Newly Develop Technology For Managing Water Supply in Urban Areas With Computational Grid System.

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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 minimize 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 utilize 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 utilization 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.

I INTRODUCTION

Today, half of the world's population lives in cities and, by 2030, this will grow to nearly 60%.1 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."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.2 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 minimization 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.

II 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 optimize operational and capital expenditure. The performance of water utilities in the INDIA is monitored by the Economic Regulator, , which seeks to ensure that performance is achieved in an efficient way, thus protecting the interest of the consumers. Since economic regulation of the INDIA water sector began in the late 1980s, It has facilitated over £98bn of private investment and delivered safe drinking water, a much improved environment and improved customer service.3 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 discolouration or contaminant intrusion.4,5\ 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.6,7 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).

III DSS SYSTEM

The DSS was designed in a modular fashion to maximise its extensibility. Figure 1 provides a highlevel 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).

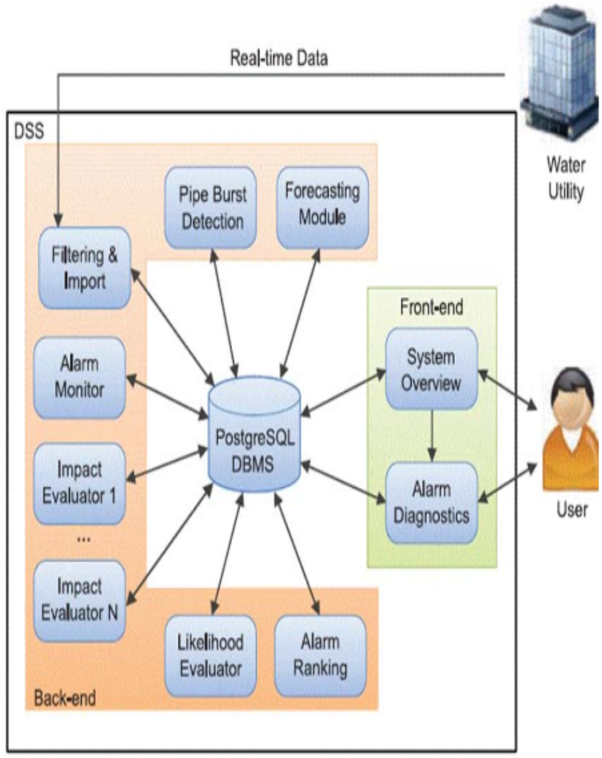

Fig 1 : An overview of a risk-based DSS for WDS management.

(a) Alarm Monitor

The Alarm Monitor periodically checks the contents of the "source alarm" table in the Database (DB) for new (fresh) alarms.

(b) 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 evidence14 has been applied to combine the evidence from those sources of information, as shown in Figure 2.

(c) Impact Evaluator

Similarly to the Likelihood Evaluator described above, the process also monitors the alarms table for newly generated alarms. 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).

(d) 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 Postgre SQL DBMS (as shown in Figure 1).

(e) 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 headloss that creates measureable drops in pressure at the location of pressure loggers in the vicinity of the burst pipe.

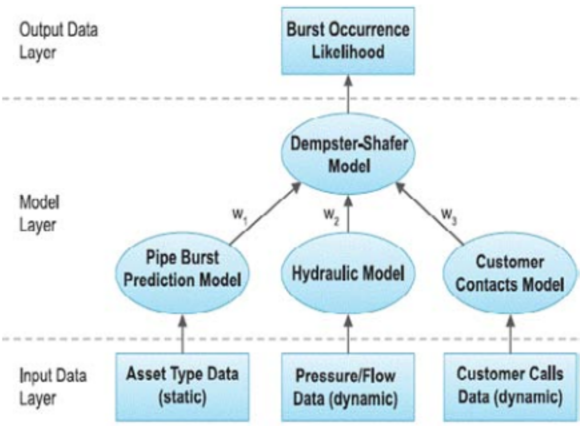

Fig 2 : An information fusion concept to estimate the most likely location of a failure.

IV DSS APPLIED - CASE STUDY ON UK WATER SYSTEM.

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 3). 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 6–1s and the overall daily water consumption was almost 106 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).

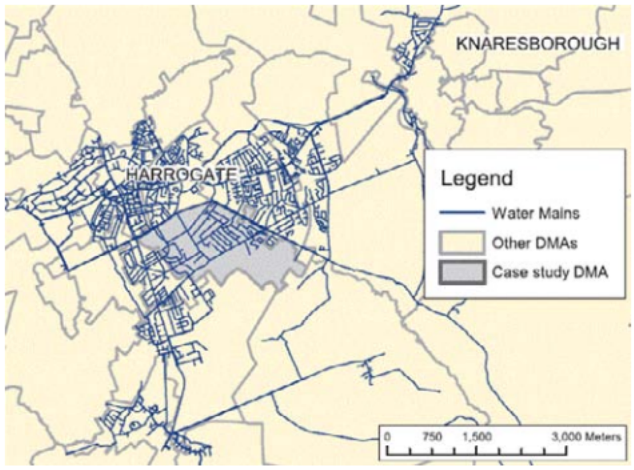

Fig 3 : An overview of the case study area.

(a) Risk Based Decision Making

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 4) 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 normalized 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 4 does not indicate geographical proximity of candidate pipes. Therefore, suitable visualization techniques that allow easy exploration of the risk maps and the scatter plots need to be investigated in the future.

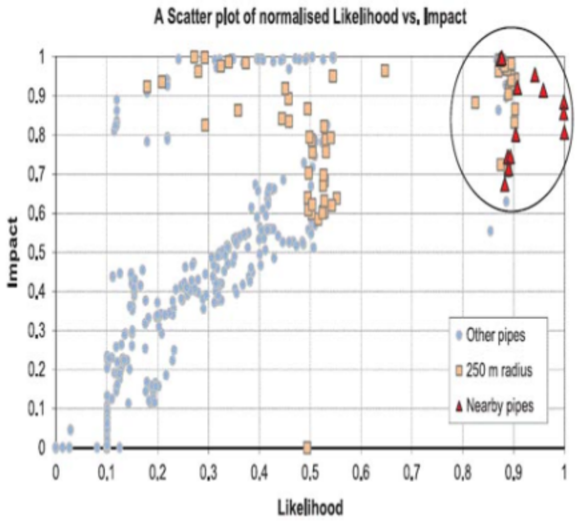

Fig 4: A scatter plot capturing the non-aggregated risks of a pipe burst at various locations in a DMA.

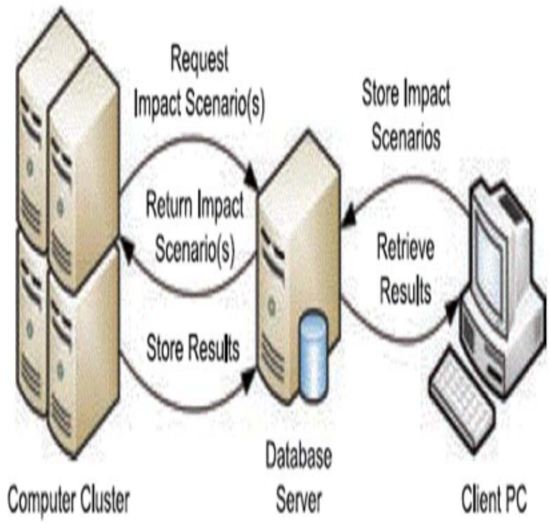

Fig 5 : A database-centric distributed architecture for pipe burst impact evaluation

V 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 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 5).

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.

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.

(a) Hydraulic Model

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.

(b) Early Warning System for Urban Flood Management

The ANN model is based on a 2-layer, feed forward Multi-Layer Perceptron (MLP).32,33 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 ('time step'). 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.

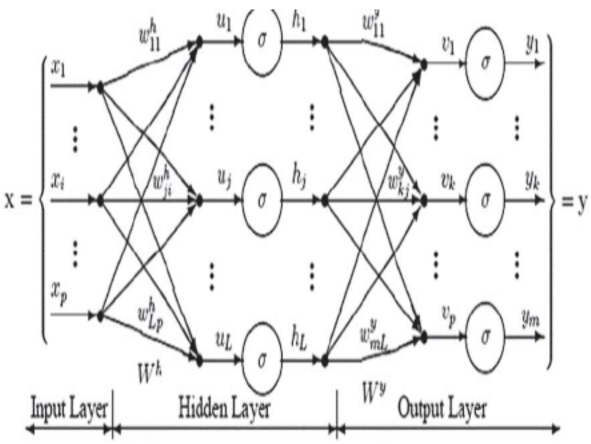

Fig 6 : Architecture of Multilayer Perceptron (ANN).

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 re verse 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.

VI CONCLUSION

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.41 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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