keep pace with fast-changing situations such as pipe bursts or manhole flooding and thus the systems described above are able to react in close to real time. As measurement devices proliferate in water distribution and hydrology systems, so the water industry will undergo a 'data explosion' similar to that seen in the biosciences. The challenge

for the computational methods, therefore, is to make sense of increasingly large volumes of data, in real time, to aid decision makers and significantly improve the operation of these important systems.

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**Dragan A. Savić** is the first Professor of Hydroinformatics in the UK having held this post at the University of Exeter since 2001. He is Head of Engineering at Exeter and a founder and Director of the Centre for Water

Systems. Dragan has made an outstanding contribution to the development and adoption of optimisation techniques for management of urban water networks as well as to real-time management of these systems involving smart monitoring, telemetered systems and sensor networks. He leads a consortium of 9 European partners on the FP7 iWIDGET project ([www.iwidget.eu](http://www.iwidget.eu)) aimed at improved water efficiencies through the use of novel ICT technologies.



**Dr. Josef Bicik** received his masters in Computer Science and Engineering from the Czech Technical University in Prague in 2006. He then joined the Centre for Water Systems at The University of Exeter as an associate research fellow to work on an EPSRC funded project NEPTUNE. The project dealt with the development of a risk-based decision support system for management of Water Distribution Networks (WDN). Josef received his PhD in Engineering from The University of Exeter in 2010 and currently works in the industry. Amongst his research interests belong Evolutionary Optimisation, Decision Support Systems, WDN modelling, and Geographic Information Systems (GIS).

Dr. **Mark S. Morley** is a Software Engineer with over 15 years professional experience. At present he is a Research Fellow in the Centre for Water Systems at the University of Exeter. He has worked for, and with, numerous companies and public-sector organizations on large-scale Information Technology projects across many business sectors including the water, gas and electricity utilities and the oil and gas industry. His key areas of expertise include object-oriented analysis and design, software development in C++/C#, engineering optimization, parallel computing, human computer interaction and user interface design.



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**Andrew Duncan** is reading for a PhD in Computer Science, working within the Centre for Water Systems at University of Exeter, researching “Applications of Machine Learning to Early Warning Systems in Hydrology and the Environment”. His interests include the hydrological applications of Artificial Neural Networks (ANNs) and Cellular Automata (CA) to prediction of urban flooding and water quality at bathing beaches. His research contributes to the FRMRC2, CADDIES, UKWIR(RTM) and Environment Agency Bathing Water projects.



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**Zoran Kapelan** is a Professor of Water Systems Engineering at the University of Exeter with 24 years of experience in academia and water industry. His expertise covers a wide range of topics related to urban and other water systems. He pioneered new technology for real-time detection and diagnostics of bursts and other events in distribution systems which is now used in a large UK water company. He is an IWA Fellow and Associate Editor of ASCE Journal of Water resources Planning and Management. He has more than 200 technical publications and 2 patents.



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**Slobodan Djordjević** is Professor of Hydraulic Engineering at the University of Exeter. Previously he was Assistant Professor at the University of Belgrade, Serbia and he also worked in Holland and USA. He has thirty years of experience in research, teaching and consulting in the development and application of advanced tools for simulation, design and management of water systems. His main interests are in urban flooding, performance of sewer networks and risks from extreme weather under climate change. Professor Djordjević is the Coordinator of FP7 EU-Asia CORFU project on flood resilience ([www.corfu7.eu](http://www.corfu7.eu)) and an Editor of Water Science & Technology.

**Dr. Edward C. Keedwell**, FHEA is a Senior Lecturer in Computer Science at the University of Exeter. His research interests are focussed on the use of nature-inspired computing techniques (e.g. evolutionary algorithms, swarm algorithms and neural networks) to solve difficult problems in bioinformatics and the water industry. Dr. Keedwell has published over 70 conference and journal publications and one book in the fields of computer science, bioinformatics and hydroinformatics. He is a Fellow of the UK Higher Education Academy and committee member of the AISB.



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