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Development of a data driven FDD approach for building water networks: Water Distribution System Performance Assessment Rules

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ABSTRACT

While fault detection and diagnosis is a popular tool in the process industry, its application in building water distribution systems is however still largely absent. In this study, a new set of Water Distribution System Performance Assessment Rules (WDSPARs) were developed to identify common faults in a building water distribution system. The WDSPARs comprise a three-phase process which can be applied using flow and pressure sensor signals obtained in real-time and/or via analysis of historic data in conjunction with knowledge of water distribution system layouts. The performance assessment rules originated from analysis of behaviour in water consumption at two non-residential pilot sites over a 6 month trial. Implementation of WDSPAR at the two pilot studies revealed a number of faults and cases of non-optimal performance which were diagnosed and costed accordingly. The WDSPAR approach is intuitive and can be easily integrated into existing building management systems using sensor data. This study serves as the first practical guide for the implementation of the WDSPAR approach for adoption by large non-residential building end-users. Using the WDSPARs, the case studies outlined in this paper demonstrate 62% savings in water consumption which resulted in energy and carbon emission savings of the order of 50 kW.hr and 29.9 kg.CO_2 per day respectively.

Keywords: Rule Based; Fault detection and diagnostics; Flow signature; non-residential building water distribution systems; smart meters; Waternomics.

1. Introduction

1.1. Overview

Building services such as water distribution systems (WDSs), Heating Ventilation Air Conditioning (HVAC) systems and other electrical services are subject to failure. These can often go unnoticed for extended periods of time until deterioration results in noticeable increases in operational costs, significant resource wastage, loss of comfort and a disruption in day-to-day activity (Schein et al, 2006). The failures are termed system "*faults"*, generally defined as a departure from an acceptable range of an observed variable or a calculated parameter (known as a redundancy) associated with a process (Himmelblau, 1978). Fault detection and diagnosis (FDD) is the approach whereby system faults or failures are detected, isolated, and guidance on measures to remediate the problem is provided. The application of FDD methodologies is common in the control and automation community and has been successfully applied in industrial disciplines including; chemical and petrochemical processes (Himmelblau, 1978), the automotive industry (Ahmed et al, 2015), the aerospace industry (Zolghadri et al, 2010), heating ventilation and air conditioning (HVAC) systems (House et al. 2001; Schein et al, 2006; Bruton et al., 2013), wind farms (Yang et al., 2010; Yu et al, 2018) and water and wastewater treatment processes (Baggiani et al., 2009; Corominas, 2011).

In recent years, with increasing energy and water costs coupled with the advent of smart metering technologies (Clifford et al, 2017), and advanced metering infrastructures (Dai and Gao, 2013), there has been a growing need for FDD in water distribution systems (WDSs) (Ragot and Maquin, 2006; Izquierdo et al, 2007; Gertler, 2010; Lee et al, 2012; Curry et al., 2014). Faults in WDSs can include mechanical failures such as malfunctioning pumps, actuators or heating elements, control sensor issues including data drift, loss of data or loss of communication and sensor uncertainty, water quality issues (e.g. stagnation), non-optimal performance, water leakage and other forms of unanticipated continuous flows. The latter two faults are the most common types of issue in municipal WDSs where it has been reported that 25 – 35 % of water is lost in the WDS due to leaks (BIO Intelligence Service, 2012; Kingdom et al., 2006; Choi et al, 2017). Non-optimal performance of a system can result from a fault which has gone unnoticed for extended periods of time or from inefficient use of water. Over an extended period of time, despite non-optimal performance, this may be regarded by an FDD system as 'normal operation'. For example, in the context of HVAC systems it has been long accepted that key savings in the future will be obtained mainly through optimal control (Bruton et al., 2013; Hyvarinen and Karki, 1996). Thus, it is essential that an FDD methodology adopts relevant approaches to update the rule set and thresholds after the system has been optimised.

In general, leaks and wastage are said to account for a significant portion of water demand. For example, 20 to 40% of Europe's water is said to be wasted (BIO Intelligence Service, 2012; Choi et al, 2017) due to poor infrastructure, consumer negligence and lack of proper resource management while 270 billion litres of water losses per day occur in the United States alone (Hendrickson and Horvath, 2014). Because a municipal WDS captures and aggregates building level water usage activity (which in Europe accounts for 21% of the total water usage (BIO Intelligence Service, 2012), it can be assumed that a sizeable portion of the leaks or wastage may manifest within building (both non-residential and residential) WDSs. Thus, there is a scope for significant leak reduction by ensuring FDD practices are encouraged at the end-user level. Furthermore, due to the strong nexus between water and energy use, it is said that up to 7% of global energy use is associated with the treatment, delivery and disposal of water (James et al. 2002; Hendrickson and Horvath, 2014). Thus, it is apparent that there is also significant scope to reduce energy demand and associated greenhouse gas emissions associated with the water sector. Apart from leak detection and mitigation, FDD could also facilitate further performance improvements through identification of areas of poor system performance and other consumption 'hot spots' where optimisation measures can induce significant water and energy savings in buildings. Prognosis of minor problems before they become major problems is also a strong component of FDD (Schein et al, 2006).

However, to date it appears that no, systematic FDD approaches are available for WDSs in buildings that cover a wide range of fault conditions simultaneously. To address this, an FDD approach must be practical and intuitive such that the approach can be easily implemented to impact building resource efficiency. In this article, a set of Water Distribution System Performance Assessment Rules (WDSPARs) which can be coupled to general WDS optimisation practices, were developed to deliver the primary constituent of a fault detection, diagnostics and optimisation tool for application in the domain of residential and non-residential buildings. The study discusses how a rule based approach can be developed and integrated in the context of WDSs where two case studies were analysed for six months using the proposed WDSPAR methodology. The WDSPARs were applied manually to demonstrate FDD over the initial six-month period where the detection algorithm was compared to known reported faults in the network. Example faults are also presented in this paper together with potential water and energy savings that may be acquired through WDSPAR FDD implementation.

2. A Review of Fault Detection and Diagnostics Approaches

As building services systems develop, service infrastructure is becoming so complex that the average operator/end-user faces difficulty in interpreting operational behaviour and identifying underlying problems (Clifford et al. 2017). For example, if a problem exists in a WDS, existing building management systems (BMSs) currently available to monitor water usage do not support FDD (Hyvarinen and Karki, 1996; Clifford et al. 2017). Moreover, despite comprehensive water monitoring methods (Clifford et al. 2017), existing faults may go undetected for extended periods of time resulting ultimately in non-optimal performance as discussed previously. These 'unknown' faults would not be detectable without an external monitoring system. To avoid this, the operator should continuously monitor the process and identify defective systems, sub processes or components (Hyvarinen and Karki, 1996; Clifford et al. 2017) as well as seek expert advice on system optimisation. This section will focus on the available methods, tools and application of FDD in (i) the general process industry and (ii) WDSs.

2.1. Classification of FDD methods

Various FDD methods have been widely classified by Venkatasubramanian et al, (2003a, 2003b and 2003c) into three distinct categories: (i) quantitative model-based methods, (ii) qualitative model-based methods and (iii) process history, data driven methods as outlined in Figure 1 where the latter is also referred to as model-free approach (Nozari et al, 2018). Venkatasubramanian et al.'s (2003a, 2003b and 2003c) review is a comprehensive and generalised appraisal of FDD state-of-the-art in the process control industry. The aforementioned categories have also been considered through (i) model based FDD, (ii) signal based FDD and (iii) knowledge based (history-data-driven) FDD by Dai and Gao (2013). Each category will be discussed briefly in this section.

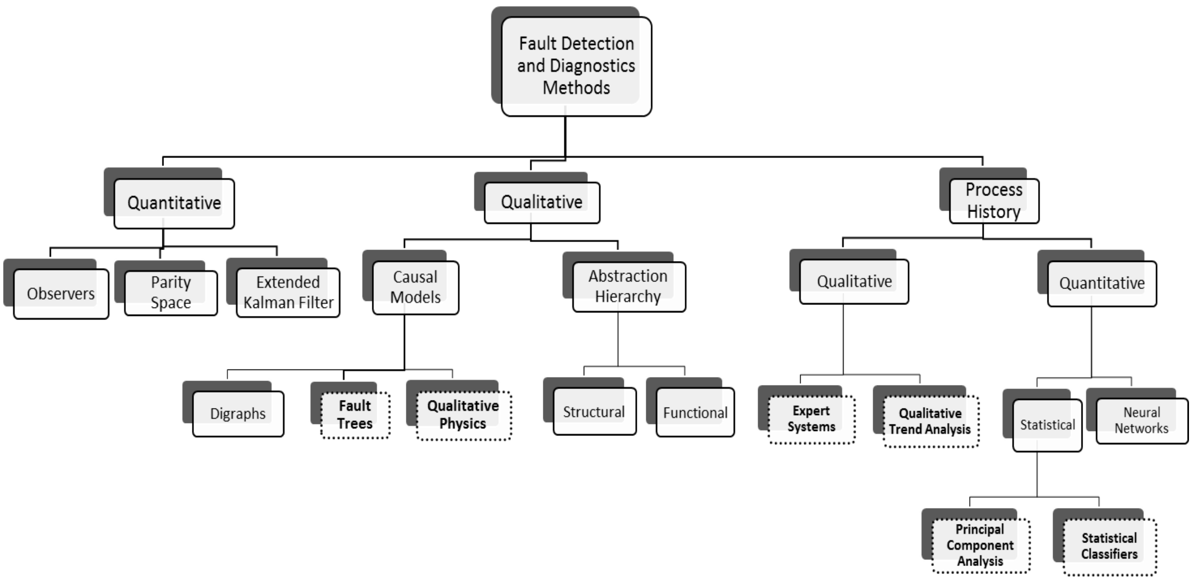


Figure 1. Fault Detection and Diagnostics Methods; Adopted from Venkatasubramanian et al (2003)

Quantitative model-based FDD has become the mainstream of research since the 1980s (Dai and Gao, 2013). In the quantitative model based approach, use is made of a mathematical model (M) together with a model parameter (θ) that classifies the generated residual (R). The residual is the difference between a parameter defining the normal mode of operation and analyses of real-time (or quasi real-time) values of the parameter that designate the 'current' status. In other words, the residual is the difference between a certain water usage metric (e.g. flow, pressure, temperature) and its average value during normal operation. WDS system output (i.e. flow sensors) is fed into the FDD process engine which generates a residual based on comparing the measured data to the models predictions (Venkatasubramanian et al, 2003a; Dai and Gao, 2013). Once this residual exceeds a critical threshold, an alarm is triggered to indicate a fault. Quantitative model-based approaches can be further sub-divided into parameter estimation (Young, P., 1981; Issermann, 1984), Parity relations (Gertler and Singer, 1990) and observer/filter based approaches (Frank and Ding, 1997).

In contrast to quantitative approaches, qualitative models are based around qualitative functions (Venkatasubramanian et al, 2003b). There are fundamentally two methods: topographic search and symptomatic search (Venkatasubramanian et al, 2003b). Topographic search approaches perform FDD using a template or signature for normal operation and are therefore quite similar to signal-based methods outlined by Dai and Gao (2013). Thus, in a WDS, qualitative FDD could be adopted based on known water usage flow signatures (Clifford et al., 2017). Symptomatic searches look for symptoms to direct the FDD search to the origin of the fault. These are often termed a 'shallow' search given that the FDD system does not have a deep physical understanding of the systems behaviour.

Process history (model-free) based FDD employs a 'learn-by-example' mechanism based on process history data. This type of approach is mostly applicable in systems which are too complicated to have an implicit/explicit system model or qualitative search approach. The process history based approach is often enabled by artificial intelligence and machine learning (Ntalampiras, S., 2014) which acquires knowledge from empirical data to determine normal, fault-free operating conditions and subsequently to monitor system redundancies for faults during the faulty system state.

2.2. Industrial Applications of FDD

A common application of FDD is in mechanical services of commercial buildings, namely HVAC systems. These relate closely to WDSs given the dependence on fluid flow and heating. Determination of building key performance indicators often depend on HVAC metrics such as energy efficiency, indoor air quality, comfort and reliability is becoming an increasingly difficult process calling on the need for higher more advanced FDD techniques and practices. For example, Haberl and Claridge (1987) developed an expert system for building energy consumption analysis. Anderson et al, (1989) utilised a statistical analysis pre-processor to screen incoming data and estimated system operating parameters coupled with a rule-based expert system which analysed system redundancies on an hourly basis. House et al., (1999) classified a range of approaches for FDD in air handling units and observed that the Bayes classifier is most suitable for fault-detection while a rule-based approach is most suitable for diagnosis. Schein and Bushby (2006) developed a rule-based, system-level FDD approach which provided an interface between equipment specific FDD and a human operator.

In the chemical industry, data driven methods include principal component analysis (Russell et al., 2000; Jiang, 2013), fisher discriminant (Chiang, 2000), canonical variate analysis (Russell et al., 2000), partial least squares (Leo, 2000). A comprehensive summary of techniques and practices in the context of chemical engineering is provided by Russell et al (2012). FDD has also seen extensive application in the aerospace industry (Kiyak et al, 2010), metal production (Hongm, 2009), wind farms (Yang et al., 2010) and water and wastewater treatment processes (Baggiani et al., 2009; Corominas, 2011; Fuente et al, 2012) using quantitative, qualititiave and process history based approaches. Hybrid approaches have also been studied (Venkatasubramanian et al, 2003a) as frequently no single method has all the desirable features required (Parvanov, 2016).

2.3. FDD in Water Distribution Systems – State-of-the-Art

Isermann (1984) provided an early review of FDD methods in fluid flows using two examples of a centrifugal pump parameter and leak detection in a pipeline. It was observed that physical methods for locating leaks such as ground penetrating radar, infrared spectroscopy, hydrostatic testing and acoustic devices could be outperformed by simpler methods for leak detection in the WDS. For example, a simple balance between day and night water demands may reveal data anomalies directly indicative of a leak (Pudar and Liggett, 1992). In recent years there have been advances in developing FDD for WDS. Advanced sensor technologies and modelling techniques evolved over time, which helped to identify and rectify WDS faults (Perfido et al., 2016). Also, model-free approaches using machine learning is becoming topical in the area of WDSs at the municipal scale. For example, Ntalampiras, S., (2014) developed a holistic modelling scheme for fault identification in distributed sensor (pressure and flow) networks of the Barcelona WDS. Their approach was able to understand whether the data anomalies belong to the fault dictionary, are fault-free, or represent a new fault type. Key studies in this field and their key findings and knowledge gaps are summarized in Table 1 in chronological order. However, as can be seen in this Table, there are little to no studies carried out on a non-residential building water network. Moreover, the studies tend to focus their FDD approach on a specific fault category (for example leaks). In a non-residential building water network however, wide variations of faults of can occur simultaneously which would be difficult to address using the techniques outlined in these studies. Therefore, the authors identified that there is a gap for a practical, fault catalogue and performance assessment rule set for intuitive application in building WDS as is proposed in this study.

Table 1. Review of literature pertaining to FDD in water distribution system

Reference	Objective	Method	Key findings	Knowledge gaps
Colombo & Karney, 2002	Characterizing energy and water loss of a leaky pipe	Derivation of analytical parameters relating to leak size and location using EPANET	Percentage increase in energy cost was found to be a function of leakage	Focused on tying energy costs to head loss in pipes than on the leakage impacts on pumps.
Colombo & Karney, 2003	Pipe breaks and the role of leaks from an economic perspective	Analytical expression for sizing and locating leaks in a pipe defined by energy consumption and hydraulic transients	Pressure management and life cycle analysis can be used to improve the leaks and water system performance and efficiency	Focused on relating energy cost to leakage in pipes than the faults in entire WDS. There is a need to take into account life cycle analysis
Colombo & Karney, 2005	Impact of leakage in systems with storage on energy use	Analysis of leakage impacts on pumps and energy costs of three WDS configurations: two with storage tanks at different points and one without storage	Storage does not guarantee lower energy consumption and in some cases higher if tank water levels and pressures are high.	Results derived from hypothetical systems and very much system specific. Non-optimal performances are not considered
Eliades & Polycarpou, 2010	Development of mathematical framework for control, fault diagnosis and security of WDS	Mathematical problem formulations, which included state-space representation of contaminant propagation and reaction dynamics along with impact dynamics. Single and multi - objective evolutionary algorithm optimization for optimum sensor placement in networks	It was found that a suitable number of sensors can be estimated for sensing the impacts caused by water contamination, thus avoiding impacts	This approach mainly dealt with water contamination faults and lacked focus on leaks and other pipeline faults.
Gertler et al., 2010	Methodology to detect and localize leaks in a regional water distribution network	Application of principal component analysis (PCA) and structured residuals to diagnose faults	The developed methodology was successfully applied to a case study water network	Dimensionality problem due to PCA was limited by disturbances in nodes. Also could not overcome the problem of spatial separation of faults from normal data
Isermann, 1984	Review of FDD methods in fluid flows	Review and example illustration of FDD of CF pump by parameter monitoring and	Process fault detection and diagnosis methods improve the overall reliability and	Methods developed for one fault type may not be suitable for another and vice versa, therefore several methods to be used in parallel

		leak detection for pipelines by special correlation method	safety of processes to a high degree	
Izquierdo et al., 2007	Suitable state estimation for diagnosis of leaks and faults in a large water supply system	Deterministic and neuro fuzzy based mathematical model for clustering and pattern classification	The ability of the model to correctly detect water losses depended not only on the magnitude, but also on the importance of the pipeline.	Small continuous water losses were not correctly identified and affected by noise in the data
Perfido et al., 2016	FDD in an airport WDS	Hydraulic modelling of the WDS using EPANET to train an Anomaly Detection with fast Incremental ClustEring (ADWICE) algorithm	The developed approach was useful when multiple parameters are considered simultaneously to determine faults. False positive rate, detection rate and accuracy results indicate good functioning of the model	The results described were for simulated training scenarios with synthetic faults and would be different for a real case scenario
Perez et al., 2009	Detecting and locating leaks in WDS using an efficient mathematical model	Pressure sensitivity analysis using integrated DMA, flow/pressure sensor data and hydraulic models	Non-optimal distribution of sensors caused poor results in real test.	Pressure drops due to leaks in a highly looped network are not identified and uncertainties in demands cause errors
Pudar & Liggett, 1992	Leak detection in WDS	Solving inverse problem using measurements of pressure and/or flow	Continuous measurements of pipe flow/pressure increases effectiveness of leak detection	Method not suitable for leak detection by static methods and is data intensive
Quevedo et al., 2014	Diagnosis/isolation of leaks in critical infrastructure systems like water, gas & electricity networks with centralized control systems	Two stage system integrating data validation and reconstruction techniques with 'Learning in the Model Space' for effective fault diagnosis. SVMs are used in model space for fault detection/isolation	Combined spatial and time series models successfully detected communication faults in tele-control system and learning in the model space successfully implemented by fitting generative models	Requires more in-depth studies of different generative (fitted) models and learning algorithms which best suit the proposed framework
Ragot & Maquin, 2006	Faults and abnormal system operation detection and isolation on urban water network	Fuzzy residual analysis, which used the analytical redundancy to detect and isolate faults on sensors and based on this	Found that there existed a high proportion of simultaneous faults in real processes. Fuzzy reasoning	Difficult to handle simultaneous faults in a real process, which requires further research. Also, non-

		approach a supervision software was developed	could be well adapted to uncertain data and model cases and alleviated difficulties in implementation of supervision procedure	optimal performances were not studied
Soldevila et al., 2016	Optimal placement of pressure sensors for leak detection in water networks	Simulations using different sensor configurations and using that data train *k*-Nearest Neighbours (*k*-NN) and neuro-fuzzy classifiers. Use of Genetic Algorithms (GA) to obtain the optimal configuration	Obtained sensor configuration using the methodology maximized leak isolation ability. For a moderate population size, GA provides better performance than Exhaustive Search Algorithm	Suitable for moderate population sizes only. The effectiveness of the method needs to be examined in a real WDS
Ntalampiras, S., 2014	Develop a holistic modelling scheme for fault identification in distributed sensor (pressure and flow) networks	Hidden Markov model (HMM) trained on the parameters of linear time-invariant dynamic systems	The approach was able to understand whether the data anomalies belong to the fault dictionary, are fault-free, or represent a new fault type.	Relatively difficult to implement by practitioners or end-users without in depth knowledge into the Hidden Markov model approach

To date the majority of FDD research studies regarding WDS were applied to large scale urban water supplies (Pudar and Liggett, 1992; Perez et al, 2009; Vento and Puig, 2009; Ragot and Maquin, 2006, Ntalampiras, S., 2014) as opposed to building water networks (Perfido et al., 2016). The majority of these studies exclusively focused on leak detection and there has been limited work on the adoption of FDD as a method for system optimisation. Furthermore, there is a distinct lack of application of FDD in residential and non-residential (commercial and domestic) buildings. Thus, this study presents a simple set of water distribution system performance assessment rules (WDSPAR) for the purpose of fault detection, diagnosis and building water network optimisation. The study presents these rules in the context of two non-residential case study buildings and evaluates the water and energy saving outcomes of these rules within the case-studies.

3. Methodology

3.1. WDS Description: Two Pilot Sites

Two pilot sites were used as part of this study; Pilot Site 1 – a large school facility and Pilot Site 2 – a university building facility. Both pilot sites underwent a preliminary evaluation over the course of 6 months to determine normal operational conditions (Clifford et al., 2017). The Pilot Site 1 water system (see Supplemental Figure 1) was fed primarily from a single mains water supply (MWS) which supplied (i) potable water, (ii) a 6 m^3 cold water storage tank and (iii) the domestic hot water (DHW) circuit in the building. The cold water storage tank supplied the cold water supply (CWS) to all cold water end-uses (taps, showers etc.). The water infrastructure also housed a rainwater harvesting system which collected rain water run-off from surfaces in a 37 m^3 underground storage tank and pumped it to a 9 m^3 grey water storage tank in the attic which in turn fed the grey water supply (GWS). This system supplied toilets and urinals. The MWS provided a back up to the grey water storage tank during dry-periods. The water infrastructure was monitored by 14 in-line water meters (B-Meters, Italy: meter model type varied) equipped with a magnetic pulse output. The in-line displacement meters recorded data at a frequency of 1 pulse/litre. The measurement error for the inline meters was dependent on the level of flow with a maximum reported error value of $\pm$ 5 %. A programmable logic controller (PLC) logged data at 7.5 minute intervals which was stored on a cloud database.

The Pilot Site #2 WDS comprised a system of pressurised copper pipes supplied principally by the MWS (see Supplemental Figure 2). The rainwater harvesting system comprised a 75 m^3 tank which collected rainwater and subsequently pumped it to two header tanks (8 m^3 each) located on the east and west side of the building's roof. The GWS conveyed grey water to the toilets and urinals in the building by gravity. The MWS fed both cold water supply and DHW and provided a top-up to the RWH system when required. The water network was fitted with 11 in-line positive displacement meters (B Meters, Italy) fitted with a magnetic pulsed output and 8 ultrasound flow (USF) meters (*VTec*, Netherlands).

The in-line displacement meters recorded data at a frequency of 1 pulse/litre. The building management system (BMS) logged data from 8 of the in-line meters at 7.5 minute intervals and the remaining 3 in-line meters at 15 minute intervals. During this study, the velocity and flow were reported at a high-resolution of one second intervals. More details on the pilot sites are provided in Clifford et al. (2017) and www.waternomics.eu.

3.2. Water Distribution System Performance Assessment Rules (WDSPAR) Methodology

There are mainly three types of approaches in FDD as used by various studies, which are quantitative, qualitative and process history as discussed in Section 2.1 and outlined in Figure 1. For relatively complex building services such as HVACs, which have a broad range of operating conditions (Schien and Bushby, 2005), rule-based approaches can offer a number of advantages including transparency and adaptability (Tzafestas, 1989; Viser, 1999; Schien and Bushby, 2005). Essentially, Rule Based approaches fall under the category of process history FDD and adopt a mixture of qualitative and quantitative techniques. House et al. (2001) and Schien and Bushby, (2005) demonstrated how rule based approaches can be effective for HVAC systems; given the complexity of WDS in large buildings this approach may offer greater capabilities for FDD.

The rule set and methodology developed in this study was named "Water Distribution System Performance Assessment Rules" (WDSPAR) - analogous with the HVAC Air handling unit Performance Assessment Rules (APAR). The WDSPAR (outlined in Figure 2) is not just a rule set but is also a methodology comprising three phases: Phase 1 – Assessment and Threshold Selection, Phase 2 – Performance Monitoring and Phase 3 – Diagnosis as described in detail in the following sections.

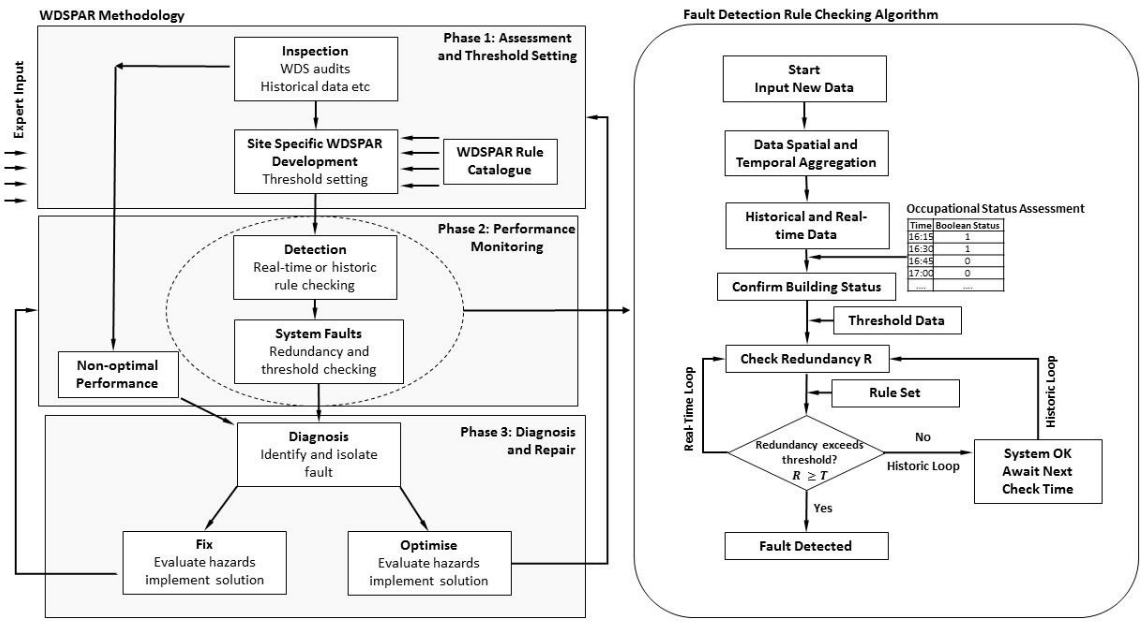


Figure 2. Flow chart of WDPSAR methodology outlining (a) 3 Phases and (b) the fault detection rule checking algorithm

3.2.1 Phase 1: Assessment and Threshold Selection

As outlined in Figure 2, Phase 1 of the WDSPAR process involves a comprehensive review of the existing WDS status through the analysis of WDS physical layout, historical data, water meter readings and the implementation of a water audits where appropriate. The current WDS monitoring infrastructure should be assessed to determine if additional sensors or meters should be installed. Then, using installed water usage sensors, Phase 1 is used to establish the normal water usage baseline activity prior to FDD intervention. Such baseline activity can be characterised by daily water usage data, diurnal flow patterns and high-resolution flow signatures which are described extensively by Clifford et al. (2017). Based on the established normal operating conditions, the residual during new operating conditions and a relevant threshold for the residual is used to notify the system of a fault and its severity. The threshold for the residual can be specified using one of two approaches:

1. Heuristic Methods: Expert knowledge from initial assessment is employed whereby the fault alarm level is adjusted/tuned by trial and error (Dexter and Pakanen, 2001)
2. Statistical Methods: Determined from confidence intervals and hypothesis testing using estimates of means and standard deviations (Dexter and Pakanen, 2001).

A statistical approach is formulated and adopted in the current study to determine residuals (for example, quantifiable variations in flowrate) between new and normal fault-free operating conditions as it provides the greatest opportunity to leverage detailed and robust data from water meters within buildings. The residual threshold, if exceeded, can then indicate abnormal flow conditions ultimately leading to the detection of faults. The WDSPAR also utilised high level occupancy information, which informs when water usage activity should be expected in a building. In this study occupied status is defined using Boolean logic, where 1 indicates that the building is occupied and 0 indicates that it is unoccupied. This analysis was performed manually in this study. Indeed, a next step would be to integrate automated data querying and analytics into a programmable logic controller to compile the multiplier, average, standard deviation in a similar approach to manual analytics. Some human intervention through a domain expert may always be necessary, however.

3.2.2 Phase 2: Performance Monitoring

In Phase 2 water usage information is queried either on a historic or real-time basis to determine any deviations from the WDS normal behavioural state to determine non-optimal flow conditions, system faults or component faults. In this study the algorithm outlined in Figure 2 was developed to achieve this. As the rule checking algorithm initiates at the required time interval, it first queries new data and performs the required spatial or temporal data aggregation (Clifford et al., 2017). The status of the building (e.g. occupancy) and environment (e.g. rainfall) is then confirmed and comparisons with the relevant rulesets (Section 3.4) are used to determine if faults or non-optimal performance may be occurring.

3.2.3 Phase 3: Diagnosis and Repair

Phase 3 required fault diagnosis through fault definition and isolation, ultimately leading to repair. In this study the building water networks were represented using Dendrograms to aid the fault diagnosis and isolation process (detailed in Section 5.1). The signature of the abnormal usage activity was then linked to the relevant water meter at the lowest point of the Dendrogram hierarchal structure to help isolate the approximate location of the fault without the requirement for a manual search within the WDS. Once the fault had been isolated and repaired, the building reverted to the Phase 2 state. Whereas, if non-optimal performance has been detected, the WDS is optimised accordingly and the WDSPAR process returns to a Phase 1 state due to the fact that new water usage baselines may need to be obtained (see Figure 2 flow chart).

3.3. WDSPAR Data Requirements

In general, WDSPAR requires one or more of the following data:

- Water consumption volumes via metering (aggregated over the required duration – e.g. hourly or daily water consumed);
- Water consumption rates Q_t via metering (at suitable time intervals);
- Real time pressure sensor signals P_t;
- Occupancy information (1 for occupied, 0 for unoccupied);
- Tank storage water level sensors;
- Tank water storage information (sizes, volumes);
- Water network layout.

3.4. WDSPAR Preliminary Rule Set

The rule set introduced in this study was developed on the basis of hydraulic logic and simple mass flow balance considerations across meters and sensors located at various locations in the WDS. These are based on the performance variables defined in Table 3 and the current study mostly leveraged data from flow meter sensor readings. Regarding cases where the sensor is of the 'mass flow meter' type (i.e. an inline or ultrasonic flow meter) the meter readings can either be an instantaneous flow reading Q at time stamp t or a volume aggregation over a time interval Δt. In the latter situation, the flowrate for time stamp t is assumed to be averaged over Δt such that $Q_t^m = V_t^m/\Delta t$.

Table 2. Performance variables for WDSPAR methodology

Parameter	Description	Unit
P_t^m	= pressure at time stamp t at meter m	kNm^{-2}
Q_t^m	= flowrate at time stamp t at meter m	m^{3}s^{-1}
$V_{\Delta t}^m$	= volume accumulated over an interval Δt at time stamp t at meter m	m^3
$V_{t\ norm}^m$	= baseline water usage volume aggregated over time Δt at time stamp t	m^3
$Q_{t\ norm}^m$	= baseline water usage flowrate at time stamp t	m^{3}s^{-1}
T	= duration of observation	s
ΔV	= volume change	m^3
Δt	= aggregation interval or sampling rate of the meter	s
$V_{t+\Delta t}$	= volume accumulated at time stamp $t + \Delta t$	m^3
ε_t	= critical volume usage residual threshold	-
q_t	= critical flowrate residual threshold	-
ε_{Ost}	= threshold unoccupied to occupied water usage ratio	-
k	= threshold factor	-
$Q_{t\ in}^{m_i}, Q_{t\ out}^{mj}$	= flow in, out of meter i, j	m^{3}s^{-1}
Q_{RWS}, Q_{MWS}	= flow in rainwater harvesting system (RWS) or mains water system (MWS)	m^{3}s^{-1}
$V_{t\ acc}^m, V_{pipe}^m$	= volume accumulated at meter over time t and volume of pipe section leading to water fountain	m^3
$O_{st} = 0, 1$	= occupancy status where 0 is unoccupied and 1 is occupied	-
T_d, T_n	= day time and night time durations	s
R	= residual (e.g. $R = V_t^m - V_{norm}^m$)	Varies

The preliminary rule set for the WDSPAR is outlined in Table 4 together with a brief description of each rule.

Table 3. Preliminary rule set for the WDSPAR

Fault Description	Rule No.	Detection Rule	Description	Manual Observation
Low pressure (Prognosis)	*1*	$P_t^m < P_{LCrit}$	Pressure readings are monitored in real time to detect a drop below critical threshold	N/A
	2	$Q_t^m < Q_{LCrit}$	Flowrate readings are monitored in real time to detect drop below critical threshold	Visual, auditory sign of escaped water or evidence of structural damage
High pressure (Prognosis)	*3*	$P_t^m > P_{HCrit}$	Pressure readings are monitored in real time to detect exceedance of critical threshold	N/A
Continuous flow (Leak)	*4*	$\lvert V_t^m - V_{norm}^m \rvert > \varepsilon_t$	Difference/residual (between volume used during time Δt at time stamp t and the baseline volume) exceeds the critical volume usage redundancy ε_t	N/A
	5	$\lvert Q_t^m - Q_{norm}^m \rvert > q_t$	Difference/residual (between flowrate at time stamp t and the baseline flowrate) exceeds the critical flowrate residualq_t	N/A
	6	$\frac{\sum Q_t^m . T_n \, for \, O_{st} = 0}{\sum Q_t^m . T_d \, for \, O_{st} = 1} \geq \epsilon_{Ost}$	Ratio of night time T_n ($O_{st} = 0$) to day time T_d ($O_{st} = 1$) volume usage exceeds the critical occupied status ratio	N/A
	7	$\left(\frac{V_{t+1} - V_t}{T_{t+1} - T_t}\right) > k \frac{\Delta V}{T}_{norm}$	Volume consumption accumulated over a time period $T_{t+\Delta t} - T_t$ exceeds the normal volume accumulation by a factor k	N/A
Tank overflow	*8*	$Q_{t\,in}^{m_i} \geq Q_{t\,out}^{m_j}$	Flow into tank exceeds flow leaving the tank	Reports from shower and kitchen users
Potable water retention time	*9*	$V_{t\,acc}^m \leq V_{t\,pipe}^m$ for $\Delta t = t_{Crit}$	Real-time	N/A

Similar to Schien et al., (2006), a fault is detected when a rule is resolved to 'Yes'. Rules 1, 2 and 3 rely on the a 'critical' or a hard ultimate threshold which if exceeded (or undershot) will immediately indicate a fault as is a requirement for flow shortage or high/low pressures in a network. The critical threshold should generally be established using the heuristic methods as outlined in Section 3.2.1. Rules 4 to 7 use thresholds (ε_t, q_t, ϵ_{Ost}, k) which are determined from datasets obtained within Phase 1. This study proposes a robust threshold selection process to limit Type I errors (where a type I error is the rejection of a true null hypothesis also known as a "false positive" finding). In order to reduce sensitivity to false positives, a dual alarm process is established by using two thresholds. For example, in Rule 4 the threshold redundancy ε_t is defined by $\lvert V_t^m - V_{norm}^m \rvert$ (i.e. the difference between the current water volume consumption and the normal 'baseline' usage conditions). For a population size n of water usage within a dataset (i.e. statistically similar datasets can be clustered - see Clifford et al., 2017; Cardel-Oliver, 2013), the threshold levels were set by defining a multiplier γ_l to the standard deviation σ of the dataset as follows:

$$\varepsilon_{t_1} = \gamma_1 \times \sigma \qquad \text{(for a level 1 alarm)} \quad (1)$$

$$\varepsilon_{t_2} = \gamma_2 \times \sigma \qquad \text{(for a level 2 alarm)} \quad (2)$$

where γ_1 and γ_2 are then derived from exceedance probabilities of 0.002 and 0.01 respectively representing 1/500 and 1/100 water usage events. These values were adopted as deemed suitable for municipal building studies, however the values are site specific and may change for other end-users such as industrial water use where water usage thresholds may be tighter. A Level 1 alarm occurs when a single flow event has been exceeded significantly (i.e. when ε_{t_1} is exceeded indicating an abnormal peak flow event) whereas a Level 2 alarm takes advantage of the time series nature of the flow data, with an alarm being triggered when two consecutive days have daily flow exceedance probabilities of 0.01 i.e. two consecutive 1 in 100 daily flow events which is archetypal of a continuous flow phenomenon developing. An example of threshold selection is provided in Section 4 and examples of fault anomalies, detectable using this dual alarm approach, for a daily water usage time series is outlined in Figure 3.

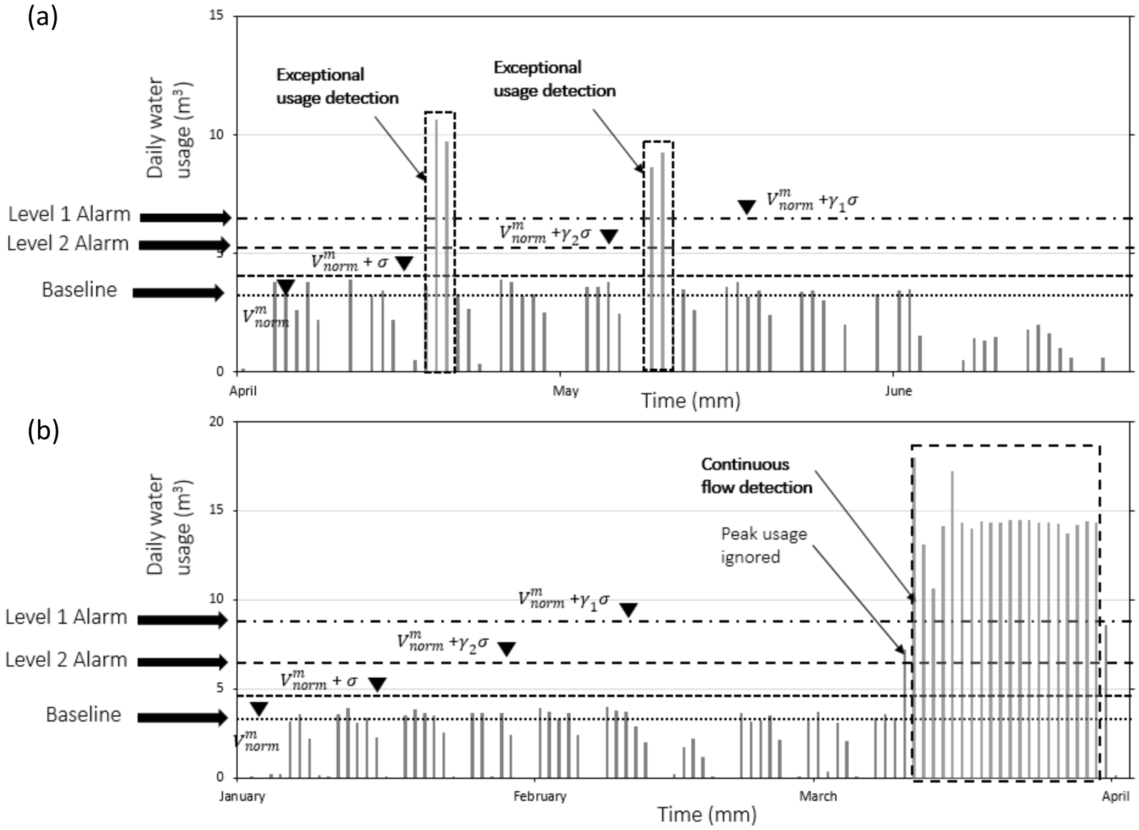


Figure 3 Example of the dual alarm approach to (a) exceptional usage detection and (b) continuous flow detection

4. Phase 1 Case Study Application: Assessment of Normal Usage Conditions and Threshold Selection

A 6-month evaluation period was used to evaluate normal operational conditions at each pilot. As displayed in Figures 4(a) and 4(b), daily water consumption time-series were established for each meter in order to determine the typical daily water usage baselines and diurnal flow signature patterns. During this initial phase, anomalies experienced in the flow trace were tied with evidence of known faults and non-optimal usages occurring within the pilot and were subsequently removed from the data set to ensure the data represented normal operating conditions.

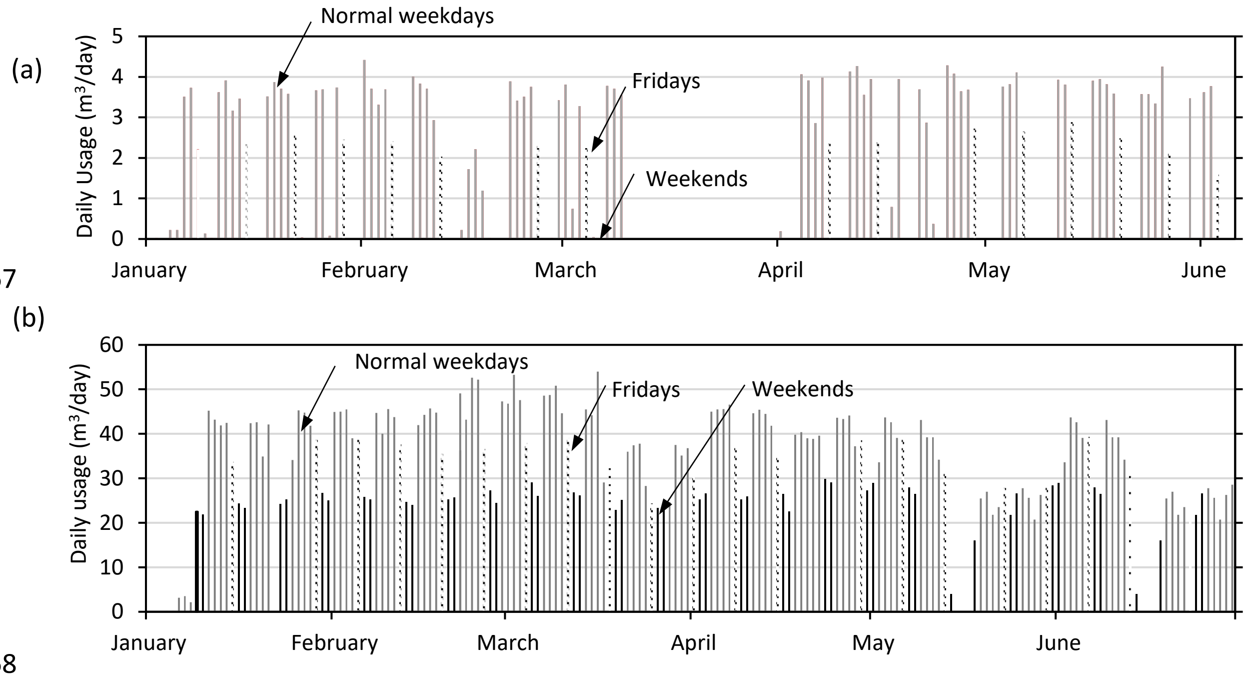


Figure 4. Medium resolution flow traces for the main water supply line of (a) pilot site # 1 and (b) pilot site #2 highlighting each sub-cluster: Grey = Normal weekday, Pattern filled = Friday and Black = weekend usage.

Through statistical analysis, it was found that the data was normally distributed within three clusters: (1) weekdays (Monday to Thursdays) (2) Fridays and (3) weekends; a summary of the baseline usage data is presented in Table 4 for both pilots. The normality of each individual data cluster was confirmed using the Anderson-Darling test, with a p-value of 0.05 and via histograms and Q-Q plots. The mean (baseline) daily water usage V_d and standard deviation σ_d for each daily flow cluster was then calculated. Further application of ANOVA to weekday groups (Monday, Tuesday, Wednesday and Thursday) indicated that there was no difference between each of the group means (Clifford et al., 2017).

Critical daily flow volume thresholds were then derived based on the statistical method proposed in Section 3.4. The alarm threshold redundancies ε_{t_1} and ε_{t_2} for Alarm Levels 1 and 2 respectively are outlined in Table 4 and were determined from a single tail test. It is important to note that a two-tailed approach could be implemented for cases where water usage may fall below a minimum threshold, this would then result in threshold multipliers of 3.10 and 2.58 for alarm level 1 and 2 respectively. Such a scenario could be suitable for applications such as programmed water usage in the process water industry and machinery water usage. For the current study, a fault in both pilot studies would be characterised by an excessive flow as opposed to a minimum flow.

Table 4: Summary of baseline statistics and threshold values for the dual alarm approach for both pilot sites

Detail	Notation	Pilot Site #1			Pilot Site # 2		
		Cluster					
		1	***2***	***3***	***1***	***2***	***3***
Average daily flow volume (m^{3}day^{-1})	V_d	4.42	2.73	0.00	43.29	36.76	25.50
Daily standard deviation usage ($\pm$ m^3)	σ_d	0.40	0.27	0.00	4.74	2.40	1.99
Level 1 Redundancy Threshold*	$\varepsilon_{t_1} = 2.9\sigma$	1.16	0.78	0.00	13.75	6.96	5.77
Level 2 Redundancy Threshold **	$\varepsilon_{t_2} = 2.3\sigma$	0.92	0.62	0.00	10.90	5.52	4.58

Cluster 1 = Monday to Thursday, Cluster 2 = Friday, Cluster 3 = Weekend

* $\gamma_2 = 2.9$ representing a 1 in 500 day flow event determined from a one tailed test. Upper usage threshold is $V_d + \varepsilon_{t_1}$. One-day exceedance can indicate an exceptional usage event which may be due to a fault or non-optimal water usage

* $\gamma_2 = 2.3$ representing a 1 in 100 day flow event determined from a one tailed test. Upper usage threshold is $V_d + \varepsilon_{t_2}$. Exceedance over one day indicates a peak usage event (possibly exceptional usage) and two consecutive days (or more) can indicate a continuous flow or leak. It may also indicate short periods of abnormally high occupancy in some buildings.

5. Results and Discussion: Case Study FDD and Optimisation (Phase 2 and 3)

As this study provides the first comprehensive catalogue and rule set for characterizing faults in a non-residential building, the results and discussion of the paper will be by way of practical examples from each pilot study as outlined below to demonstrate how the rule set can be applied accordingly.

5.1. Example 1: Rain Water Harvesting System Fault (Rule 1, 2, 3 and 8)

Rainwater harvesting systems have been shown to provide significant savings in building water supplies by offsetting mains water usage with harvested rainwater (Grant et al, 2012). The rainwater harvesting system at Pilot Site #2 was in a non-operational status for a number of months as a result of a faulty pressure sensor which was used to control pumping from the collection tank to the distribution tanks at roof level. This was established primarily through Rule 8 where a flow was present despite the fact that a full status was recorded in the storage tanks. Analyses of the meter readings on the line conveying flow to the grey water tank top-up also showed no activity for a number of months despite ongoing rainfall conditions (see rainfall distribution in Figure 5). Notification of the pressure sensor fault resulted in the replacement of the unit on the 26th November 2016. Figure 5 highlights the impact of the repaired rainwater harvesting system on the global building water usage averaged on a weekly basis.

Following periods of sufficient rainfall (as displayed by the dotted line in Figure 5), up to 33 % of total mains water usage was saved.

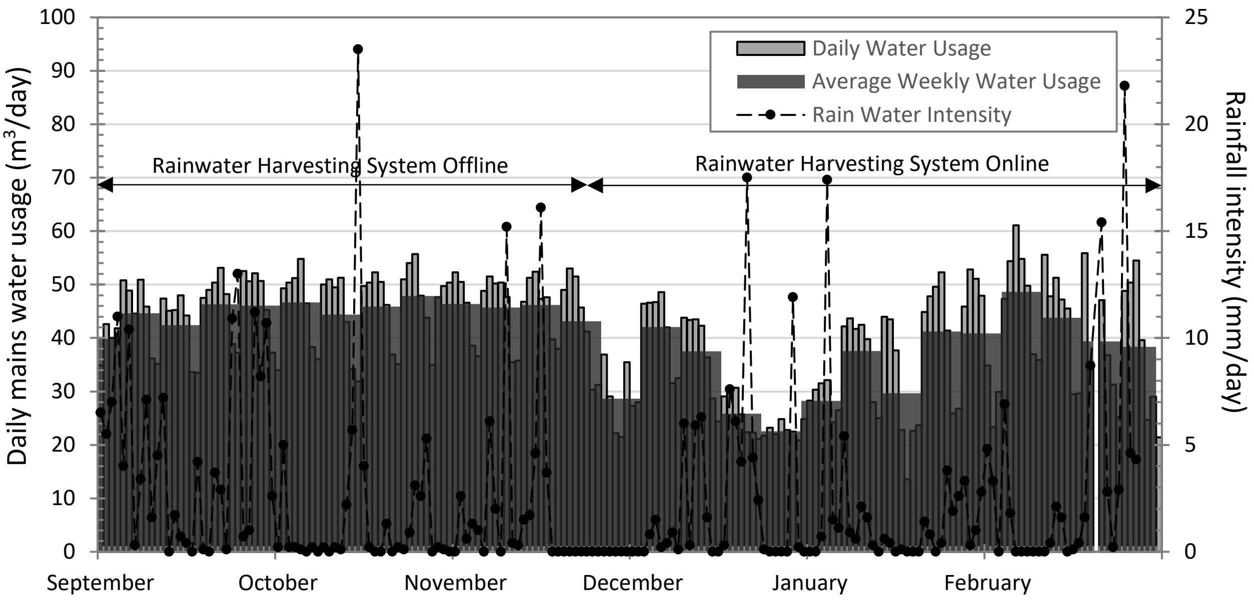


Figure 5. Variation of mains water usage as a before and after the repair of the rain water harvesting system. Mains water usage is presented on a daily and weekly basis alongside the local rain fall intensity.

What was particularly useful about the failure of the rainwater system was also its effect on non-optimal performance of the grey water end-users. For example, in this case it was found that urinals in the building consumed 0.8 m^3/hour of grey water. During dry periods, or during times when the rain water harvesting system was not operational as described previously, this quantity of mains water was equivalent to an annual cost of €12,045 to the building. From a manual investigation of the urinal flush rate, it was determined that each of the 16 urinals in the building flushed 25 times per hour (approximately 2 litres utilised per flush). Furthermore, it was observed that the quantities of mains water used to top-up the grey water tanks in Pilot Site #2 were significantly in excess of rain water supply from rain water tank – despite there being ongoing rainfall in this period (see Figure 5 and Figure 6). Subsequent to this analysis grey water usage conditions in the pilot site were subsequently reduced using more efficient urinal operation conditions. Although this particular example was not exemplar of any of the aforementioned rule sets, it demonstrates WDS optimisation and significant savings that can be gained through end-use insight.

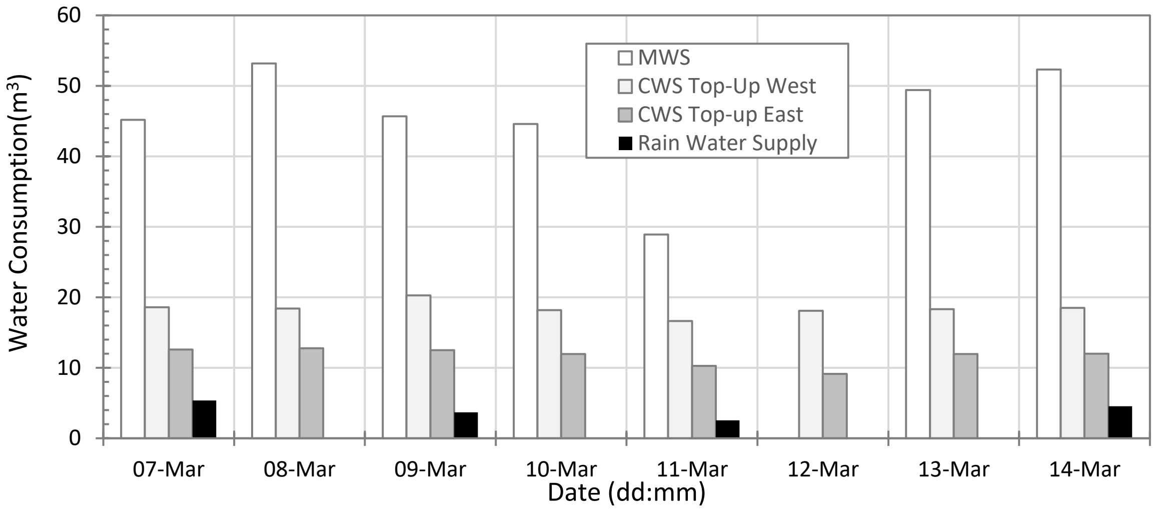


Figure 6. Comparison of water meter readings at Pilot Site #2 indicating the consumption stresses imposed on the existing rainwater harvesting system.

5.2. Example 1: Continuous Flow 1 – Resolved Historically (Rules 4, 5, 6 and 7)

A continuous flow is defined by a large and relatively constant use of water maintained for 24 hours or more and are typically attributed to a leak(s) but can also be attributed to non-optimal water usage (Cardell-Oliver, 2013; Clifford et al., 2017). As a result, they are generally straighforwarward to detect from a mains water meter when the data is either aggregated on an hourly or daily basis. Figure 7(a) provides typical mains water flow trace obtained for the MWS of Pilot Site #1 wherby a continuous flow event was observable for 21 days in March 2016. By imposing the dual alarm approach threshold for Rule 4 (Table 3), it was possible to identify from historic data the day on which the fault occurred. In the current example a value of $V_{crit} = V_d + \varepsilon_{t_2} = 5.34$ m^3 was imposed. One alarm may simply indicate that the fault was a peak usage whereby a consecutive alarm on the following day (and subsequent days) indicated the likelihood of a continuous flow occurring. To compliment this threshold checking method, Figure 7(b) presents a time series of the residual ($R = V_t^m - V_{norm}^m$). The anomaly was also identifiable by a sharp departure of the redundancy away from the optimal value of $R = 0$. The value of R also marks the severity of the peak or continuous flow. Finally, a third approach to identification of the anomaly which can complement the latter two identification methods is outlined in Figure 7(c) using a volume usage accumulation chart. Here, the slope of the volume accumulation V_{acc} over a certain time interval provides an indication of the normality of water usage conditions (Rule 7). A significant deviation of this slope was also observed with the change of slope being indicative of the severity of the anomaly (e.g. for $k = \left(\frac{V_{t+1}-V_t}{T_{t+1}-T_t}\right)\frac{T}{\Delta V_{norm}}$ where $k \approx 1$ normal conditions apply and $k > 1$ outlines excessive usage conditions). The consumption accumulation method is also helpful for determining the cost of a fault as it occurs or when it lapses. For example, as shown in Figure 7(c), the identified fault resulted in a loss of approximately 210 m^3 of mains water.

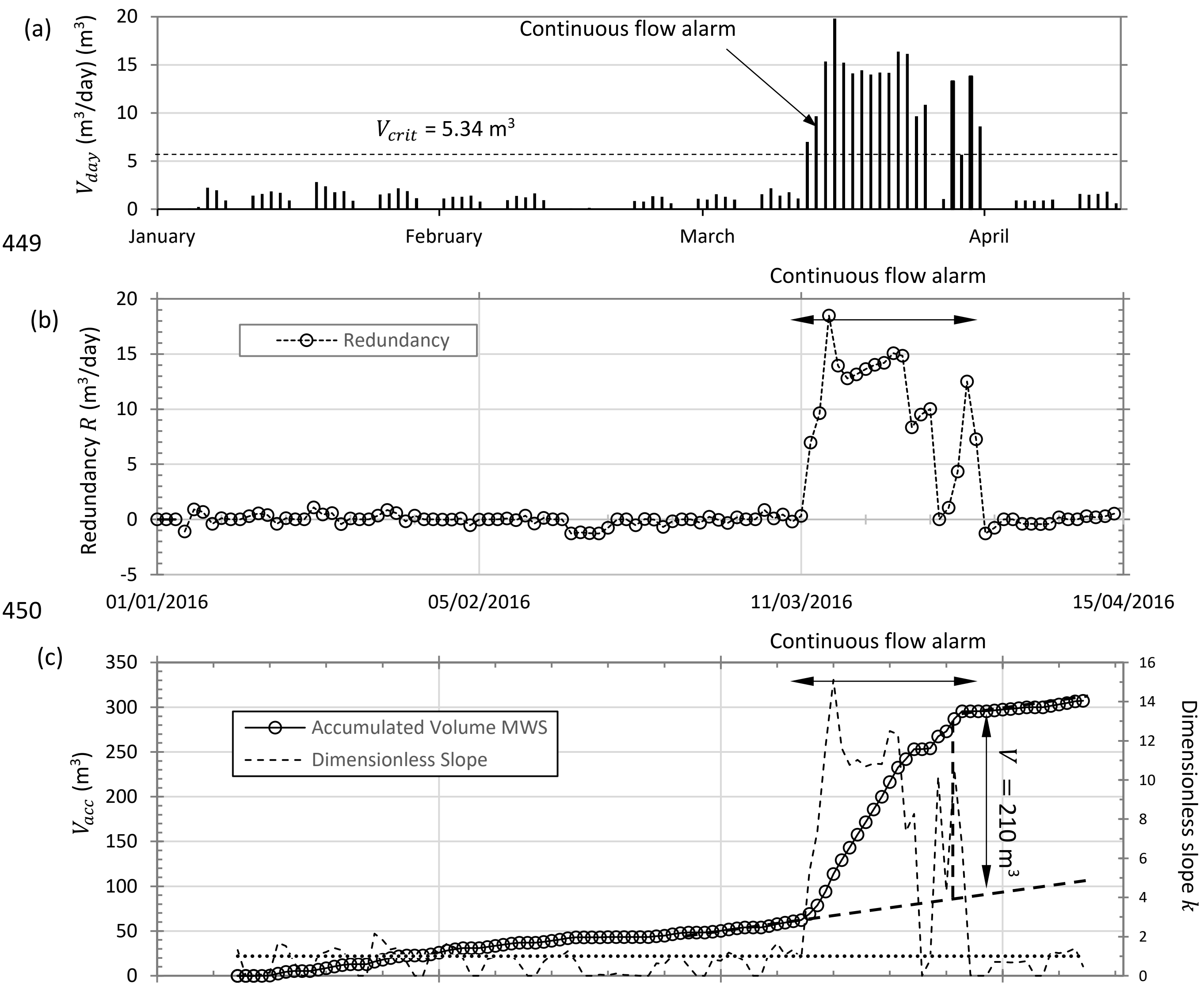


Figure 7. Fault detection of a continuous flow anomaly within the WDS using (a) threshold checking (Rule 4), (b) Redundancy monitoring (Rule 4) and (c) volume accumulation method through the dimensionless slope (Rule 7)

It was possible to diagnose the above fault by tracking and isolating its approximate location using a Dendrogram-like hierarchal description of the water network complimented by the available data for each water meter as depicted in Figures 8(a) – (e). In this approach, the signature of the continuous flow was identified in the mains water meter. These meters are highlighted in the Dendrogram (Figure 8(a)) and thus indicated that the water consumption was isolated to within the GWS sub-system. The signature did not appear on any further meter data sets in the GWS indicating that the fault was located on an unmetered connection in this region. The fault was attributed to a defective toilet cistern responsible for conveying a continuous flow of approximately 0.6 m^3/hour.

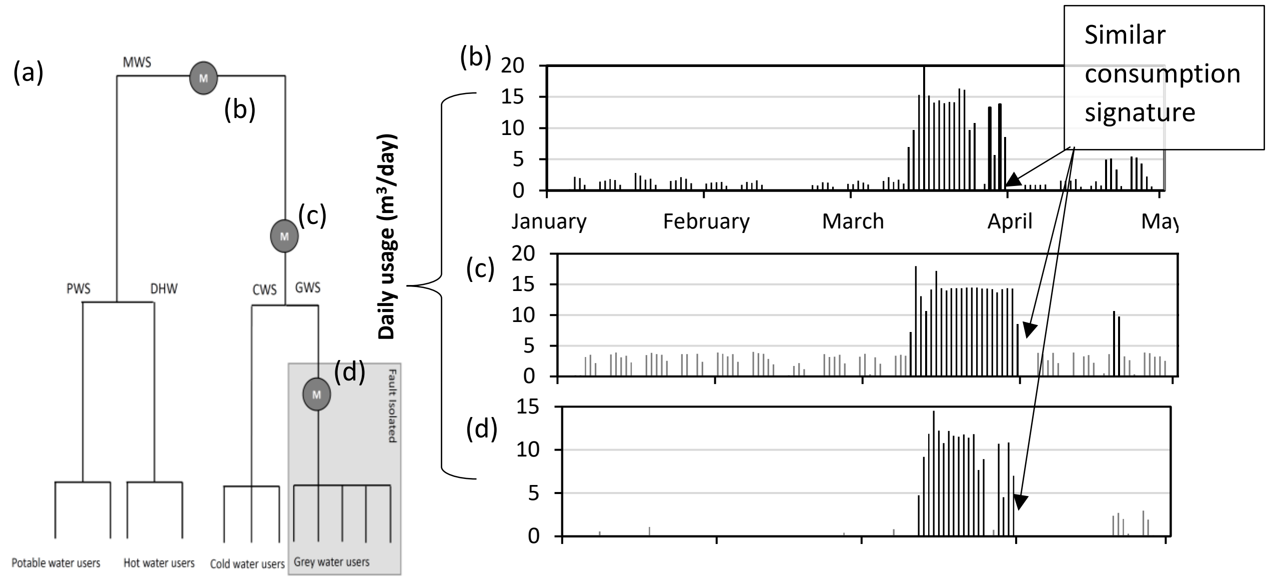


Figure 8. (a) Representing the WDS using a Dendrogram combined with meter time series (b) MWS (c) MWS (d) GWS and signature matching to isolate and diagnose faults.

5.3. Example 2: Continuous Flow 2 – Day Time to Night Time Usage Ratio (Rules 4, 5, 6 and 7)

Similar to Example 1, a second continuous flow fault was observed in Pilot Site #1 using the dual alarm approach. This was found to increase the mains water usage to approximately 10 m^3 per day. An alternative method to detect such a fault would be to consider the balance between occupied and unoccupied water consumption which was proposed by Pudar and Liggett (1992) as a simple and robust leak detection method. This is outlined in Table 4 by Rule 6.

To implement this Rule, use is made of occupancy information obtained in Phase 1. A flow trace of the fault occurring in Pilot Site #1 is outlined in Figure 9 where flow readings at 7.5 minutes intervals were recorded. The Boolean status of the pilot site across the time series by a 1 or 0 on the secondary vertical axis. As can be seen, normal operation is observed between 10/05 and 14/05 where ϵ_{Ost} varied between 0.14 and 0.2. However, from the 16/05, the ratio between nighttime and day time flows increased to ϵ_{Ost} $\approx$ 1 to 2 (i.e. night time equated to more than half the total usage). Similar dual alarm conditions can be applied to ϵ_{Ost} in order to desensitise the fault detection scheme to Type I and Type II errors.

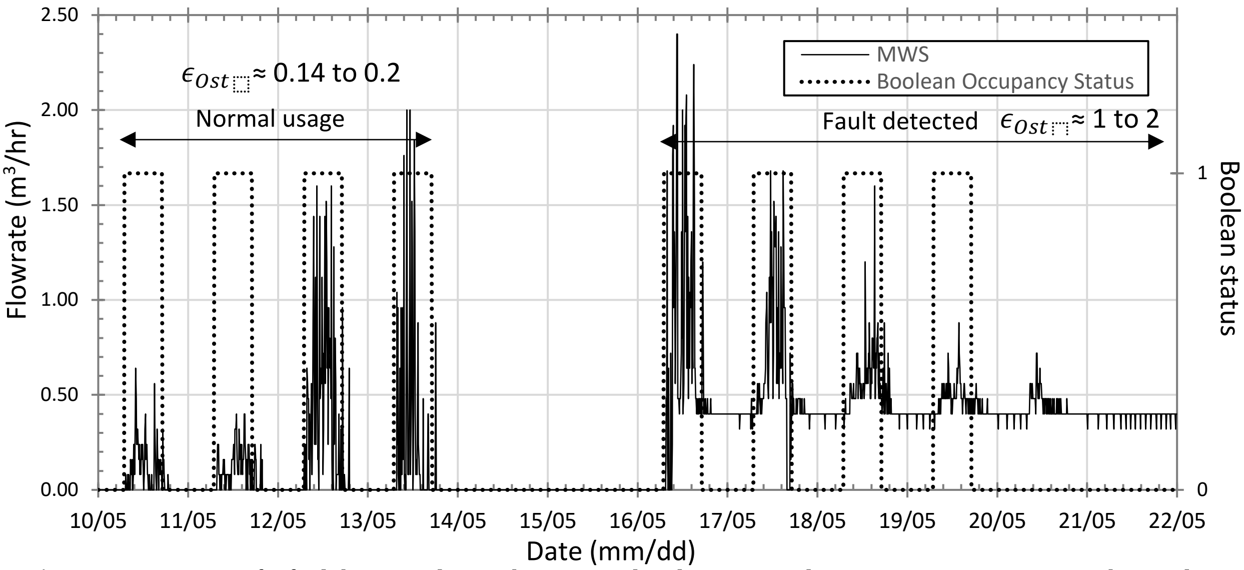
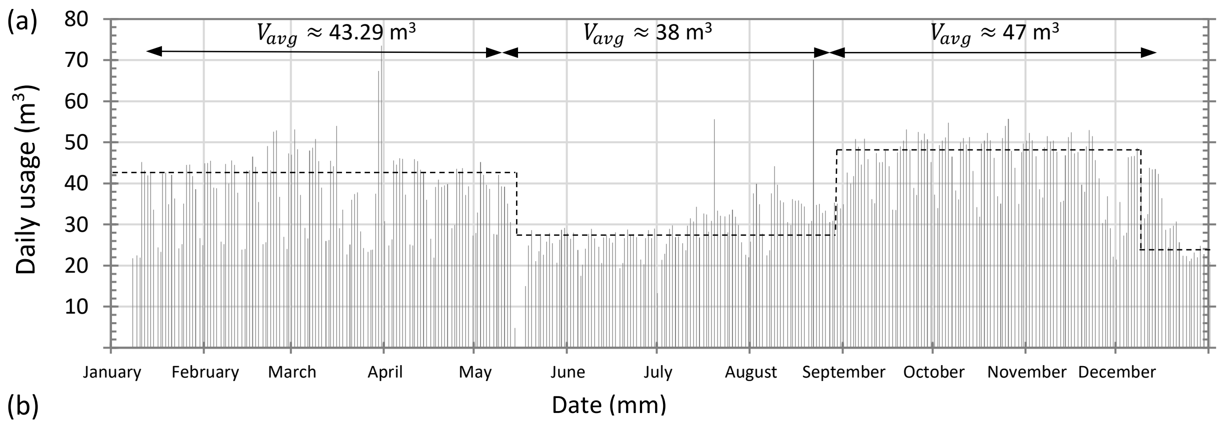


Figure 9. Detection of a fault by considering the occupied and unoccupied water usage activity using the Boolean status outlined in Table 1.

5.4. *Example 3: Continuous Flow 3 - Tank Overflow (Rule 7)*

This example demonstrates a fault that may normally go undetected due to the low levels of water loss, however such a fault may result in a significant water loss due to its persistence in the long-term. The fault was found to result in a relatively small continuous flow which was identified due to continuous top-up of the grey water storage tanks. Figure 11 (a) shows the flow trace for Pilot site #2 between January and December 2016 (which comprises the initial monitoring period where baselines were established – Table 3). It was determined that the fault originated between the 2nd and 3rd of September; however, due to the small increase of flow amounting to an additional 3.5 m^3 consumed each day (7 % of total usage), it was relatively difficult to discern the activity in the aggregated, daily flow trace as is evident by Figure 11(a). Thus, the statistical thresholds of the dual alarm approach may be sufficiently large such that the fault activity would be masked. However, combining the volume accumulation method (Rule 7 together with the dimensionless slope of the curve, it was possible to observe the anomaly occurring on the September 2nd as k values exceeded unity for a sustained period. The analysis found that a fault existed in a solenoid valve leading to the inlet of a rainwater supply tank.



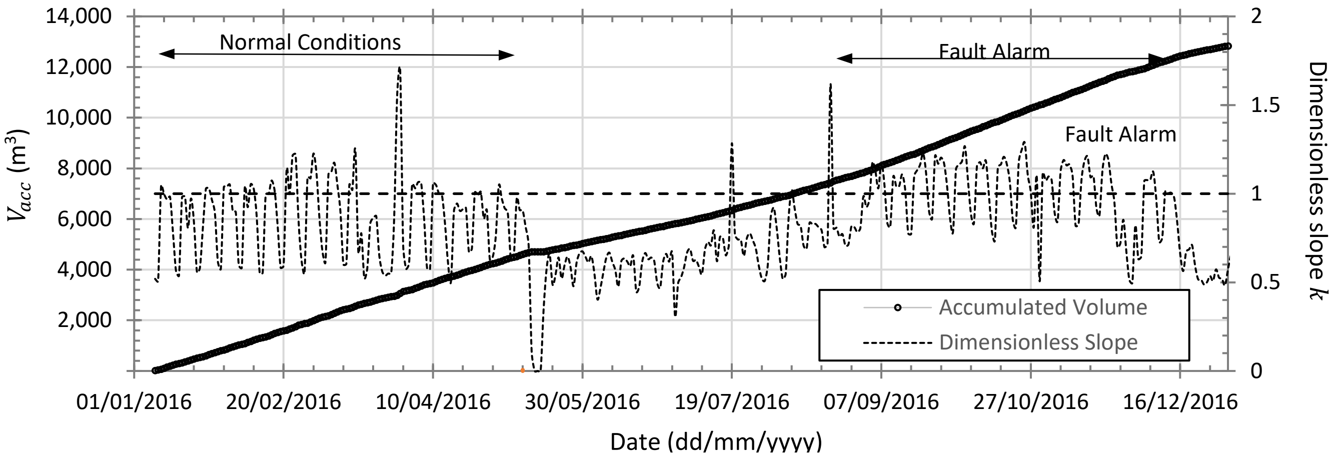


Figure 11. (a) Medium resolution flow traces for the main water supply in Pilot site #2 highlighting the variation of the average normal day water usage from the 6 month assessment stage (V_{avg} ≈ 43.3 m^{3}day^{-1}, SD = 4.74 m^{3}day^{-1}), 4 months summer period (V_{avg} ≈ 38 m^{3}day^{-1}) and return of students in the first semester (V_{avg} ≈ 47 m^{3}day^{-1}) where the increase of water usage was found to be as a result of a tank over flow fault. Figure 11(b) outlines fault detection using the dimensionless slope method (Rule 7). Example 6: Potable Water Retention Time (Rule 9)

It is advised that a potable water system should be designed such that water does not stagnate at any position of the WDS (BS EN806). Within large building water networks it has been found that drinking water fountains can be sporadically used and this can lead to water being stagnant in pipe feeding these systems. As a result, a simple algorithm was developed which can be integrated into water meters used to monitor potable water fountain usage. The decision tree of the algorithm (Rule 9) is outlined in Figure 12 (a) and simply requires knowledge of the pipe volume (length and diameter) connecting the mains supply to the fountain. If the consumption in the fountain is small such that water is resident in the pipe for relatively long periods, an alarm will indicate that preventative action is required (e.g. flushing of the network by opening the required fountain for the required period). An example of the algorithm applied in Pilot Site #2 building water network is outlined in Figure (12(b)). In this case, the meter in question required two separate checks to ensure that the water was safe for drinking due to its position in the water network - Figure 12(b). A conservative approach identified that a critical time of 48 hours be imposed in that rule set (i.e. potable water remaining static in the pipe system for over 48 hours be discharged).

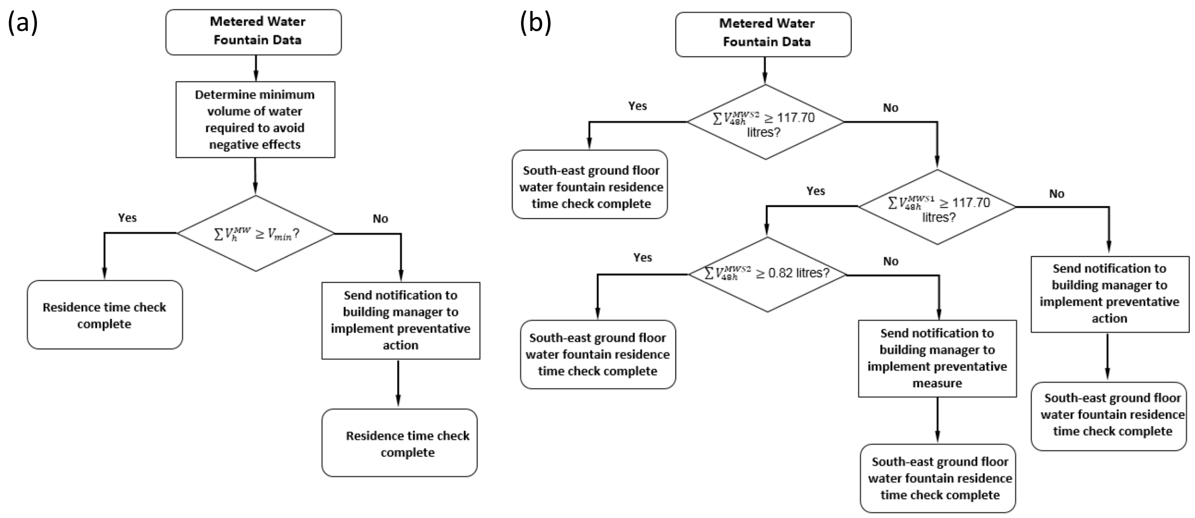


Figure 12. (a) General water retention time algorithm and (b) water retention time check algorithm applied to two fountains on the same water supply line of Pilot Site #2

5.5. Example 8: Non-Optimal Performance 1 – Showers Water Usage

By using distinct flow signature patterns of shower activity observed on the high-resolution flow traces (as per Clifford et al., 2017), it was possible to evaluate the shower activity occurring in a typical day in Pilot Site #2. A total of 145 shower events were isolated in the WDS and it was found that there are approximately 12 – 18 showers events per day (between 7.00 am and 10.30 am). From this dataset, the average shower time was found to be 5.8 minutes (minimum and maximum of 1.5 and 15 minutes respectively) with an average of 200 litres consumed per shower (minimum and maximum volumes consumed 50 and 660 litres respectively). The average usage of 200 litres is approximately 4 times larger than that used in a domestic shower. This significant usage was reinforced with anecdotal reports of high pressure and excessive flows experienced in the showers facilities. In order to optimise and reduce the flow conditions in the shower facilities, it was proposed that the existing showers be fitted with water saving heads which could reduce water flows from 87.5 litres/min to 20 litres/min. When implemented, it was estimated that the overall shower usage in the engineering building (consisting of both pumped and heated water) was reduced from 9.45 m^3/day to 2.16 m^3/day rendering a saving of 77 % in heated water.

6. Discussion of the WDSPAR Approach: Water-Energy Nexus

From a comprehensive assessment of the WDS for the two case studies, it was found that the WDSPAR introduced a methodical, easy to understand and implement rule set that could be used to diagnose faults and non-optimal performance in the WDSs. The use of smart meters positioned throughout the network, together with the initial assessment phase, resulted in increased transparency of the networks normal and seasonal operational behaviour. The rule set developed exposed numerous faults throughout both pilot sites during the monitoring period; eight of which were discussed in this study. The rules also helped to suggest instructions on corrective action to be taken in a simple and understandable way. A summary of resources lost due to faults are outlined in Table 4 (Note: Fault # refers to examples 1 to 8 outlined in section 4).

Table 5: Summary of resources lost due to faults and non-optimal performance within the WDS

Fault Description	Rate (per)	Volume Consumed (m^3)	Water Cost[1] (€)	Energy (see references) (kWh)	Energy Cost[2] (€)	Carbon emissions ($kg.CO_2$)	Comment Reference
Continuous Flow 1 Faulty Cistern	Daily	11.0	20.5	18.8	3.4	11.2	3
	Event	210.0	389.6	359.1	64.6	214.2	
Continuous Flow 2 Leak	Daily	9.4	17.5	16.1	2.9	9.6	3
	Event	340.0	630.7	581.4	104.7	346.8	
Continuous Flow 3 Tank Overflow	Daily	3.7	6.9	6.8	1.2	4.0	3 & 4
	Event	334.0	619.6	607.6	109.4	359.4	
RHW System Fault	Daily	4.3	7.9	7.8	1.4	4.6	3 & 4
	Event	1566.0	2904.9	2848.6	512.7	1685.0	
MWS Peak Usage	Daily	11.5	21.4	19.7	3.6	11.8	3 & 4
	Event	13.5	25.0	23.1	4.2	13.8	
Shower Peak Usage	Daily	5.8	10.7	9.9	1.8	5.9	3 & 4
	Event	4.2	7.79	7.2	1.3	4.3	
Urinal Flushing	Daily	11.5	21.4	22.2	4.0	13.0	3 & 4
	Event	4205.0	7800.3	8107.2	1459.3	4760.1	
Showers	Daily	7.3	13.5	14.1	2.5	8.3	3 & 4 & 5
	Event	2661.0	4936.2	5130.4	923.5	3012.3	

[1] Cost based on the Irish price of water equating to €1.85/m^3 of water supplied (http://www.citizensinformation.ie)

[2] Cost based on an average of four Irish electrical energy retailers equating to approximately 18 cent per kW.hr.

[3] Energy due to treatment and conveyance to the building where energy per unit is 1.71 kWh/m^3 (Clarke et al. 2009)

[4] Calculated specifically based on historic pumping energy requirements of Pilot Site #2

[5] Calculated specifically based on historic calorifier heating energy requirements of Pilot Site #2

What is of notable interest is the significant daily volumes that can be consumed within a WDS fault (for example, Fault # 1 & 2). In the event of non-detection through the absence of a WDS FDD system, it is clear that significant additional costs can be imposed on a building in terms of water and energy as a result of the water energy nexus. For example, excessive and non-optimal water usage in showers at Pilot Site #2 can result in a cost to the building of approximately €4,936 per annum if not mitigated. Due to additional heating costs required for hot water usage in the showers, the additional energy required to treat, transport and heat the water totals to approximately 5130 kW.hr per annum which equates to the annual energy usage of a typical Irish home. The carbon emissions associated with this translates to 3,012 $kgCO_2$ (or 1,745 kg of coal burnt). By introducing measures to eliminate existing faults and optimising the WDS performance of Pilot Site #2 it can be shown that 26.81 m^3/day of treated water can be saved at the pilot site (approximately 9786 m^3/annum) amounting to approximately 62 % of a pre WDSPAR intervention normal days mains water usage. The energy savings associated with treatment, transport and heating this water equates to 266.5 kW.hr per day (7.6 % of the buildings total energy usage) with an accompanying carbon emissions equivalence of 29.9 $kg.CO_2$ per day. Although such savings of energy may not seem significant on an individual building basis, extrapolation and integration of such effects on a national or global scale would suggest that substantial conservational impacts are achievable, both in terms of water and energy usage, through WDSPAR implementation.

A logical progression in the development and implementation of this research would be to integrate the WDSPAR set into an automatic controller (integrated into a BMS) within a pilot site where faults can be detected in a real-time or historical basis as preferred by the end-user. Some aspects of the WDSPAR were trialled in an ICT platform developed by the Waternomics project team (waternomics.eu). The 'Building Managers Dashboard', which permitted online observation of water usage characteristics in each trial site was used to check various thresholds. In the instance of threshold exceedance, a notification was sent to the building manager. The Building Managers Dashboard also allowed the end-user to view the balance of water usage between occupied and unoccupied times and also included the water retention time observer. Automatic detection of faults through this real-world application verified the potential for WDSPAR application in the ICT-water domain. "Furthermore, testing of the rule set was based on a relatively small number of faults, presented as examples in this paper. A fruitful future study would be to develop an experimental campaign to rigorously test the ruleset under known fault-free and faulty conditions in order to fully understand the advantages and limitations of the approach.

7. Conclusions

According to past literature, there has so far been little attempt to formulate a robust FDD approach for building WDS. In this study, a comprehensive set of performance assessment rules for a building water distribution system were developed which form the basis of a fault detection, diagnostics and optimisation tool. This Water Distribution System Performance Assessment Rules (WDSPARs) set are applied in 3 Phases: Phase 1: Assessment and Threshold Selection, Phase 2: Performance Monitoring and Phase 3: Diagnosis and Repair. A novel dual alarm approach was used to establish robust thresholds for fault alarms determined statistically using Phase 1 water usage data. Historic and real-time data from two real world trial sites made available after an initial assessment phase of 6 months was used as the input data. The available data from the trial sites was in the form of water flow meter data of varying temporal resolutions and positioned spatially at various locations across both networks. When implemented, the WDSPAR highlighted numerous faults in the WDS. Examples of non-optimal performance were also defined from the case study and resolved. Faults detected, which otherwise would have gone undetected in the absence of the FDD system, were shown to result in significant wastage in the building. The faults and non-optimal performance extrapolated on an annual basis demonstrates the importance of FDD and optimisation in water distribution systems to help reinforce conservation efforts. It was shown that elimination of problems that are most easily resolved can immediately result in significant water usage savings. It is worth noting that proactive building maintenance, as presented for the pilot studies herein, would be required to ensure such FDD systems are optimally used. It was shown in Pilot Site #2 that implementation of the WDSPAR process yielded savings in water accounting to approximately 62 % of the pre-intervention normal day's mains water usage. For this specific case, this suggested savings of energy and carbon emissions of the order of 50 kW.hr per day (1.3 % of the buildings total energy usage) and 29.9 kg.CO_2 per day respectively.

Acknowledgements

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