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NEAR REAL-TIME DETECTION OF PIPE BURST EVENTS IN CASCADING DISTRICT METERED AREAS

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A fully automated Event Recognition System (ERS) for the near real-time detection of pipe bursts and other network events such as boundary valve status changes and pressure management valve faults has been recently developed by the authors. This paper focuses on the further development of this system. The aim is to enhance the ERS approximate event location and alarm handling capabilities by developing and testing a new methodology that, in the case of cascading District Metered Areas (DMAs), automatically determines in which DMA an event occurred. The newly developed methodology makes use of a set of heuristic rules based on engineering knowledge, the Water Distribution System (WDS) schematic and the ERS outputs. The results of applying the new methodology to the historical pressure/flow data from several groups of cascading DMAs in the United Kingdom (UK) with real-life burst events are reported in this paper. The results obtained illustrate that the developed methodology not only enabled detecting the burst events occurred in a timely (i.e., within 30 minutes) and reliable (i.e., without any false alarm) manner but also allowed to always successfully determine in which DMA the event happened. The latter capability enables water companies to target the resources for the identification of the exact burst location to the greatest effect. Additionally, it enables reducing the potential of false alarms and the overall number of detection alarms, thereby facilitating interpretation of the ERS results.

INTRODUCTION

Pipe bursts in Water Distribution Systems (WDSs) represent an environmental concern (i.e., waste of water and energy), cause economic losses and have a negative impact on the water companies' operational performance, customer service and reputation. As water supply pipes continue to age and deteriorate it is likely that pipe bursts will occur more and more often. New and more efficient techniques for the detection of these events are therefore required.

Currently, a wide range of pipe burst event detection techniques exists that are based on various principles [1]. However, none is ideal and the number of techniques currently practised by the water companies is limited. In many cases, pipe bursts are brought to the attention of a water company only when someone calls in to report a visible event. Water companies embracing modern leakage management technologies devote considerable manpower and resources to proactive detecting and locating the pipe bursts by utilizing techniques that make use of highly

specialised hardware equipment (e.g., leak noise correlators, ground penetrating radars, etc.). Despite some of these techniques being the most accurate ones used today [1], they are also costly, labour-intensive, and slow to run. Consequently, much research has been focussed on finding cost-effective techniques that can help the water companies significantly reducing the pipe bursts' lifecycle by making them aware of the occurrence of these events much faster, and guiding the water company personnel straight to the problem areas.

Many techniques exist that promise low cost and faster solutions by endeavouring to solve the pipe burst detection problem by numerical analyses only [1]. Among these, those that make use of statistical and Artificial Intelligence (AI) techniques for automatically processing the operational variables (e.g., pressure and flow) in an on-line fashion [2-4] have shown to be of particular interest for providing a rapid response to the pipe burst events. Indeed, statistical/AI-based techniques can automate mundane tasks involved in the data analysis process and can efficiently deal with the vast amount of often imperfect sensor data collected by modern SCADA systems in order to extract information useful for making reliable operational decisions. These techniques also presents several advantages over other numerical techniques such as the steady state analysis-based [5], transient analysis-based [6], and negative pressure wave-based [7] techniques. For example, they have a requirement for pressure and/or flow measurements sampled much less frequently (e.g., every 15 minutes) than those required for transient analysis. Moreover, they rely on the empirical observation of the behaviour of a WDS. Therefore, precise knowledge of the WDS and instrumentation parameters is not required.

Despite their initial success, the aforementioned statistical/AI-based techniques can be further improved in terms of detection reliability and speed. Additionally, they can be also improved in terms of event location accuracy (i.e., to indicate more precisely the likely location of an event). Romano *et al.* [8] described a data-driven methodology for the near real-time detection of pipe bursts and other events which induce similar abnormal pressure/flow variations. They showed that their methodology, which is implemented in a fully automated Event Recognition System (ERS), was able to provide more reliable and timely detection alarms than other existing statistical/AI-based techniques. Bearing this in mind, the focus of this paper is on the further development of the ERS aiming at enhancing its approximate event location and alarm handling capabilities. Similarly to what proposed in Mounce *et al.* [9], this is achieved here by developing and testing a new methodology that, in the case of cascading District Metered Areas (DMAs), enables the ERS automatically determining in which DMA an event occurred.

The remainder of this paper is organised as follows. After this introduction, an overview of the ERS and a description of the newly developed methodology for the detection of events in cascading DMAs are given in the methodology section. This is then followed, in the case study section, by details of the results obtained from the application of the new methodology to the historical pressure/flow data from several groups of cascading DMAs in the United Kingdom (UK) with real-life pipe burst events. Finally, the main conclusions of this study are drawn.

METHODOLOGY

Event Recognition System overview

An automated ERS has been recently developed by the authors and presented in Romano *et al.* [8]. This sub-section provides an overview of this system necessary to describe the methodology improvement associated with the development of the additional capability to

determine in which DMA an event occurred when cascading DMAs are considered. A more detailed description of the ERS is available in the above reference and in Romano *et al.* [10; 11], which respectively focus on the ERS calibration and on the development of the capability to microlocate bursts within DMAs (assuming the DMAs are observed by using a larger than currently used in the UK practice number of pressure sensors).

The current UK practice normally involves deploying pressure and flow sensors at a number of locations in each DMA, typically at import/export points and a pressure sensor at the critical point in the DMA. The DMA sensors typically collect and transmit the data at regular time intervals (e.g., every 15 or 30 minutes). Given this, the data processing in the ERS starts by receiving the data communicated by the DMA sensors. For each signal and at each communication interval u readings are obtained (e.g., 2 readings – assuming 15 minute sampled data, which are communicated every 30 minutes). These readings update a time series record which is stored in the Time Series database. Once the data from all the DMA pressure/flow sensors are fully processed as described below, the resulting u probability values that an event has occurred in the DMA and any additional information that may be used to perform a diagnosis of the incident occurring (e.g., to determine the event magnitude) are stored in the Alarms database. If any of the u probability values exceed a fixed detection threshold an alarm is generated. In order to avoid raising unnecessary detection alarms for the same event at the following communication intervals, however, any further detection alarm is suppressed for a user specified ‘alarm inactivity time’ period.

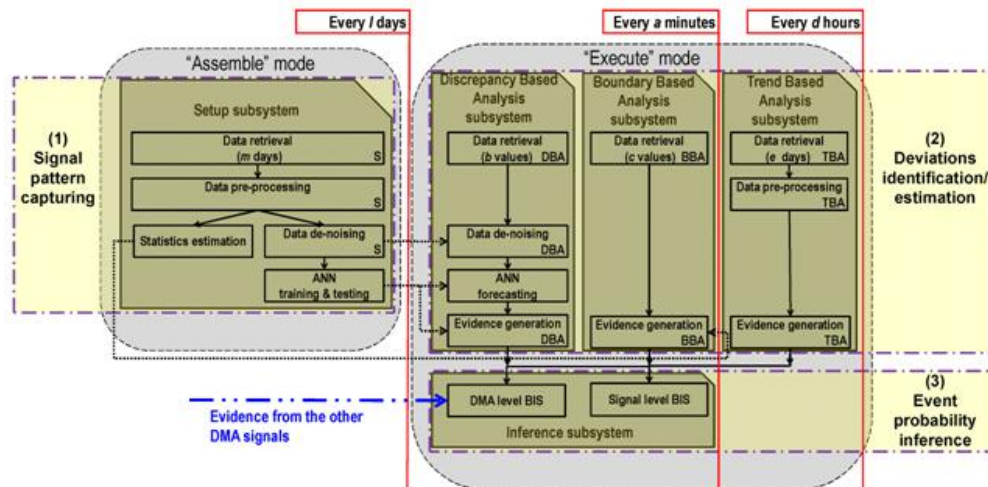


Figure 1. Diagrammatic representation of the ERS

Figure 1 shows a diagrammatic representation of the ERS. As it can be observed, the ERS enables event detection by performing three basic actions (i.e., shown as dotted dashed rectangles) as follows: (1) to “capture” (i.e., learn/estimate) the expected patterns of the pressure/flow signals assuming that no event occurred in the DMA being studied - i.e. the Normal Operating Patterns (NOPs), (2) to identify and estimate the event induced deviations between observed and “captured” DMA signal patterns, and (3) to infer the probability that an event has occurred in the DMA being studied based on the identified deviations. These basic actions are performed in the ERS by making use of five subsystems (i.e., shown as solid snipped corner rectangles) each containing a number of different modules (i.e., shown as solid

rectangles). The five ERS subsystems are as follows (1) the Setup subsystem, (2) the Discrepancy Based Analysis (DBA) subsystem, (3) the Boundary Based Analysis (BBA) subsystem, (4) the Trend Based Analysis (TBA) subsystem, and (5) the Inference subsystem.

The first subsystem is used to perform the first basic action (i.e., signal pattern capturing). Its first two modules (i.e., data retrieval, and data pre-processing) are used for retrieving the historical data from the Time Series database and assembling a set of data that best represents the most recent NOP of the signal being analysed (i.e., NOP data set). Once this is done, the third module (i.e., statistics estimation) is used for estimating several vectors of descriptive statistics from the NOP data set. These vectors provide a basic statistical information about the signal's NOP. The remaining modules (i.e., data de-noising, and ANN training & testing), on the other hand, are first used for de-noising the NOP data set and then for: (i) building an ANN model for the short-term prediction of future DMA signal values, and (ii) estimating the ANN model prediction error's variability. Since the resulting ANN model assumes that no event occurred in the DMA, it provides a model-based type of information about the signal's NOP.

The second, third and fourth subsystems, are used together to perform the second basic action (i.e., deviations identification/estimation) as follows: (i) the DBA subsystem checks that the discrepancies between the incoming observed signal values and their ANN predicted counterparts do not exceed pre-defined limits based on the estimated ANN model prediction error's variability, (ii) the BBA subsystem checks that the incoming observed signal values lie inside a "data envelope" whose boundaries are defined by using the vectors of descriptive statistics estimated from the NOP data set, and (iii) the TBA subsystem monitors, on a Control Chart, how the mean of the historical signal values recorded during a particular time window during the day (e.g., from midnight to 4 am, 4am to 8 am, etc.) varies over time. The reason for using three analysis subsystems is that by performing the above tasks in parallel they provide more conclusive event occurrence evidence and enable the detection of different event types.

Once all the DMA signals have been analysed as described above, the last subsystem is used to perform the third basic action (i.e., event probability inference). On the one hand, a DMA level BIS is used here for combining all the event occurrence evidence resulting from the three ERS analysis subsystems and coming simultaneously from all the DMA signals, inferring the probability of an event occurrence at the DMA level, and raising detection alarms. On the other hand, several Signal level BISs (one for each DMA signal) are used for inferring the probability of an event occurrence at the signal level and provide additional information for incident diagnosis such as a measure of the actual pressure/flow deviation from the analysed DMA signal's NOP (captured by means of the vectors of descriptive statistics computed in the statistics estimation module).

Figure 1 also shows that the ERS has two main modes of operation, the "Assemble" mode and the "Execute" mode. The "Assemble" mode is used for 'tuning' the data-driven ERS when it is initialised (i.e., used for the first time in a DMA). Later on, it is used: (i) regularly (e.g., weekly) when the ERS is updated (to capture the latest normal operating conditions of a DMA) thereby providing a continuously adaptive ERS and (ii) periodically when the ERS is reinitialised (following occasional operational/other DMA changes - e.g., re-valving). The "Execute" mode is the normal operating mode used at every communication interval to detect the events occurring and raise the alarms.

Event detection in cascading District Metered Areas

This sub-section provides a description of the novel methodology that enables the ERS to automatically determine the location of an event (at the DMA level) within a group of cascaded DMAs. The main motivation for the development of this methodology has been to overcome an important ERS's limitation. Indeed, it can be easily inferred from the ERS overview provided in the previous sub-section that, in the case of DMAs arranged in a cascading layout (e.g., a DMA export point is another DMA import point), a single event such as a pipe burst may result in alarms being generated in multiple DMAs. These alarms may furthermore be raised at different communication intervals. Consequently, the operator may be presented with several, apparently unrelated alarms. Bearing this in mind, it is clear that, by automatically determining in which DMA the event occurred and hence reducing the overall number of raised alarms, the ERS not only enables the water company personnel to quickly target the correct problem area but also facilitates the operator's results interpretation.

The newly developed methodology makes use of a set of heuristic rules that combines the ERS outputs to produce a "high-level" (i.e., composite) alarm state for a group of cascading DMAs. These rules attempt to capture the architecture of a particular WDS by taking into consideration what can be observed from analysis of real-life WDS configurations. For example: (i) a DMA can, in all cases, be classed as either isolated or interconnected, (ii) an interconnected set of DMAs can be treated as a group of cascading DMAs, and (iii) interconnected DMAs usually have a precise ordering relationship in terms of their inputs and outputs. Furthermore, these rules attempt to capture engineering knowledge of what can be observed from analysis of the hydraulic behaviour of real-life WDSs. For example, the effect of a pipe burst (i.e., the flow increase observed at the DMA import point) always propagates from the "most downstream" leaf DMA to the root DMA. Bearing this in mind, the simultaneous analysis (using the proposed heuristic rule set) of the outputs of specific Signal level BISs (i.e., those relative to the flow signals coming from the import point of each DMA in a particular cascading DMAs group) enables providing the aforementioned "high level" detection alarm. That is to say, by taking into consideration the actual WDS layout and the "sign" of the flow variations (i.e., increasing/stable/decreasing) at the import point of the DMAs in a cascading DMAs group, a single alarm (which is associated to the DMA where the burst occurred) can be raised for a group of interconnected DMAs. All this is illustrated in Figure 2 together with a rule example.

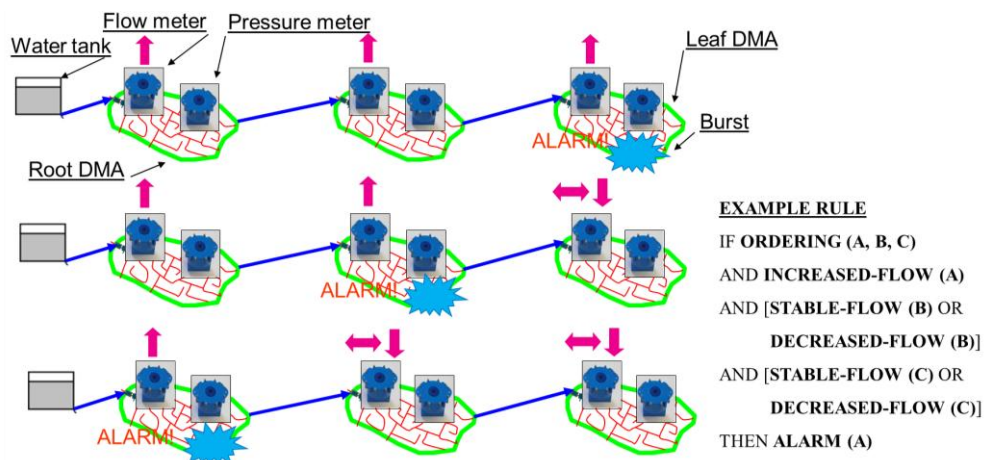


Figure 2. Graphical representation of the rules that enable event detection in cascading DMAs

CASE STUDY

This section reports the results of applying the newly developed event detection in cascading DMAs methodology to the historical pressure and flow data coming from nineteen United Utilities' DMAs with real-life burst events. The considered DMAs have different characteristics and varying sizes. As an ensemble, they contain light industrial, urban and rural regions. The number of customer connections in each of these DMAs approximately varies between 400 and 3,000. Their individual total mains length approximately varies between 10 and 30 km. They are all equipped with a flow sensor at the DMA import/export points and a pressure sensor at the critical point in the DMA. As it can be observed from Figure 3, the considered DMAs are arranged in such a way that they form five groups of interconnected DMAs. These groups have different layouts and each of them contains between two and seven DMAs.

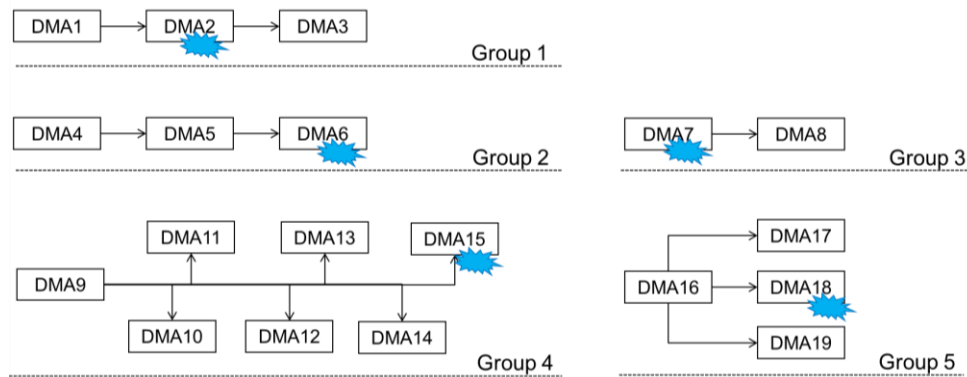


Figure 3. Cascading DMAs groups and pipe burst events locations

A total of five real-life burst events were considered in this case study. The locations of these events (i.e., DMAs where the bursts occurred) are shown in Figure 3. These locations and the likely events' start dates and times were identified by using the water company's records of: (i) customer calls reporting problems with their water supply and (ii) main repair works carried out on the network. Following manual inspection of the flow signals coming from the DMAs where the bursts occurred, the bursts' flow rates were estimated as approximately ranging between one fifth and five times the relevant DMAs' average daily net flow. This said, it is important to stress here that these "inspections" of the water company's records and historical data were all carried out after fixing the heuristic rules (and related parameters).

Flow and pressure data recorded at a 15 minute interval were used for the analyses carried out here. For each group of cascading DMAs the utilised pressure and flow data referred to the approximately three months period (i.e., evaluation period) that goes from exactly (i.e., starting at 00:00) 60 days prior the likely burst start date to exactly (ending at 23:45) 30 days after that date. Note that although historical data were used, the pressure/flow measurements were fed to the ERS in a simulated 'on-line' fashion (i.e., as the ERS would have been used in real-life).

After performing this case study's detection tests, the following results were obtained. The ERS identified all five burst event and, in all cases, it successfully determined in which DMA the event happened. It did this without raising any false alarm in the various evaluation periods. One event was identified within 15 minutes from its likely start time whilst the remaining four events were identified within 30 minutes. These results clearly demonstrate the effectiveness of

the novel methodology for event detection in cascading DMAs presented in this paper and, more generally, the excellent ERS performance in terms of detection reliability and speed.

Bearing in mind the above, a detection example is shown in Figure 4. This figure shows the available pressure and flow signals coming from the three DMAs in group 1 on the day (i.e., the 2nd of July 2012) the relevant real-life burst event occurred. The figure shows that, at 8:45, following the occurrence of this (large) burst event, the ERS returned probabilities of an event occurrence (i.e., P_{global}) as equal to 0.92 and 0.86 for DMA1 and DMA2, respectively. At 9:15, it returned a probability of an event occurrence as equal to 0.67 for DMA3. These event occurrence probabilities were all greater than the pre-defined threshold probability for generating alarms (i.e., 0.5) and would have therefore resulted in three independent alarms. By using the proposed heuristic rule set, however, the ERS only raised a single composite alarm at 8:45 associated to DMA2, which is the DMA where the burst event actually occurred. Having said this, it is also worth reporting here that the first customer contact was received only at 9:49 (i.e., more than one hour after the ERS alarms). This highlights the fact that by using the ERS an intervention could have been quickly initiated and the repair could have (possibly) been carried out before the consequences of this event were even noticed by the customers.

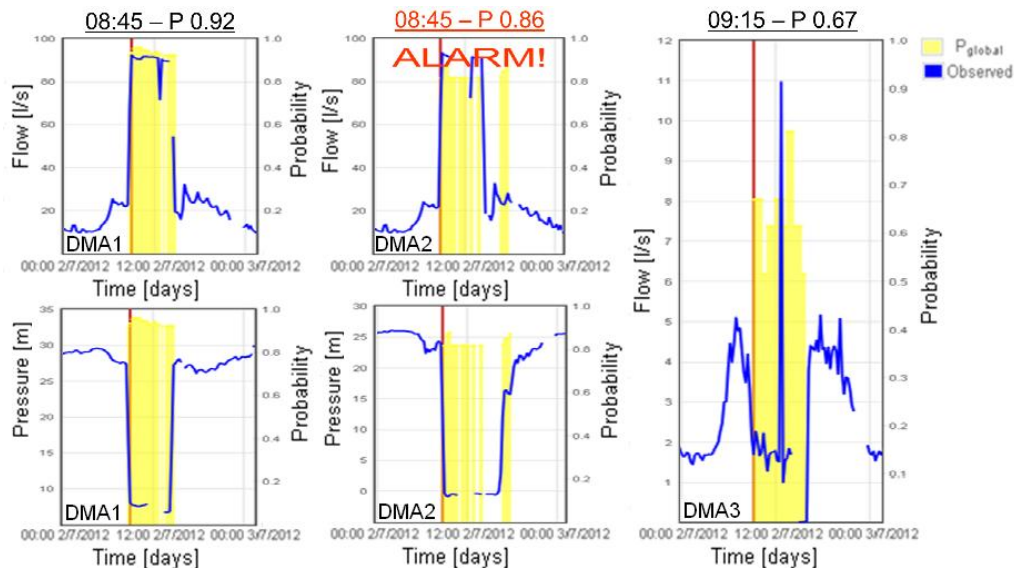


Figure 4. Detection example in cascading DMAs group 1

CONCLUSIONS

The pressure and flow measurements collected by modern SCADA systems provide a potentially useful source of information for detecting pipe bursts and other similar events in WDSs both quickly and economically. An ERS that makes use of these measurements has been recently developed by the authors. An improvement of this system concerning the development of a novel methodology for automatically determining in which DMA an event occurred when cascading DMAs are considered has been described in this paper.

This novel methodology has been tested here on historical data from five groups of cascading DMAs with real-life burst events. The results obtained have clearly demonstrated the

methodology effectiveness in automatically determining in which DMA the event occurred (five out of five correct DMAs identifications) and further confirmed the excellent ERS performance in terms of detection reliability (zero false alarms) and speed (all events detected within 30 minutes from occurrence).

Effective event localisation at the DMA level enables water companies to target the exact event localisation resources to the greatest effect and facilitates the operator's interpretation of the ERS results. Reliable and timely event detections may enable the water company's personnel to gain confidence in the raised alarms and facilitate prompt interventions and repairs. All this, in turn, may reduce the potential damages to the infrastructures and to third parties and improve the water companies' operational performance and customer service thereby yielding substantial improvements to the state-of-the-art in near real-time WDS incident management.

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