Giovana Santos Almeida

DEVELOPMENT OF TOOLS FOR AN EFFICIENT WATER USE AND REUSE

Doctor of Philosophy in Civil Engineering, with specialization in Hydraulics, Water Resources and Environment, under supervision of Professor José Manuel Vieira and Professor José Alfeu Sá Marques and submited to the Department of Civil Engineering of the Coimbra University.

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UNIVERSIDADE DE COIMBRA

University of Coimbra
Faculty of Sciences and Technology
Department of Civil Engineering

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A DISSERTATION
SUBMITTED TO THE DEPARTMENT OF
CIVIL ENGINEERING
OF COIMBRA UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Giovana Almeida

UNDER SUPERVISION OF
Professor José Manuel Vieira (supervisor)
Professor José Alfeu Sá Marques (co-supervisor)

Resumo

Esta tese propõe e analisa diferentes técnicas informáticas que visam contribuir para o aumento do conhecimento sobre o uso da água e a sua reutilização. Inicialmente, é proposto um sistema de apoio à decisão (DSS) que identifica o nível do potencial rural e urbano de reutilização de água, considerando características relacionadas com a escassez de água, tais como seca, indice de exploração da água e tipos de uso. O DSS proposto utiliza um sistema de inferência fuzzy (FIS) para a tomada de decisão multicritério e foi concebido com base nas informações de uma base de dados composta por 155 regiões para agricultura e 183 cidades para ambientes urbanos. A fim de verificar se as características levantadas seriam adequadas para compor o FIS, as informações fornecidas pela base de dados foram correlacionadas ao nível de reutilização da água. Observou-se que fatores ambientais, tais como a gravidade da seca e disponibilidade de hídrica, e fatores estruturais, tais como o índice de exploração de água (WEI), usos da água, a densidade populacional e a taxa de tratamento de águas residuais, são bem correlacionados com a reutilização agrícola e urbana. Dadas as características ambientais e estruturais, o FIS proposto é capaz de identificar se a amostra estudada tem potencial de reutilização ou não, com 96% de precisão no caso de reutilização urbana e 90%, no caso de reutilização agrícola. A análise do potencial de reúso de água indicou que actualmente o potencial urbano é menor que o agrícola. Para incentivar o reúso urbano, também são propostas, neste trabalho, técnicas para estimar a quantidade e a qualidade da água residual cinzenta total em domicílios. Para estimar a quantidade e identificar o tipo de uso da água, foi desenvolvido um novo método que utiliza sinais de caudal e pressão para identificar qual o dispositivo hidráulico que estava em uso (i.e. torneira, autoclismo, chuveiro). Para simular uma casa de banho e uma cozinha foi construída uma instalação experimental. A primeira fase dos experimentos tiveram como objectivo identificar as "assinaturas" dos dispositivos hidráulicos e, para tanto, o mesmo comprimento de tubo foi utilizado. Consideraram-se cinco classes para identificação de dispositivos hidráulicos: torneira da cozinha (C1), torneira do lavatório (C2), torneira do bidé (C3), chuveiro (C4) e autoclismo (C5). GDX e SVM foram os classificadores usados

para identificar o padrão dos sinais. As características foram extraídas no domínio do tempo e frequência e um selector de características (*feature selector*) foi usado para seleccionar as características mais representativas do sinal visando uma melhor classificação. A fusão por *Majority vote* dos resultados de classificação do SVM no domínio do tempo apresentou os melhores acertos: 92% para C1, 94% para C2, 94% para C3, 100% para C4 e 100% para C5. Estes resultados indicaram que cada dispositivo possui uma "assinatura" específica já que, mesmo posicionados em uma mesma distância em relação ao medidor, os classificadores foram capazes de reconhecer os diferentes padrões de sinal em cada classe. Numa segunda fase procurou-se identificar a influência da diferença de pressão nos acertos, sendo assim, os tubos foram instalados com diferentes comprimentos. Os resultados utilizando classificador SVM indicaram que as diferenças de pressão melhoraram os acertos na classificação em 4%. A composição de sinais proveniente do uso simultâneo de dois dispositivos também foi analisada. Os resultados também foram bons para sinais de pressão no domínio do tempo: 99% para torneira da cozinha e torneira do lavatório, 97% para torneira da cozinha e torneira do bidé, 99% para torneira da cozinha e chuveiro e 100% para torneira da cozinha e autoclismo. A expectativa futura é completar o sistema de identificação com composições de uso dos dispositivos e testar o algoritmo em um ambiente real. Os dados fornecidos pelo sistema de aquisição desenvolvido neste trabalho também foi útil para o cálculo de perdas de carga e estudos sobre coeficiente de simultaneidade. Os resultados do cálculo das perdas de carga e do coeficiente de simultaneidade indicaram que os dados fornecidos pela instalação experimental são adequados para esse tipo de estudo pois os valores encontrados são compatíveis com os apresentados pelos fabricantes e pela literatura. Em relação à qualidade da água para reutilização, foram apresentados neste trabalho métodos de recolha e de análise de água residual domiciliária. De uma forma geral, os estudos apresentados neste trabalho indicaram que os fluxos de cozinha e lavandaria apresentam maior concentração de poluentes do que os do lavatório e do banho. Este resultado está de acordo com muitos estudos nesta área. A carga poluente, a taxa de remoção dos tratamentos e a limitação das normas de reutilização de água foi utilizada para estimar qual água residual seria mais adequada para reutilização em domicílios. Considerando-se as quatro casas analisadas, estima-se que a implementação do sistema de reúso em autoclismos é viável e pode contribuir para poupar cerca de 15% de água potável. Além disso, a reparação dos vazamentos identificados em algumas casas resultaria na poupança de mais de 35% do volume de água medido. Estes valores indicam que a promoção da eficiência no uso da água e reúso traria benefícios significativos para a poupança de água em edifícios.

Abstract

This thesis proposes and analyzes different techniques which aim to provide better and more reliable information about water use and reuse. Initially, this thesis proposes a decision support system (DSS), which identifies the agricultural and urban potential level of water reuse considering features that appear to be relative with water shortages, such as drought, water exploitation index and water use. The proposed DSS uses a fuzzy inference system (FIS) for multi-criteria decision making and was designed based on the information from a data-set composed of 155 regions for agriculture and 183 cities for urban environments. In order to identify the suitable factors to compose the FIS, the information provided by data-set was correlated with the water reuse level. It was observed that the environmental factors, such as drought severity and water availability, and structural factors, such as the water exploitation index (WEI), water uses, population density, and waste-water treatment rate, are satisfactorily correlated with agricultural and urban reuse. Given the environmental and structural features, the proposed FIS is very reliable in identifying whether the studied sample has reuse potential or not, with 96% accuracy in urban reuse and 90% in agricultural reuse. The potential water reuse analysis indicated that there is less demand for urban water reuse than for agricultural water reuse. In order to improve the urban reuse, this work also proposes techniques to estimate the quality and quantity of a household's gray water streams. To estimate water use (quantity), a new method was developed that uses flow rate and pressure signals to identify which fixture was in use (e.g. tap, toilet flush, shower, etc.). In order to simulate a bathroom and kitchen, an experimental facility was constructed. The intention of the first phase of experiments was to identify the electronic signatures of each fixture. Five classes for fixtures identification were being monitored: kitchen tap (C1), washbasin tap (C2), Bidet tap (C3), shower (C4) and toilet flush (C5). GDX and SVM were both used to identify the best classifier for the data. The features characteristics were extracted in both the time and the frequency domains and a feature selector was used to select representative features from the signals in order to improve the process of classification. The fusion by majority vote of the SVM classification results in the

time domain presented the best accuracies: 92% for C1, 94% for C2, 94% for C3, 100% for C4 and 100% for C5. This result indicated that each feature has a specific signature that can be recognized by the classifiers. In the second experimental phase different pipe lengths were used. The results using the SVM classifier indicated that differences in pressure improve the classification accuracies in 4%.. Signals composition with kitchen tap signals was also analyzed in order to test signal accuracy with two fixtures in use. The results were also good for pressure signals in the time domain: 99% for kitchen tap and washbasin tap, 97% for kitchen tap and bidet tap, 99% for kitchen tap and shower and 100% for kitchen tap and toilet flush. The future expectation is to complete the identification system with fixtures composition and test the algorithm in a real building. The data provide by the acquisition system developed in this work was also used for head losses and the coefficient of simultaneity studies. The results indicated that the data provided by the experimental facility are suitable for these studies because they are compatible with those presented by manufacturers and literature. To estimate the water quality for reuse, some methods were presented in this work for household stream collection and analysis. The studies presented in this work indicated that the kitchen and laundry streams present a greater concentration of pollutants than the washbasin or the bath. This result is in accordance with many studies in this field. The pollutant charge, the treatment removal rate and the water reuse standards limitation was used to estimate which streams are more suitable for reuse in households. Considering the four houses analyzed, it is estimated that the implementation of the toilet flushing reuse system is feasible and could contribute to save about 15% of drinking water. Furthermore, the reduction of the water losses presented in two households could save up to 35% of the volume. These values indicated that significant amounts of water could be saved if water use efficiency and reuse techniques are implemented in buildings.

Acknowledgment

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I dedicate this thesis to my parents, who gave me life and education, to my husband for his unconditional support during this endeavor, and to my daughter, who gave me happiness, teaching me what is really important.

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List of Acronyms

ADC	Analog-to-digital Conversion
AICT	Advances in Information and Communication Technology
BBN	Bayesian Network
BOD	Biochemical Oxygen Demand
COD	Chemical Oxygen Demand
DALYs	Disability Adjusted Life Years
DAQ	Data Acquisition Card
DFT	Discrete Fourier Transform
DO	Dissolved Oxygen
DSP	Digital Signal Processing
DSS	Decision Support System
EPA	Environmental Protection Agency
EPAL	Empresa Portuguesa de ÁGuas Livres S/A
ERSAR	Entidade Reguladora dos Serviços de Águas e Resíduos
FFS	Final Part of the Flow Signal
FFT	Fast Fourier Transform
FIS	Fuzzy Inference System
FPS	Final Part of the Pressure Signal
FS-GAIT	Feature Selector based on Genetic Algorithms and Information Theory
GCMs	Global Climate Models
GDP	Gross Domestic Product
GDX	Gradient Descendent with Adaptive Learning Rate
IFIP	International Federation for Information Processing
IFS	Initial Part of the Flow Signal
IPS	Initial Part of the Pressure Signal

LDA	Linear Discriminant Analysis
MBR	Membrane Bioreactor
MCDM	Multi-Criteria Decision Making
MMCS	Modified Method for the Coefficient of Simultaneity
MSE	Mean Squared Error
MSVM	Multiclass SVM
NILM	Non-intrusive Electric Load Monitoring Systems
NIWM	Non-intrusive Water Monitoring System
NN	Neural Network
OAA	One-Against-All
OECD	The Organization for Economic Co-operation and Development
ORP	Oxidation-reduction Potential
PDSI	Palmer Drought Severity Index
PEX	Cross-linked Polyethylene Pipe
QMRA	Quantitative Microbial Risk Assessment
RBC	Rotating Biological Contactor
RBF	Radial Basis Function
RVI	Rainfall Variability Index
SAR	Sodium Adsorption Rate
SMAs	Soil Moisture Anomalies
SPI	Standardized Precipitation Index
SPL	Same Pipe Length
SVM	Support Vector Machines
TSS	Total Suspended Solids
UPL	Unequal Pipe Length
USA	United States of America
USB	Universal Serial Bus
UWS	Urban Water Supply
WASP	Weighted Anomaly Standardized Precipitation
WEI	Water Exploitation Index
WHO	World Health Organization
WTRNet	Water Treatment for Reuse with Network Distribution

Chapter 1

Scope and Introduction

THIS thesis addresses water scarcity problems and water reuse necessities and proposes techniques that would be useful for efficient water use and reclamation. Fuzzy inference system (FIS) for water reuse potential identification, automatic water use identification using pattern recognition and a simplified method for household water reuse evaluation are the techniques proposed in this work. Sustainable water management demands immediate control and efficient actions and passes through the control in activities that involve water use and progressive legal regulation. It is estimated that the techniques developed herein may help water managers in planning for the future in the areas of water efficient use and alternative water resources necessities. Some basic conceptions proposed here come from the ideas developed after the Master dissertation titled, "Metodologia para caracterização de efluentes domésticos para fins de reúso: estudo em Feira de Santana, Bahia" [Alm07]. This dissertation presents methods and results from water reuse surveys and quantity/quality water use research. Near the completion of this research, some questions about water reuse and efficient water use remained to be answered, questions such as: what reasons drive agricultural and urban water reuse? How to accurately identify waste-water quality and quantity in inhabited households for large scale studies? How to automatically and accurately monitor household water use? What are the volume/flow rates of the household streams that are suitable for reuse? And, what level of treatment is required with regard to current standards? The results of this current research were able to answer some of these questions and give indications for future developments in efficient water use and reuse.

1.1 Motivation of the Research

The increase in water consumption and climate change can be considered the two major reasons for water stress intensification in many European regions [EEA09]. In European Union Directive 2000/60/CE, a water policies framework for Community action was implemented where it demonstrates concern for increasing pressure on the demand of water for different uses. This Directive proposed, among other measures, the use of economic instruments which take into account the principle of cost recovery for services related to water and resources conservation.

Currently, forming a new vision of water management is a counterpoint to the traditional supply-side policies. It is necessary to defend other measures which are aimed at better water management, such as: infrastructure improvements to reduce the pipe water losses, support programs and citizen awareness, alternative water supply programs and/or decision-making measures to prevent excessive water use [FG04] .

Portugal has no serious shortage problems, but in the areas where the majority of the population are concentrated, Lisbon and O'Porto, there has been an increase in pressure from the healthcare industry in favor of the consumption of drinking water [APA12]. Despite this increase for the consumption of water by the public, the agricultural sector is still the biggest consumer of water (6,560 hm^3/year, 74% of the total), where the highest areas of consumption are on the Tejo and Douro river basins [PEA07]. The water supply is the second biggest consumer (620 hm^3/year, 7% of the total) and industry (355 hm^3/year, 4% of the total) is the third. Although agriculture water use is representative at 28% of the total, the urban sector is more relevant in terms of actual production costs at 46% of the total, and industry at 26% [PNU14].

The tourist sector in Portugal is growing faster and is demanding quality and continuity of the water supply. In the high season, the Algarve region usually faces water supply problems because the population increases by more than 200%. Agricultural irrigation from the Algarve region in 2000 represented 2/3 of the total water consumption (golf courses watering contributed with this total). In 2003 there were 25 golf courses around the watershed, representing 41% of the total in Portugal, and 33 new ones were under construction [SNF$^+$]. Some projects for water reclamation in golf courses is taking place and will give some relief on water resources withdrawal.

In Portugal, agriculture accounts for 85% of total water loss, water supply accounts for 8% and industry 4%. The costs of these losses represents 39% of the estimated value for water demand and 0.64% of the Portuguese GDP [PNU14]. Studies in Portugal ([BAM+06] and [PNU14]) indicated that in order to improve the water supply energetic efficiency it is necessary to implement strategic changes in certain areas, such as: decreased losses, demand management, gray-water reuse and treated waste-water reuse.

It is observed that treated waste-water is accepted as an alternative water resource in many countries and studies worldwide intend to provide more information about quality, quantity, suitable treatments and standards in order to reduce the health risks associated with reuse. Successful water reuse depends on suitable treatment and concerns over human contact. However, some regions experiencing unexpected water shortages previously reused untreated waste-water in agriculture ([MMNG05] and [MRAQ+08]). A predictive reuse planning development is useful to control water reuse applications and minimize environmental and health problems. Urban reuse application is less common than agricultural, but is representative of the level of interest in this type of reuse. However, health problems associated with reuse in urban environments are important concerns due to close human contact.

1.2 Objectives

Considering treated waste-water as a suitable alternative water resource, this thesis proposes and analyzes different techniques that improve both general and specific knowledge about water use and reuse. Hence, efficient water use and reuse are the main objectives that drive the conceptions and developments in this work. A fuzzy inference system (FIS) was utilized to estimate water reuse potential, as well as an automatic system for water use identification and a simplified method for household water reuse evaluation.

1.3 Organization of the Thesis

Chapter 1 presents the objectives, motivation that drove this research, organization of the thesis and the papers that presented some aspects of the research findings.

Chapter 2 presents a fuzzy inference system (FIS) tool that estimates the reuse potential in regions and cities considering agricultural and urban water uses. Thus, 155 regions and 185 cities were surveyed in order to identify some representative factors that drive water reuse. The FIS which was developed could help decision makers in identifying future water reuse necessities considering trends on climate, population, water use, water tariffs and others representative features as input. The future potential of reuse estimation can give water managers information on when to prepare suitable infrastructure and environmental conditions for a safety reuse.

Agricultural reuse has significant reuse potential in comparison with urban reuse due to high water consumption and less water quality requirements. However, in mega-cites with scarcity problems, urban water reuse can be more representative. It is estimated that close human contact with the reclaimed waste-water in urban environments limits the interest in these reuse applications, mainly because of concerns about the risks of waterborne diseases. Thus, more studies in this field are necessary to develop a safe and efficient urban reuse program.

In order to promote urban water reclamation it is necessary to have more information in large-scale about the quantity and quality of water use. This work focuses on the household environment in order to develop new techniques for water use identification and reuse. Chapter 3 describes household water use identification through the transient signal classification method. Two experimental facilities were set up at the Hydraulics, Water Resources and Environment Laboratory of the Department of Civil Engineering of the Faculty of Science and Technology (University of Coimbra) in order to develop the experiments. The objective was to create an algorithm using machine learning techniques that recognize the signals of consumption in each hydraulic fixture utilized. The easy installation and inexpensive equipment used at the developed data acquisition system seems to be suitable for large-scale water use monitoring. The water quantity characterization can help identify whether the effluent produced is enough for desired water reuse. Also, future developments in water consumption monitoring can help users to follow-up and to control water consumption or leakage using a PC or even a mobile device.

The developed data acquisition system can also contribute with water supply system research studies. Chapter 4 contains an analysis of the coefficient of simultaneity and head losses in pipes, the distribution manifold and the water heater. The objective of this study is to propose an indoor building water pipe system analysis method that could be used in large-scale. The research may contribute with an evaluation of parameters used for networks design. This study also aims to contribute with information for water supply design developments considering higher efficiency in buildings' water supply systems.

Besides the water use identification, the quality of a households' stream gives valuable information for water reuse systems and treatment development. Chapter 5 presents the methodology and results of the gray-water streams quality assessment of the households being tested. Stream quality analysis took place in Brazil and Portugal. The parameters considered in Brazil were: fecal coliforms, sodium, COD, phosphorus, total nitrogen, potassium, total suspended solids, calcium, hardness and magnesium; in Portugal, the parameters were: pH, oxidation-reduction potential (ORP) chloride, nitrate and conductivity. These parameters were chosen because they are often cited in studies and water reuse standards, but they are also relevant indicators of contamination. The water use (quantity) identification and the gray-water streams quality allowed for the calculation of the pollutant loads. This information was needed to assess whether treatment systems are suitable for gray-water reuse considering the standards limits.

Chapter 6 summarizes the most important conclusions of this thesis and points out some topics for future research.

1.4 Publications and Conferences

Most chapters of the thesis were submitted to international peer-reviewed journals (Chapters 2 and 3). One chapter (Chapter 3) was published by Springer, IFIP AICT series (and submitted for indexation in Web of Science) with concern to the proceedings of a Doctoral Conference on Computing, Electrical and Industrial Systems (DoCEIS). The list of publications can be seen below:

1. Almeida, G.A., Vieira, J., Marques, J. A., Cardoso A., Kiperstok A. 2013. Estimating the potential water reuse based on fuzzy reasoning. Journal of Environmental Management, 128, 883-892.

2. Almeida, G.A., Vieira, J., Marques, J. A., Cardoso A., Ludwig O. 2015. Identifying Household Water Use through Transient Signal Classification. Journal of Computing in Civil Engineering, 10.1061/(ASCE)CP.1943-5487.0000476, 04015007.

3. Almeida, G.A., Vieira, J., Marques, J. A., Cardoso A. 2010. Pattern Recognition of the Household Water Consumption through Signal Analysis. Luis M. Camarinha-Matos (Ed.): DoCEIS 2011 - Doctoral Conference on Computing, Electrical and Industrial Systems, IFIP AICT 349, Springer series, pp. 349-356, 2011.

4. Almeida, G.A., Vieira, J., Marques, J. A., Kiperstok A. 2011. Uma análise das cargas de poluentes da água residual cinzenta para fins de reutilização. 11^{o} Congresso da Água. Porto.

5. Almeida, G.A., Vieira, J., Marques, J. A., Cardoso A. 2010. Identificação de padrões de consumo domiciliário através da análise de sinais. 14^{o} Simpósio Luso-Brasileiro de Engenharia Sanitária e Ambiental (SILUBESA). Anais do Silubesa/ Abes. Porto.

6. Almeida, G.A., Vieira, J., Marques, J. A., Kiperstok A. 2010. Caracterização de efluentes domiciliários para fins de reutilização. 14^{o} Simpósio Luso-Brasileiro de Engenharia Sanitária e Ambiental (SILUBESA). Anais do Silubesa/ Abes. Porto.

Chapter 2

Water Reuse Potential: Fuzzy Inference System Tool

ALTHOUGH planned water reuse projects have been identified around the world, there are circumstances where alternative water resources are only sought once an emergency situations has arisen. Water shortages cause substantial damage in the loss of crops and livestock in many countries, while posing a risk to human health when clean water for drinking and cleaning is not accessible or when contaminated water sources are used. The identification and discussion of the factors that drive risks on water supply security are important for decision making in system development and also useful in managing water resources efficiently.

Global warming, water consumption and population growing trends suggest a worsening in water shortages [Pro09]. The trend toward an increasingly persistent drought constitutes a warning about the safety and security of a reliable water supply. Simulations based on Global Climate Models (GCMs) demonstrate significant increases in consecutive dry days and Soil Moisture Anomalies (SMAs) for two time horizons, 2046-2065 and 2081-2100, in comparison with late 20th-century values (1980-1999) [IPC12]. The trend toward reduced precipitation and/or increased evapotranspiration, has led scholars to confidently predict that droughts will intensify in the 21st century. The data applies to southern Europe and the Mediterranean region, central Europe, Central North America, Central America, northeastern Brazil, and southern Africa. Another simulation [Dai11] presents the 20th and 21st century Palmer

Drought Severity Index (PDSI) calculated by using a 22-model ensemble with variables such as mean surface air temperature, precipitation, humidity, net radiation and wind speed (Figure 2.1). These results confirm a tendency toward drought. It is expected that the worst disturbances which affected regions will face will involve water, not temperature as such.

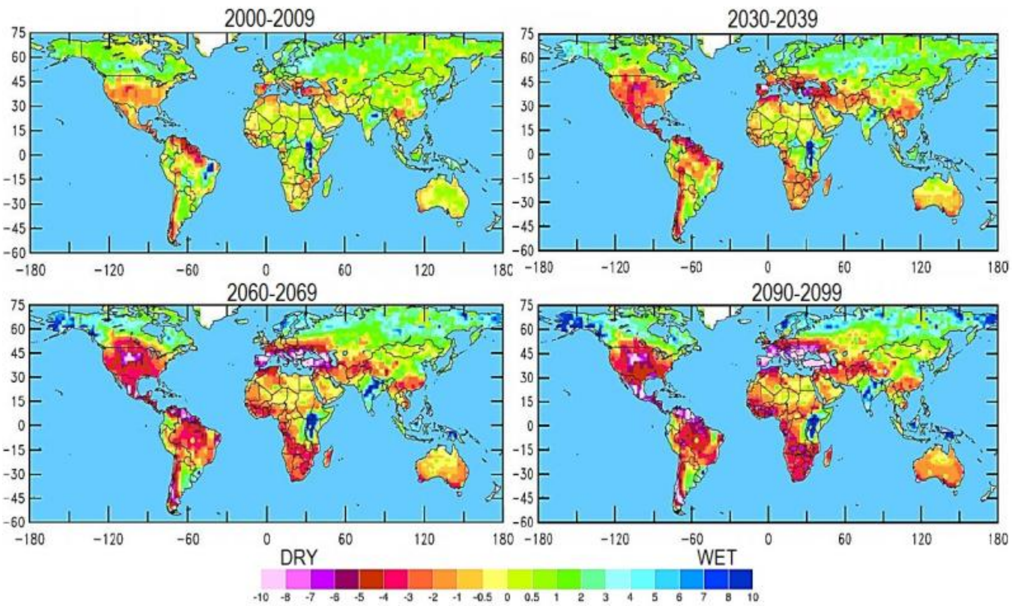

Figure 2.1: Mean Annual sc-PDSI (Palmer Drought Severity Index) in four time horizons, 2000-2009, 2030-2039, 2060-2069 and 2090-2099 [Dai11].

The risks of water supply shortages due to climate extremes and disasters must be managed if the impacts generated by the greenhouse effect, rising temperatures and rainfall variability are to be prevented with the aid of advisor systems. Examples of risks in water assessment, considering the future scenarios, include:

1. In the semi-arid region of East Asia a 10% increase in demand for agricultural irrigation due to a 1^{o}C temperature rise is expected.

2. It is predicted that, under a range of climate change scenarios, the arid and semi-arid areas in Africa will increase by the 2080s.

3. South eastern Australia, New Zealand's North Island and other eastern regions will face constant water security problems due to a decline in runoff and the reduced flow of Australia's Murray-Darling river basin.

4. Annual runoff is forecast to increase in northern Europe, whereas it will decrease by up to 36% in southern Europe, and summer low flows are expected to fall by up to 80% by the 2070s.

5. Water shortages are predicted as well in arid and semi-arid regions of Argentina, Chile and Brazil due to reductions in rainfall.

Aside from climate change, population growth in mega-cities also increases water access vulnerability in densely populated regions such as Beijing (China), Tokyo (Japan) and Delhi (India). Water shortages in these regions will become more frequent because of higher water consumption and water stress intensification [BKWP08]. Studies indicate that water consumption is growing at almost twice the rate of the population growth (Figure 2.2) which can be explained in part by improved access to drink water in many regions.

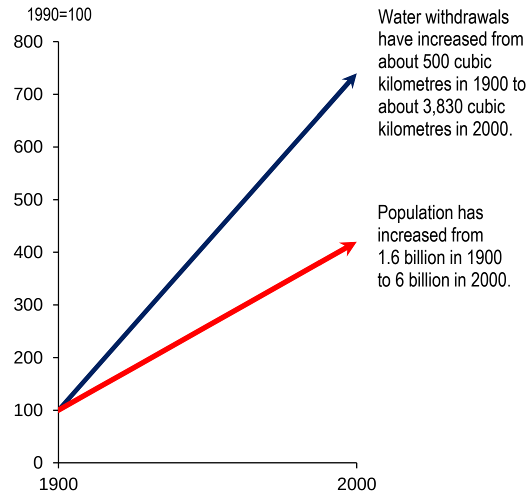

Figure 2.2: Trends in population and water withdrawals [UND06].

The rate of water consumption may decrease when water price increases (Figure 2.3), however, higher water tariffs are a limitation to water access in some regions. More expensive inputs of chemicals, energy, labour and infrastructure replacement are the main reasons for the rising costs. But the scale of the increase depends on local factors. A prolonged drought is one of the factors that may increase the price of water. For instance, San Diego (USA) and Barcelona (Spain) have already imported water from regional wholesale suppliers and by boat transport during droughts, which means higher payments for raw water [Wal11].

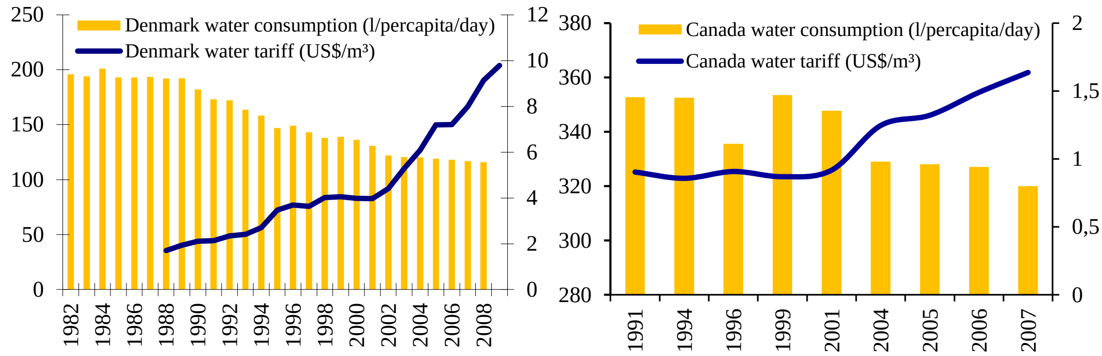

Figure 2.3: Trends in water consumption and tariff: Denmark [DAN11] and Canada [AN09].

The inverse correlation between water prices and *per capita* consumption indicates that the price could be used to regulate consumption. There is, however, a minimum consumption that meets daily water needs without compromising human health and the modern lifestyles. Therefore, if a water tariff accounts for a significant portion of people's income, then alternative sources of supply must be found.

The scenarios presented for water availability have shown the necessity of alternative sources of supply for the future. In regions with high scarcity, treated waste-water may be an important resource. Irrigation is the main activity related to treated waste-water use since it consumes the greatest amount of water [AQU11]. Urban water reclamation for golf course irrigation, toilet flushing and street cleansing is also considered, although water reuse for artificial aquifer recharge, industrial cooling and irrigation in restricted areas are better accepted.

Researchers worldwide are developing more efficient and more effective water management systems in order to solve many water supply problems. The AQUAREC Project has developed integrated concepts for reusing upgraded waste-water in European countries. As part of the AQUAREC Project, it was decided to support Water Treatment for Reuse with Network Distribution (WTRNet) in developing software which would provide an integrated framework for the treatment and distribution aspects of the optimization of water reuse and the selection of end-users. [JSW+08]. In light of the flexibility needed to deal with environmental data other authors (e.g.

[ZS09]; [TS97]; [HMC05]) have proposed Multi-Criteria Decision Making (MCDM) tools to solve various water management problems. The evaluation of these alternatives in water resources necessities depends on the development of adaptive management tools. The environmental model, which aims to identify those necessities, must take into account some aspects related to water stress.

Realizing the importance of tools that support decisions in water management, this chapter presents the rationale and results of a Fuzzy Inference System (FIS) which estimates the potential for regional water reuse using factors considered relevant to the perceived need for reuse (i.e. drought, water exploitation, water uses, waste-water treatment rate among others). The main objective of this chapter is to present the agricultural and urban water reuse potential model by utilizing results from a data-set for 155 regions and 185 cities. It also aims to support decision makers, provide insights to tackle water shortage and to promote discussions about factors that encourage water reuse.

2.1 Multi-criteria decision making (MCDM) and fuzzy logic design considerations

MCDM is one of several tools that solve problems by evaluating a set of alternatives, assuming predefined criteria, and looking for the optimal decision to take. MCDM can deal with many real life problems, but there is a special challenge when dealing with environmental data, because there is very high uncertainty [TSSR98]. Therefore, developments that aid in understanding the potential of waste-water reuse depend on having access to good quality data.

One method of classifying MCDM's methods is according to the kind of data they use. The main types are: deterministic, stochastic, and fuzzy MCDM methods. Due to the uncertainty of the data sets used in this research (i.e. drought, WEI, water consumption, water tariff, etc.), the fuzzy logic method was considered the most suitable option. The fuzzy logic system uses formal models of reasoning (IF-THEN models) to approximate reasoning when the resulting evaluation is uncertain. Uncertainty in fuzzy systems is expressed through subjective languages that capture the concept of relative relation [LSL04], such as: moderate drought, low water tariff, and high water consumption. The mathematical theory to quantify linguistic concepts was created in 1965 by Lofty Zadeh [Zad65]. In his paper titled "Fuzzy Sets", Zadeh demonstrated that a fuzzy set can deal with the ambiguous nature of data, meaning, it is possible to be a member of two different classes (fuzzy set) depending on the design of the membership function. The weight in each class defines whether the member should be a part of one membership function or another. Zadeh explains a fuzzy set as: with the space of points X (objects), with a generic element of X, denoted x, a fuzzy set, A, in the ranges of value, X, can be defined as a set of ordered pairs,

$$A = \{(x, \mu_A(x)) \,|x \in X\} \tag{2.1}$$

where $\mu_A(x)$ is the degree of the membership of x in A (the degree of certainty that x is a member of set A). A fuzzy set (class) A in X is characterized by a membership (characteristic) function $\mu_A(x)$ which associates each point in X with a real number in the interval [0,1], with the value of $\mu_A(x)$ at x representing the "grade of membership" of x in A.

The membership function can be represented by four basic shapes: triangular, trapezoidal, sigmoid and Gaussian. These shapes give an indication of how the grade of memberships varies along the $y - axis$. However, experimental evidence suggests that the membership function design is more important than the shape. In this work a Gaussian curve with uncertain mean (bell-shape) was chosen because the results are able to fit with the common perception of how environmental conditions change (Figure 2.4).

The footprint of uncertainty in the Gaussian curve with uncertain mean varies in magnitude, when based on the values of both the position of the member along the $x - axis$ (Domain) and the membership function range of the $x - axis$ (Support Set). The greater the distance is between the values and the center of the range, the greater the uncertainty. This membership function has both an uncertain mean value within the closed interval $[m_1, m_2]$ and a fixed standard deviation, σ, such as:

$$f_\gamma(x) = exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right] m \in [m_1, m_2] \tag{2.2}$$

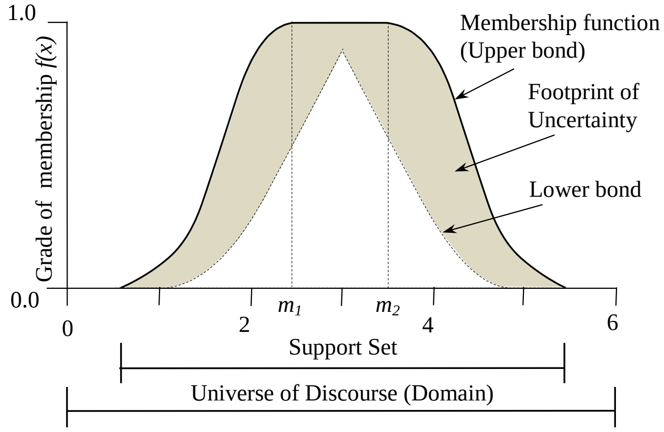

Figure 2.4: Gaussian curve with uncertain mean (bell shape). Adapted from [She06]

This membership function is suitable to characterize the antecedents and consequents in approximate reasoning (IF-THEN models), in situations where the rules deal with words or uncountable concepts [She06]. The logic operation in fuzzy logic is based on Boolean truth tables that determine the results of the logical operation of AND, OR and NOT values that are truth (1) and false (0). The union between two fuzzy sets is indicated by the OR operator and represents the maximum value (max (A, B) or A ∪ B). The minimum value is indicated by AND which represents the intersection between two fuzzy sets (min (A, B) or A ∩ B). The NOT operator is the complement of the fuzzy set.

Employing a process called *defuzzification*, the consequent fuzzy set is converted into measurable values (crisp numbers) by using methods such as the center of gravity and maximum output. In this research work the center of gravity was used as a *defuzzification* method, and the crisp result is calculated by the equation:

$$R = \frac{\sum_{i=0}^{n} d_i f_i}{\sum_{i=0}^{N} f_i} \tag{2.3}$$

where d_i is the domain value and f_i is a grade of membership for that domain point.

2.2 Materials and Methods

The identification of the main types of recycled water use was the first step in this research. Taking into account the largest water reclamation users (Europe, Israel, California, Japan and Australia), more than a half of recycled water is used for agricultural purposes, with urban use (i.e. buildings, streets, landscapes, parks and so on) as the second most common, immediately followed by ground water recharge (Table 2.1).

Table 2.1: Water reuse by type

Regions	Water reuse (Mm^3/a)						
	Total	Agricultural	Ground Water Recharge	Industrial	Ecologic use	Urban use	Domiciliary
Europe and Israel	963	674	164	39	48	39	0
California-EUA	434	213	61	22	56	82	0
Japan	206	16	0	16	66	78	29
Australia	166	50	0	66	5	40	5
Total (Mm^3/a)	1,769	953	224	143	175	239	34
Percentage (%)		54	13	8	10	14	2

Adapted from: Report on integrated water reuse concepts ([Win06])

Due to agricultural and urban water reuse tendencies, factors that stimulate these two types of reuse were considered when developing the system. In this work the urban water reuse was considered for watering (gardens, parks, landscapes, etc.), washing (streets, vehicles, public monuments, etc.), firefighting and toilet flushing in metropolitan public areas. Crop irrigation was classified as agricultural water reuse. Other urban reclamation options were not considered because it was observed that stimuli from the government are usually responsible for large scale water reuse. In addition, some measure of industrial, residential and commercial water reuse is related to private incentives that are driven by economic concerns rather than reasons of water conservation.

The factors that encourage agricultural and urban water reuse were identified and were taken into account in the proposed system. The features used to analyze agricultural water reuse potential were drought, the Water Exploitation Index (WEI) and the ratio between agricultural water use and urban water supply use.

For urban water reuse potential, the features were WEI, drought, demographic density and waste water treatment rate. 155 regions from around the world were selected in order to analyze the features that determine agricultural water reuse in order to design the water reuse potential model. 185 cities were surveyed for urban water reuse. The regions and cities were chosen by accounting for its water reclamation relevance and available data. Some regions initially selected due to their water reuse relevance were left out of this work due to difficulties in finding reliable data. Environmental companies and government statistics were the preferred data sources. A partial agriculture data-set is illustrated in Table 2.2 [AVM+13]. The full data-set can be accessed at *www.dec.uc.pt/ giovanaalmeida/Dataset.xlsx*. The data on regions and cities were evaluated separately in order to identify local characteristics.

Table 2.2: Sample of agriculture data

Region	Water Supply (Mm3/y)	Agric. use (Mm3/y)	AGR[1]/ UWS ratio	WEI[2] region %	Drought region	% WW[3] recycling for agric.	class
Mendoza (AR)	271.15	4299.36	15.86	35	6	60	5
Queensland (AU)	340.20	2144.30	6.30	40	10	6.3	3
Ceará (BR)	232.50	1426.00	6.13	20	5	0.6	1
Alberta (CA)	379.12	498.50	1.31	23	5	2	2
British Columbia (CA)	461.92	233.24	0.50	10	0	2	2
Beijing (CN)	1267.5	1235.50	0.97	45	7	25	5
Tianjin (CN)	419.14	1217.71	2.91	20	5	3.2	2
Crete (GR)	34.43	676.64	19.65	24	5	20	5
Israel	685.00	1016.00	1.48	109	9	67	5
Delhi (IN)	956.30	606.09	0.63	80	7	80	5
Isole (IT)	798.00	2191.00	2.75	30	6	9.21	4
Jordan (JO)	54.37	226.25	4.16	100	9	100	5
Valey of Mexico (MX)	1261.0	1419.00	1.13	45	7	86	5
Algarve (PT)	52.01	247.12	4.75	45	5	2	2
South (KR)	698.62	5198.20	7.44	10	0	0.03	1
Andalusia (ES)	532.16	4579.25	8.61	45	5	12	5
Valencia (ES)	342.83	2056.835	6.00	60	8	26.72	5
Tunisia (TN)	348.10	2110.4	6.06	57	5	25	5
California (USA)	395.16	42141.1	106.64	35	8	36	5
Florida (USA)	274.95	5927.38	21.56	30	5	9	4
New Mexico (USA)	43.38	3951.59	91.08	50	5	1	1
Texas (USA)	181.00	11923.8	65.88	42	4	3.5	2

Source:[AVM+13]

The fuzzy logic toolbox of MATLAB was used to build the Fuzzy Inference System (FIS) and a Simulink model was developed to process the data. Explanations about the featured choices and data-set can be found in section 2.3. The development process of the Decision Support System (DSS) is described in section 2.4.

2.3 Data set evaluation

Worldwide, agriculture represents about 70% of all water consumption, taking the overall sum of withdrawals, while industry accounts for 20% and domestic use 10% [AQU11]. In general, the high level of consumption required for watering crops has made agriculture water reuse more significant than urban reuse. However, in developed and over-populated regions, more than half of the water available for consumption is used by industry (manufacturing and thermoelectric power generation) and for the supply of clean drinking water (Figure 2.5). Belgium, for example, uses 53% of the water available for electricity generation (power plants), 31% for industry (manufacturing) and 15% for drinking water supply. Over-exploitation of groundwater in Belgium's Flemish region has made it necessary to carry out an urban waste-water reclamation project, which has been under way since July 2002. About 2.5 $Mm^3/year$ of treated waste-water is used to recharge an artificial aquifer for drinking water abstraction and to create a saline intrusion barrier [USE04].

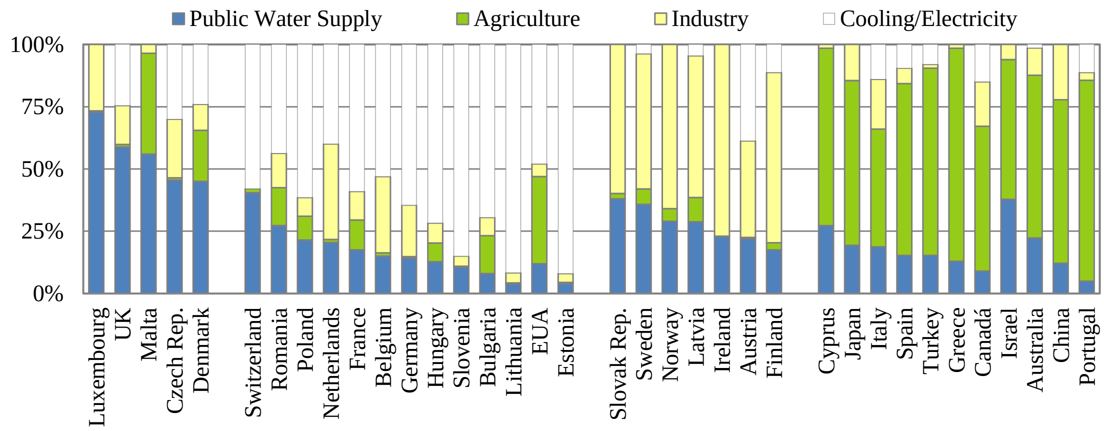

Figure 2.5: Worldwide water use [AQU10].

Analyzing the data from 155 regions, it is observed that persistent drought and the WEI are the important indicators required to find alternative water supply resources. This information confirms that the lack of water is the main impetus in choosing an alternative water reuse project. Correlations between water reuse and the analyzed parameters indicate that agriculture water supply problems due to scarcity are more sensitive to the drought than to the high water exploitation (Table 2.3).

Presuming that the urban water supply will produce waste-water that could be

Table 2.3: Correlation between agricultural water reuse features

		Water supply Use	Agriculture use	Ratio AGR-UWS	WEI	Drought
Agriculture Reuse	Pearson Correlation	0.045	0.382**	0.317**	0.570**	0.614**
	Sig. (2-tailed)	0.578	0.000	0.000	0.000	0.000
	N	155	155	155	155	155
Classif.	Pearson Correlation	0.029	0.395**	0.424**	0.639**	0.804**
	Sig. (2-tailed)	0.718	0.000	0.000	0.000	0.000
	N	155	155	155	155	155

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

recovered to satisfy irrigation demands, it is considered that the higher the ratio between these two parameters (water supply volume and irrigation demands) the greater the agricultural water reuse potential. The Figure 2.6 presents the comparison between reuse level and the analyzed features.

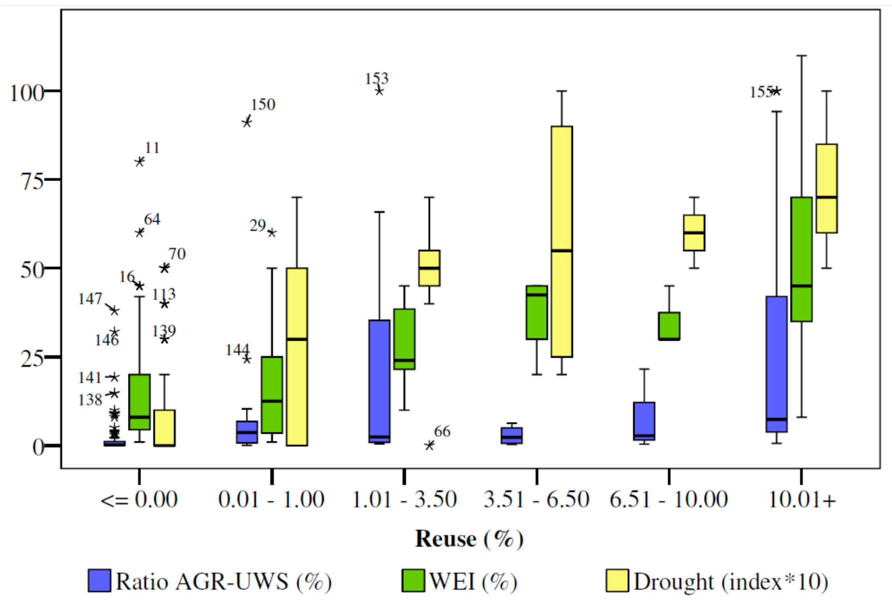

Figure 2.6: Evaluation of 155 regions' features that may drive agriculture water reuse.

In analysing the 183 cities surveyed, it is observed that the high level of water consumption in densely populated cities is the trigger for pressure on water availability. Correlations between water reuse and water exploitation (Table 2.4) indicate that urban water supply problems due to scarcity are more sensitive to high WEI (correl.= 0.40) than drought (correl.= 0.11).

Table 2.4: Correlation between urban water reuse features

	N=183	Urban recycling (%)	Classif.
Resid. water consumption (lpcd)	Pearson Correlation	0.137	0.365**
	Sig. (2-tailed)	0.064	0.000
Resid. water tariff ($US\$/m^3$)	Pearson Correlation	-0.078	-0.317**
	Sig. (2-tailed)	0.296	0.000
Ratio water bill-income percapita	Pearson Correlation	-0.116	-0.249**
	Sig. (2-tailed)	0.117	0.001
Population density ($peop/Km^2$)	Pearson Correlation	0.024	0.014
	Sig. (2-tailed)	0.747	0.854
Waste-water treatment rate (%)	Pearson Correlation	0.029	0.023
	Sig. (2-tailed)	0.693	0.760
Water Supply ($Mm^3/year$)	Pearson Correlation	0.147*	0.261**
	Sig. (2-tailed)	0.047	0.000
WEI	Pearson Correlation	0.400**	0.706**
	Sig. (2-tailed)	0.000	0.000
Drought	Pearson Correlation	0.107	0.416**
	Sig. (2-tailed)	0.149	0.000

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

From the data-set considered it can be seen that cities whose WEI is above 40% have a high urban water recycle tendency, as depicted in Figure 2.7.

About 30% of the 183 cities in the survey recycle waste-water for urban uses. Cities in Japan, Australia, Spain and the United States are very successful examples of urban and/or irrigation waste-water reuse thanks to their efficient control, and management policies. The guidelines and orientations identify the suitable parameters and minimum water quality requirements for water reuse to reduce the risk to human health. Thus, the waste-water treatment rate can be considered an important indicator to estimate urban reuse potential.

The tendency to increase the water tariff could be an extra incentive for urban water reuse but, for some regions, the long history of government subsidies makes the annual water bill less of a consideration in people's income. The Figure 2.8 presents the relation between *percapita* water consumption and three other features: Water tariff, ratio of water bill-income and urban recycling. It is observed that urban recycling is for consumptions greater than 200 l/p/d while the tariff and ratio of water bill-income are smaller when consumption is higher.

The average proportion of the annual residential water bill in the annual household *percapita* income in the 183 cities analysed is 2.9%, in a range from 0.25% to 9.17%.

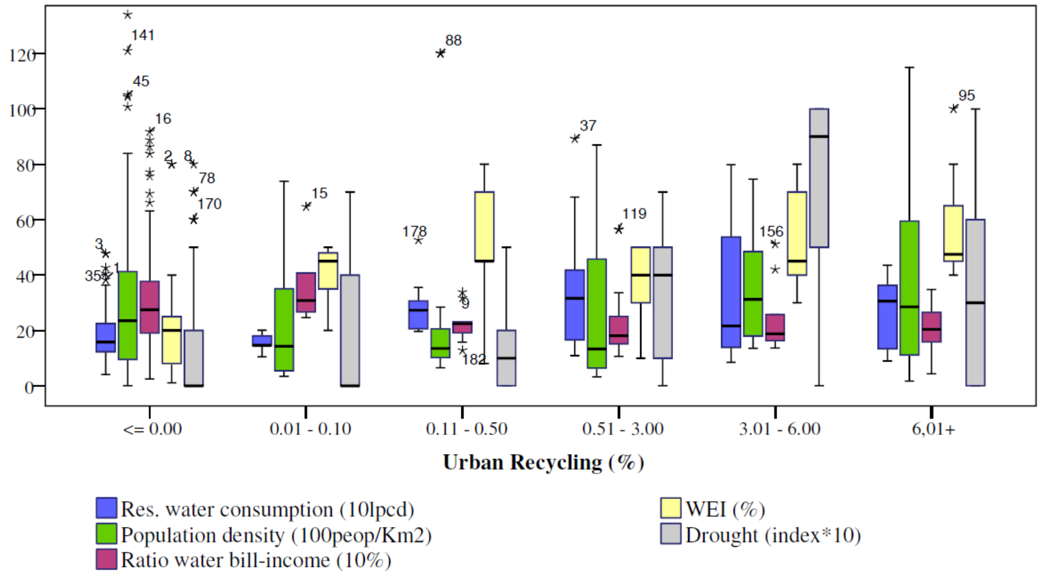

Figure 2.7: Evaluation of 183 cities' features that may drive urban water reuse.

Even though the highest rate is almost 10%, it is noted that 90% of the figures are below 5%. The majority of the cities that commit more than 5% of their income toward water bills are among the cities with the lowest aggregate income. This analysis demonstrates that income has little influence on water costs. It is presumed that the international prices of the inputs for water treatment and distribution such as chemicals and infrastructure replacement are the main reason that drives the water costs variations.

Although there is little relation between water price and recycling, it is observed that the cities with the highest water bill/income relation, which are located in high water scarcity areas such as Incheon-KR (126), Los Angeles-USA (156), Faro-PT (119) and São Paulo-BR (15), have good potential for urban water reuse (Figure 2.9). The water scarcity level was calculated and explained in subsection 2.4.2.

However, an inverse correlation was found between water costs *percapita* and water consumption (Figure 2.10), suggesting that water tariffs can be devised to promote water conservation. Japan is one country that uses this economic aspect to motivate water reuse. Its government has generally subsidized 50% of the capital cost of large scale water reuse facilities and the average cost for non-potable reuse water is 0.83 US$/$m^3$ whereas potable water supply cost ranges from 1.08 US$/$m^3$ to 3.99 US$/$m^3$ [Cle10].

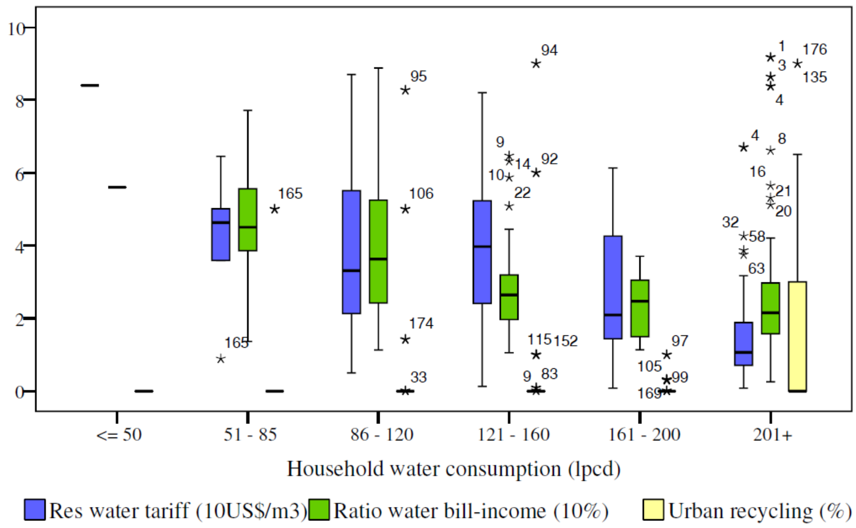

Figure 2.8: Evaluation of the influence of household consumption on urban recycling.

While it is important to identify variables in regional features through micro monitoring so as to support decision making, it is also a constraint for the adaptive management required under conditions of climate change. The variety of micro-climates and local characteristics applying to an extensive area could underestimate the real scarcity of the situation. Furthermore, the greatest potential for water reuse is in those areas where distances between the reclamation location and the waste-water treatment plant are shorter. The cost of reclamation essentially grows with the rate of flow and the distance, because the pipeline alone represents approximately 90% of the total infrastructure in water reuse [And08].

2.4 Fuzzy Inference System Model

For the process of building a model of the agricultural and urban water reuse potential, FIS employed the data set information (section 2.3) in order to identify the features and variables of the membership function.

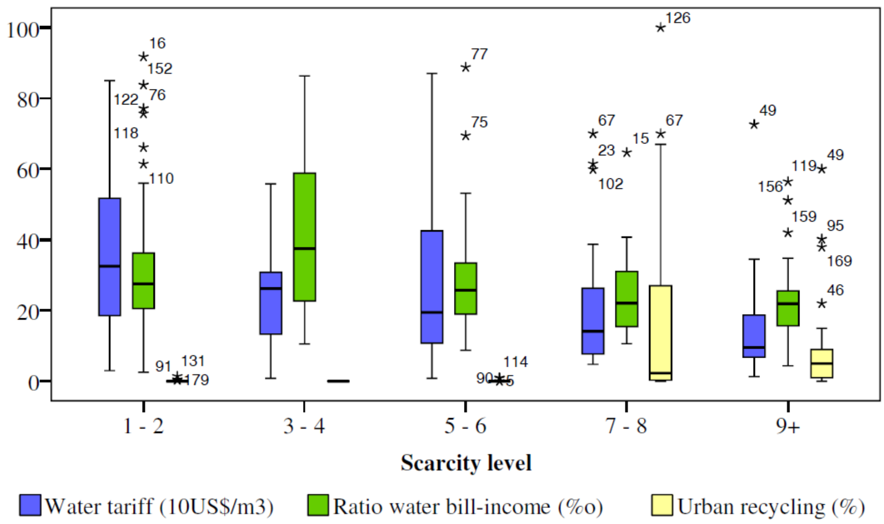

Figure 2.9: Evaluation of the influence of household per *percapita* income and scarcity on urban recycling.

2.4.1 Model of agriculture water reuse potential

The identification of the data and the range for each membership function according to the features' variables was necessary to build the FIS for agricultural water reuse potential (Figure 2.11). A Simulink model was used for data processing purposes.

A drought index is a single number that makes the data easily understandable for decision making. Negative values indicate less rainfall while positive values indicate excessive rainfall. Meteorological agencies around the world use different indexes to manage drought, making it difficult to choose only one index to express the drought severity level in a region. In this research a new feature based on the three most common drought indexes (SPI - Standardized Precipitation Index, PDSI - Palmer Drought Severity Index and WASP - Weighted Anomaly Standardized Precipitation) was developed (Table 2.5), thereby creating the range of membership function variables (Figure 2.12).

Understanding a region's water dynamic is fundamental to developing an effective local strategy to adapt to climate change. The WEI is a feature that measures water stress, or the ratio between the annual water withdrawal and water availability [BM11]. Values above 20% indicate that a country has medium-high water stress,

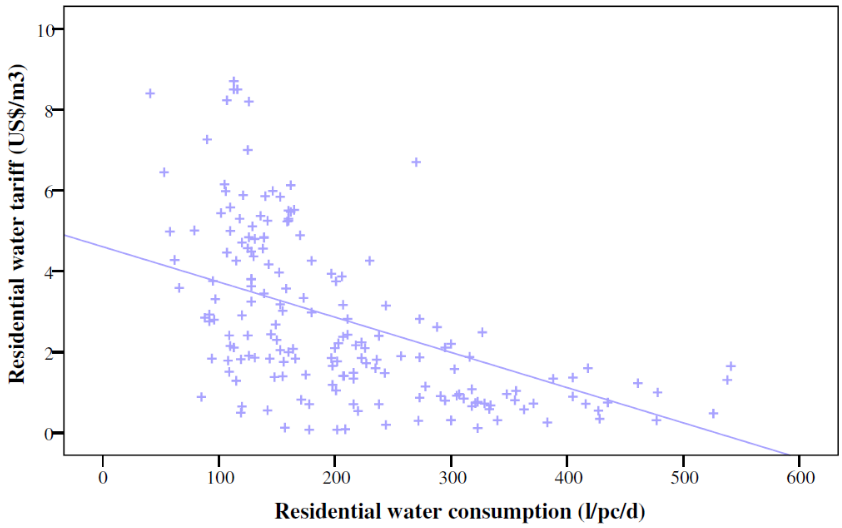

Figure 2.10: Correlation between water residential consumption and tariff.

Table 2.5: Membership function of input variable Drought.

Drought severity features	Drought variables	SPI	PDSI	WASP
Near normal	0 to 1.99	0.50 to -0.50	0.49 to -0.49	1 to -1
Abnormally dry	2 to 2.99	-0.51 to -0.79	-0.50 to -0.99	-1 to -1.5
Moderately dry	3 to 3.99	-0.80 to -1.29	-1 to -1.99	-1.5 to -2
Severely dry	4 to 5.99	-1.30 to -1.59	-2 to -2.99	-2 to -3
Extremely dry	6 to 7.99	-1.60 to -1.99	-3 to -3.99	-3 to -4
Exceptionally dry	8 to 10	-2 or less	-4 or less	-4 or less

Source: [Hay99]

while values below 10% are considered low water stress [OEC03]. The OECD classification was used to build the range of the membership function variables (Table 2.6 and Figure 2.13).

The feature representing the AGR-UWS ratio was created to identify agricultural water use in a region. For this, a set of membership functions for the AGR-UWS ratio was created (Table 2.7 and Figure 2.14). This classification was based on estimations using AGR-UWS ratios and levels of agricultural reuse in the 155 regions analysed (data-set information).

Even though the use of untreated waste-water in agriculture could present a high risk to human health, some regions make large use of sewage effluent, pumping it directly onto crops ([MMNG05] and [MRAQ+08]) because of its low waste-water

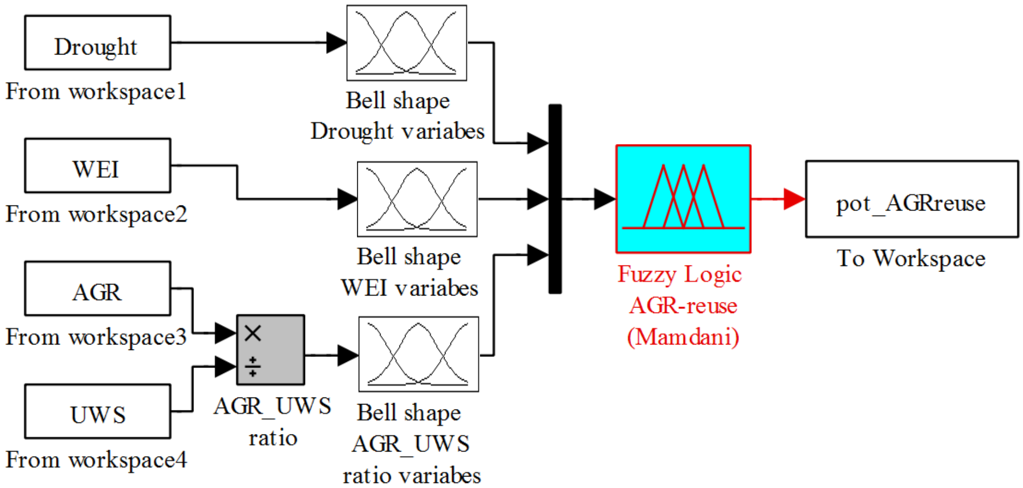

Figure 2.11: Scheme of agricultural water reuse potential FIS.

Table 2.6: Water Exploitation Index features.

Water Stress features	WEI variables (%)
High	> 40
Medium-high	> 20 and ≤ 40
Moderate	> 10 and ≤ 20
Low	≤ 10

Source: [OEC03]

treatment rate. A high level of waste-water reuse in regions with low treatment rate and the opposite, a low level of reuse in regions with high treatment rate, is noticeable which lowers the correlation between the agricultural water reuse and waste-water treatment rate. This is why the "waste-water treatment rate" was not considered a feature for the agricultural water reuse system.

The output classification for agricultural water reuse potential was developed based on the percentage of waste-water recycling for agriculture. It was considered that

Table 2.7: AGR-UWS ratio variables

Features	AGR-UWS ratio variables
Very-high	> 4.0
High	1.5-4.0
Average	0.5-1.49
Low	< 0.5

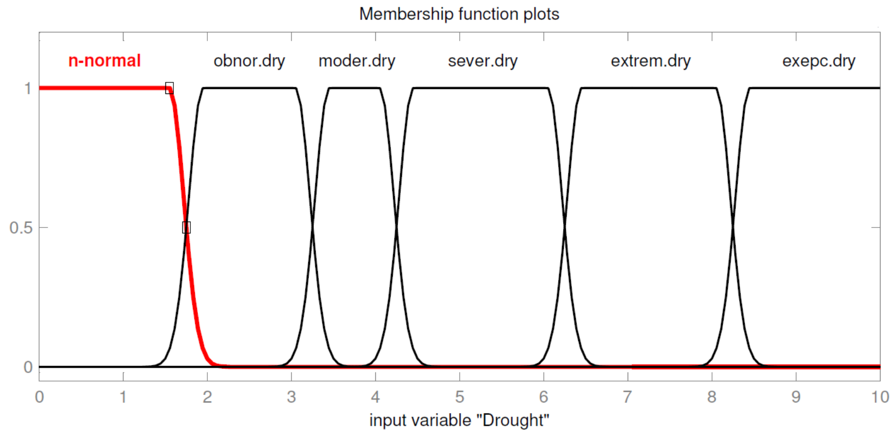

Figure 2.12: Membership function of input variable Drought.

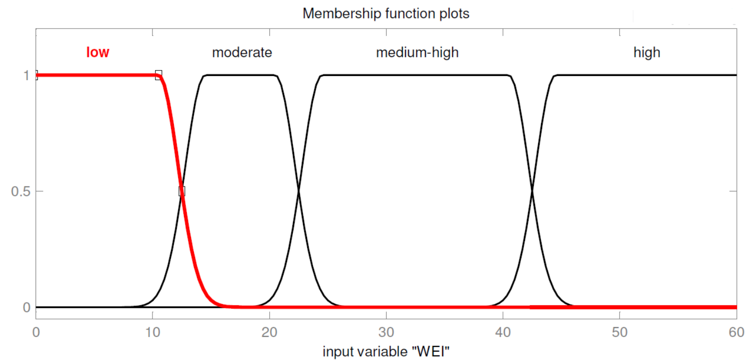

Figure 2.13: Membership function of input variable WEI.

values above 6.5% express a high agricultural water reuse and below 3.5% the reclamation is low. Table 2.8 presents the classification and Figure 2.15 illustrates the membership function configuration.

A number of rules were created to correlate all the fuzzy sets with the relevant membership function. The logical operator AND (Table 2.9) was used to create the rules in order to get the minimum value that represents the intersection between two fuzzy sets (min (A, B) or $A \cap B$). The center of gravity method was used for *defuzzification*.

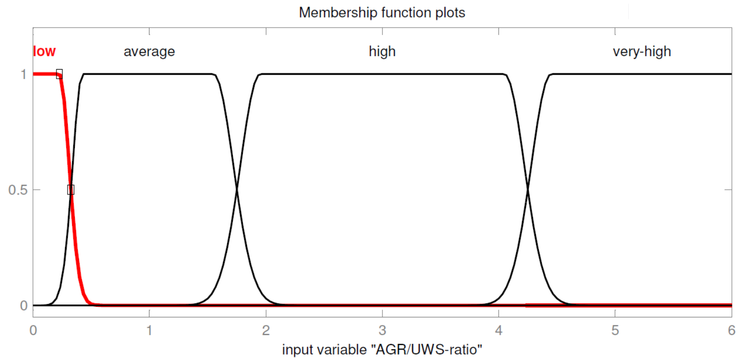

Figure 2.14: Membership function of input variable AGR-UWS.

Table 2.8: Agricultural water reuse potential classification.

AGR water reuse potential	Waste-water recycling for agriculture (%)	Classification (output variable)
Very-high	> 10	5
High	> 6.5 and ≤ 10	4
Average	> 3.5 and ≤ 6.5	3
Low	> 1 and ≤ 3.5	2
Very-low	≤ 1	1
No reuse	0	0

2.4.2 Model of urban water reuse potential

The features analyzed for the urban water reuse potential were: scarcity-level, demographic density and waste-water treatment rate. The scarcity-level values are the result from the output of a scarcity-level FIS, using two Fuzzy sets: WEI and drought as input (Figure 2.16).

The scarcity-level FIS was devised in order to give additional weight to the WEI feature. It was observed in the process of data-set analysis that the WEI is related more to urban water reuse than to drought (Figure 2.7). The concepts behind the WEI and drought features are the same as those used for agricultural water reuse, but the rules for scarcity-level take into account the significance of the WEI values. The output classification for the FIS scarcity-level is shown in Table 2.10 and Figure 2.17.

The urban water reuse software/program FIS uses the data of scarcity-level FIS output as input data, but the variable for scarcity-level input was built with a different range (Table 2.11). The range was modified to simplify the system, using fewer rules

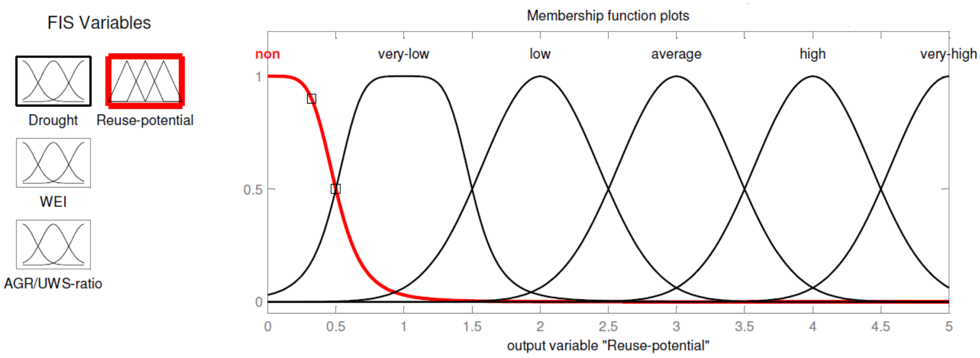

Figure 2.15: Membership function of output variable agricultural reuse-potential.

Table 2.9: Fuzzy Inference System rules for agricultural reuse potential

1. (Drought==n-normal)&(WEI==low)&(AGR/UWS-ratio==low)=>(Reuse-potential=non)
2. (Drought==n-normal)&(WEI==low)&(AGR/UWS-ratio==average)=>(Reuse-potential=non)
3. (Drought==n-normal)&(WEI==moderate)&(AGR/UWS-ratio==low)=>(Reuse-potential=non)
4. (Drought==n-normal)&(WEI==moderate)&(AGR/UWS-ratio==average)=>(Reuse-potential=non)
5. (Drought==n-normal)&(WEI==medium-high)&(AGR/UWS-ratio==high)=>(Reuse-potential=very-low)
6. (Drought==n-normal)&(WEI==medium-high)&(AGR/UWS-ratio==very-high)=>(Reuse-potent=very-low)
7. (Drought==n-normal)&(WEI==high)&(AGR/UWS-ratio==low)=>(Reuse-potential=non)
8. (Drought==n-normal)&(WEI==high)&(AGR/UWS-ratio==average)=>(Reuse-potential=low)
9. (Drought==n-normal)&(WEI==high)&(AGR/UWS-ratio==high)=>(Reuse-potential=average)
10. (Drought==n-normal)&(WEI==high)&(AGR/UWS-ratio==very-high)=>(Reuse-potential=high)
11. (Drought==abnor.dry)&(WEI==low)&(AGR/UWS-ratio==average)=>(Reuse-potential=non)
12. ...
96. (Drought==exepc.dry)&(WEI== high)&(AGR/UWS-ratio== very-high)=>(Reuse-potential= very-high)

without a loss of accuracy in the output results. The method which was used to define the range of the variables took into account the relation between the scarcity values and waste-water reuse rate. It was observed that most reuse cases occur for a scarcity-level greater than 7. Fewer cases were found for scarcity levels 5 to 7, and no cases were detected for 0 to 5 (Figure 2.18).

In addition to human water consumption, urban water infrastructure is needed which can support an overpopulated city (with hospitals, schools, parks, gardens, streets, etc.) that demands a large amount of water resources for non-agriculture or industrial purposes. It is thus anticipated that a densely populated city with scarcity problems will have a greater potential for urban water reuse potential. To identify the urban water reuse potential, the range of demographic density variables to be considered in this research was set with the correlation between population data and level of urban reuse in 183 cities (Table 2.12).

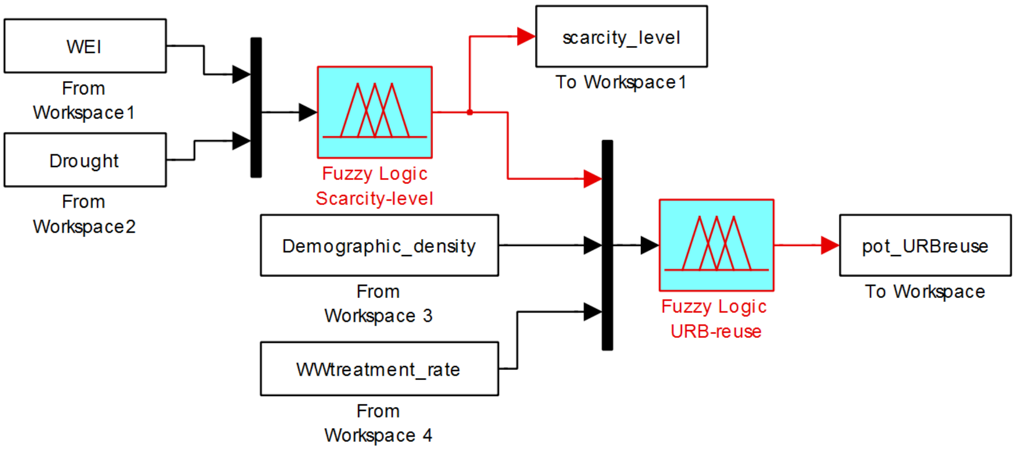

Figure 2.16: Urban reuse potential data processing model.

Table 2.10: Scarcity level classification.

Scarcity-level	Classification
Very-high	8 to 10
High	6 to 8.99
Average	4 to 5.99
Low	2 to 3.99
Very-low	0 to 1.99

Since human health requirements are related to the waste-water treatment rate, this parameter is extremely important for establishing urban water reuse potential. Table 2.13 identifies the waste-water treatment rate range utilized in this work.

The output classification was created based on the real percentage of urban waste-water recycling. The same method was applied for data analysis and agricultural water reuse potential. The classification of urban water reuse potential expresses the level of water reuse in a city. It was considered that values above 3% express high urban water reuse and below 0.5% reclamation is low. The differences between agricultural and urban waste-water recycling ranges results in the imbalance of water reuse potential. The water reuse potential for agriculture is greater than for urban

Table 2.11: Scarcity-level variables.

Scarcity-level	Variables
High	7 to 10
Average	5 to 6.99
Low	0 to 4.99

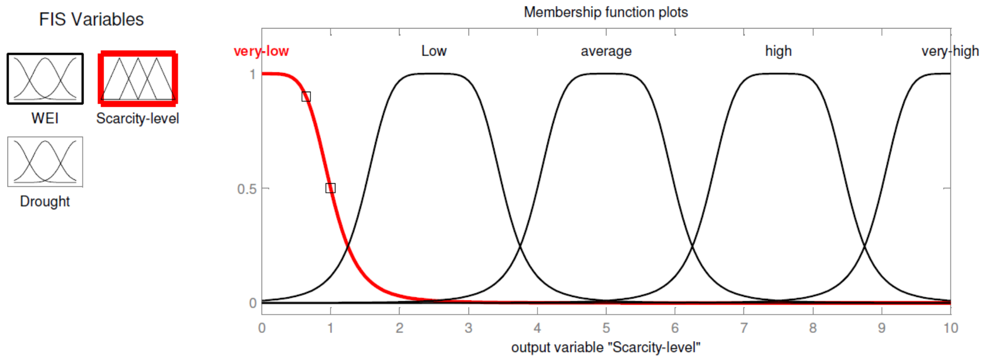

Figure 2.17: Membership function of output scarcity-level variable.

Table 2.12: Demographic density variable.

Demographic density	Variables ($pop/Km2$)
High	> 500
Average	300-500
Low	100-300
Non	< 100

water reclamation because of the large demand for irrigation. Moreover, waste-water quality requirements for irrigation are lower than for urban uses, and so a less complex treatment system is needed (Table 2.14).

Thirty-six rules were created to correlate all the fuzzy sets and the relevant membership function. The logical operator AND was applied in order to obtain the minimum value that represents the intersection between two fuzzy sets (min (A, B) or A ∪ B). The center of gravity method was used for *defuzzification*.

2.5 Results and discussion

The developed models were tested in order to verify whether they simulate the real situations described by the data-set. The results indicate that the selected features'

Table 2.13: Wastewater treatment rate variable.

Waste-water treatment rate	Variables (%)
High	> 60
Average	30-60
Low	< 30

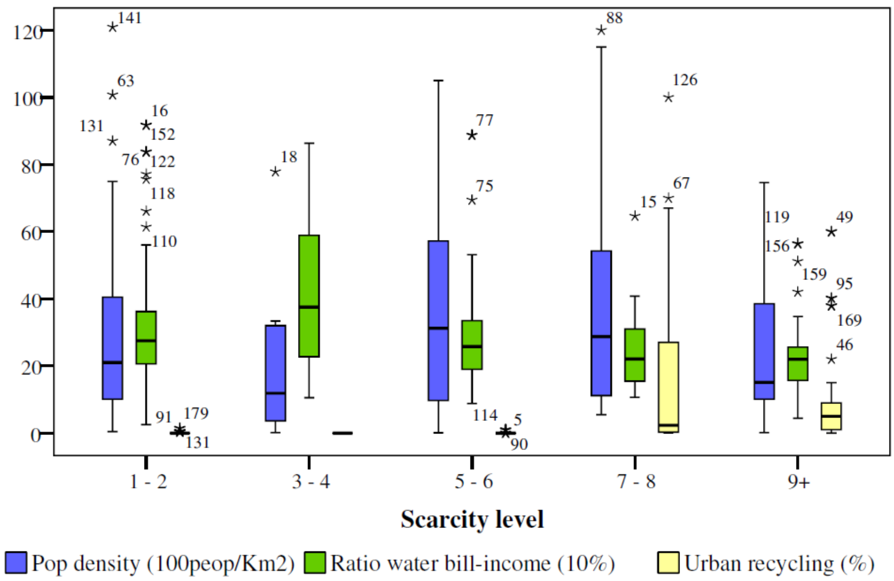

Figure 2.18: Influence of scarcity level on population density, ratio water bill-income and urban recycling.

Table 2.14: Urban water reuse potential classification.

Urban reuse potential Output variable	Urban Waste-water recycling (%)	Classification
Very-high	> 6	5
High	> 3.0 and ≤ 6	4
Average	> 0.5 and ≤ 3.0	3
Low	> 0.1 and ≤ 0.5	2
Very-low	≤ 0.1	1
No reuse	0	0

variables provide a suitable value for the reuse potential level. The final models are a result of several iterations and adjustments of variables' ranges in order to get the best data fit. The output of the final model for agricultural water reuse potential matches with the data-set classification in 90% of the cases (Figure 2.19).

The major difference between classification and simulation values is found in the data for New Mexico (USA). Whereas the environmental characteristics of the region indicate a high level of water reuse resulting in a high simulation value, the classification value is not high. However, regions near to New Mexico and with similar characteristics, such as Arizona and Utah, have high water reuse. Research shows [Her06] that the variations in water reuse in different parts of the USA can be explained by the variability of water availability, as measured by the Rainfall Variability Index.

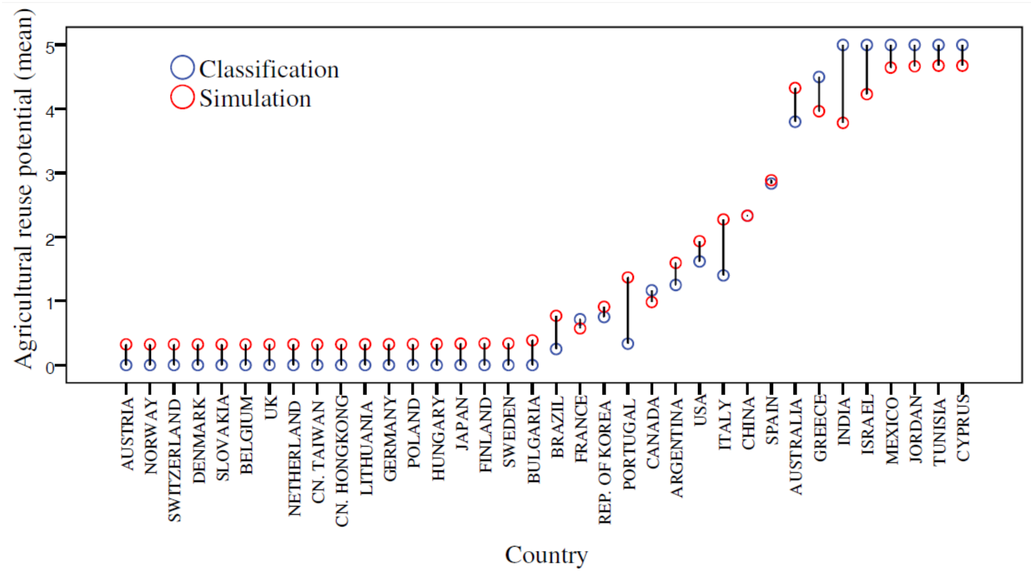

Figure 2.19: Results of FIS agricultural water reuse potential for 155 regions by country.

The Rainfall Variability Index (RVI) is calculated by the coefficient of the variation combined with the Hurst exponent. It would be quite difficult to use this method to calculate the rainfall variability index for all regions analysed in this work, therefore the variability of water supply was not included in the measurement. However, it would be interesting to use this feature in a narrower scope to estimate the potential for water reuse in these regions.

Differences between classification and simulation were also found for Auvergne (FR), Maharastra (IN), southern Italy, Alentejo (PT) and Colorado (USA). These differences could be explained by specific situations, including the uncertain values between variables, adjustments of variables, inaccurate data and evaluation errors. Although some of the output data is imprecise, the general results can be regarded as a good indicator for agricultural reuse potential.

The data processing results for the FIS for urban water reuse potential indicate that the output values had a good relation with the reuse classification values (Table 2.14). About 85% of the output data match the classification (Figure 2.20).

The fit of the simulation values for urban water reuse potential FIS with the classification values was less good than it was for the agricultural water reuse FIS. The complexity of the urban environment is a challenge to finding suitable features for

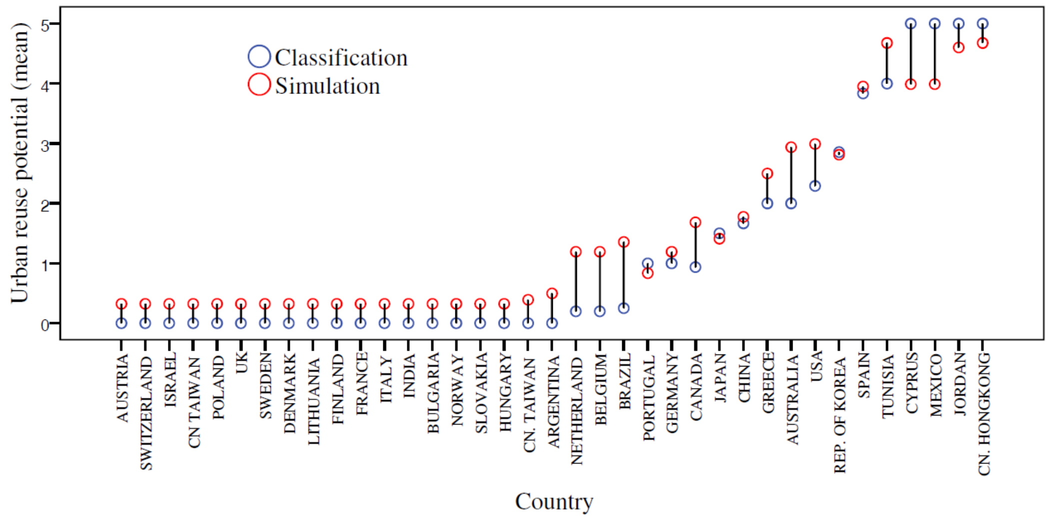

Figure 2.20: Results of FIS urban water reuse potential for the 183 cities by country.

water reuse potential. The features employed in the urban FIS represented the worldwide data best, but regional contexts could require some adjustment of the features.

Some differences were found between the classification and simulation values in the three Japanese cities of Sapporo, Fukuoka and Osaka. These results can be explained by specific characteristics such as, localized drought, high water consumption due to overpopulated cities, pollution and geographical conditions, all of which have contributed to water shortages in Japan. Despite average rainfall in Japan being 1700 mm, which is twice the world average, the annual *percapita* rainfall is about 1/4 of the world average (5100 m^3), because it is a small strip of land with overpopulated cities, which further aggravate water supply problems [TMN02]. Japan has also experienced severe droughts, for example in 1939 in Lake Biwa, 1964 during the Tokyo Olympic Games, 1967 in Nagasaki, 1973 in Takamatsu, and 1978 in Fukuoka (with rationing of the municipal water supply for 283 days) [SOY$^+$03], although, some cities exhibit low drought persistence (long term drought severity index), which lowers the simulation value of the urban potential water reuse FIS.

Despite the scarcity, many cities are not allowed to reclaim water owing to policy restrictions imposed by local water facility boards and worries about the risk to human health. Much research has been carried out and many guidelines have been published on water quality and on procedures for urban water reuse, but it has taken some countries a long time to draft policy and procedure documents, operations and maintenance plans, user agreements, design standards, and training and public information programs. Dallas (USA) took five years to initiate its first reuse project. The city completed its "Recycled Water Implementation Plan" in 2005 [DWU05] and in 2010 saw the start of urban reuse projects for golf course irrigation [Gro11]. Water reuse can also involve court cases that have an impact on future reclamation. In March 1998 the United States Bureau of Reclamation set out to seek approval for an application to appropriate 43.78 million m^3 per year of sewage effluent in the Salt Lake Valley (Utah) but, after six years, there was no decision due to a disagreement over interpretations of water rights [UDW05].

Given the environmental and structural features, the proposed FIS is able to identify whether the studied sample has reuse potential or not, with 96% of accuracy in the case of urban reuse and 90% in the case of agricultural reuse. The approach utilized to model the water reuse potential indicated that some variables can give a warning to decision makers about the risks of water shortage and the consequent alternative water supply necessities. The decision parameters of agricultural FIS rules indicate that the highest water reuse potential is verified for extreme and exceptional drought events (values between 6 and 10) in regions with WEI above 25% (Figure 2.21-a). For low droughts the WEI could affect the water supply when it reaches 45% or more. AGR/UWS-ratio is the last representative feature for the analysed model. For instance, it has been observed that a greater influence on the drought index exists in the relation between AGR/UWS-ratio and drought (Figure 2.21-b). Water reuse potential is representative for the highest AGR/UWS-ratio and WEI above 40% (Figure 2.21).

The decision parameters of urban FIS rules show that the highest water reuse potential is verified for areas subject to high scarcity (6-10), demographic density above 300 and a waste-water treatment rate above 60% (Figure 2.22).

It is expected that the model could be useful for decision making in order to estimate future water reuse potential using new data-sets despite the eventual need of model adaptation when considering local factors that drive water scarcity. Water resources management entities and municipal authorities would be the key stakeholders for this system. Other models or tools could be used to create an inference system which reflects the model's conception. For instance, the Bayesian network (BBN) is also used by researchers [KM12] as an alternative to fuzzy logic rule-based systems, so,

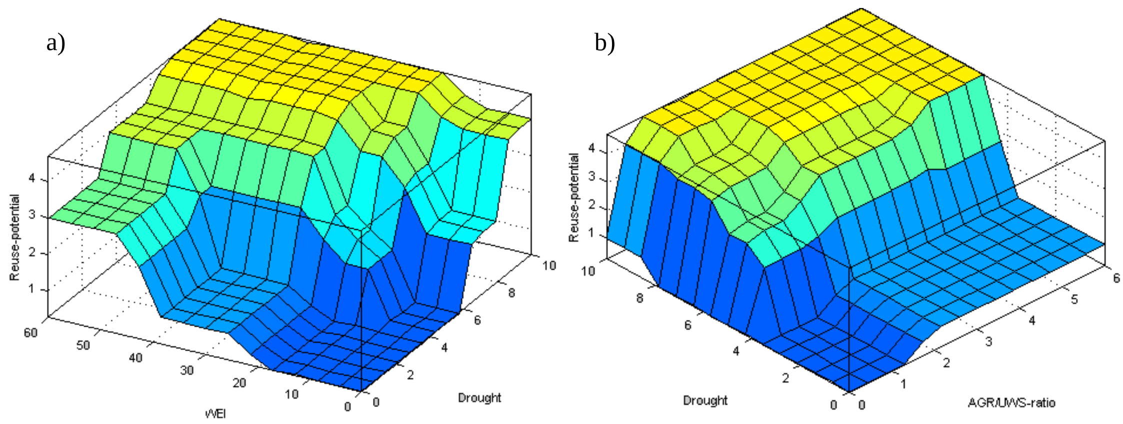

Figure 2.21: Decision surface for agricultural water reuse potential: a) WEI and drought; b) AGR/UWS-ratio and drought

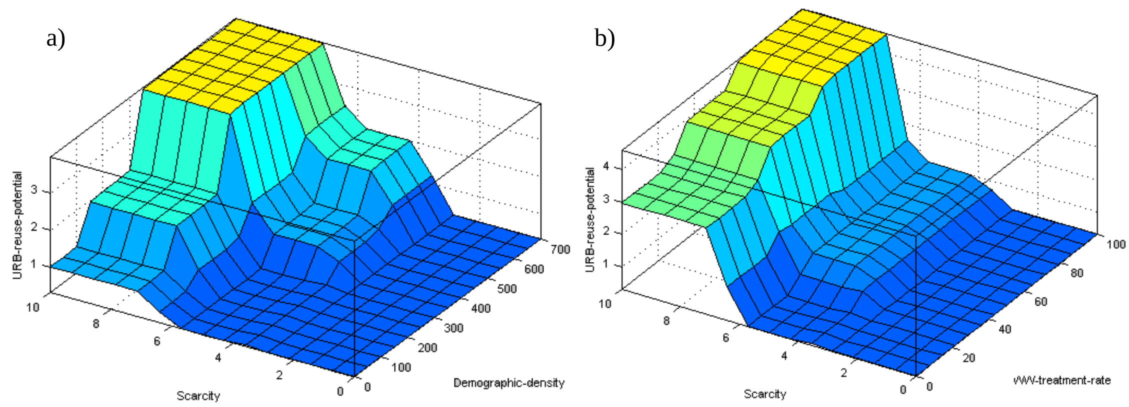

Figure 2.22: Decision surface for urban water reuse potential: a) demographic density and scarcity; b) WW treatment rate and scarcity.

BBN could be used in the future to compare results. It is also recommended that future research should focus on developing a system which evaluates water reuse potential for a smaller scope in order to utilize local features in identifying water reuse potential more accurately. It was observed that the uncertain values between variables, adjustment of variables, inaccurate data and evaluation errors contributed to discrepancies between classification and simulation data.

2.6 Conclusion

The development of a new decision tool that disseminates water availability trends and identifies the alternative water resources necessities may be helpful for decision makers in regions with scarcity problems. This study suggests that "water reuse potential" is a good indicator to support decision-making with respect to alternative water supplies resources necessities. Information on water reuse potential is important because it can warn about future alternative water supply needs, and thus predict water shortages. The complexities of the environment define the features needed to determine suitable simulation data. Features such as drought, water exploitation, water uses and wastewater treatment rate are considered relevant to the perceived need for reuse. The model built for agricultural and urban water reuse potential takes into account a data set of 155 regions and 185 cities around the world. The information provided by data set was useful in arranging the features' variables under FIS membership functions. The decision parameters which were the result of the FIS rules indicated that the drought index is the most representative feature for agricultural water reuse potential. On the other hand, it is estimated that WEI is more related to urban water reuse potential. Other features, although less representative, allow for adjusting the model in order to simulate the classification data. The results have demonstrated that it is possible to identify the water reuse potential through a fuzzy inference system tool. However, other tools can be used and tested in future works, such as BBN. The developed model can be adapted by applying local characteristics in order to help decision makers meet future water reuse needs. The results of this work also promote the discussion of water supply challenges when considering climate change scenarios.

Chapter 3

Water uses identification through signals classification

THIS chapter presents the results of a research project which aims to develop a household water use identification system through signal pattern analysis. The information provided by water use identification is useful for efficient water supply systems developments. Some interventions, such as water losses reduction techniques and water reuse systems are considered important to save representative amount of water, mainly in regions under scarcity. High scarcity resulting from warmer climates represent risks to the water supply and the increasing demand for drinking water is resulting in water shortages in many regions, as described in Chapter 2. The trends concerning persistent drought and growing water exploitation amount to a warning about water supply safety and security. The OCDE 2014 climate change report estimates that 150 million people currently live in cities with water shortage problems and future scenarios suggest a large increase in this number, possibly up to 1 billion by 2050 [IPC13]. In Portugal, as well as in other Mediterranean countries in the 2050 and 2100 scenarios, it is estimated there will be lack of water quality and a severe reduction in the availability of the water supply due to climate change [SFM02]. These scenarios demand efficient water management; however, annual water losses in Portugal equate to three billion cubic meters where 30% of this volume is lost in the urban environment: buildings and public water systems ([PNU14] and [ERS12]). The new technological techniques that could contribute to controlling water losses and efficient water utilization are now essential to promote water resource sustainability.

Studies which aim to support supply security characterize household water use to identify opportunities to save and/or reuse water [SS09]. High water consumption and damaged water pipes (allowing leakage) are indicators of inefficient water use.

A telemetry system provides more detailed and reliable household water consumption data through automatic data acquisition and analysis. The system is both inexpensive to install and accurate, so it is being increasingly utilized by water supply companies as a management tool. Precise flow rate data is needed to identify uses patterns, and the automation of data acquisition and analysis is useful for large scale studies. The daily data processed by telemetry systems use to be converted into monthly consumption information in order to manage water bills. However, the large amount of data produced by this telemetry offers an opportunity to develop new models and algorithms to characterize water consumption [MLM+07]. Detailed information about water use by each fixture can provide important indicators about water users' behavior. This information can be useful by making it possible to design new household water supply systems that promote water use efficiency. Consumption at unusual times such as late at night or when there is no-one at home could be registered and water users informed in time to prevent significant water losses.

Independent studies on water use characterization have been growing in number due to the possibility of improving the management and efficient use of water. Studies in the USA [Aqu05], Spain [GRL08] and Brazil [AKDL06] have presented methodologies to characterize water consumption in households. These works were examined in three stages: data collection, data analysis and assessment of the information collected. A telemetry system was used for data acquisition in the studies, but procedures used to characterize water consumption were different. Water meters with pulsed output and data loggers were the main equipment used.

TraceWizard 4.0 was developed in the USA to identify water use. This software requires the prior input of data on the parameters related to water users' behavior and ownership of the fixtures. Parameters such as flow rate, duration and periods of use, have to be adjusted by the researcher to allow the system to distinguish between a tap use and a toilet flush. The disadvantage of this methodology is the inaccuracy of the results if the parameters are not well adjusted. The system also has difficulties in recognizing water use when three or more fixtures are used simultaneously. In Spain, Madrid's main water supply company (Canal de Isabel II) carried out a water consumption characterization study in 2001. A review of the explanatory variables provided by 4,625 domestic consumption surveys in a random sample was deemed to represent all Madrid households. The ratio of water consumption and characteristics of each household allowed an assessment of the consumption functions and variables. The signal pulse information from the representative residences provided by telemetry was compared with the previous characterization (functions and variables) of its amplitude and temporal patterns, which made it possible to identify the water use at any moment and in any house. A similar study was undertaken in Bahia (Brazil) in 2006 in which the information on water use provided by a survey was compared and correlated with the flow signal provided by telemetry. The correlation did identify the signals of some uses, however, the low accuracy of survey information prevented the accurate estimation of all water fixtures' uses.

Recent developments for household water use monitoring [SSW13] and [LFC+12] use sensors to help with fixtures identification. The algorithm presented by [SSW13] uses data fusion between the smart meters and other sensors or infrastructure already installed in the home (i.e. home security or home automation system) in order to enable fixture recognition and disaggregation. Other investigations in this field [LFC+12] propose single-point pressure sensors within a home's water infrastructure to provide water fixture use information for identification as well as estimation of the amount of water being used at each fixture. The pressure sensors developed for this investigation generate a unique pressure wave that can be classified by the system as fixture usage events. These two methodologies use transient signals for classification and present good accuracies for fixture recognition, but the quantity of sensors needed depends on the number of fixtures at home. News developments in data acquisition propose a sensor network node equipped with a one dimensional accelerometer to measure the vibration and estimate the flow rate [KSC+08]. This autonomous water monitoring is considered less intrusive, auto-calibrated and has to be installed in each pipe. Other methods that require a single sensor per fixture ([JS10], [GOB11], [Fer07] and [Bar08]) use to provide good results in recognition and disaggregation, but more studies are needed to estimate the costs with sensors and pipeline retrofit necessities, mainly for large-scale investigations. Differently from the previous approaches, our work proposes a low price data acquisition system composed by only two sensors: one water meter with pulsed output and one pressure transducer to provide flow rate and pressure signals.

It is observed that signal processing, optimization and machine learning techniques have been used for automatic water and electrical monitoring developments [DDL+10]. These techniques can be used for signal recognition and/or disaggregation. Studies in this field [SSW13] have indicated that recognition techniques are used to identify when the fixtures are turned-on or turned-off and that thee disaggregation techniques identify how much energy or water is used by each fixture. Recognition techniques for electric households' load monitoring and identification has been proposed since the 1980s [JLL+11] and the electrical current and voltage signatures are used to identify load types and power utilization. The methods used to identify electric loads can be divided into two additional main categories: transient state based and steady state based [ZGIR12]. The steady state based (e.g. methods based on real and reactive power) requires waiting until the transient behavior settles down to measure the values, however, some loads do not yield reliable steady-state measurements [LLC+03]. Besides, the steady-state systems process data in batch format which may limit the on-line monitoring. On the other hand, transient-based signal recognition permits near-real-time identification, especially in turn-on events [JLL+11]. A frequency domain spectrum resulting in a Fast Fourier Transform (FFT) is also recommended for a households' load identification due to its proprieties in highlight features characteristics ([DDL+10] and [LLC+03]). Multi-layer-perceptron and Support Vector Machines (SVM) based models presented good performance in identifying the particular loads' presence based on input current waveform harmonic signatures ([CSL00] and [SV12]).

Considering the importance of water management this work proposes a non-intrusive water monitoring (NIWM) system that uses recognition techniques for a household's fixtures identification. As suggested for some non-intrusive electric load monitoring systems (NILM) [ZGIR12], the NIWM proposed here aims to recognize fixtures from the aggregated data acquired from a single point of measurement at the entrance of the household water supply. Signal processing tools (e.g. digital filters and FFT) and pattern recognition technics (i.e. SVM and GDX) were used to classify transient flow and pressure signals. Time and frequency domain transient signals were used to train and test data samples in order to enable on-line water use monitoring. Five residential water fixtures were considered for classification: C1 - kitchen tap (KT), C2 - washbasin tap (WT), C3 - bidet (BD), C4 - shower (SH) and C5 - toilet flush (TF).

3.1 Materials

Two experimental facilities were set up at the Hydraulics, Water Resources and Environment Laboratory of the Department of Civil Engineering of the Faculty of Science and Technology (University of Coimbra) in order to develop the experiments. The first, the "simplified experimental facility", was used to develop and test the data acquisition system tool for data processing while the second was being constructed. The second, the "developed experimental facility", was built to simulate a household water distribution system and was useful in the acquisition system development and also in continuing the experimental data analysis while evaluating more reliable household water use signals.

3.1.1 Simplified experimental facility

The considered hydraulic system includes two volumetric water meters with pulsed output (*Actaris Aquadis+*, class D) and two taps (Figure 3.1). The calculated volume is converted in a pulse sequence through a sensor (*Cyble^{TM}Sensor*) installed on the water meter. A data acquisition card with USB interface (*USB card NIdaq 6009 data acquisition - DAQ*) interconnects the *Cyble^{TM}Sensor* and the laptop. This card allows the data to be acquired through various analog input channels and stores the data in the computer using *MatLab/Simulink* software. Some features were developed in *Simulink* for data acquisition and processing thus enabling the analysis and development of classification algorithms based on the flow rate signal. The *Simulink* data acquisition block was configured by selecting the channels involved, the sampling frequency and the number of samples provided by the DAQ for each channel [AVMC11].

3.1.2 Developed experimental facility

The second experimental facility was built to simulate a household water distribution system (Figure 3.2). The water supply system was constructed in cross-linked polyethylene pipe (PEX), chosen for its easy installation and adaptation. Furthermore, PEX is widely used in interior water supply systems in Portugal. The PEX

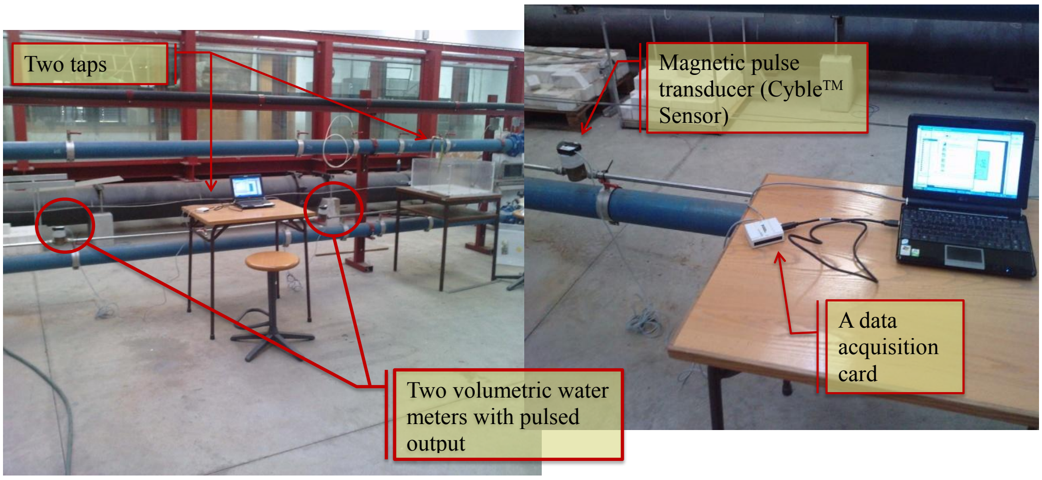

Figure 3.1: Simplified experimental facility.

system included five fixtures: sink, washbasin, shower, bidet and toilet flush. Two different taps mechanisms were installed: compression (threaded spindle) and cartridge (lever handle). This would be useful for analyzing differences between the signals triggered by activating the fixtures.

Figure 3.2: Developed experimental facility.

One check valve, one manometer, one hydraulic pump and pressure transducers were also installed at the new experimental facility (Figure 3.3). The pressure transducer was included for comparison between pressure and flow signal classification, the hydraulic check valve was needed to reduce and stabilize the pressure at the entrance of the system and the manometer identifies the pressure value in the pipe. The pressure in the experimental facility pipes was stabilized at 3.5 bars because it is the pressure normally used for household water supply in Portugal. Also, pressure stabilization helps identify patterns which will help avoid pressure oscillations that may modify the pressure signals. The hydraulic pump was useful to bring the water used at the experimental facility to a reservoir and to be reused in other laboratory facilities.

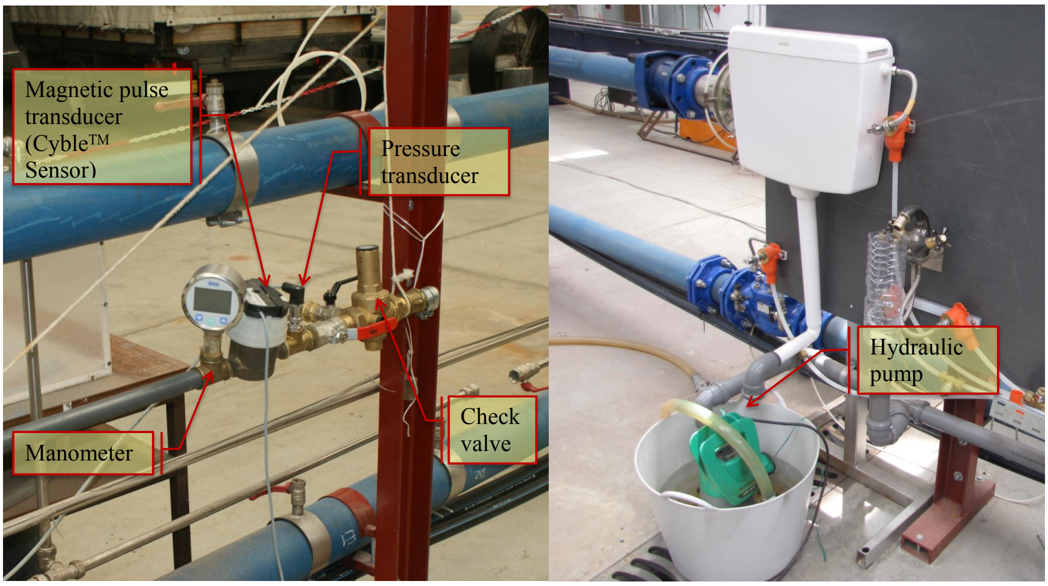

Figure 3.3: Devices installed at the developed experimental facility.

The data acquisition devices in this new facility consist of one volumetric water meter with pulsed output ($Cyble^{TM} Sensor$), pressure transducer, data acquisition card (DAQ) and a computer. The acquisition system developed at $MatLab/Simulink$ software was the same used at the simplified experimental facility. The design of experimental facilities took into account data acquisition and a processing simplification that could be replicated in large scale. Therefore, inexpensive and standard devices were used to build the water system.

3.2 Methods

The proposed methods to collect, treat and analyse the data were developed under this research project. The literature review provided the theoretical subsidies for the approaches presented here. Experimental investigations in controlled environments were conducted in order to explore the different possibilities for setting up the facilities and to test the developed techniques.

3.2.1 Data acquisition tools

This subsection describes the flow rate and pressure data acquisition process and how the devices (i.e. sensor, water meter, pressure transducer and DAQ) were set up at the experimental facility in order to collect the data. The *Cyble Sensor* at the flow rate acquisition system generates pulses similar to those generated by Reed Relays, however, the pulses are electronically generated (hence perfectly squared shape) and are not sensitive to magnets. The sensor can take into account the direction of the flow (backflows). The low-frequencies (LF) signal transmitted by the *Cyble Sensor* detects each rotation of the water meter and then it emits 1 pulse per revolution. Each revolution means that 0.1 l of water passed by the water meter. It remains active whenever there is a flow, whatever the flow direction is. Each sensor is connect to an analog input (AI) channel of the DAQ card using a two wired cable (Figure 3.4). After the analog-to-digital conversion (ADC) in the DAQ card, the data in digital format is sent to the computer through a USB cable.

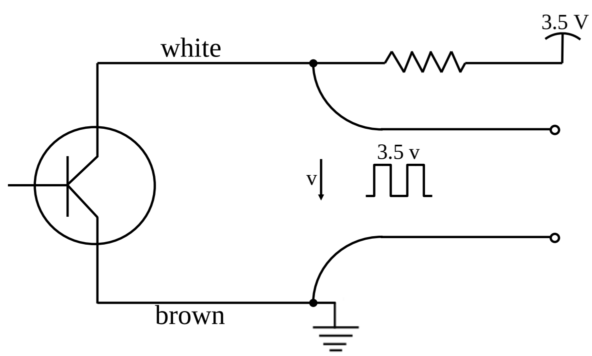

Figure 3.4: *Cyble Sensor* circuit connections.

The *Cyble Sensor* was installed on two water meters at the simplified experimental facility requiring two channels to connect the water meters and the DAQ. For the developed experimental facility one more channel was necessary in order to connect the transducer. A pressure transducer is a transducer which converts pressure into an analog electrical signal. The conversion of pressure into an electrical signal is achieved by the physical deformation of strain-gauges which are bonded into the diaphragm of the pressure transducer and wired into a Wheatstone bridge configuration. Pressure applied to the pressure transducer produces a deflection of the diaphragm which introduces strain to the gauges. The strain will produce an electrical resistance change proportional to the pressure. So, a continuous analog signal is provided by the transducer and the values conversion (volts-bar) is made by a simple relation: 1V = 2 bars. One 2200X-A3 Series Pressure transducer with 0-5 Vdc output range and 0-10 barG of pressure Range was used at the acquisition system. The transducer wired cables is connected to an analog input (AI) channel at the DAQ and to the power supply as depicted at the Figure 3.5.

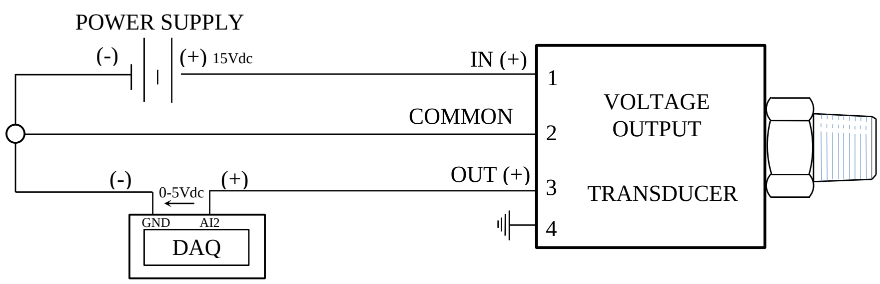

Figure 3.5: Pressure transducer circuit connections.

The functionalities for data acquisition and processing at the computer were developed in MatLab/Simulink, a commercial tool for modeling, simulation and analysis of dynamic systems. The data acquisition block with multiple analog input channels was used as interface in the Simulink model. The water meter signals and transducer were connected to input channels and they are represented by the signals HWChannel 0, HWChannel 1 and HWChannel 2 as shown in Figure 3.6. Output blocks for data storage in the Matlab workspace (pulse signals) and a Scope block (to show the signal during the data acquisition) were also considered. To distinguish the signals from the water meters, the analog output block generates two different values for the reference voltage of each pulse signal (3.5V and 1.5V for the signals from the water meter 1 and 2, respectively). A clock block was added to generate the current simulation time.

The Simulink data acquisition block was configured by selecting the DAQ channels involved (channels 0, 1 and 2) and the sampling frequency. The DAQ was configured to acquire 50 samples per second from each sensor, but it emits to the PC sample-packages of two samples per channel. So, the PC receives from the DAC 25 sample-packages per second. The highest frequency of the sensor expected for the considered system is 6 pulses/s, so the number of samples is based on the Nyquist-Shannon sampling theorem [IJ02] which says that the sampling rate must be more than twice the highest frequency of the signal.

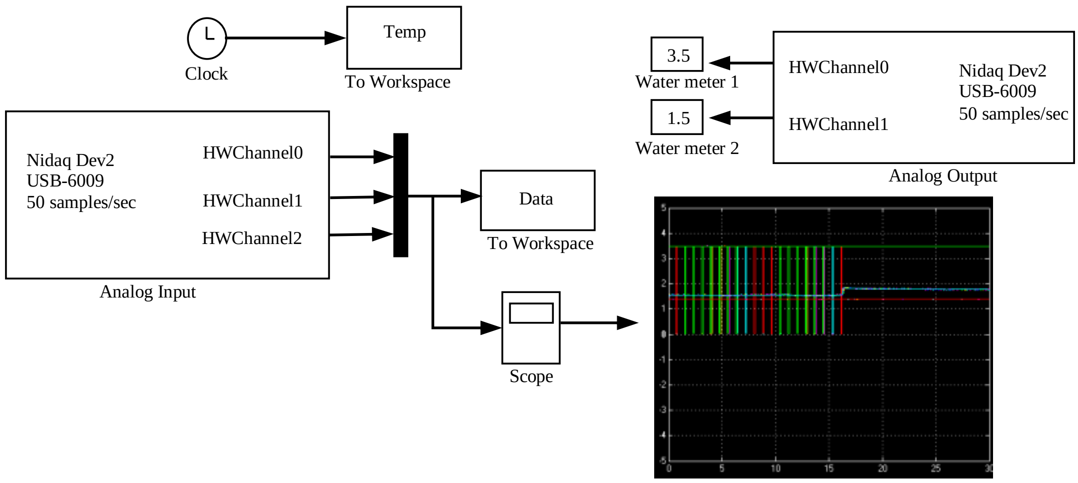

Figure 3.6: Simulink data acquisition model.

3.2.2 Flow rate acquisition system calibration

This procedure was needed to identify gaps in the readings of meters, sensors or data acquisition board. Calibration consists of opening a tap for the period of time needed to fill a cube of known volume (50 liters). Then compares the volumes measured in cubic meters with the data presented in the MatLab/Simulink code and model. In comparing the volumes recorded in the water meters with those obtained by the developed tools it was observed that the values are similar (Table calibration). Therefore, it can be concluded that the developed tools and the flow rate acquisition system (water meter and *Cyble sensor*) give suitable information for data processing.

Table 3.1: Flow rate acquisition system data

Statistical analysis	Water meter		Simulink		Diference	
	meter 1	meter 2	meter 1	meter 2	meter 1	meter 2
Mean	50.53	50.73	50.6	50.83	0.07	0.1
Median	50.5	50.8	50.6	50.9	0.1	0.1
Std. deviation	0.1528	0.1155	0.1	0.1155	-0.05	0

3.2.3 Data collection method

The methodology for collecting data obtains the opening and closing fixtures usage information to analyse the transient signals. The transient signal acquired from the faucets represent 30 seconds of fixtures usage, 15 seconds before and 15 seconds after turn-on or turn-off events. In the case of the toilet flush, the signal was acquired during the filling of close coupled cistern. The number of features acquired is 1500 for faucet signals and 5000 for toilet flush signals. Transient flows usually occur when the velocity and pressure changes over time [SMS09] and they give valuable information for classifying signal fixtures. The turbulence characteristics in the transient signals when starting or stopping flow probably depend on the type of fixture (working mechanisms) and the pipe system design. Thus, the time or frequency characteristics of the transient response of the hydraulic system to the activation of hydraulic fixture vary according to their characteristics and their positions in the hydraulic supply system. It is assumed that there is a distinct signature for each fixture, even when the flow rate signal or pressure signal in the pipe supply is used as an input for the classifier.

The first collected data was used for signal signature identification (subsection 3.3.1). To identify the signal signature, the experimental apparatus was set up with the same pipe length for all fixtures (SPL) with one fixture in use. Afterwards, the collected data was used to classify the signals using unequal pipes length (UPL), first with one fixture in use (subsection 3.3.2), and then with two (subsection 3.3.3) fixtures in use (Figure 3.7).

In each group of classification thirty samples were collected from each fixture: fifteen for training and fifteen for test. Fifteen additional samples were collected afterward from each fixture to validate the classification. Three different flow intensities were used in the kitchen tap (KT), washbasin tap (WT), bidet (BD) and shower (SH) experiments: minimum, medium and maximum intensity and the same number

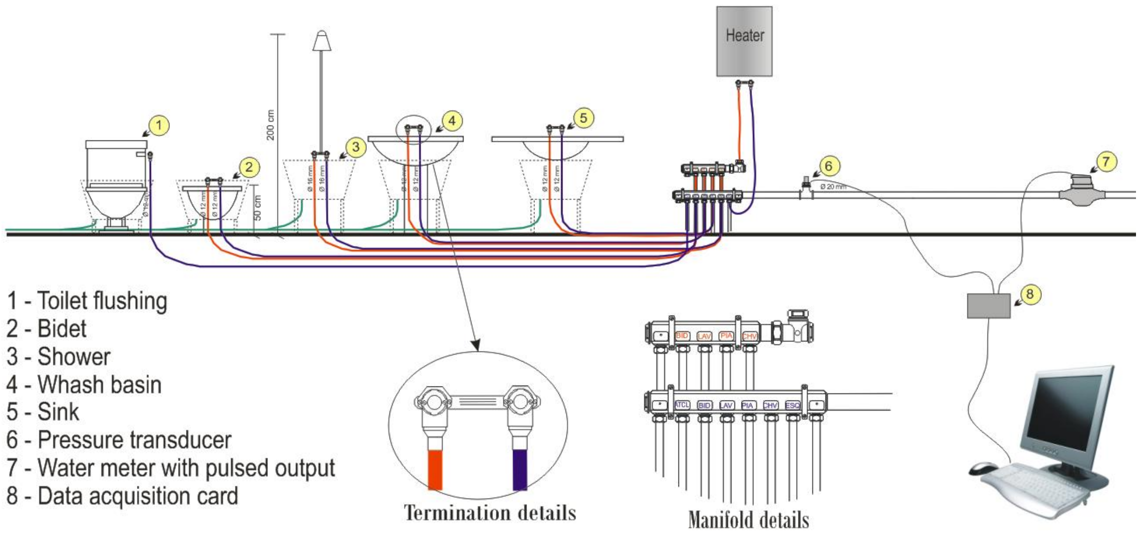

Figure 3.7: Fixtures position at the experimental facility

of samples were taken from each one (Table 3.2). The number of samples in each classification group (SPL, UPL one fixture and UPL two fixtures) for all five fixture's water flow and pressure data was 900, when accounting for time and frequency domains.

Table 3.2: Flow rate intensity considered for the experiments

Flow rate intensities (l/s)	Taps			
	KT	WT	BD	SH
Min	0.06 to 0.08	0.09 to 0.10	0.06 to 0.08	0.09 to 0.15
Med	0.10 to 0.13	0.11 to 0.14	0.09 to 0.11	0.16 to 0.19
Max	0.14 to 0.16	0.18 to 0.20	0.12 to 0.13	0.20 to 0.22

3.2.4 Data treatment tools

The models used for digital signal processing at the developed experimental facility were almost the same as for the simplified experimental facility. Some adjustments were necessary in order to introduce the pressure signal and signals treatment. Given that the DAQ card sends packages of samples to the computer, it was necessary to develop code to organize sequentially the signals samples sequentially (Algorithm 1). This algorithm also calculates the volume and flow rate of the experiments.

The volume and flow rate values provided by this algorithm was used to compare

Algorithm 1 Organizing the collected samples

Input: nc, tp, a, l : number of input channels, vector encoding time intervals between pulses, signal package, total of signal packages, respectively;
Output: S, $flow$: matrix whose columns are assembled by the concatenation of the signal packages (one column per channel), flow rate, respectively;

$sp \leftarrow a/nc$;
for $c = 1 : nc$, **do**
  for $k = 1 : l$, **do**
    $(sp * l, nc) \leftarrow S$;
    The signals presented in each signal package are separated per input channel sp and then they are concatenate with the others signal's package to assemble the matrix S considering one column per channel;
  end for
end for
$volume \leftarrow 0.1$;
for $c = 1 : nc$, **do**
  $time \leftarrow tp(1)$;
  for $k = 2 : m$, **do**
    if $S(k, c) < 1$ *and* $S(k-1, c) \geq 1$, **then**
      $\Delta tp \leftarrow tp(k) - time$;
      $flow \leftarrow volume/\Delta tp$;
      $caudal(k, c) \leftarrow flow$;
      $time \leftarrow tp(k)$;
      The flow rate $flow$ is calculated using the volume by pulse (0.1) and the time intervals between pulses Δtp.The bigger the time intervals between pulses, the greater the flow rate;
    end if
  end for
end for

with those recorded in the water meters. The admeasurement procedure can been seen at the Subsection 3.2.2.

Up to this point the signals are acquired as data pulses. However, to enable the signal analysis using pattern recognition it is necessary to convert them to discrete time flow rate signals, treat with filters and identify the transient flow and pressure information. Therefore, another Simulink model was developed to convert data pulse into data flow rate (Figure 3.8).

After reading the pulses from the MatLab workspace, they are counted in the "hit crossing" block. The "hit crossing" block detects when the input signal reaches the parameter value (0.1) in the direction specified (falling) and output 1 in the crossing time. The "data type conversion" block converts the input data to a suitable data type for integration and the "zero order hold" block converts the discrete-time signal to a continuous-time signal. The volume is calculated through the "integration" of the data pulse of both 0.1 liters and 50 samples per second as a "gain". The volume

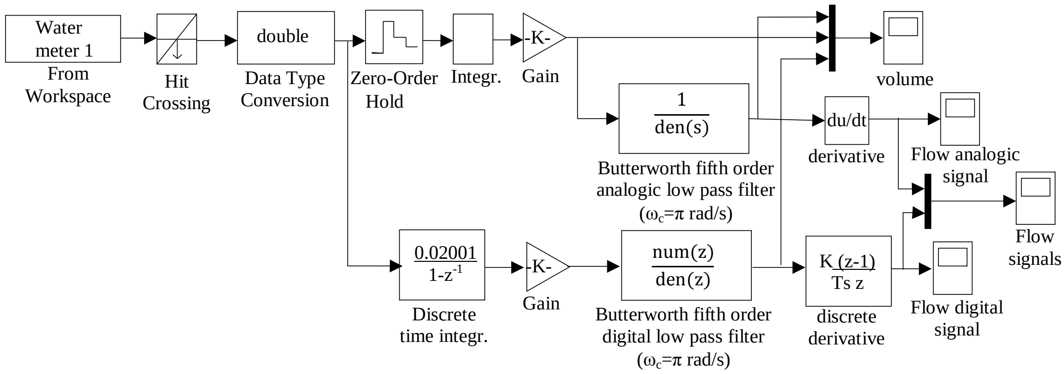

Figure 3.8: Simulink data treatment model.

block plots the volume signals resulting from the simulation process.

The models used for digital signal processing for the developed experimental facility were the same as for the simplified one. However, the Butterworth low-pass filter transfer function was changed from the second to the fifth order due to the new signals configuration. While the filter for flow signals have been developed to allow the flow rate identification through calculation of volume signal derivative (Figure 3.9), the pressure signal is filtered just to reduce the number of features and increase the algorithm processing speed. The output of the digital filters was used for the classification process because it is more suitable for digital signal processing (DSP) and involves a lower computational effort.

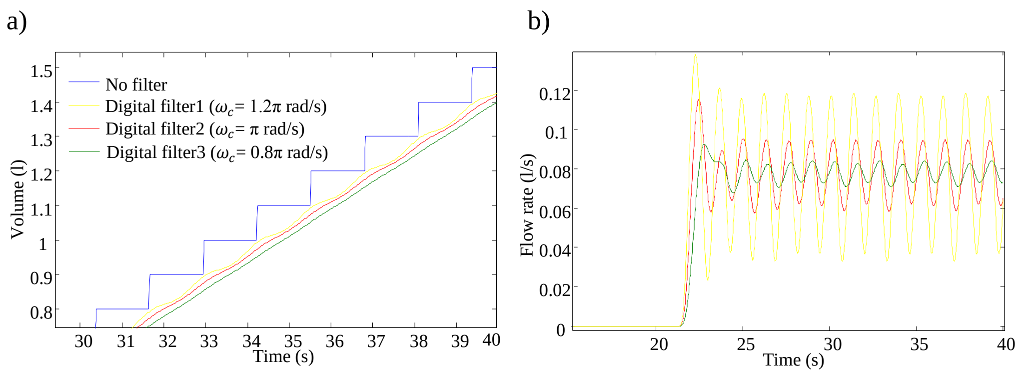

Figure 3.9: Filtered sink flow signals: a) volume; b) flow rate.

Many simulations were performed to identify the best filter model. It was empirically observed that frequency components over π rad/s for flow signals and 8π rad/s for pressure signals decrease the performance of the pattern recognition algorithms in identifying the currently used fixtures. Therefore, these two cutoff angular frequencies were used for a Butterworth digital filter development. The transfer function H(z) utilized is given by Equation 3.1(a) for flow signals and Equation 3.1(b) for pressure signals.

$$\begin{aligned} H(z)_{an} &= \frac{\left(0.276887z^5+1.384435z^4+2.768871z^3+2.768871z^2+1.384435z+0.276887\right)\times 10z^{-7}}{z^5-4.796681z^4+9.207242z^3-8.840369z^2+4.245786z-0.815976} \ (a) \\ H(z)_{di} &= \frac{\left(0.489436z^5+2.447180z^4+4.894360z^3+4.894360z^2+2.447180z+0.489436\right)\times 10z^{-3}}{z^5-3.378011z^4+4.751775z^3-3.439713z^2+1.273999z-0.192388} \ (b) \end{aligned} \tag{3.1}$$

After the signal treatment, the samples were extracted considering the same feature vector size and transition point position. It was observed that the maximum or minimum transition point for all analyzed instances should be aligned at the same position for classification. In this sense, a function able to identify whether signal is rising or falling, the Matlab function *upordown*, was used to identify the transition points, in order to define the time window of the transient signal. Five seconds time window of the acquired transient signal was considered suitable to get representative transient information, and then a feature vector composed by 250 features was extracted from the acquired signal. For instance, the initial part of the flow signal (IFS) was extracted considering the maximum *upordown* position provided by the *idx* function. The IFS vector was composed by the concatenation with the latest 125 features and the first 125 features of the flow signal, allowing for the *upordown* position. The opposite happens with the initial part of the pressure signal (IPS) where the minimum *upordown* position is reflected (Figure 3.10). The same logic is utilized for the final part of the flow signal (FFS) and the final part of the pressure signal (FPS).

This function would be also used in disaggregation algorithms to identify turn-on and turn-off fixture events in order to calculate the flow-rate considering the water meter or transducer information provided during the water use.

3.2.5 Frequency domain data

DSP tools, such as Fourier transforms and wavelets, are important when there is interest in identifying suitable features for classification. Signals characteristics, such

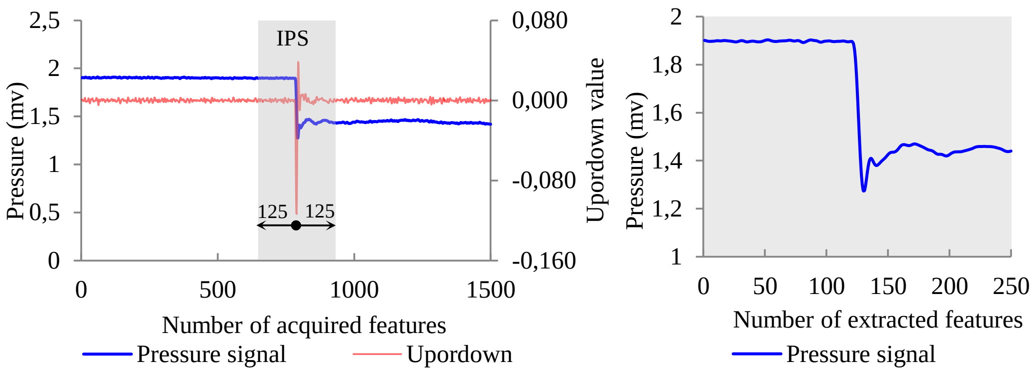

Figure 3.10: IPS shower and *upordown* signal extraction representation.

as frequency, phase and amplitude, are essentials and provide valuable information for DSP, image processing and communication. Sometimes it is difficult to identify some characteristics in the time domain; however, the frequency domain can improve the features analysis. The Fourier transforms was used in this work because it is useful to highlight the signals characteristics. The Fourier transform (FT) is defined as a F function that associates each absolutely integrable function $x : \mathbb{R} \to \mathbb{R}$ to $X : \mathbb{R} \to \mathbb{C}$ and is given by expression:

$$X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-j\omega t}dt \tag{3.2}$$

The Fourier transforms $X(\omega)$ are transformations over time (t) in terms of angular frequency (ω). It is observed that the time domain function $x(t)$ presents real values while the $X(\omega)$ is defined at the plane with complex values [Lat98].

For computer applications, whether for scientific applications or DSP, it is necessary to use discrete values $x[n]$ or $x[nT]$. In this case, it is assumed that the sinusoid is sampled in regular time intervals T generating sequential samples $x[n]$ with N samples values, where n represents the number of the samples ($n = 0$ to $n = N-1$). The $x[n]$ values are real only for time domain. In frequency domain they are sequential complex values $X(k\Omega)$, where Ω is the first harmonic frequency given by $\Omega = 2\pi/NT$ [IJ02]. The most used frequency domain representation for discrete signals is the discrete Fourier transform (DFT). In general, the $X(k\Omega)$ values have real and imaginary values. The DFT value is given by:

$$X\left(k\Omega\right)=F\left[x\left[n\right]\right]=\int_{n=0}^{N-1}\left[x\left[n\right]e^{-jk\Omega n}\right],k=0,1,...,N-1 \quad (3.3)$$

were k represents the number of harmonics from transform components.

The equation 3.3 is similar to the equation 3.2 (continuous time Fourier transform - FT), when $x(t) = 0$ for $t < 0$ and $t > (n-1)T$. With $x[n] = x[t]$, $k\Omega = \omega$ and $n = t$, it is expected that both Fourier transforms have similar proprieties.

The Fast Fourier Transform (FFT) is an efficient algorithm used for DFT calculation. The FFT provided by Matlab was used in this work to calculate the DFT for the tested samples. The real and imaginary frequency components compose the analyzed features.

3.2.6 Feature selector

A feature selector tool was used to compose the optimum feature set. The feature selector tool used in this work was developed by [LN10] who proposes a new approach to feature selector techniques based on genetic algorithms and information theory (FS-GAIT). The FS-GAIT fitness function application is based on the principle of max-relevance and min-redundancy (mRMR). This technic maximizes the mutual information of $I(y; x_1, , x_n)$ between the set of features of $\{x_1, , x_n\}$ (e.g. the samples) and the target y (e.g. the class label). The objective is for the outputs of the selected features to present discriminant power, thus avoiding redundancy. This new technique demands less computational effort, but can result in a different selection in each data processing (Figure 3.11). So, more than one selection is recommended for each feature number tested in order to find the best accuracy provided by classifiers. The numbers of features selected and tested in this work were: 20, 40, 60 and 80. The total features in each sample (i.e. 250) were also tested to compare with those selected.

3.2.7 Multi-layer Perceptron Trained by GDX

Gradient descendent with momentum term and adaptive learning rate (GDX) is faster than other basic gradient descendent methods for neural network (NN) training [LNA14]. The most usual objective function of GDX is the mean squared error

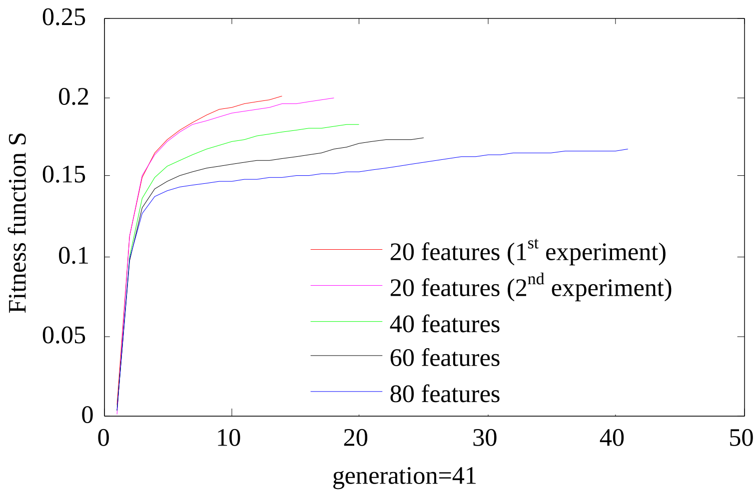

Figure 3.11: Fitness function from initial part of flow signal in time domain.

(MSE), given by:

$$e = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y}_i)^2 \tag{3.4}$$

where N is the cardinality of the training data-set, y_i is the target output, and $\widehat{y}_i$ is the output estimated by the multilayer perceptron (MLP) for the input x_i belonging to the training data-set. Back-propagation is used to calculate MSE derivatives with respect to the weights and biases. Each variable is adjusted according to the gradient descent with momentum:

$$\Delta x\,[k+1] = m\Delta x\,[k] + l\ m\,\frac{de}{dx} \tag{3.5}$$

where Δx is the change in the vector x that encodes the weights and biases, k is the index of the iteration, m is the momentum constant, l is the learning rate, e is the MSE and $dedx$ is the gradient vector. For each epoch, if the MSE decreases toward the goal then the learning rate is increased by a given factor η. If the MSE increases by more than a given threshold γ, the learning rate decreases by a given factor μ, and the synaptic weights updating which increased the MSE is discarded [JDGN09].

The MATLAB Neural Network Toolbox was used to train a NNs type multilayer perceptron (MLP) with a single hidden layer, using the GDX method. In this work, the accuracy of the MLPs in the analyzed signals was evaluated for 30, 40 and 50 training epochs with the number of hidden neurons varying from 11 to 16.

3.2.8 Support Vector Machine-SVM

Support vector machines (SVMs) are based on the statistical theory of learning [Vap00]. The SVM training algorithm creates a model using a set of training examples and constructs a hyper-plane in the feature space to separate the training data according their class. In the case of hard-margin SVM, a good separation is achieved by the hyper-plane that furthest from the nearest training data point of any class [VK06]. If the training data cannot be linearly separated without error, the soft margin SVM is the best method [CV95]. This is the method used in this work and it consists of inserting non-negative slack variables ξ_i encoding the degree of margin-constraint violation of the training data x_i. Therefore, the optimization becomes a tradeoff between a large margin, the first term of Equation 3.7, and a small error penalty, the second term of the same equation. Such a tradeoff is controlled by the penalty parameter C, as seen below:

$$arg \min_{w,\xi,b} \left\{ \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{N} \xi_i \right\} \tag{3.6}$$

where w is the normal vector to the hyper-plane.

Some classification problems cannot be address by linear classifiers, however [BGV92] suggested creating nonlinear classifiers by applying the kernel "trick". The kernel functions map the training data-set from its original space (input) to a new high dimensional space. A suitable kernel function choice can classify the training data-set by using the optimal hyper-plane. Currently, it is possible to choose from many types of kernel functions, but the most usual are the linear, the polynomial function, and the radial basis function (RBF), see Table 3.3.

Given the large training data-set used in this work, it was chosen the RBF because of its suitable computational cost and accuracy. A grid searching arrangement was used to predict the optimal settings of hyper-parameters (C, γ) through a 10-fold cross-validation on the training data. In this work, a specific Algorithm 2 was developed to test a (C, γ) composition and identify the best accuracy.

Table 3.3: Usual SVM Kernels.

Kernel name	Kernel function
Linear	$H(x, x') = x^T x'$
Polynomial	$H(x, x') = \left(x^T x' + 1\right)^{nd}$
RBF	$H(x, x') = exp\left(-\gamma \left\|x - x'\right\|^2\right)$

Source: [JDGN09]

The SVM was originally designed for binary classification, however, strategies are applied that allow multiclass classification [HL02]. This work uses the one-against-all (OAA) strategy. This consists of building one classifier trained to distinguish the samples in a single class from the samples in all the other classes [RK04]. Let $D = B_1, B_2, ..., B_V$ be a set of nonlinear binary classifiers, $B_i : \mathbb{R}^n \rightarrow \mathbb{R}$. The OAA scheme aims at assigning a class label, $\widehat{\omega} \in \Omega$, to $x \in \mathbb{R}^n$. Each one-against-all ensemble of SVMs (OAA-SVM) receives as input an n-dimensional vector, x, composed of a set of features, $x_1, ..., x_n$, and a target, y. In this approach, $y_i = 1$, if i is the target class, and all the other positions of y are assumed to be -1. The OAA-SVM, $D : \mathbb{R}^n \rightarrow \mathbb{R}^c$, outputs a c-dimensional vector $y_i(x) = [d_1(x), ..., d_c(x)]^T \in \{-1, 1\}^c$, such that $d_j(x) = 1$, if j is the index of the predicted class, otherwise $d_j(x) = -1$.

3.2.9 Fusion by majority vote

The fusion by majority vote has the potential to offer an improvement over the individual classifiers accuracy. Combining classifiers means finding the most representative class label for x based on the L classifier outputs. In this work, the input for the fusion, i.e. the output of the i^{th} ensemble OAA-SVM, is a c-dimensional vector $y_i(x) = [d_{(i,1)}(x), \ldots, d_{(i,c)}(x)]^T \in \{-1, 1\}^c$, organized in a decision profile as the matrix:

$$DP(x) = \begin{bmatrix} d_{(1,1)}(x) & \ldots & d_{(1,j)}(x) & \ldots & d_{(1,c)}(x) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{(i,1)}(x) & \ldots & d_{(i,j)}(x) & \ldots & d_{(i,c)}(x) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{(L,1)}(x) & \ldots & d_{(L,j)}(x) & \ldots & d_{(L,c)}(x) \end{bmatrix}$$

When evaluating the (crisp) decision profile $DP(x)$, the majority vote method is

Algorithm 2 SVM accuracy calculation

Input: $\{x_{train}, y_{train}\}$: training dataset
$\{x_{test}, y_{test}\}$: testing dataset
fs: features selected by FS-GAIT on $\{x_{train}, y_{train}\}$
ic: is the initial value of the penalty parameter C
pc: is the slope of C
nc: is the final value of C
ip: is the initial value of the RBF kernel free parameter γ
pp: is the slope of parameter γ
np: is the final value of parameter γ
Output: $svmStruct$,$\{y_{est}\}$,acc: the trained SVM structure, the estimated output and the final accuracy respectively.

```
acc_max ← 0;
for C = ic : pc : nc do
    for γ = ip : pp : np do
        calculate the average accuracy, \overline{acc}, on a 10-fold cross-validation over {x_train, y_train}, using the current hyper-parameters, C and γ, and the selected features fs;
        if \overline{acc} > acc_max then
            acc_max ← \overline{acc}
            C* ← C
            γ* ← γ
        end if
    end for
end for
train the SVM on whole training dataset, {x_train, y_train}, setting the hyper-parameters as C* and γ* and store the trained structure in svmStruct;
evaluate the accuracy, acc, of the trained SVM on the testing dataset {x_test, y_test} and store the estimated output in {y_est}.
```

implemented by summing up the $DP(x)$ columns and taking the index of the column with the highest value as the class label of x [Kun02], according to:

$$c_{maj} = arg\ max_j\ u\ DP\,(x) \tag{3.7}$$

where $u = [1, 1, ..., 1]$ is a unitary vector with L elements and c_{maj} is the index of the selected/estimated class.

In order to improve independence among classifiers, and so the gain on the individual accuracies ([KWD03] and [Lud12]), this work applies majority vote to an OAA-SVM trained on different domains, specifically the time and frequency domains. An example of an analysis scheme (SVM and fusion) can be seen in Figure 3.12.

For an experiment to be carefully controlled means that a reasonable effort has been made to find correct settings for the hyper-parameters (C, γ) of the OAA-SVM and that the best available binary classifiers are used for fusion.

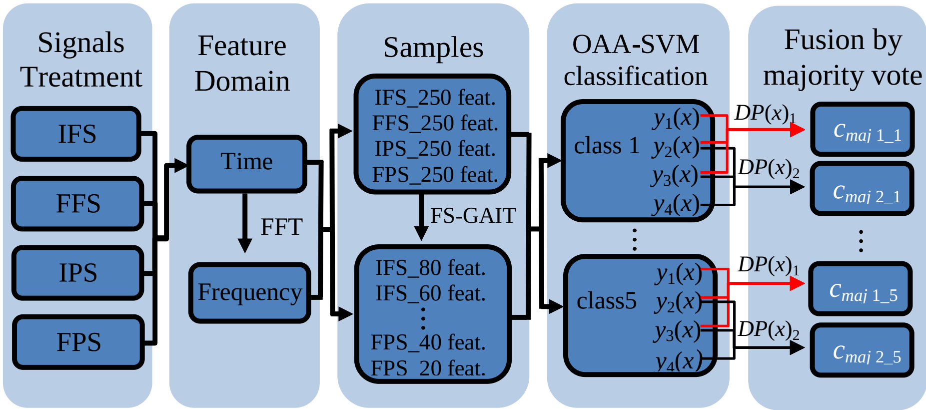

Figure 3.12: SVM and fusion analysis scheme.

3.3 Signals classification

Machine learning techniques employ an inference induction principle for data analysis and an assumption is obtained from a specific set of examples. This inductive learning can be divided into two main types: supervised and unsupervised. Supervised learning presents a set of examples organized through an input and desired output arrangement [Hay94]. It is expected that the knowledge representation generated by these examples, called a pattern or model, induces a correct output when news inputs are given without previous knowledge. On the other hand, for unsupervised learning there are no patterns, the algorithm learns its inputs representation through a quality measure.

Supervised learning was the technique used in this work [Hay94], therefore, a set of examples were designed in order to create a sample model provided by the algorithms in each class. A set of news examples were used for test to verify the classifiers accuracy (Acc_T). For each type of signal analyzed; initial part of the flow signal (IFS), final part of the flow signal (FFS), initial part of the pressure signal (IPS) and final part of the pressure signal (FPS), 75 samples for training and 75 for testing (15 in each class) were used for GDX and SVM classification. A further 75 samples representing the five classes for each type of signal were used to validate the SVM classification (Acc_V). Time domain and frequency domain samples were considered for a features composition (Figure 3.13).

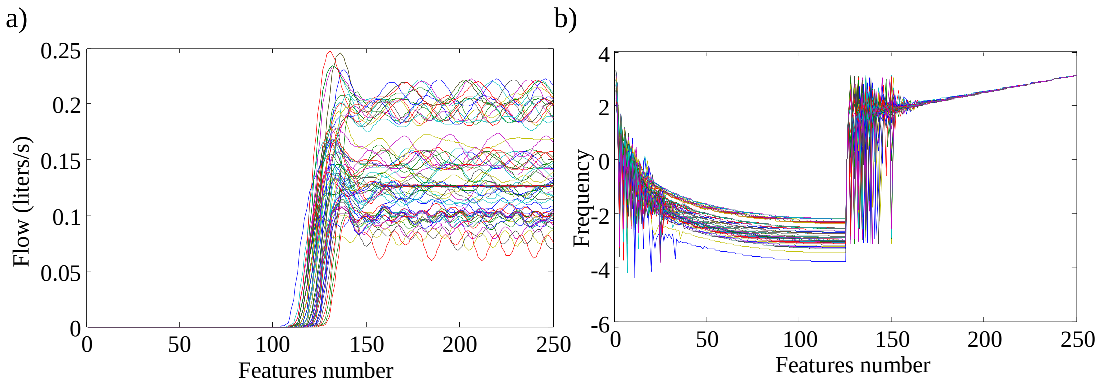

Figure 3.13: Samples for IFS training: a) time domain; b) frequency domain.

The total number of the features in each sample (signal representation) is 250. The feature selector, accounting for 80, 60, 40 and 20 features, was used to identify the best selection that characterizes the signal. The results of classification are presented next.

3.3.1 Signals classification using the same pipe length - SPL

The time or frequency characteristics of the transient response of the hydraulic system to the activation of hydraulic fixtures vary according to their characteristics and their positions in the hydraulic supply system. It is assumed that there is a distinct signature for each fixture, even if the flow rate signal or pressure signal in the pipe supply set as an input for the classifier. To identify the signals signature all fixtures were positioned at the same distance from the flow and pressure sensors.

GDX classification results

The GDX includes a multiclass analysis and the results represent the average accuracy for the five classes. Table 3.4 presents the best accuracy obtained for time and frequency domain data.

Figure 3.14 demonstrate that the signals in the time domain are better classified by GDX than those in the frequency domain. In addition, the features which demonstrate the initial part of the signal seem to be more representative than those demonstrating

Table 3.4: GDX accuracy classification

Signal	$N°$ features	Time domain Epochs	Time domain Nneu.	Time domain Acc_T	Frequency domain Epochs	Frequency domain Nneu.	Frequency domain Acc_T
IFS	250	50	16	88%	50	11	83%
	80	50	15	91%	50	15	83%
	60	50	13	88%	50	16	83%
FFS	80	10	16	87%	50	12	60%
	60	10	13	86%	50	16	60%
	20	10	15	84%	50	11	63%
IPS	250	50	11	88%	50	12	66%
	80	50	16	86%	50	13	72%
	40	50	15	90%	50	14	70%
FPS	250	50	15	90%	50	14	79%
	80	50	14	88%	50	13	75%
	20	50	12	89%	50	11	75%

the final part. The number of epochs with more suitable results was 50 whereas the number of neurons was 15 and 16.

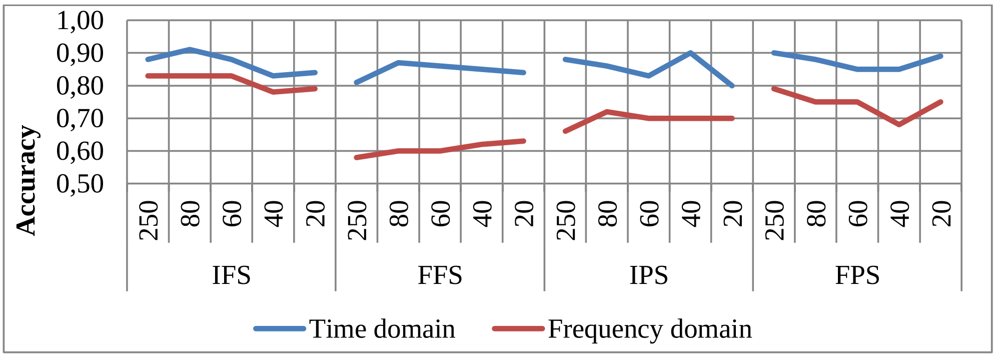

Figure 3.14: Comparison of time and frequency domain GDX accuracy.

The best general accuracy (Acc_T=91%) was found in the time domain for the initial part of the flow signal, taking into account 80 features, selected by the proposed feature selector (FS-GAIT), and 15 neurons. The feature selection was found to be useful for increasing the performance in the GDX classification. For the FFS samples, the accuracy increased by up to 9%. Table 3.5 presents the confusion matrix for the best classification of GDX.

The best accuracy cases for the individual class evaluation were found in C1 - kitchen tap (acc=96%) and C4 - shower (93%). The worst accuracy was in C3 - bidet (acc=81%). It is supposed that the differences in classification performance

Table 3.5: GDX classification based on initial part of the flow signal (%): time domain, 80 features, 15 neurons, 50 epochs.

	C1	C2	C3	C4	C5
C1	96	2	0	2	0
C2	0	90	5	5	0
C3	3	11	81	5	0
C4	0	7	0	93	0
C5	0	4	3	1	92

are most likely related to the mechanism that operates the fixtures. The kitchen tap (C1) and shower (C4) have the same tap mechanism (cartridge - lever handle), so it is supposed that these fixtures generate signs suitable for classification due to their quasi regular tap activation. The washbasin tap (C2) and bidet (C3) have a compression (threaded spindle) mechanism which could mean extra noise in the signal representation. Significant variations in the bidet pressure signal compared with the shower pressure signal can be seen in 3.15. However, despite the washbasin tap mechanism, the accuracy for class 2 was also good (90%) which means that the type of fixture is not the only explanation for differences in classification performance. The brand of the fixture, its age and regularity in opening and closing (human factor) could also explain variances in results. The toilet flush (C5) mechanism could be regarded as the most regular of the fixtures, however, the GDX accuracy from this signal was good, but not the best. (92%).

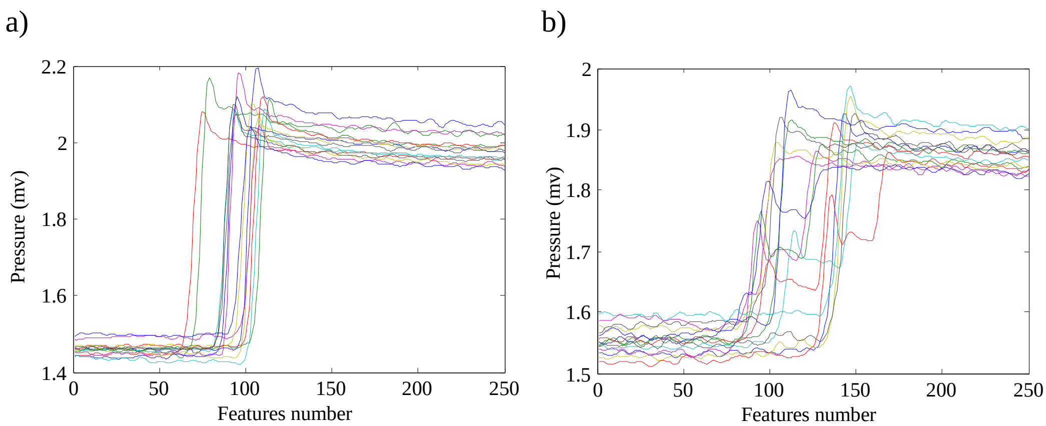

Figure 3.15: Final part of the pressure signal, time domain: a) shower; b) Bidet.

SVM classification results

An algorithm (see Algorithm 2) was developed in order to train and test the data using a set of (C, γ) compositions that were found to be useful in identifying the best OAA-SVM accuracy classification (Figure 3.16). It was observed that the accuracies are more sensitive with the C parameter than the γ.

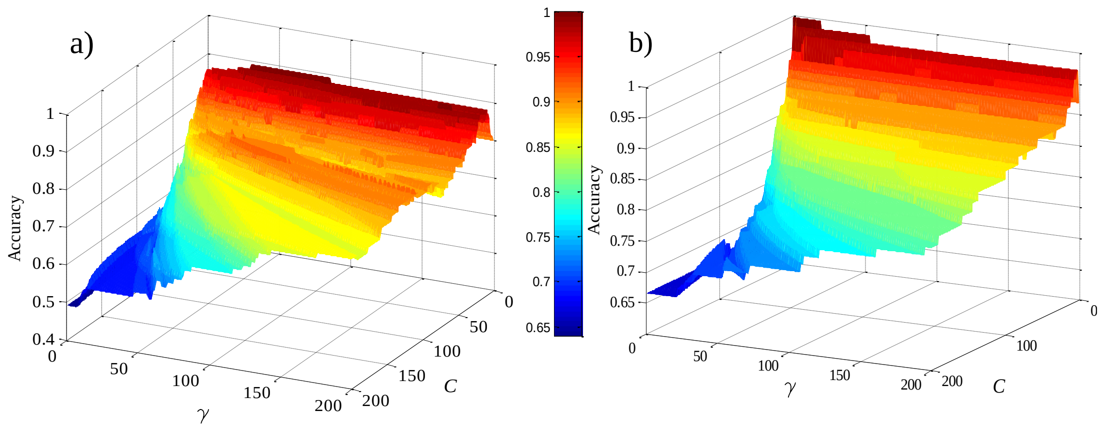

Figure 3.16: Accuracy from IFS time domain training: a) class 4, 40 feat. b) class 5, 20 feat.

As with the GDX data classification, the OAA-SVM algorithm has the best accuracy for time domain signals (Figure 3.17). Regarding the data analyzed, the feature selection did not make as significant a contribution to the OAA-SVM classification performance as it did in the GDX classification. Comparing the types of signal indicated, the initial measurement of the flow signals provided better results for the time and frequency domains. The worst accuracy was found for the final flow signal classification.

Given its better performance in classification compared with the GDX classifier, the accuracy structure resulting from the train/test OAA-SVM classifier was used to validate new data (Acc_V). The Table 3.6 presents the most accurate readings that were found in the time and frequency domain for flow signals. It was observed that the best average accuracy for validation data was found in the initial part of the flow signals. The best accuracy in the time domain for the individual class evaluation was found in IFS, C5 - toilet flush (Acc_T=100% and Acc_V=100%) and C1 - kitchen tap (Acc_T=96% and Acc_V=91%). The worst accuracy was found in FFS, C2 -

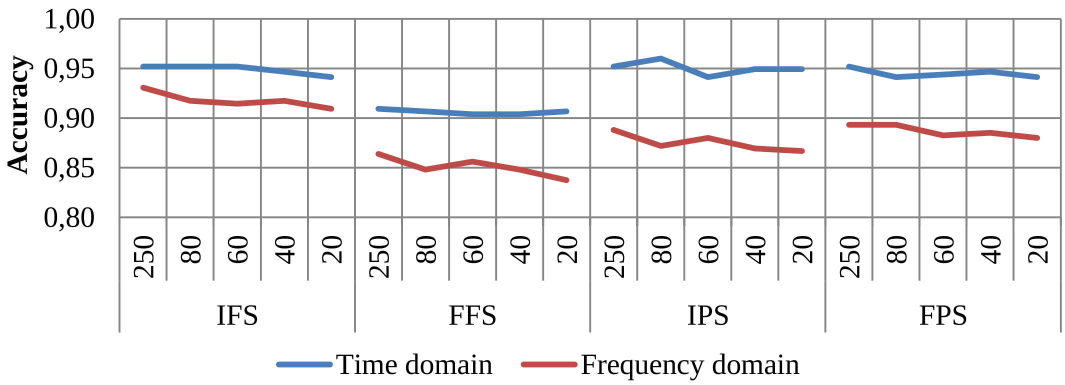

Figure 3.17: Comparison between of time and frequency domain for SPL SVM accuracies.

washbasin tap (Acc_T=81% and Acc_V=77%).

Table 3.6: Accuracy for initial and final part of the flow signal.

Class	Domain	IFS					FFS				
		$n°$ feat.	C	γ	Acc_T (%)	Acc_V (%)	$n°$ feat.	C	γ	Acc_T (%)	Acc_V (%)
1	Time	60	24	1.5	96	91	20	1	1.2	99	85
	Freq.	250	2	7	93	87	250	1	9	91	81
2	Time	250	1	7.3	92	92	250	67	1.5	81	77
	Freq.	250	15	15	92	81	80	6	5	83	89
3	Time	250	17	2.2	92	88	250	4	2.5	93	93
	Freq.	250	3	5.3	89	83	250	1	6.8	88	87
4	Time	60	64	1.7	95	91	40	180	2.6	89	84
	Freq.	80	1	3.4	93	85	40	2	2	87	84
5	Time	60	2	0.4	100	100	60	10	7	95	93
	Freq.	80	2	4	99	100	60	190	9.7	91	89
Aver.	Time				95	92				91	87
acc	Freq.				93	87				88	86

Table 3.7 presents the best accuracy for pressure signals. Despite providing a reasonable accuracy reading for frequency and time domain data on the train/test OAA-SVM classification, the validation does not confirm the same performance. The accuracy reduction in validation was up to 21% for pressure signals. The best accuracy for the train/test and validation data was found for the time domain of SPS, C2 - washbasin tap (Acc_T=93% and Acc_V=95%). The worst accuracy was found in the frequency domain for the same signal, SPS, C2 - washbasin tap (Acc_T=84% and Acc_V=75%).

Table 3.7: Accuracy for initial and final part of the pressure signal.

Class	Domain	IPS					FPS				
		$n°$ feat.	C	γ	Acc_T (%)	Acc_V (%)	$n°$ feat.	C	γ	Acc_T (%)	Acc_V (%)
1	Time	80	2	3.5	92	77	250	26	12	97	83
	Freq.	250	0.5	10	84	81	40	2	5	91	75
2	Time	80	4	4	93	95	250	23	10	93	73
	Freq.	60	32	7.3	84	75	250	120	9	87	80
3	Time	250	7	4.2	96	76	40	4	1.7	96	80
	Freq.	40	1	4	87	80	250	15	10	88	79
4	Time	20	91	12	97	87	60	38	4.3	95	100
	Freq.	60	2	9.1	93	87	60	2	6.4	95	97
5	Time	250	2	4	97	80	20	37	0.9	97	91
	Freq.	80	1	5	97	92	80	1	4.3	91	97
Aver.	Time				95	81				96	85
acc	Freq.				89	83				90	86

Fusion by majority vote classification results

The majority vote technique was used to improve OAA-SVM accuracy through signal composition. The best OAA-SVM classification results in each class were taken and many configurations were tested for the fusion. Flow and pressure signals in the time domain were used for fusion because they achieved the best accuracy. Table 3.8 presents the best configuration for the SVM train/test (Acc_T) and validation data (Acc_V). The performance increases provided by the fusion technique, i.e. the deviation between the OAA-SVM best accuracy in each class (Tables 3.6 and 3.7) and majority vote validation accuracy, is represented by ΔAcc_V.

A significant performance increase is observed when a fusion technique is implemented, mainly for the validation data. It is also observed that the differences between train/test and validation accuracy after fusion are much smaller than those observed in OAA-SVM classification. The results demonstrate that the robustness and good generalization of fusion classification allows the system to recognize different signal patterns in each class.

After fusion, the best classification was found for class 4 - shower and class 5 - toilet flush, both with one-hundred percent accuracy (Table 3.9). A good classification was expected for these two fixtures because their mechanism operates in a more standardized way, as explained in subsection 3.2.3. Despite the cartridge mechanism in the kitchen tap, this fixture had the worst accuracy (Acc_V = 92%), but even

Table 3.8: Fusion by majority vote accuracies.

Class	SVM's best composition	Acc_T	Acc_V	ΔAcc	ΔAcc_V
1	$y1(x) \rightarrow (FFS, 20feat., C = 1, \gamma = 1.2)+$ $y2(x) \rightarrow (IFS, 60feat., C = 24, \gamma = 1.5)+$ $y3(x) \rightarrow (FPS, 250feat., C = 26, \gamma = 12)$	99%	92%	-7%	1.5%
2	$y1(x) \rightarrow (IFS, 250feat, C = 1, \gamma = 7.3)+$ $y2(x) \rightarrow (IPS, 80feat., C = 4, \gamma = 4)+$ $y3(x) \rightarrow (IPS, 40feat., C = 3, \gamma = 3)$	96%	95%	-1%	0%
3	$y1(x) \rightarrow (IFS, 250feat., C = 17, \gamma = 2.2)+$ $y2(x) \rightarrow (FFS, 80feat., C = 4, \gamma = 1.2)+$ $y3(x) \rightarrow (FPS, 250feat., C = 200, \gamma = 11)$	97%	95%	-3%	1.4%
4	$y1(x) \rightarrow (FPS, 60feat., C = 38, \gamma = 4.3)+$ $y2(x) \rightarrow (FPS, 40feat., C = 6, \gamma = 1.9)+$ $y3(x) \rightarrow (IPS, 20feat., C = 91, \gamma = 12)$	96%	100%	4%	0%
5	$y1(x) \rightarrow (IFS, 60feat., C = 2, \gamma = 0.4)+$ $y2(x) \rightarrow (FFS, 60feat., C = 10, \gamma = 7)+$ $y3(x) \rightarrow (IFS, 80feat., C = 163, \gamma = 0.6)$	100%	100%	0%	0%
Average / general Δacc		98%	96%	-1%	4.34%

Table 3.9: Classification of majority vote validation data using SVM compositions (%)

	C1	C2	C3	C4	C5
C1	92	2	3	3	0
C2	0	95	0	5	0
C3	0	5	95	0	0
C4	0	0	0	100	0
C5	0	0	0	0	100

so, this classification could not be considered bad. It is supposed that the fusion technique mitigates the noise effect observed in the threaded spindle mechanism of the bidet. This fixture had the worst classification in the GDX and SVM analysis, but the fusion increased the accuracy about 1.4% for training and validation data (Figure 3.18).

Regarding the OAA-SVM classifier, the flow signal is considered more suitable for classification than pressure signals. The IFS was accurate with all signals types, but the fusion by majority was better than all the others.

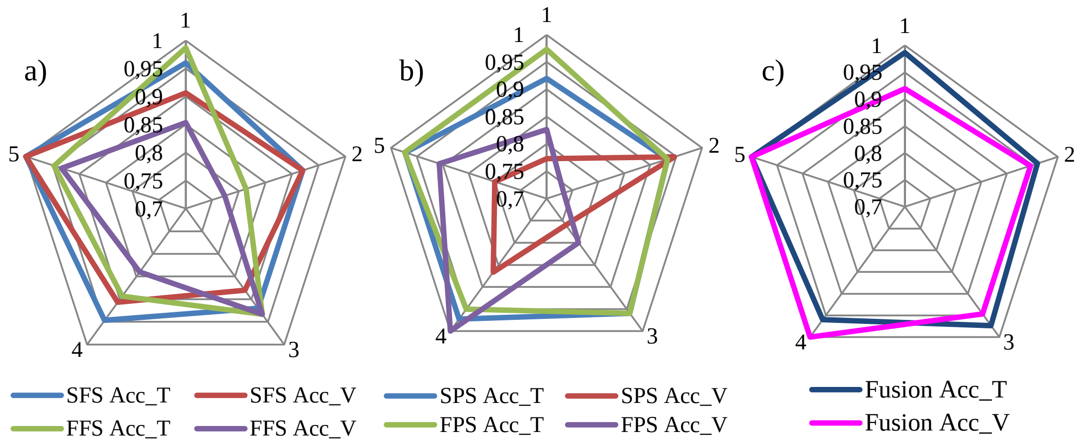

Figure 3.18: Comparison of classification accuracy for train/test and validation data: a) IFS and FFS OAA-SVM; b) IPS and FPS OAA-SVM; c) fusion.

Comparison between classifiers and recommendations

GDX and SVM classifiers proved to be suitable techniques for classifying flow and pressure signals. However, SVM showed better accuracy for almost all types of signals analyzed, whereas GDX optimization falls into a different local minimum in each analysis process, even when using the same parameters. It occurs because the initialization of the synaptic weights in GDX is random, so good accuracy in analyzed signal data does not mean a good classification for new signals. However, the SVM always provides the same result for a given set of parameters which makes this technique more reliable (Figure 3.19).

Regarding the data analyzed, the frequency domain signals were less reliable for classification than the time domain signals. This is observed in both classifiers, but GDX gave the lowest accuracies in frequency domain signals. The OAA-SVM classifier applied to analyze FPS in the frequency domain showed a significant improvement in validation data. So, it is recommended that the frequency domain be employed for testing new fusion configurations to verify accuracy levels.

The fusion by majority vote was outperformed relative to other techniques, but improvements could be made by using frequency domain signals. Other SVM kernels or classifiers, such as linear discriminant analysis (LDA) or multiclass SVM (MSVM),

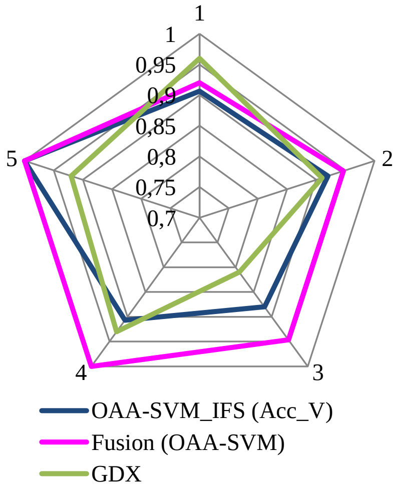

Figure 3.19: Comparison of classifier techniques.

could be used in future work for individual analysis and/or fusion. Wavelet coefficients or Lyapunov exponents could also be used for feature extraction using flow and pressure signals. Investigations into-electric households' load identification conclude that wavelet transform is more suitable for transient signals than FFT because it can provide both frequency domain information and the corresponding locations in time simultaneously ([DDL+10], [CSL00] and [ZGIR12]. So, future works would combine transient and steady-state signatures to improve recognition accuracy [JLL+11]. News analysis with different sample rate values could also be made to reduce data processing time.

3.3.2 Signals classification using unequal pipe length - UPL

Unequal pipe lengths are found in most of household water supply systems, so the experimental facility was set up in a similar manner in order to simulate this situation. It is expected that an increase in accuracy for the pressure signals evaluation will occur due to different pressure responses (Figure 3.20).

The samples collection methodology was the same used for the signal of each fixture signature's identification, however, because of general suitable validation data accuracies presented at the Subsection 3.3.1 validation data samples were not collected for analysis. So, only the train/test OAA-SVM accuracies were identified in this section.

Figure 3.20: Unequal pipe length was set up at the experimental facility.

The SVM classifier presented the best results for flow and pressure signals classification, thus, the SVM was the only classifier used to identify the patterns in each class in this subsection.

Regarding the data analyzed, the OAA-SVM algorithm presented as most accurate for time domain signals when reviewing only the pressure signals. However, flow signals were the most accurate in the frequency domain. Besides, in UPL classification, few differences were found between time and frequency accuracies (Figure 3.21) in comparison with SPL classification (Figure 3.17). In comparing the types of signal indicated, the Final part of the pressure signal (FPS) provided better results for the time and frequency domains. The worst accuracy was found for the final part of the flow signal (FFS) classification.

The Table 3.10 presents the best accuracy for flow signals in the time and frequency domains. It was observed that the best average was found in the initial part of the flow signals. The best accuracy in the time and frequency domain for the individual class evaluation was found in IFS, C5 - toilet flush (Acc_T=100%) and C2 - washbasin tap (Acc_T=92%). The worst accuracy was found in FFS, C2 - washbasin tap and C4 - shower (Acc_T=83%). The difference between SPL and UPL test/train SVM accuracies is represented by ΔAcc_T. It is observed that the average accuracies for

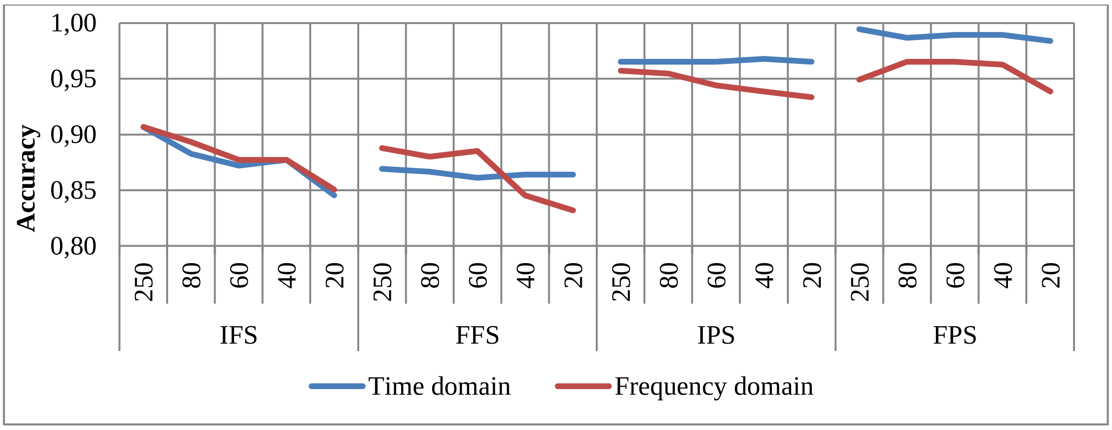

Figure 3.21: Comparison between of time and frequency domain for UPL SVM accuracies.

the UPL time domain flow signals drops 4% comparing with SPL flow signals. On the other hand, in the frequency domain, there was less of an accuracy decrease for the initial part of the flow signals (-2%) while the accuracy of the final part of the flow signal increased about 2%.

Table 3.10: Accuracy for initial and final part of the UPL flow signal.

Class	Domain	IFS					FFS				
		$n°$ feat.	C	γ	Acc_T (%)	ΔAcc_T (%)	$n°$ feat.	C	γ	Acc_T (%)	ΔAcc_T (%)
1	Time	60	1	0.1	88	-8	250	1	5.5	85	-14
	Freq.	80	61	1.9	87	-6	80	4	1.3	91	0
2	Time	250	20	8.1	91	0	80	63	1.1	83	2
	Freq.	250	27	3.2	92	0	60	2	0.7	84	1
3	Time	250	149	14.8	87	-5	80	2	6.5	91	-2
	Freq.	80	74	5.2	87	-2	60	6	5.3	87	-1
4	Time	80	8	10.3	88	-6	80	7	0.8	83	-7
	Freq.	250	2	3.1	89	-4	250	6	1.9	88	1
5	Time	250	197	3.2	100	0	60	16	1.7	95	0
	Freq.	80	6	1.8	100	1	250	183	18.6	97	7
Aver. acc	Time				91	-4				87	-4
	Freq.				91	-2				89	2

Table 3.11 presents the best accuracy for pressure signals. As expected, the pressure signals present the best accuracies when comparing all analyzed samples. The five classes presented 100% of accuracy for the FPS time domain. The increase in accuracy when comparing UPL time domain pressure signals and SPL is 2% for IPS and 4% for FPS. However, for the frequency domain the accuracy increased to over 7%.

Table 3.11: Accuracy for initial and final part of the UPL pressure signal.

Class	Domain	IPS					FPS				
		$n°$ feat.	C	γ	Acc_T (%)	ΔAcc_T (%)	$n°$ feat.	C	γ	Acc_T (%)	ΔAcc_T (%)
1	Time	80	7	3.8	100	9	60	140	15	100	3
	Freq.	250	197	19.8	99	18	80	16	13.4	100	10
2	Time	40	22	20	99	6	250	26	8.8	100	7
	Freq.	80	2	4.9	96	14	60	4	4.3	91	5
3	Time	60	2	3	97	1	60	3	3	99	3
	Freq.	80	20	10.4	93	7	60	21	11.5	97	10
4	Time	250	51	6.8	89	-9	60	48	4.7	100	5
	Freq.	250	56	13.5	93	0	60	183	19	99	4
5	Time	60	6	19.4	100	3	40	9	1.1	100	3
	Freq.	60	10	3.9	100	3	60	6	4.5	97	7
Aver. acc	Time				97	2				100	4
	Freq.				96	8				97	7

It is estimated that the accuracies in frequency domain with the unequal pipe length present a major "discriminant power" because the frequency components from each pipeline have different signatures that also contribute to patter recognition. Reasoning within the frequency domain, the signal detected by the sensor is a composition of the frequency components generated by the source/fixture and the natural frequencies of the channel/pipeline. Therefore, in the case of the experiments in which the pipeline lengths are the same for all the fixtures, the frequency components of the hydraulic system channel have no "discriminant power". However, when the pipeline has different lengths, in the function of the fixtures, the frequency components of the pipeline channel are relevant features in classifying the signal, since the poles of the pipeline transfer function change according to the fixture, improving the accuracy of the detection system when compared with the experiments in which the pipeline length is the same for all the fixtures. The Figure 3.22 presents the comparison between flow and pressure signals in the time and frequency domains.

3.3.3 UPL signals classification considering two fixtures in use

This subsection describes the experiments and the results of OAA-SVM classification when two fixtures of an unequal pipe length are in use. It is common for two or more fixtures drawing from a real household water supply system to be in use at the same time, so the simultaneous fixture's use analysis is important to verify the generalization capability of the classifier in order to recognize the signals patterns.

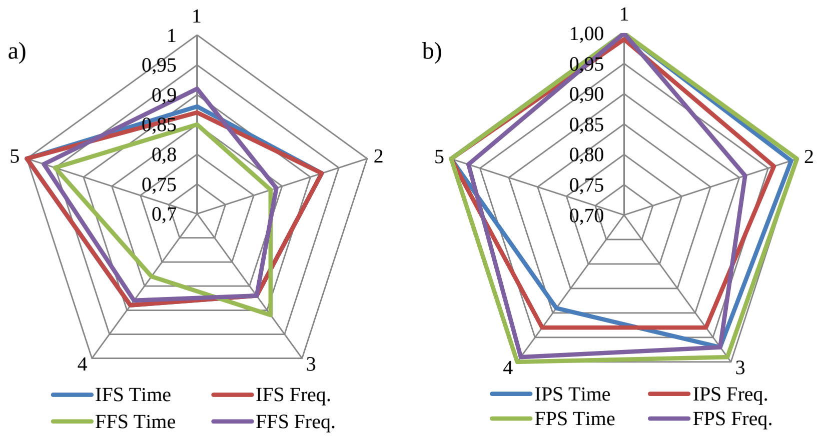

Figure 3.22: Comparison of classification accuracy for UPL train/test data: a) IFS and FFS OAA-SVM; b) IPS and FPS OAA-SVM

The experimental facility simulates a house with one kitchen and one bathroom. The design flow for a pipe size calculation considers three fixtures as a maximum for simultaneous use estimation, then, to cover all of the fixtures compositions it is necessary to examine 50 classes. It is estimated that some composition fixtures signals will be strong enough to verify the generalization capability of the classifier. This only occurred in fixtures compositions with Kitchen tap uses (C1), i.e., C6 - Kitchen tap + washbasin tap, C7 - Kitchen tap + bidet, C8 - Kitchen tap + shower and C9 - Kitchen tap + toilet flush. The samples used in each class had the same flow intensity variation used in previous experiments (maximum, medium and minimum) and the methods used for analysis were also the same.

The flow signal for one fixture in use is in a steady-state before the transient point, but when two fixtures are in use there is information about a signal before the transient point and after that there are two signals composition (Figure 3.23). This means that a group with only one fixture in use and a group with two fixtures (or more) in use have significant differences which allow for separated train/test OAA-SVM classifications. For instance, when the class 1 samples were trained and tested with two fixtures compositions samples the accuracy for them was always 100%.

The differences between the time and frequency domain accuracies are low as seen in the sub-section 3.3.2 signals analysis. Besides, the frequency domain provided better features for classification for IFS samples (Figure 3.24). Comparing the types of signal indicated that the final part of the pressure signal (FPS) provided better

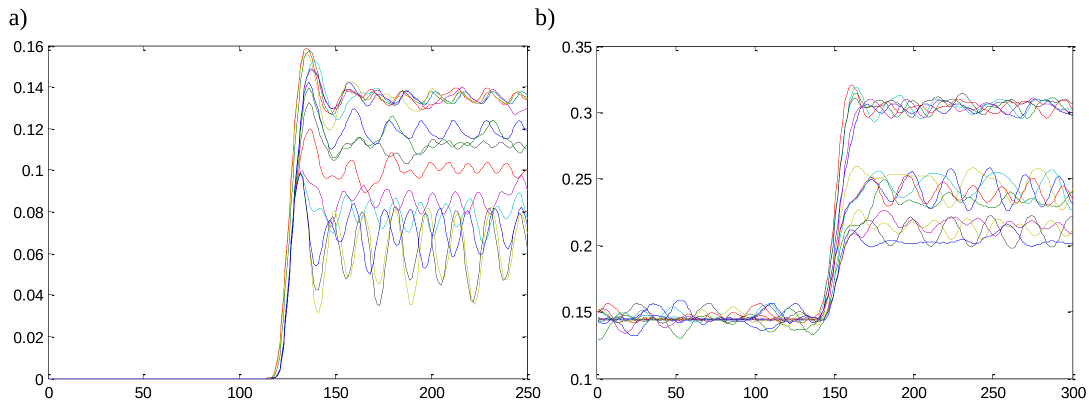

Figure 3.23: Flow signals: a) kitchen tap IFS (class 1); b) kitchen tap + washbasin tap IFS (class 6)

results for the time and frequency domains. The worst accuracy was found for the final part of the flow signals (FFS) classification.

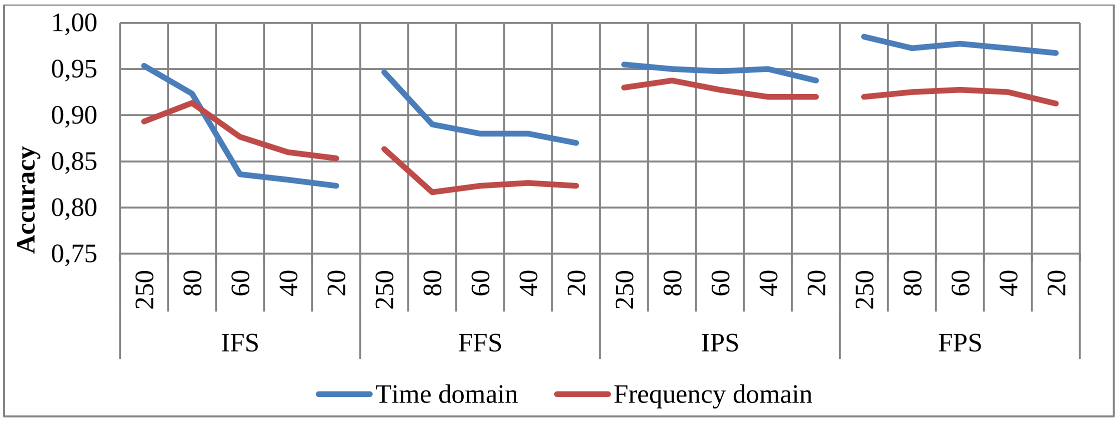

Figure 3.24: Comparison between of time and frequency domain accuracies for two fixtures in use.

The pressure signals results confirm its major "discriminant power" compared with flow signals when there is unequal pipe length. The open and close transient response seems more suitable to pattern recognition (Figure 3.25).

The Table 3.12 presents the best accuracy for flow signals in the time and frequency domains. As occurred in the previous subsection analysis, the best average accuracy was found for the initial part of the flow signals. The best accuracy in the time domain for the individual class evaluation was found in IFS and FFS samples, C9 - Kitchen

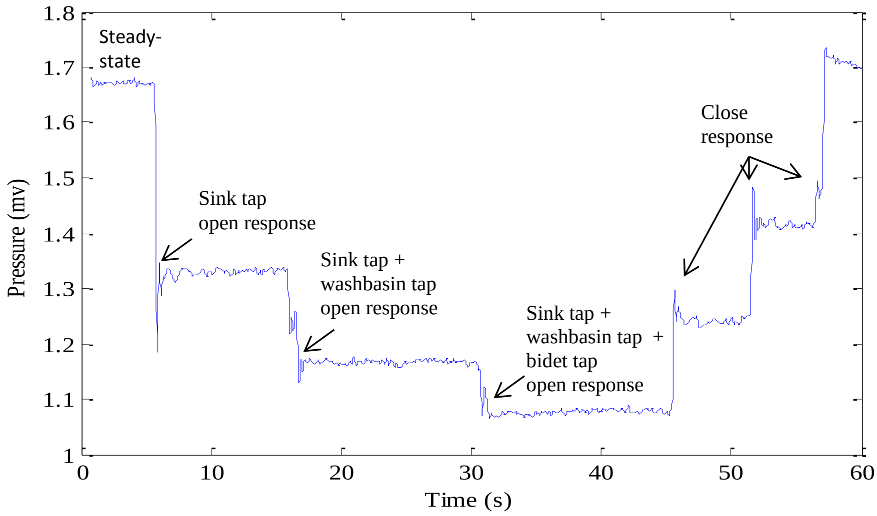

Figure 3.25: Pressure signal transient response.

tap+ toilet flush (Acc_T=100%) and C8 - Kitchen tap + shower (Acc_T=95%). The worst accuracy was found in the frequency domain, FFS samples, C8 - Kitchen tap + shower (Acc_T=84%).

Table 3.12: Accuracy for initial and final part of the UPL flow signals (two fixtures).

Class	Domain	IFS				FFS			
		$n°$ feat.	C	γ	Acc_T (%)	$n°$ feat.	C	γ	Acc_T (%)
6	Time	80	36	0.9	91	250	3	1.3	93
	Freq.	80	55	2.2	89	250	15	3.5	85
7	Time	250	2	1.4	95	250	4	1.1	91
	Freq.	80	16	4.8	91	100	13	3.5	85
8	Time	250	45	2.7	96	250	11	4.5	95
	Freq.	80	18	5.3	91	250	23	2.5	84
9	Time	250	28	1.1	100	250	12	1.5	100
	Freq.	80	7	4.8	95	250	58	5.3	91
Aver. acc	Time				96				95
	Freq.				92				86

Table 3.13 presents the best accuracy for pressure signals. The pressure signal was outperformed relative to the flow signals. The best accuracy in the time and frequency domain for the individual class evaluation was found in IPS and FPS samples, C9 - Kitchen tap + toilet flush (Acc_T=100%), C6 and C8 (Acc_T=99%). The worst accuracy was found in the time domain, IPS samples, C8 - Kitchen tap + shower (Acc_T=89%).

Table 3.13: Accuracy for initial and final part of the UPL pressure signals (two fixtures).

Class	Domain	IPS				FPS			
		$n°$ feat.	C	γ	Acc_T (%)	$n°$ feat.	C	γ	Acc_T (%)
6	Time	60	2	0.2	97	80	73	0.2	99
	Freq.	250	73	18.1	95	250	180	15.8	90
7	Time	250	23	0.3	96	250	16	0.4	97
	Freq.	80	37	6.8	91	100	169	13.6	96
8	Time	250	30	0.6	89	250	19	0.4	99
	Freq.	60	9	4.6	91	100	5	18.4	97
9	Time	250	30	0.1	100	250	47	0.2	100
	Freq.	80	3	5.9	100	80	3	6.3	97
Aver. acc	Time				96				99
	Freq.				94				95

The fusion by majority vote technique can improve the SVM classifiers flow signals occurrence. In this sense, some fusion compositions were made in order to identify the best ones. The Figure 3.26 presents the best accuracies provided by flow signal, pressure signal and flow signal OAA-SVM fusion. Despite the fusion accuracy improvement, the pressure signals still have the best accuracies for the considered data.

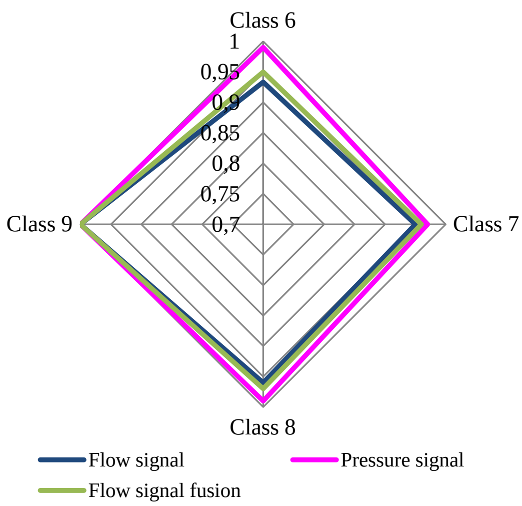

Figure 3.26: Best accuracies results considering flow signals, pressure signals and flow signals fusion.

3.4 Conclusion and recommendations

Information provided by telemetry data acquisition systems creates opportunities to develop algorithms for water consumption management. Many techniques can be used to process and classify signals, but this work used Fourier transform to convert time domain into frequency domain signals, FS-GAIT as feature extractor, and multiclass GDX and one-against-all SVM as classifiers. Fusion by majority vote was also used to improve OAA-SVM accuracy. An experimental apparatus was built to identify the fixtures' signals' signatures, and so they were positioned the same distance from the water meter and the transducers (SPL).

It was thought that the mechanism of each fixture might affect the classification results, but the classification findings indicated that the fixtures have only a slight influence on classification. The brand of the fixtures, their age, regularity in opening and closing them (human factor) could also explain variances found in the results. It is supposed that the signal noise provided by threaded spindle tap it was overcome by the fusion technique. The toilet flush and shower provided the most suitable signals for classification and the IFS in the time domain showed the best accuracy of the all classifications. The results indicated that each fixture has a signature or pattern that can be recognized by classifiers. It is estimated that signals provided by fixtures with standard start/stop work mechanism is more suitable for classification. For instance, the toilet flush signal presented the best accuracy among all.

It is assumed that if the fixtures are positioned at unequal distances, the classification accuracy could be improved due to the different remaining head losses. A head loss in pipes and fittings gives a new signature for the fixtures. In this sense a new set of experiments were carried out in order to identify the accuracies when there is an unequal pipe length (UPL). The pressure signals were outperformed relative to the flow signals for UPL samples when one and two fixtures were in use. Besides this, the frequency domain UPL samples present a major "discriminant power" comparing with SPL samples because the frequency components from the each pipeline also have different signatures which contribute to patter recognition. The general analysis indicates that it is possible to identify household water supply signal patterns in order to develop an algorithm to provide water use identification by fixture. It is estimated that pressure sensors could be used to develop the water use identification system when there are unequal pipe length and the flow sensors can be used to improve the accuracy with fusion by majority vote.

The results presented in this work are not aimed present a complete water uses fixtures identification methodology because of explores a specific subset of fixtures. Future work intended complete the set of fixtures using different fixtures compositions, hot and mixed water. The training and validation data provided for a complete number of classes will be needed to develop an algorithm for real household water use monitoring. The future expectation is that the users could follow up and control the water consumption using a PC or even a mobile fixture.

It is presumed that the real building water uses fixtures identification will be a challenge because of the same instant water fixture uses and the number of flow rates provided by the majority taps and showers open/close mechanism (e.g. cartridge - lever handle, threaded spindle). Part of these issues could be solved by using an electronic or self-closing tap due to more standardized start/stop work mechanisms. More developments in tap work mechanisms could also be made in order to limit the flow rate into two or three levels as occurs with toilet flush fixtures.

New developments at the algorithm could be made to track the open/close fixtures considering transient's signals identification in order to detect the usage time and flow rate (provided by water-meter) for water consumption quantification. To disambiguate the hot water from the cold water usage could be proposed use two pressure sensors, one at the cold water pipe and another at the hot water heater intake line. In this sense, the signals could be classified considering two independent systems.

As occur in studies for electric loads disaggregation [KJ11] it is intend in the near future setting up a dataset with water uses information using the data acquisition system developed in this work in order to incentive news water uses identification and disaggregation methods development.

Chapter 4

Aspects of water supply systems for buildings with PEX

THIS chapter presents an analysis of the indoor building PEX water supply network using the information provided by the data acquisition system which was developed and presented in Chapter 3. Standards for building water system design and pipe sizing calculations could be improved by utilizing large scale information about water flow conditions in pipes. Similar to other regions, the standards in Portugal for interior water supply design, the *Decreto Regulamentar* DR $23-95$ [DR296], were established a long time ago and do not add efficiency measures, nor do they encourage this practice. The principles of pipe sizing calculations in Portugal consider the pipe system design, the minimum flow rates of each device and the coefficient of simultaneity as basic requirements. The European Normative - EN $\texttt{n}^{\texttt{o}}$ $806-3:2006$ [80606] has some developments in relation to efficiency measures and presents a simplified calculation method for interior water pipes that result in smaller diameters. Although the EN $806-3$ takes into account pressure and flow rates in the pipe size calculation, the main criteria for design is the speed limit [SA07]. The basic concepts presented at the EN $806-3$ indicate that the installation should be designed to avoid waste, undue consumption, misuse and contamination. To accomplish this it is necessary to maintain a suitable flow velocity provided by controlled pressure in order to avoid low flow, formation and trapping of air. The pressure monitoring could help to control the ideal conditions for the efficient operation of the water supply system, because of pressure fluctuations in the public water network.

Studies that contribute toward innovative designs for interior water supply are important because some aspects in conventional plumbing systems may represent water losses. Advances in metallurgy and materials science have led to relative reductions in the cost of construction and also improved the efficiency of water supply and sewer systems. The materials have evolved from stone and wood, lead, copper, ceramics and clay, cast iron, ductile iron, concrete, steel and most recently, plastics [Jam98]. The cross-linked polyethylene pipe, PEX, used at the experimental facility has been in use in Europe since approximately 1970, and was introduced in the U.S. approximately in 1980 [TS06]. At this time, PEX was used in replacing copper pipe in many applications, especially radiant heating systems installed in the concrete slabs under floors or walkways. However, the pipe expansion that occur during the PEX life time make it difficult to remove and replace the material. The main advantages of PEX Plumbing are:

- Lower shipping and handling costs due to decreased weight and improved storage options;
- PEX requires fewer fittings than rigid piping. For instance the flexible tubing can turn 90 degree corners without the need for elbow fittings;
- Does not require soldering to attach fittings thus avoiding health hazards due to lead-based solder and acid fluxes use;
- PEX is much more resistant to freeze-breakage than rigid plastic pipe;
- PEX is less expensive than rigid plastic pipe and does not transfer heat as readily as copper;

Aspects about PEX's design, flow rate and pressure are important for investigation. When the flow rate is higher than what the system is designed to support it leads to wasted water through back-ups and water losses. On other hand, installation with a relatively large number of bends and fittings can significantly decrease the pressure due to local head losses and could result in damage to the device and discomfort for users [PGSM12]. High pressures provided by public water supply, i.e. pressure greater than that required in the pipe system, could result in water supply system inefficiency due to water losses or high water consumption.

The water heater unit used by the water supply system is another factor that may represent water supply system inefficiency. Depending on the water heating system used, head losses and water waste could be significant. The so-called *tankless* water heating system, used in this research, is a very popular device due to its capacity to provide unlimited hot water, with lower energy consumption and smaller physical dimensions which allows installation in a smaller space. Hot water storage issues, as well as legionella contamination, is also largely avoided when *tankless* is used because the majority of thermoplastics material used for water supply systems, i.e. polypropylene, polybutene, PEX and PVC-C, would be a good environment for biofilms production [SAL06]. Putting these advantages aside, the start-up delay of the tankless water heater system results in some wait for hot water. The start-up delay leads to water waste and it is as big as the distance between the heater and the tap. For instance, if the hot water takes 5 seconds to reach the tap that provides 0.90 l/s of water, considering 3 uses per day, the waste would be more than 400 l per month. Moreover, the waste in a house with four devices represents 1.5 m^3 per month. This amount would be enough to supply a house with 3 persons for 4 days, considering 130 l/pc/d. Besides the waste, the *tankless* water heater works as a huge barrier for the water flow causing high head losses in the hot water supply system. The pressure can be decreased up to four times as can be seen in the subsection 4.2.3. Some developments in this system were set up with the Electric point-of-use (POU) *tankless* water heater (Figure 4.1) which provides hot water locally, thus reducing water waste. However, the cost of installation and energy can outweigh the money saved in water which can explain its low popularity. The most economic design may vary according to the relative electricity, gas and water prices in the locality, the layout of the building, and how much (and when) hot water is used. In many regions the household water tariff is lowest in comparison to other consumables, as can be seen in Chapter 2.

In this piece head losses in PEX pipes, distribution manifold and heater, as well as the coefficient of simultaneity were analyzed. The objective of this study is to propose an interior pipe system analysis method that could be used in large scale for any type of water supply pipe. This research may contribute with an evaluation of parameters used for pipe sizing calculations. This study also aims to contribute with information for water supply design developments considering high efficiency interior water supply systems.

Figure 4.1: Examples of POU tankless water heater used in Britain and Germany.

4.1 Materials

The data acquisition system which was developed for signal pattern analysis and described in Chapter 3, subsection 3.1.1, was used for the coefficient of simultaneity research. However, for head losses research it was necessary to install additional transducers to measure the pressure drop in specific points throughout the pipe system. A new data acquisition unit was assembled (Figure 4.2) and is composed of four pressure transducers (3100 Series) with pressures ranging between 0 and 10 bars. The pressure information was acquired by the Data logger Campbell CR800s. It also used a Track-It^{TM} 150 MicroDAQ Pressure-Temperature Data Logger with analog output (micro data logger) to acquire the toilet flush pressure data and provide simultaneous pressure information for the distribution manifold head losses research (Section 4.2.2). Another computer was used to copy and process the information acquired by data loggers. Moreover, it was necessary install the PC 200W software (Data logger CR800s) and the Track-It software. The data analysis was prepared using the MsExcel spreadsheets and SPSS Statistics software.

4.2 Head losses

This section presents the results of the PEX water supply system head losses at the experimental apparatus. The pipes, manifold and water heater head losses were compared with the data provided by manufacturer.

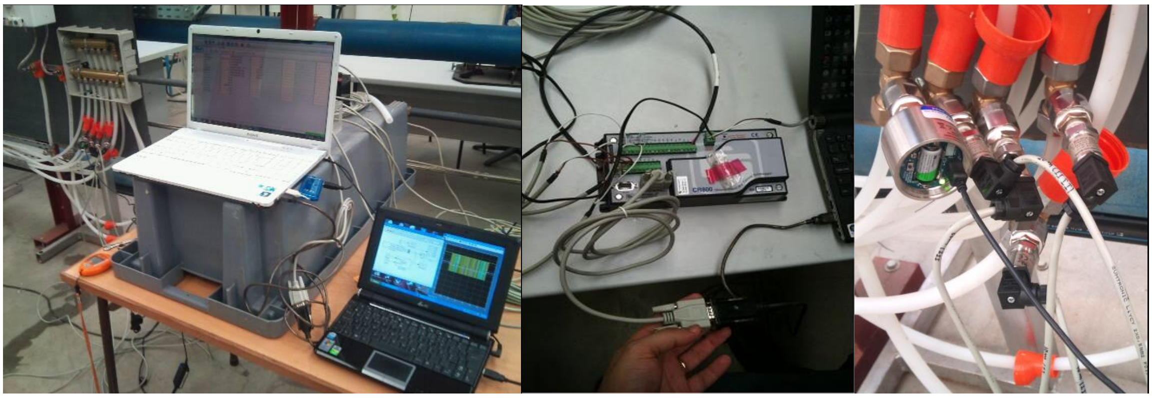

Figure 4.2: Head losses acquisition system.

The energy loss phenomena which occurs in pipes and fittings could be related to fluid characteristics (e.g. viscosity) and/or the environmental characteristics through which the fluid is flowing (e.g. roughness of the inner surface of the pipe) [SMS09]. The turbulence dissipates even more energy as higher Reynolds numbers demonstrate. The head loss is the most significant energy loss in pipe systems and can be divided in two groups: friction head losses ΔH_c, associated with energy loss per length of pipe, and local head losses ΔH_L, associated with bends and fittings. The most common equation used to calculate friction head losses is the Darcy-Weisbach equation that is given by:

$$\Delta H_c = \frac{f \times L}{D} \times \frac{V^2}{2g} = \frac{8f \times L}{g \times \pi^2 \times D^5} \times Q^2 \tag{4.1}$$

were ΔH_c is the friction head losses (m); f is the Darcy friction factor; V is the mean flow velocity (m/s); Q is the flow rate (m^3/s); g is the gravitational acceleration (m/s^2); D is the inside pipe diameter (m); and L is the length of pipe (m).

The Darcy friction factor depends on the Reynolds number R_e, that is given by:

$$R_e = \frac{V \times D}{\nu} \tag{4.2}$$

were ν is the kinematic viscosity (m^2/s). The kinematic viscosity for water can be estimated by the empiric Poiseuille equation:

$$\nu = \frac{1.78 \times 10^{-6}}{1 + 0.0337 \times T + 0.000221 \times T^2} \tag{4.3}$$

were T is the water temperature ($°C$ - degrees Celsius).

The absolute pipe Roughness ϵ (mm)indicates the roughness resistance of the inner surface of the pipe and its calculation depends on the flow regime. The principal flow under pressure regimes are the laminar and turbulent. For low Reynolds numbers (R_e<2000) the behavior of a fluid depends mostly on its viscosity and the flow is usually smooth, viscous, or laminar; on the other hand, for high Reynolds numbers the momentum of the fluid determines its behavior more than the viscosity and the flow is unsteady, roiling, or turbulent. The regime in water supply systems is usually turbulent, so the roughness coefficient can be calculated by Colebrook-White equation:

$$\frac{1}{\sqrt{f}} = -2.0 \log \left(\frac{\epsilon}{3.7D} + \frac{2.51}{R_e \ \sqrt{f}} \right) \tag{4.4}$$

were ϵ (mm) is the absolute pipe Roughness. The explicitly equation that allows calculate the pipe roughness is given by:

$$\epsilon = 3.7D \left(10^{-\frac{V}{2\sqrt{2gDJ}}} - \frac{2.51\nu}{D\sqrt{2gDJ}} \right) \tag{4.5}$$

were J is the hydraulic slope or linear hydraulic head loss (m/m).

The local head losses is considered the less significant loss for the water supply system design and is usually estimated from tables using coefficients or a simpler and less accurate reduction of local head losses to equivalent length of pipe. However, for relatively short pipe systems, with a relatively large number of bends and fittings, local head losses can easily exceed friction head losses. The local losses are estimated taking into account the flow kinetics height using the follow equation:

$$\Delta H_L = K \times \frac{V^2}{2g} = \frac{8K}{g \times \pi^2 \times D^4} \times Q^2 \tag{4.6}$$

were ΔH_L is the local head losses (m); K is the local head loss factor; V is the flow velocity (m/s); Q is the flow rate (m^3/s); g is the gravitational acceleration; D is the inside pipe diameter (m).

In the next sub-sections, the results of the head losses research from the experimental apparatus PEX water supply system are presented.

4.2.1 Friction Head losses

This research took into account two different pipeline sizes to calculate the friction head losses: 12mm pipeline from the sink tap (T1) and 16mm pipeline from the shower (Sh). The main objective of this research was to compare the friction head losses, provided by pipeline characteristics, with those presented by manufacturer pressure loss diagrams [SpA13]. Additionally, it also identified the roughness in pipelines by taking into account the pressure and flow rate. The pressures were measured through two pressure transducers located as presented in Figure 4.3. It was constructed with five transducers: one before and two after the manifold (T1 and Sh pipes), one at the sink tap and another at the shower.

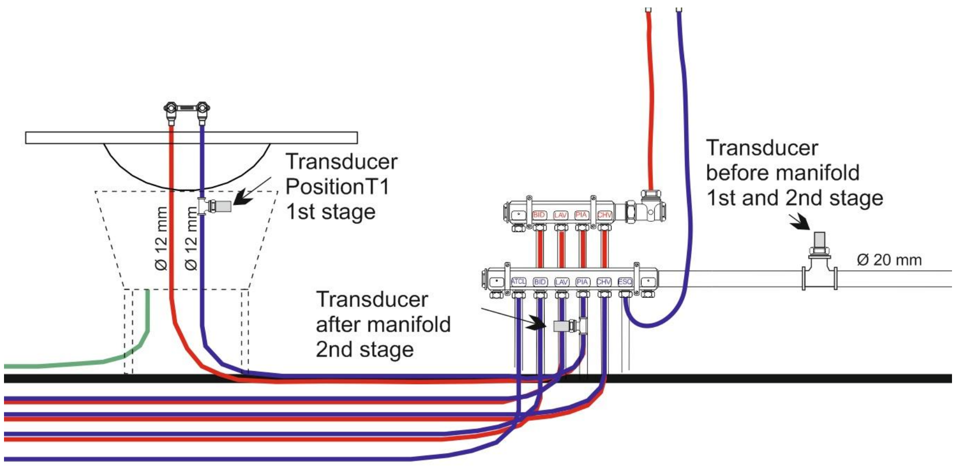

Figure 4.3: Transducers position for pipe head losses research.

Two stages were necessary to carry out the experiments. In the first stage data was collected in the transducer located before the manifold (BM) and at the devices (T1 and Sh). Data provided by the transducers before (BM) and after the manifold (AM) was collected in a second stage. Four flow intensities were applied for the experiments: low (Lo), medium low (Ml), medium high (Mh) and high (Hi). Opening different devices allowed for the achievement of the flow rates values (Table 4.1). Three samples were collected in each intensity flow experiment.

Table 4.1: Flow rate intensities

Samples flow rate intensities	Pipeline	
	Q_{T1} (12mm)	Q_{Sh} (16mm)
$Lo(l/s)$	0.04 to 0.05	0.06
$Ml(l/s)$	0.065 to 0.08	0.11 to 0.12
$Mh(l/s)$	0.092 to 0.11	0.15 to 0.17
$Hi(l/s)$	0.134	0.19

Friction head losses in 12 mm PEX pipes

The data collected at the experimental apparatus for 12 mm PEX pipe research is presented in Table 4.2. It measured pressure (p), flow (Q_{T1}) and calculated the friction head losses (ΔH_c) data.

Table 4.2: Friction head losses for 12 mm PEX pipe

Samples	Q_{T1} (l/s)	1^{st} stage			2^{nd} stage			ΔH_c
		p_{T1} (bar)	p_{AM} (bar)	Δp_1 (bar)	p_{BM} (bar)	p_{AM} (bar)	Δp_2 (bar)	Δp_1-Δp_2 (bar)
Lo_1	0.05	2.63	2.72	0.09	2.68	2.74	0.06	0.03
Lo_2	0.04	2.63	2.72	0.08	2.70	2.73	0.03	0.05
Lo_3	0.05	2.59	2.70	0.11	2.68	2.73	0.05	0.05
Ml_1	0.07	2.53	2.68	0.15	2.56	2.68	0.12	0.03
Ml_2	0.065	2.51	2.67	0.16	2.58	2.67	0.09	0.07
Ml_3	0.08	2.46	2.66	0.20	2.49	2.65	0.15	0.04
Mh_1	0.092	2.34	2.63	0.30	2.43	2.64	0.21	0.09
Mh_2	0.10	2.32	2.70	0.38	2.38	2.61	0.23	0.16
Mh_3	0.11	2.17	2.60	0.43	2.30	2.59	0.28	0.15
Hi_1	0.134	2.03	2.60	0.57	2.11	2.56	0.45	0.13
Hi_2	0.134	2.03	2.61	0.58	2.11	2.56	0.44	0.13
Hi_3	0.134	2.02	2.60	0.58	2.11	2.56	0.45	0.13

The internal diameter D_i from the 12 mm PEX pipe in the experimental apparatus is 8 mm (PEX 12x2), however, the manufacturer provided linear hydraulic head losses J information only for the D_i=9.8 mm, i.e. PEX 12x1.1. because of this, it was necessary calculate the linear hydraulic head losses for PEX 12x1.1 in order to compare with data from the manufacturer pressure loss diagrams. Considering the flow rate, pipe length L=1.14m, kinematic viscosity ν=1.01E-06 (20°C), ΔH_c and Darcy friction factor f for 12x2 pipe, it was calculated as ΔH_c and J for the 12x1.1

PEX pipe using the Reynolds (4.2) and Darcy-Weisbach equations (4.1). The table 4.3 presents the calculated values.

Table 4.3: Linear hydraulic head losses for 12x2 and 12x1.1 PEX pipe

Samples	Q_{T1} (l/h)	ΔH_c 12x2 (mH_2O)	J 12x2 (mm/m)	V(m/s)	R_e	f	ΔH_c 12x1.1 (mH_2O)	J 12x1.1 (mm/m)
Lo_1	180.0	0.26	229.82	0.995	7883.06	0.0364	0.09	83.31
Lo_2	180.0	0.52	455.03	0.995	7883.06	0.0720	0.19	164.95
Lo_3	216.0	0.55	482.08	1.194	9459.67	0.0530	0.20	174.76
Ml_1	252.0	0.33	293.07	1.393	11036.28	0.0237	0.12	106.24
Ml_2	252.0	0.74	648.96	1.393	11036.28	0.0524	0.27	235.25
Ml_3	288.0	0.44	389.42	1.592	12612.90	0.0241	0.16	141.17
Mh_1	352.8	0.87	761.87	1.951	15450.80	0.0314	0.31	276.19
Mh_2	360.0	1.58	1389.64	1.990	15766.12	0.0550	0.57	503.76
Mh_3	417.6	1.51	1326.58	2.309	18288.70	0.0390	0.55	480.9
Hi_1	486.0	1.31	1146.56	2.687	21284.26	0.0249	0.47	415.64
Hi_2	486.0	1.37	1205.06	2.687	21284.26	0.0262	0.50	436.85
Hi_3	486.0	1.33	1163.27	2.687	21284.26	0.0253	0.48	421.70

The results presented in Figure 4.4 indicate that the linear hydraulic head losses J information provided by the manufacturer in its pressure loss diagrams is similar with those calculated for PEX 12x1.1.

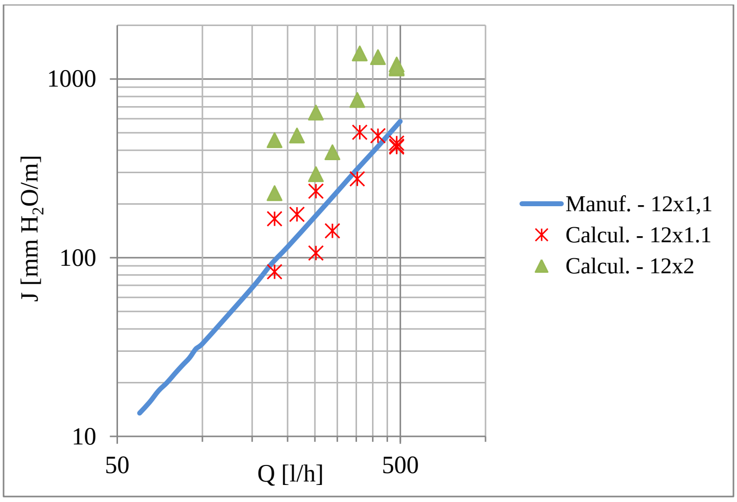

Figure 4.4: Comparison between manufacturer diagram and calculated linear head losses data for 12x1.1 pipe.

The roughness coefficient for the 12 mm PEX pipe was calculated using the Colebrook-White equation (4.5). The arithmetic mean of the calculated values is ϵ=0.02mm

(Table 4.4). This value is similar to PVC roughness (0.01mm to 0.06mm), as presented in the literature [SMS09], which is considered a suitable result because both PEX and PVC are thermoplastic materials.

Table 4.4: Absolute roughness coefficient for 12x2 PEX pipe

Samples	ΔH_c (mH_2O)	V (m/s)	R_e	f	ϵ (mm)
Lo_1	0.262	0.995	7883.06	0.0364	0.024
Lo_2	0.519	0.995	7883.06	0.0720	0.022
Lo_3	0.549	1.194	9459.67	0.0530	0.020
Ml_1	0.334	1.393	11036.28	0.0237	0.021
Ml_2	0.739	1.393	11036.28	0.0524	0.018
Ml_3	0.444	1.592	12612.90	0.0241	0.019
Mh_1	0.868	1.951	15450.80	0.0314	0.014
Mh_2	1.584	1.990	15766.12	0.0550	0.010
Mh_3	1.512	2.309	18288.70	0.0390	0.009
Hi_1	1.307	2.687	21284.26	0.0249	0.008
Hi_2	1.374	2.687	21284.26	0.0262	0.008
Hi_3	1.326	2.687	21284.26	0.0252	0.008

Friction head losses in 16 mm PEX pipes

The data collected at the experimental apparatus for 16 mm PEX pipe research is presented in Table 4.5.

Table 4.5: Friction head losses for 16 mm PEX pipe

		1^{st} stage			2^{nd} stage			ΔH_c
Samples	Q_{Sh} (l/s)	p_{Sh} (bar)	p_{AM} (bar)	Δp_1 (bar)	p_{BM} (bar)	p_{AM} (bar)	Δp_2 (bar)	$\Delta p_1 - \Delta p_2$ (bar)
Lo_1	0.06	2.65	2.69	0.04	2.67	2.68	0.01	0.03
Lo_2	0.06	2.67	2.72	0.05	2.72	2.72	0.00	0.05
Lo_3	0.06	2.65	2.71	0.06	2.68	2.69	0.01	0.04
Ml_1	0.11	2.51	2.63	0.12	2.54	2.60	0.06	0.06
Ml_2	0.11	2.52	2.62	0.10	2.55	2.59	0.04	0.06
Ml_3	0.12	2.50	2.63	0.13	2.55	2.61	0.06	0.07
Mh_1	0.15	2.36	2.58	0.21	2.49	2.58	0.09	0.12
Mh_2	0.15	2.32	2.55	0.23	2.46	2.55	0.09	0.13
Mh_3	0.17	2.27	2.53	0.26	2.41	2.55	0.13	0.13
Hi_1	0.19	2.21	2.53	0.32	2.28	2.48	0.20	0.11
Hi_2	0.19	2.21	2.53	0.32	2.30	2.49	0.19	0.13
Hi_3	0.19	2.23	2.53	0.30	2.28	2.48	0.20	0.10

The linear hydraulic head losses $J(mmH_2O/m)$ for 16x2.2 for the experimental apparatus PEX pipe were calculated based on the pipe length L=2.77m and ΔH_c.

The results presented in Figure 4.5 indicate that the linear hydraulic head losses J information provided by the manufacturer in its pressure loss diagrams is similar to those calculated for PEX 16x2.2, however the differences are bigger for low flows.

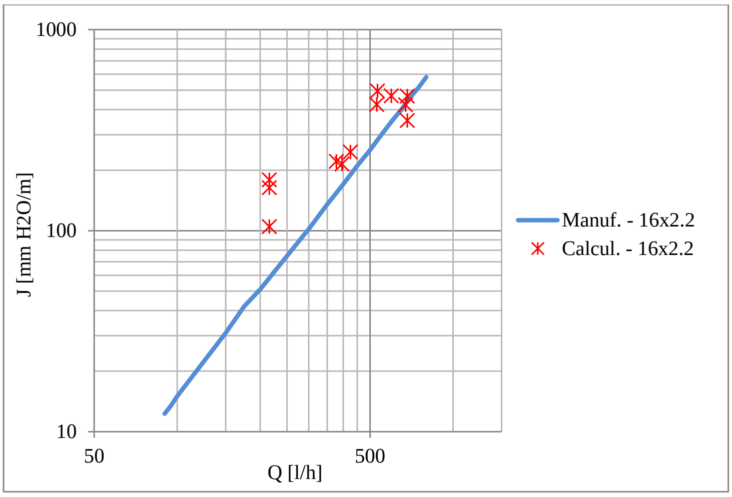

Figure 4.5: Comparison between manufacturer diagram and calculated linear head losses data for 16x2.2 pipe.

The internal diameter D_i=11.6mm, flow rate (Q_{Sh} - Table 4.5), pipe length L=2.77m, kinematic viscosity ν=1.01E-06 (20°C), ΔH_c, the Darcy friction factor f (Equation 4.1) and the Reynolds number (Equation 4.2) were calculated in order to identify the 16 mm PEX pipe roughness coefficient ϵ (Equation 4.5). Table 4.6 presents the results.

Table 4.6: Absolute roughness coefficient for 16x2.2 PEX pipe

Samples	ΔH_c (mH_2O)	V (m/s)	R_e	f	ϵ (mm)
Lo_1	0.290	0.568	6523.91	0.0737	0.039
Lo_2	0.495	0.568	6523.91	0.1260	0.038
Lo_3	0.452	0.568	6523.91	0.1150	0.038
Ml_1	0.593	1.041	11960.51	0.0449	0.033
Ml_2	0.612	0.994	11416.85	0.0508	0.033
Ml_3	0.682	1.117	12830.36	0.0448	0.032
Mh_1	1.175	1.392	15983.58	0.0498	0.026
Mh_2	1.372	1.401	16092.32	0.0574	0.025
Mh_3	1.295	1.572	18049.49	0.0430	0.024
Hi_1	1.170	1.770	20332.86	0.0306	0.023
Hi_2	1.293	1.799	20659.05	0.0328	0.022
Hi_3	0.979	1.799	20659.05	0.0248	0.024

The arithmetic mean for the roughness coefficient is ϵ=0.03mm. Similar to the 12 mm pipe, the PEX roughness coefficient average value is similar to PVC roughness (0.01mm to 0.06mm), as presented in the literature [SMS09].

4.2.2 Local head losses in distribution manifold

Identifying the local head losses and comparing against those presented by the manufacturer are the main objectives of the the local head losses research in the PEX distribution manifold. The local head loss factor K was also analyzed to identify the manifold characteristics. One eight-output manifold without lock shields (3/4"x16) and six pressure transducers was used at the experimental apparatus. The transducers position can be seen at Figure 4.6.

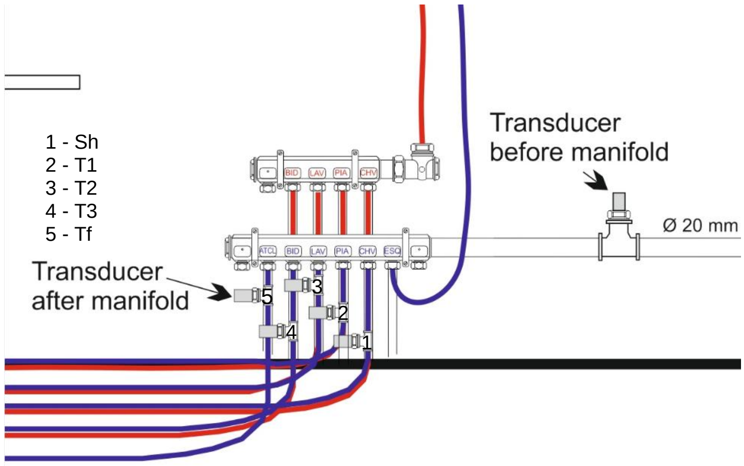

Figure 4.6: Transducers position for manifold head losses research.

Only one stage was necessary to carry out the manifold head losses experiments, using the maximum cold water flow rate for one, two and three devices. Three repetitions of each device experiment were performed. Figure 4.7 presents the pressure dynamics of the manifold experiment.

The manifold manufacturers' diagrams present numbers which correspond to each curve, indicating the lock-shield-opening turns (e.g. curve 1 - one turn, curve 2 - two turns, and so on). The manifold with a lock-shield is normally used for underfloor heating in order to control the hot water circulation through the pipes. However, manifolds installed in water supply systems do not have a lock-shield. The diagrams provided by the manufacturer for a 3/4"x16 manifold with and without a lock-shield

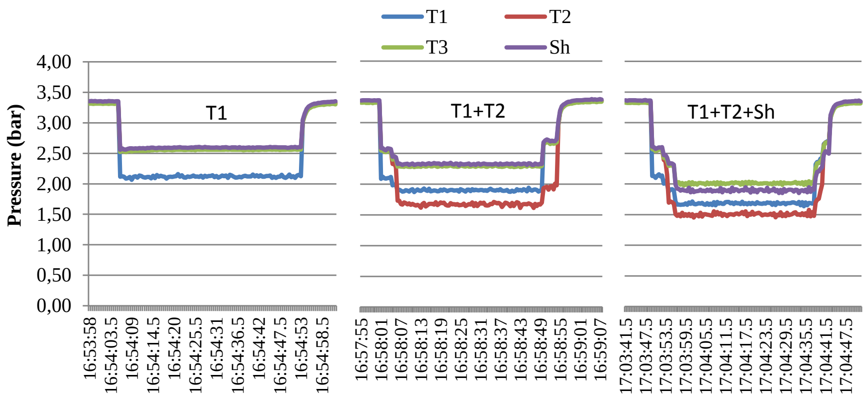

Figure 4.7: Pressure dynamics in manifold.

are the same, which demands different analysis. The comparison between experiment head losses and the data provided by manufacturer is presented in Figure 4.8.

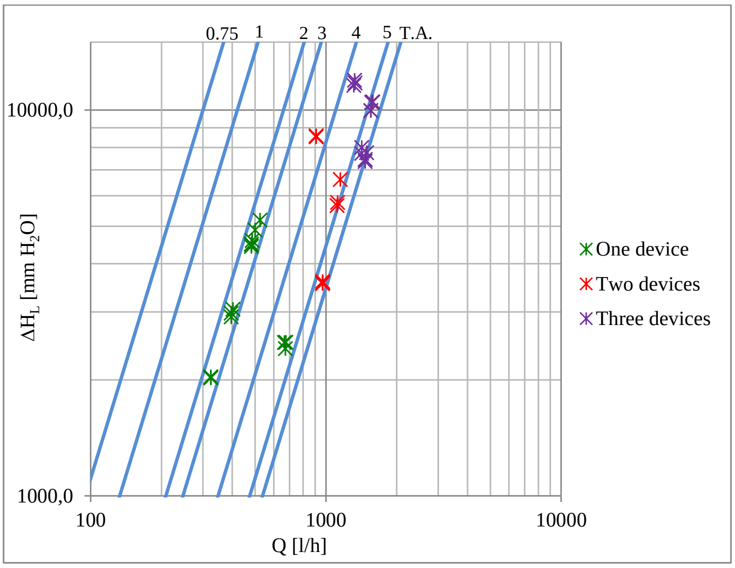

Figure 4.8: Distribution manifold (3/4"x16) head losses.

The data provided from the experimental apparatus for a single working device is located between curve 2 and 3, using a 12 mm pipe. For a 16 mm pipe, the data are more close to curve 5. When more than one working device is in operation it is observed that the working device compositions with the shower (16 mm pipe) have fewer head losses and are closer to the T.A. curve, otherwise, the measurements using only the 12 mm pipe are closer to curves 4 and 5. Information about manifold head loss experiments were not provided by the manufacturer, however, it is supposed that manifolds without a lock-shield are more closely related to T.A. curves (fully open) when more than one output manifold is in use.

The manufacturers' documents indicated that in addition to the adjustments diagram, the specific feature of each regulating element (Kv experimental values) should be used when determining the pressure loss. In the case of water, the Kv factor can be used by the following expression:

$$\Delta H_L = \left(\frac{Q}{Kv}\right)^2 \cdot \left(\frac{1}{100}\right) \tag{4.7}$$

where ΔH_L is the pressure loss (mmH_2O); Q is water flow (l/h); and Kv is specific feature of each regulating element. The Kv calculated for the measured data can be seen in Table 4.7.

Table 4.7: Specific feature of each regulating element Kv calculation: average sample value

Devices	Q (l/h)	ΔH_L (mmH_2O)	Kv
T1	482.40	4470.68	0.72
T2	504.00	4487.50	0.72
T3	398.40	2975.48	0.73
Tf	324.00	2026.53	0.72
Sh	672.00	2468.17	1.35
T1+T2	1568.40	10306.44	1.55
T2+Sh	1130.40	6007.75	1.46
T3+T2	910.80	8553.60	0.98
Tf+Sh	969.60	3570.31	1.62
T1+T2+Sh	1568.40	10306.44	1.55
T2+Sh+T3	1444.80	7823.56	1.63
T3+T2+T1	1323.60	11758.32	1.22
Tf+Sh+T2	1468.80	7411.27	1.71

The average Kv for 12 mm pipes is 0.72 and for 16 mm is 1.35 for one device in use. When two devices are working simultaneously the average Kv value is 1.40 and for three devices is 1.53. It is observed that the Kv value is lower for samples when the shower is not in use.

The local head losses equation (4.6) was used to calculate the local head loss factor K. The K analyzed was grouped according to the number of devices in use. The Table 4.8 presents the experimental data for one device.

The arithmetic mean of K values for a 12mm pipe is 12 and for a 16mm pipe is

Table 4.8: Local head loss factor K for one device

Device	p_{BM} (bar)	p_{AM} (bar)	Q (l/s)	ΔH_L (m)	D (mm)	K
$T1_{r1}$	2.56	2.12	0.134	4.48	12	12.36
$T1_{r2}$	2.56	2.12	0.134	4.50	12	12.39
$T1_{r3}$	2.56	2.13	0.134	4.43	12	12.21
$T2_{r1}$	2.55	2.04	0.146	5.18	12	12.02
$T2_{r2}$	2.56	2.08	0.139	4.89	12	12.52
$T2_{r3}$	2.57	2.12	0.135	5.18	12	12.46
$T3_{r1}$	2.62	2.33	0.110	2.91	12	11.89
$T3_{r2}$	2.62	2.32	0.112	3.05	12	12.01
$T3_{r3}$	2.62	2.33	0.110	2.97	12	12.15
Tf_{r1}	2.67	2.47	0.090	2.04	12	12.43
Tf_{r2}	2.67	2.47	0.090	2.02	12	12.34
Tf_{r3}	2.67	2.47	0.090	2.02	12	12.36
Sh_{r1}	2.53	2.29	0.187	2.41	16	15.05
Sh_{r2}	2.53	2.29	0.185	2.50	16	15.96
Sh_{r3}	2.53	2.28	0.188	2.50	16	15.47

15.5. When two devices are working simultaneously, the average K is 6 and for three devices the average is $K = 4$. Figure 4.9 presents the calculations K for all samples.

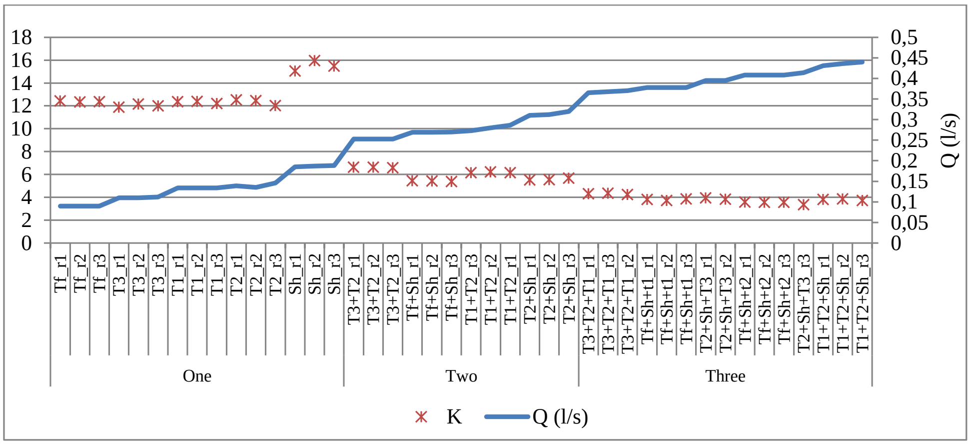

Figure 4.9: Distribution manifold local head loss factor K.

4.2.3 Local head losses at *Tankless* water heater

Identifying the local head losses is the main objective of the experimental apparatus in the *tankless* water heater research. The local head loss factor, K, was also analyzed to identify the *tankless* characteristics. Only one stage was necessary to carry out the water heater head losses experiments and the maximum hot water flow rate for one, two and three devices in use was tested. Three samples were collected for each flow rate. Figure 4.10 presents the positions of the pressure transducers.

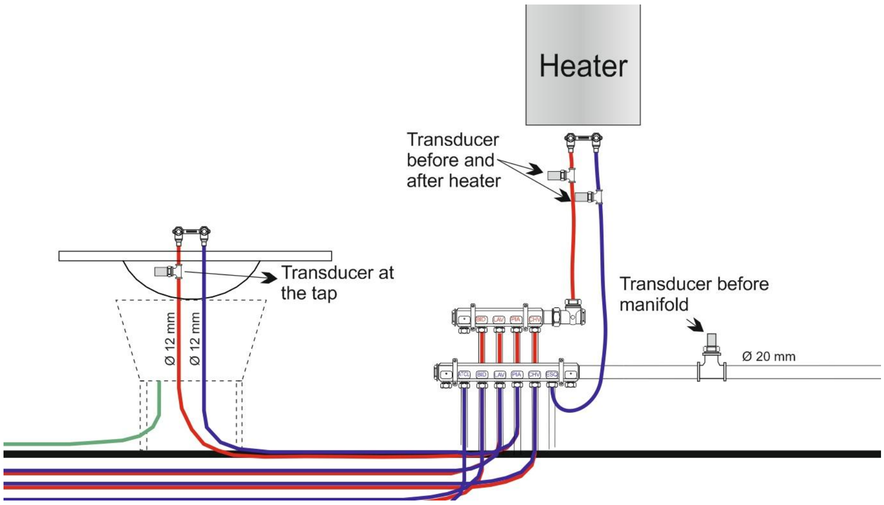

Figure 4.10: Transducers position for *tankless* water heater head losses research.

The local head losses in the *tankless* water heater are responsible for the significant drop in the flow rate in the hot water supply system. The average flow rate reduction is 40% and could be further reduced to 46% according to data from the experimental apparatus. No head losses diagram was provided by *tankless* manufacturer, so it was not possible compare our measurements against those of the manufacturer. Comparison between the *tankless* and a single working device manifold for a 12mm pipe head losses diagrams was made in order to verify the *tankless* head loss representation of the water supply system(Figure 4.11).

Significant variations in tankless local head losses values were not found, as occurred in the manifold results, possibly due to the same pipe diameters for all devices (12mm) used in the hot water supply system.

The local head losses equation (4.6) was used to calculate the local head loss factor K. The K analysis was grouped according to the number of devices in use. Figure 4.12 presents the experimental data for all device compositions.

The arithmetic mean of K value for a 12mm pipe and a single device is 170; for more than one device, the K is 179. The K values are very close, and so should be considered the K values to use as the average value, i.e. 176. For the 12 mm pipe, the pipe roughness coefficient ϵ was also calculated. The arithmetic mean value was

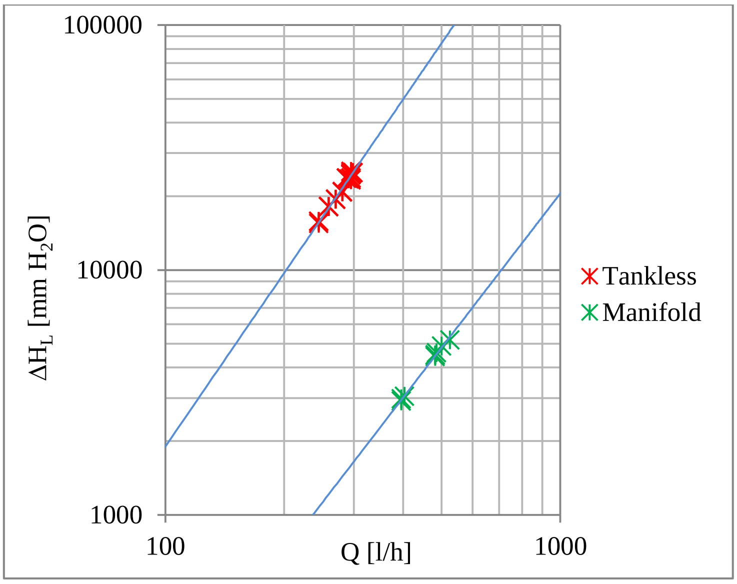

Figure 4.11: Comparison between Water heater and manifold head losses diagrams.

ϵ=0.025mm, which confirms the calculated values in the Sub-section 4.2.1.

4.3 Coefficient of simultaneity

In this section we illustrate the results of the coefficient of simultaneity research. The flow rate and the pressure from five draw-off points were analyzed: sink tap (T1), wash basin tap (T2), bidet tap (T3), shower (Sh) and toilet flush (Tf). The data from the cold and hot water supply system were analyzed. Compositions between devices were made in order to identify the flow rate results from simultaneous uses.

When we consider the definition of the coefficient of simultaneity, the ratio between the maximum expected simultaneous flow (flow of calculation or design flow rate - Q_d) and the cumulative flow from all devices in use (Q_a) supplied through a given section, the equation to calculate the design flow rate is:

$$Q_d = C_s \times Q_a \tag{4.8}$$

There are two methods, in accordance with Portuguese standards, to estimate the

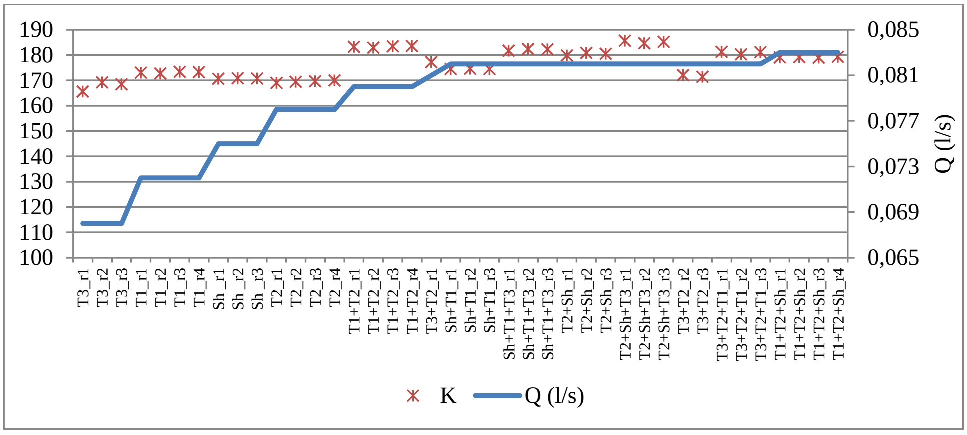

Figure 4.12: Water heater local head loss factor K.

coefficient of simultaneity: probabilistic and graphic [Ped00]. Both of these methods were used in the low flow systems: the Delebecque method that is a graphical method presented at *Diário da República* - DR23-95, and the modified method for the coefficient of simultaneity (MMCS) which is a probabilistic method presented by *Empresa Portuguesa de Águas Livres S/A* (EPAL) in its guide called "*Manual de Redes Prediais*" [EPA11]. EPAL is the Portuguese Water Company responsible for the Lisbon region water supply.

4.3.1 Delebecque method

The Delebecque method uses a graphical approach in order to estimate the design flow rate when accounting for the accumulated flow rate. The Delebecque analysis considers three levels of comfort to design the water supply system: minimum, normal and high [Bap11]. Investigators made some adjustments in these curves which resulted in more accurate solutions. The modifications allowed to include these curves mathematically and the design flow rates can be calculated directly by equations. For the accumulated low flow rate, i.e. $Q_a \leq 3.5 l/s$, the Delebecque method equations are:

$$\begin{aligned} Q_d &= 0.5099 \times Q_a^{0.5092}\,(a) \\ Q_d &= 0.5469 \times Q_a^{0.5137}\,(b) \\ Q_d &= 0.6015 \times Q_a^{0.5825}\,(c) \end{aligned} \tag{4.9}$$

where the minimum level of comfort curve is 4.9(a), the normal level of comfort curve is 4.9(b) and the equation 4.9(c) represents the high level of comfort curve.

A new coefficient of simultaneity curve was implemented in order to compare against the Delebecque method curves. The curve was built with the flow rate provided by each draw-off point used accounting for the accumulated flow rate (Q_a) and the simultaneous flow rate represented by the design flow rate (Q_d). Table 1 presents the data from the experimental apparatus.

Table 4.9: Accumulated flow rate and simultaneous uses flow rate (design) measured at the experimental apparatus

N^o of devices in use	Draw-off point	Cold water		Hot water	
		Q_a(l/s)	Q_d(l/s)	Q_a(l/s)	Q_d(l/s)
One	T1	0.135	-	0.072	-
	T2	0.170	-	0.078	-
	T3	0.115	-	0.068	-
	Sh	0.196	-	0.075	-
	Tf	0.092	-	-	-
Two	T1+T2	0.305	0.286	0.150	0.082
	T1+T3	0.250	0.234	0.140	0.081
	T1+Sh	0.331	0.310	0.147	0.082
	T1+Tf	0.227	0.215	-	-
	T2+T3	0.285	0.265	0.146	0.082
	T2+Sh	0.366	0.340	0.153	0.082
	T2+Tf	0.262	0.255	-	-
	T3+Sh	0.311	0.294	0.143	0.082
	T3+Tf	0.207	0.195	-	-
	Sh+Tf	0.288	0.275	-	-
Three	T1+T2+T3	0.420	0.374	0.218	0.082
	T1+T2+Sh	0.501	0.437	0.225	0.083
	T1+T2+Tf	0.397	0.358	-	-
	T1+T3+Sh	0.446	0.395	0.215	0.083
	T1+T3+Tf	0.342	0.310	-	-
	T1+Sh+Tf	0.423	0.374	-	-
	T2+T3+Sh	0.481	0.426	0.221	0.083
	T2+T3+Tf	0.377	0.340	-	-
	T2+Sh+Tf	0.458	0.400	-	-
	T3+Sh+Tf	0.403	0.365	-	-
Four+	T1+T2+T3+Sh	0.616	0.508	0.293	0.084
	T1+T2+T3+Tf	0.512	0.435	-	-
	T1+T2+Sh+Tf	0.593	0.490	-	-
	T1+T3+Sh+Tf	0.538	0.452	-	-
	T2+T3+Sh+Tf	0.573	0.476	-	-
	T1+T2+T3+Sh+Tf	0.708	0.554	-	-

Comparing the curves presented by the Delebecque method with the curves provided by the data from the experimental apparatus PEX water supply system (Figure 4.13) it is observed that the new curve is below of Delebecque comfort curve which could indicate that the water supply system is over dimensioned for household water use. However, the PEX water supply system of the experimental apparatus was designed according to the water supply design requirements and used the lowest diameters provided for the PEX system.

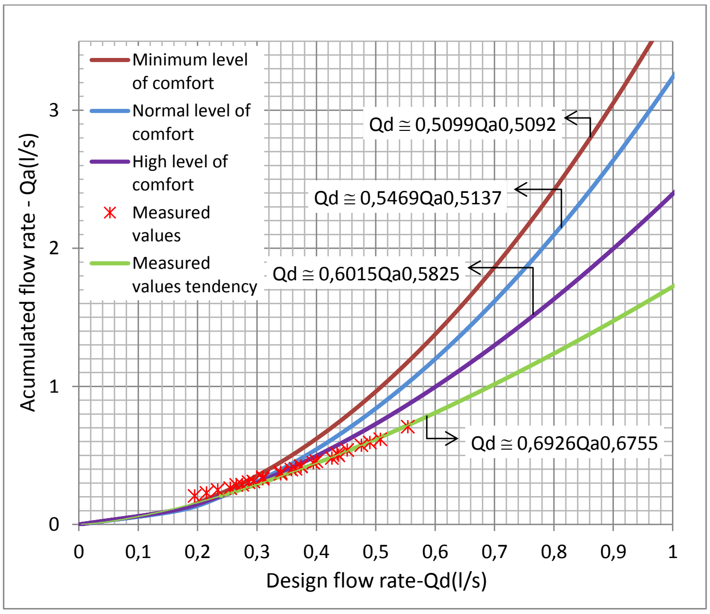

Figure 4.13: Comfort level curves representation provided by Delebecque method and experimental apparatus cold water supply system.

The comfort curve provided by data adjustment estimates the equation that represents this curve mathematically:

$$Q_d = 0.6926 \times Q_a^{0.6755} \tag{4.10}$$

The low flow rate measured at the experimental apparatus hot water supply system does not compare with the comfort curve with Delebecque method (Figure 4.14). Usually, the parameters used to calculate the pipe size for hot water supply is the same for cold water which results in lower flow values when the *tankless* water heater is used.

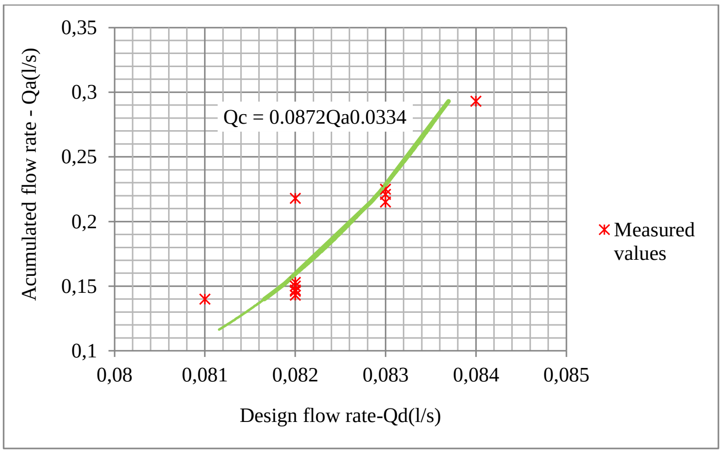

Figure 4.14: Comfort level curve representation provided by the experimental apparatus hot water supply system.

4.3.2 Modified coefficient of simultaneity method

This sub-section aims to compare the modified coefficient of simultaneity method C_{smod} against the coefficient of simultaneity values given by Equation 4.8 to verify if the methodologies have a good C_s estimation for a household water supply design.

The method presented by EPAL is based on the total number of devices that compose a household water supply system. The coefficient of simultaneity calculation C_s takes into account the number of devices supplied in each pipe system section and is given by the following equation:

$$C_s = \frac{1}{\sqrt{n-1}} \tag{4.11}$$

where n is the number of devices in each section ($n > 2$). Although the equation 4.11 assumes that the flow rate is the same for all devices, it does not usually happen. So, a modified n (n_{mod}) is calculated using:

$$n_{mod} = max\left[\sum\left(m_i \times \frac{Q_{ref}}{Q_i}\right); n\right] \tag{4.12}$$

where the reference flow Q_{ref} is the flow rate from the most used device with lower consumption; Q_i is the flow rate from device i in the analyzed section; and m_i is the number of devices with Q_i. The modified coefficient of simultaneity is calculated thus:

$$C_{smod} = \frac{1}{\sqrt{n_{mod} - 1}} \tag{4.13}$$

Table 4.10 presents the results of the modified coefficient of simultaneity calculation.

Table 4.10: Modified coefficient of simultaneity evaluation

N^o of devices in use	Draw-off point	Q_{ref} (l/s)	n_{mod}	C_s	C_{smod}	ΔC (%)
two	T3+Tf	0.092	2	0.942	1	6
	T1+Tf	0.092	2	0.947	1	6
	T1+T3	0.115	2	0.936	1	7
	T2+Tf	0.092	2	0.973	1	3
	T2+T3	0.115	2	0.930	1	8
	Sh+Tf	0.092	2	0.955	1	5
	T1+T2	0.135	2	0.938	1	7
	T3+Sh	0.115	2	0.945	1	6
	T1+Sh	0.135	2	0.937	1	7
	T2+Sh	0.170	2	0.929	1	8
three	T1+T3+Tf	0.092	2.48	0.906	0.822	-9
	T2+T3+Tf	0.092	2.34	0.902	0.863	-4
	T1+T2+Tf	0.092	2.22	0.902	0.904	0
	T3+Sh+Tf	0.092	2.27	0.906	0.888	-2
	T1+T2+T3	0.115	2.53	0.890	0.809	-9
	T1+Sh+Tf	0.092	2.15	0.884	0.932	5
	T1+T3+Sh	0.115	2.44	0.886	0.834	-6
	T2+Sh+Tf	0.092	2.19	0.873	0.918	5
	T2+T3+Sh	0.115	2.26	0.886	0.890	0
	T1+T2+Sh	0.092	2.43	0.872	0.837	-4
four+	T1+T2+T3+Tf	0.092	3.02	0.850	0.703	-17
	T1+T3+Sh+Tf	0.092	2.95	0.840	0.716	-15
	T2+T3+Sh+Tf	0.092	2.81	0.831	0.743	-11
	T1+T2+Sh+Tf	0.092	2.69	0.826	0.769	-7
	T1+T2+T3+Sh	0.115	2.98	0.825	0.711	-14
	T1+T2+T3+Sh+Tf	0.092	3.49	0.782	0.633	-19

Small differences were found when comparing the results of the modified coefficient of simultaneity calculation for two and three devices and the C_s data provided by experimental apparatus (Figure 4.15). For two devices, the average difference is 6% and for three devices the difference is -2%. For four or more devices the average difference is -13%.

Considering that the maximums from simultaneous use of three devices provide

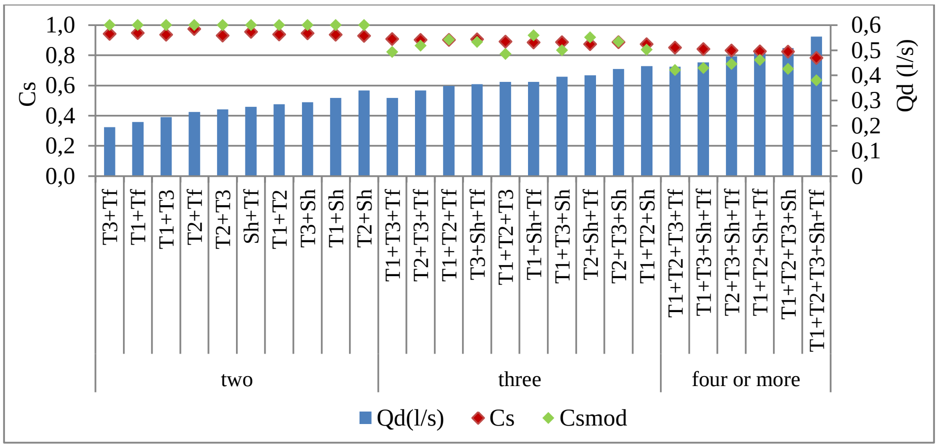

Figure 4.15: Coefficient of simultaneity evaluation for cold water system.

good use estimation, the modified coefficient of simultaneity method provides suitable information when taking into account the experimental apparatus water supply system data.

The calculation for hot water supply system design takes into account the same parameters for cold water. In this case, the coefficient of simultaneity evaluation was calculated in order to verify the experimental apparatus hot water system parameters. Figure 4.16 presents the hot water system results.

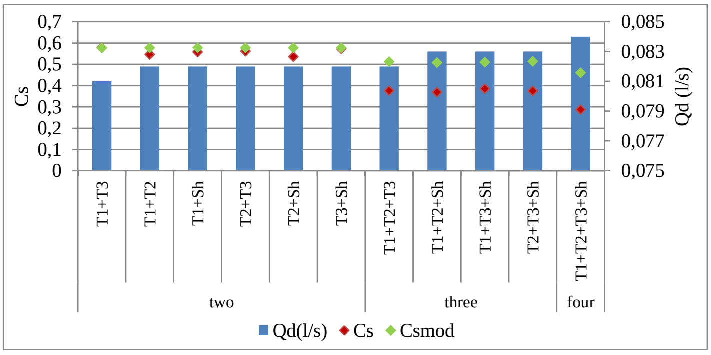

Figure 4.16: Coefficient of simultaneity evaluation for hot water system.

Greater differences were found when comparing the results of the modified coefficient of simultaneity calculation for three or more devices in use against the C_s data provided by experimental apparatus.

4.4 Conclusion and recommendations

Pressure control is necessary to avoid damage and waste in water supply systems. So this work recommends some methods for large-scale household water supply studies since the proposed techniques could be applied in any water supply system type. The data provided may help researchers and designers develop more efficient water supply systems. The analyzed parameters, i.e. head losses and coefficient of simultaneity, are considered basic information for design and evaluation.

The head loss is an important parameter for design and studies due to the attendance of speed limits necessity and the comfort for the water users. The two sizes of pipes (12mm and 16mm) friction losses and the local losses in the manifold distribution and water heater were identified. The results for 12mm and 16mm pipes head losses according to experimental data are compatible with the information provided by manufacturer diagrams, indicating that the data acquisition system is suitable for friction head loss analysis. In addition, the roughness coefficient calculated for both pipe sizes (ϵ=0.03mm for 12mm pipe and ϵ=0.04mm for 16mm pipe) is compatible with PVC roughness values which is considered a suitable result because both PEX and PVC are thermoplastic materials.

The local head loss findings in the manifold without a lock-shield are more closely related to the T.A. curve (fully open) provided by the manufacturer diagrams when more than one output manifold is in use. Therefore, the average values for one and more than one uses respect the limits found on the head loss curves in the manufacturer manifold diagrams. The manifold local head loss factor K calculated for the 12mm pipe is 12 and for the 16mm pipe is 15.5. When two devices are used simultaneously the average K is 6 and for three devices in simultaneous use the average is 4. As expected, the tankless water heater presented the greatest head loss of the entire PEX water pipe system. Due to the loss of energy provided by the tankless system the hot water pipe system flow rate drops significantly (40%). Head loss information was not provided by the tankless manufacturer, so it was not possible to compare experimental and manufacturer data. The local head loss factor K calculated for the tankless system when one 12 mm pipe is used is 170 and for more than one it is 179. The average value is 176.

The coefficient of simultaneity parameter is widely used for water supply designers in identifying the pipe sizes. Its calculation takes into account the number of devices in use and there are two methods used more than others in Portugal: the Delebecque and the modified coefficient of simultaneity method. The comfort curve identification using the experimental apparatus data does not match with any provided by Delebecque method. This could mean that the flow conditions at the PEX water supply system are different from that developed by Delebecque. More studies in this field can help researchers to identify the PEX systems comfort curve. On other hand, closer values between the experimental data and the values provided by modified coefficient of simultaneity calculation were found. So, the modified coefficient of simultaneity method provides suitable information when taking into account the experimental apparatus water supply system data.

The PEX water supply system evaluation indicated that more studies are needed in order to provide researchers and designers with valuable information for developing a more efficient water supply system. Further developments on the tankless water heater could help to avoid a big reduction in flow and get better results for the hot water comfort use. Some parameters which do not agree with the literature must be analyzed in large-scale in order to identify new patterns for PEX or others water supply systems.

Chapter 5

Characteristics of the household's gray-water streams

THIS chapter introduces the evaluation of household quantity and quality gray-water streams in order to identify water reuse opportunities. It is observed that treated waste-water is the main alternative water resource used in urban environments, as explained in Chapter 2. However, these effluents could contain pollutants from industry (i.e. phenols, heavy metals, etc.), dental clinics (lead), car washes and drainage from roofs and roads (hydrocarbon oils and other debris) that may compromise the final quality for reuse ([PH05] and [SL02]). Thus, for the purpose of the majority of waste-water being reused, it is recommended that a waste-water quality characterization, suitable for treatment identification, be implemented in order to avoid environmental and human contamination. Due to diverse contamination sources of urban waste-water, some studies have indicated gray-water as a good option for reuse in buildings and urban environments ([LZTB07], [JPJ+04a] and [AJ03]). Total gray-water (TGW) does not include toilet flush streams in its composition, which results in less contaminated loads (Table 5.1). Besides, local gray-water treatment systems for on-site reuse improve energy efficiency by avoiding effluent pumping from long pipe-lines to a centralized treatment unit and the subsequent return to the points of consumption.

It is estimated that 50% to 80% of household effluent is composed of gray-water, but the nitrogen and phosphorus concentration represents only 3% to 10% respectively [Gul07].

Table 5.1: Typical gray water composition comparing with urban waste-water

Parameter	Unit	Gray water		urban
		range	average	waste-water
Total suspended solids (TSS)	mg/l	45-300	115	100-500
Turbidity	NTU	22->200	100	300-600
BOD_5	mg/l	90-290	160	100-500
Nitrate (NO_3N)	mg/l	0.1-0.8	0.3	1-10
Ammonium (NH_4N)	mg/l	<1.0-25.4	5.3	10-30
Total nitrogen (TN)	mg/l	2.1-31.5	12	20-80
Total phosphorus (TP)	mg/l	0.6-27.3	8	5-30
Sulphate	mg/l	7.9-110	35	25-100
pH	mg/L	6.6-8.7	7.5	6.5-8.5
Conductivity	$\mu S/cm$	32.5-1140	600	300-800
Hardness	mg/l	15-55	45	200-700
Sodium	mg/l	29-230	70	70-300

Source:[Bor03]
BOD - Biochemical oxygen demand

It is observed that the potential of reuse is higher as the lack of water is greater, as explained in Chapter 2. However, for inside buildings water reuse, more detailed information about streams characteristics is necessary to identify the real reuse potential because of the close human contact with the treated effluent. Thus, the quality and quantity of information about gray-water streams are important for pollutant load calculations and treatment process identification ([Cou09]). The efficiency of gray-water pollutant load removal to satisfy the standards' limits, installation, energy and maintenance costs are the main factors that drive the choice in a suitable treatment system. However, a well-developed water reuse conception is not enough to achieve a viable water reuse system ([CB95] and [Fer09]). The governments' incentives and low tariffs for drinking water reduce the potential of gray-water reuse in buildings in many regions. For instance, due to government subsidies water tariffs in Portugal paid by the consumer account for only half of the production costs [I.P11] and residential and commercial clients in Canada pay just a third to a sixth of the marginal cost estimates for water supply and waste-water treatment [Ren99]. However, it has been observed that this situation is changing in many countries, mainly because of increased demand, scarcity, water and waste-water treatment costs and economic crises. Water supply service privatization is one of the reasons for an increase in tariffs. The water tariff in the USA increased more than ten times due to recent privatizations (Figure 5.1).

High water tariffs create opportunities for alternative water resource identification.

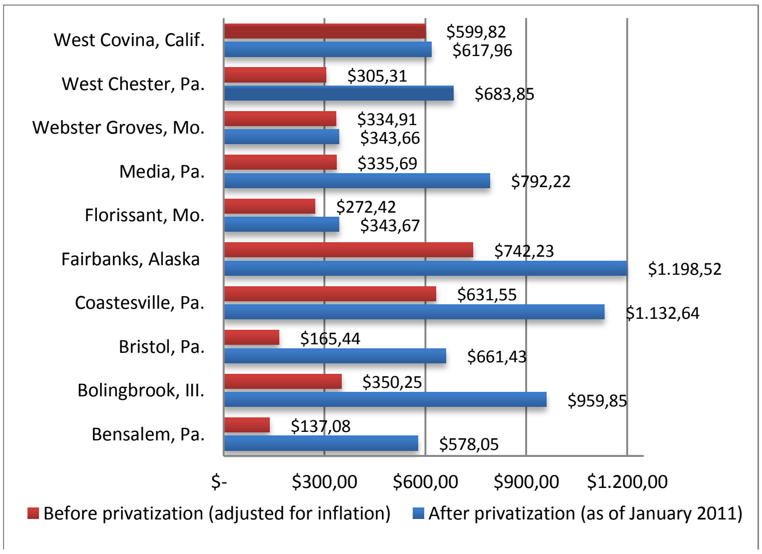

Figure 5.1: A comparison of household water bills before and after privatization: a typical annual water and/or sewer bill in January 2011 (dollars). [FW11].

To contribute with information's about gray-water characterization and reuse and meet the necessities of it, an investigation about the quality and quantity of gray-water streams is presented in this chapter. The first experimental case was performed in a semi-arid region located in Bahia-Brazil. The pollution load was calculated using information from four houses. When evaluating the removal efficiency of the biologic treatment system, it was determined to be in compliance with the standards limits. In order to verify the level of each streams' contamination and test the developed streams' collection and analysis methodology, a experiment was performed in three houses in Coimbra, Portugal.

5.1 Gray-water quality, standards, treatment and health risks information

Investigations into gray-water reuse indicated that the effluent characterization by streams is useful for efficient water reuse system development ([Gov08] and [CMH05]). Gray-water streams with low pollutant loads and high biodegradability characteristics require less treatment in order to achieve a suitable effluent quality. Depending on the gray-water streams (e.g. hand-washing, bath) and application (e.g. landscapes, toilet flush), some authors defend the direct gray-water use [KAO+]. However, it has been observed that even the least polluted gray-water streams have contaminant loads that do not achieve the actual standards limits. Hence, a specific treatment is recommended to meet the most basic standards. This section presents some gray-water information in support of the gray-water reuse potential evaluation. Information found in the literature about the quality of gray-water streams is necessary to compare with the outcomes from research, the standards information which gives the quality limits (threshold) for reuse, and information about the treatment systems' efficiency. This information is useful in identifying the best option when considering the analyzed gray-water streams. In relation to reuse in the household space, it is supposed that this may involve risks to public health. Although infectious agents are present in the effluent this does not mean that diseases will be transmitted; however, there is a potential health risk associated with this practice. For this purpose, some information is provided in this section in order evaluate the potential health risk of gray-water reuse.

5.1.1 The quality of gray-water streams

It is estimated that gray-water quality depends on the habits of the water users, cleaning products and pipeline materials, thus its characteristics can present a great variability [EAHL02]. The gray-water analysis indicated that the kitchen streams present more organic loads, while on the other hand, the sodium concentration is found to be greater in laundry water. However, the bath, washbasin and shower organic loads and sodium concentrations are all lower (Table 5.2). For this reason some authors [Cou09] indicated the light gray water (LGW) (i.e. only bath and washbasin streams) as a suitable stream for a household water reuse system.

The biodegradability of gray water in terms of Chemical Oxygen Demand (COD) and Biochemical Oxygen Demand (BOD_5) is good [LWO09], however, the COD:N:P ratio of 100:20:1 is not verified because of a nitrogen and phosphorus deficit. The results of the study [JBP+01] indicated that the macro nutrients of gray-water, when the kitchen stream is excluded, could limit the biologic process efficiency from the treatment system. The separate streams evaluation indicated that the high COD/BOD ratio is found in bath (2.3), washbasin (2.3) and laundry (3.5). For kitchen stream the COD/BOD ratio is lower (1.8) because of its higher organic load concentration

Table 5.2: Grey water quality by sources

Parameters	Bathroom	Laundry	kitchen	Mixed
pH	6.4-8.1	7.1-10	5.9-7.4	6.3-8.1
TSS (mg/l)	7-505	68-465	134-1300	25-183
Turbidity (NTU)	44-375	50-444	298	29-375
BOD_5 (mg/l)	100-633	231-2950	26-2050	100-700
COD (mg/l)	50-300	48-472	536-1460	47-466
Total nitrogen (mg/l)	3.6-19.4	1.1-40.3	11.4-74	1.7-34.3
Phosphate (mg/l)	0.11->48.8	ND->171	2.9->74	0.11-22.8
Total coliforms (cfu/100ml)	$10\text{-}2.4x10^7$	$200.5\text{-}7x10^5$	$>2.4x10^8$	$56\text{-}8.03x10^7$
Fecal coliforms (cfu/100ml)	$0\text{-}3.4x10^5$	$50\text{-}1.4x10^3$	-	$0.1\text{-}1.5x10^8$

Source:[LWO09]

(Table 5.3). Thus, others researchers defend that a blend of gray-water streams is a better option to improve the nutrient concentration in order to encourage the growth of microorganisms during biologic treatment [LWO09]. Other studies which included kitchen streams indicated that there is a good potential for gray-water biologic treatment because of the COD:BOD_5 ratio is nearly 2 [TWG08].

Table 5.3: COD:BOD_5 ratios identified in studies

Studies	Grey Water Streams		
	Washbasin and Bath	Laundry	Kitchen
[LWO09]	2.1	5.5	1.4
[EAHL02]	1.9	1.5	-
[Baz05]	3.0	2.9	2.7
[DER+10]	2.1	4.8	0.9
[Fri04]	1.7	2.9	1.9
[JPJ+04b]	3.4	-	-
[EAML09]	1.5	-	-
Average	2.3	3.5	1.8

5.1.2 Guide lines for water reuse

The Portuguese standard for the reuse of reclaimed urban waste-water ($NP4434$: 2005) [IPQ05], the "Entidade Reguladora dos Serviços de Águas e Resíduos" (ERSAR) recommendation n^o 02/2007 [IRA07] and the "Decreto Lei" n^o 152/97 [15297] indicated that treated waste-water must be reused only in scarcity situations. However, it has been observed that irrigation is the only reuse purpose adopted by the Portuguese standards and its parameter limits are more restrictive in comparison with other countries. In the context of the Europe Union (EU) there are many actions for water conservation and management. For example, the Water Framework Directive n^o 2000/60/CE and the Environment Action Programme 2020 provide incentives for sustainable water consumption patterns in the region. Although there is no specific EU water reuse directive, some member countries have their own standards. Appendix A presents a brief view of some water reuse standards which focus on quality limits of the gray-water reuse. Toilet flush, watering (i.e. gardens, landscapes) and washing (i.e. streets, cars) are the main reclaimed purposes. In comparing the countries' information, it is observed that there are some differences between considered parameters, concentrations limits and reclamation purpose. It is estimated that these differences reflect local and social necessities. It is also observed that while treated waste-water is the main resource for urban reclamation, it is estimated that these orientations can also be used for gray-water reclamation.

5.1.3 Water Treatments for reuse

Despite there being less contamination of the gray-water in comparison with urban waste-water, the varied concentration of organic compounds, microorganisms and suspended solids must be processed at the effluent that will be treated for reclamation. The current treatment systems use physical, chemical and biologic processes, or a composition between them, depending on the contamination level, installations characteristics and the necessary contamination reduction to satisfy the standards.

The physical treatment basically parallels a filtration process using coarse sand, soil or membranes. Afterword, it would pass through a disinfection process [MGO04]. This physical process does not result in a good enough contamination reduction in order to meet the standards limits, so this filtration method is usually used as a "polishing" after a chemical or biological process has been completed.

Investigations into the chemical process [LWO09] indicated that coagulation, filtration and/or disinfection present better results and effectively reduce low concentrations of suspended solids, organic substances and surfactants to meet the standards limits. However, the same result is not always achieved for medium and high contaminants concentrations, so other process are sometimes necessary to complement the treatment. Disinfection is considered a good process to complement a pretreatment because the residual organics compounds of the treated gray-water may result in biological growth in the distribution and storage systems [AJ03]. Additionally, this compound limits the chemical disinfection effect and can create disinfection by-products. It has been observed that an aerobic process presents greater efficiency comparing with an anaerobic process and it is strongly indicative for reuse treatment systems (Table 5.4).

Table 5.4: Biologic treatment systems efficiency

Process		TSS (mg/L)	Turbidity (NTU)	COD (mg/L)	BOD (mg/L)	TN (mg/L)	TP (mg/L)	fecal coliform (Ufc/100ml)
Sedimentation+RBC+UV desinf.[1]	in	-	-	100-430	50-250	5-10	0.2-0.6	$10\text{-}10^8$
	out	-	-	-	<5	-	-	$<10^2$
	% rem.	-	-	-	>90	-	-	-
Fuidized-bed reactor+UV desinf.[1]	in	-		113-633	7-30	-	-	$10\text{-}10^3$
	out	-	-	-	<5	-	-	$<10^3$
	% rem.	-	-	-	29-90	-	-	-
Screen+RBC+sand filtration +chlorination[2]	in	43	33	158	59	-	4.8	$5.6\text{x}10^5$
	out	7.9	0.61	40	2.3	-	2	0.1
	% rem.	82	98	75	96	-	58	100
MBR[3]	in	-	29	109	59	15.2	1.6	$1.4\text{x}10^5$
	out	-	0.5	15	2.3	5.7	1.3	68
	% rem.	-	98	86	93	63	19	99.9
UASB[4]	in	-	-	681	-	27.1^a	9.9	-
	out	-	-	469.9	-	20.6	9.9	-
	% rem.	-	-	31	-	24	24	-
Wetlands[5]	in	158	-	839	466	34.3	22.8	$5\text{x}10^7$
	out	3	-	157	0.7	10.8	6.6	$2\text{x}10^5$
	% rem.	98	-	81	99	69	71	99.6
SBR[6], SRT=378d HRT=6.1h	in	-	-	827	-	29.9	8.5	-
	out	-	-	100	-	26.5	5.8	-
	% rem.	-	-	88	-	11	32	-

Source: 1)[Nol00], 2)[FKG05], 3)[MSEHK07], 4)[ESWO07], 5)[GSRR07] and 6) [HLTZB10]
a) TKN
RBC - Rotating Biological Contactor
MBR - Membrane Bioreactor.
UASB - Up-flow Anaerobic Sludge Blanket.
SBR - Sequencing batch reactor.
SRT - Sludge Retention Time (days).
HRT - Hydraulic Retention Time (hours).

Effluents with high biodegradable organic substance concentrations have a significant organic load reduction when an aerobic process is used. However, for microorganisms, suspended solids and turbidity the contaminant removal provided by the aerobic process is not as efficient. Filtration and disinfection can be used as a subsequent treatment stage to improve the efficiency of aerobic process.

5.1.4 Health risk assessment of gray-water reuse

The nematodes, bacteria and viruses are pathogens more closely related to human excreta. The gray-water contains fewer of these pathogens which could be considered a lower risk of contamination in comparison with domestic waste-water. However, the potential risk of contamination from gray-water reuse should not be discarded.

The conservative approach of the microbiological quality standards is based on zero risk; however, this results in high cost treatment processes which would prevent the water from being reused. So, a risk assessment evaluation for gray-water reuse is necessary.

Regarding risk assessment and management, disability adjusted life years (DALYs) or normalized for a population over a time period are common measurements used to compare disease outcomes from different exposure routes [FB01]. DALYs is a measure of the health of a population or burden of disease due to a specific disease or risk factor. The assessment of risks can also be carried out directly via epidemiological studies or indirectly through quantitative microbial risk assessment (QMRA). QMRA can be used as a predictive tool to indirectly estimate the risk to human health by infection or illness rates, based on given concentration of particular pathogens, estimated or measured rates of ingestion and appropriate dose-response models for the exposed population [WHO06].

Tolerable risk identification is an important issue for a QMRA evaluation in order to identify waste-water quality and the treatment efficiency needed for a reuse purpose. The risk can be tolerable when it is below an arbitrarily defined threshold or below a threshold that had been tolerated [HPAB03]. The tolerable risk depends on the time and the level (e.g. ingestion or contact) of human exposure to the reused water. For instance, the tolerable microbial contamination risk for drinking water by the US Environmental Protection Agency (EPA) is 10^{-4}/percapita/year [AL98] and the World Health Organization (WHO) recommends 1 μDALY which represents 10^{-3} risks for waterborne diarrhea diseases [Org04]. On the other hand, Fecal Coliforms concentration patterns from 100 to 200 UFC/100ml are acceptable for balneary activities.

The same tolerable risk for gray-water reuse in toilet flushing and irrigation seems unsuitable because of different periods of human exposure. Studies [CKL+07] demonstrate that cumulative distributions regarding ingestion during different uses indicated that the greatest amount of exposure is related to bath use (Figure 5.2). The bath use median value is six times higher than the toilet flush use and 15 times higher than irrigation.

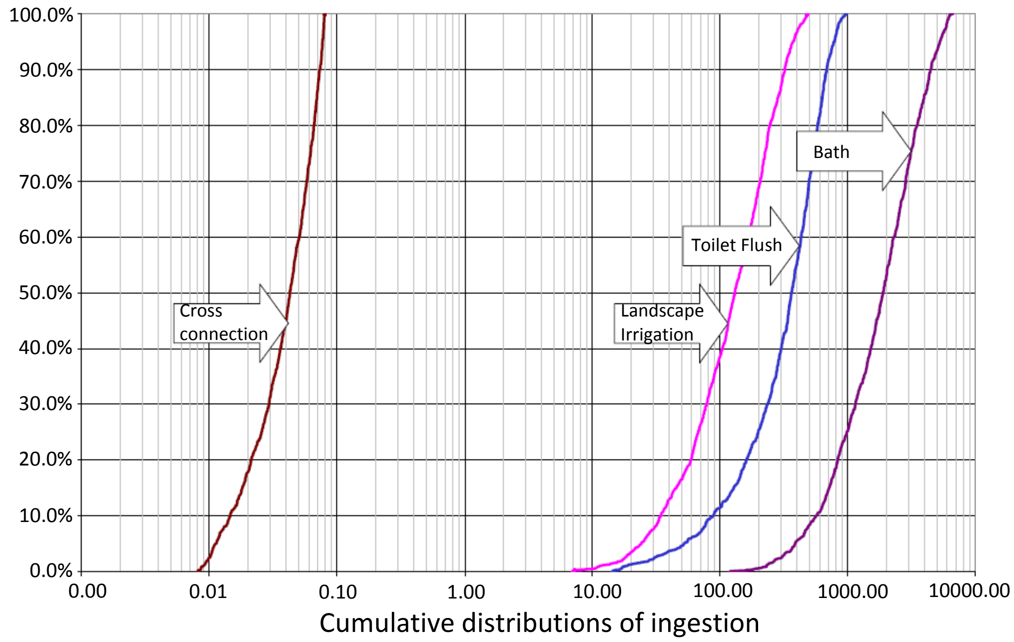

Figure 5.2: Cumulative frequency distribution of water volume ingested using the distributions proposed by [APS+05], apud [CKL+07]

Some standards presented in Appendix A indicated Fecal Coliforms density patterns of $<$10 UFC/100ml for toilet flush reuse purpose. However, studies [CKL+07] indicate that even though using effluents with fecal coliform concentrations between 10^5 to 10^6 NMP/100ml for toilet flush, the biological marker at a height of 100 cm was not found, suggesting a low potential risk for inhalation. Considering this information, it is supposed to be possible to reuse gray-water with ratings between 10^2 and 10^3 with a good safety margin. More studies in this field are necessary in order to develop less restrictive standards that encourage gray-water reuse.

Some good practices recommended for gray-water reclamation in order to avoid high health risks [(NS00] include: (a) human and animal direct contact with reclaimed water should be avoided; (b) some measure of prior treatment is recommended for water used in the toilet; (c) prevent gray-water reuse in the irrigation of agricultural crops whose product can be eaten raw; (d) prevent the interconnection of potable water and reclaimed water; (e) avoid gray-water storage (without prior treatment with disinfectant); (f) carefully identify drinking water and reclaimed water pipelines.

5.2 Household water reuse potential evaluation: case study

The gray-water investigation in Brazil took place in Feira de Santana City (Sector 1 water supply) where five households' streams were analyzed. The five households selected were out of 379 possible sector 1 houses where an inquiry survey about water consumption and reuse acceptance was previously applied [Alm07]. The water use investigation also took a place in Brazil's research, but only four houses was investigated due to technical problems with one water meter. In Portugal, the gray-water streams from three households located in Coimbra city were analyzed in order to identify the level of pollution in each home and to compare with those in Brazil and other investigations in this field. The quality and quantity data from the Brazil investigation was used to calculate the pollutant loads in four household streams. This information was useful in identifying the suitable treatment process taking into consideration the pollutant loads removal and to identify whether the estimated final quality meets the standard limits for watering, washing and toilet flush.

5.2.1 Material and methods

The collection of gray-water streams from kitchen (KTC), washbasin (WBA) and laundry (LAU) for quality investigation was assembled using plastic reservoirs connected at the stream out-puts. Plastic buckets were used to collect the bath (BAT) streams (Figure 5.3).

Gray-water stream samples collected over a 24 hour period were analyzed at the "Empresa de Águas e Saneamento" (EMBASA) laboratories (Figure 5.4). The quality parameters analyzed were: fecal coliforms, sodium, COD, phosphorus, total nitrogen, potassium, total suspended solids, calcium, hardness and magnesium. The BOD_5 is another important parameter that was formerly considered for gray-water

Figure 5.3: Gray-water streams samples collection in Brazil

investigation but it was not included in this analysis because of the laboratory's operational difficulties. However, in this work, the BOD_5 values were calculated based on COD:BOD_5 ratios identified for each gray-water stream presented previously by Table 5.3. Six samples were collected in each gray-water stream in order to identify a representative concentration value for each parameter. So, considering 4 gray-water streams, 5 houses and 10 parameters, a total of 1,200 were analyzed for quality characterization.

Figure 5.4: Gray-water streams samples analysis in Brazil

In Portugal three gray-water streams were analyzed and the methodology for collection was the same used at Brazil's research, however, the methodology for analysis and the chosen parameters were different. Laboratory analysis, besides being very expensive, also requires a great amount of time and effort to complete. For purposes of large-scale studies, this method of analysis would not be feasible. Thus, a method using a multi-parameter water quality sonde (TROLL 9500) was tested to identify the quality of gray-water streams in Portugal (Figure 5.5). The device uses datasonde log data and accepts multiple water quality sensors, as well as built-in temperature and barometric pressure sensors. It also provides the convenience of a laboratory quality measurement instrument for field use, providing true in-situ monitoring of water levels and water quality. This sonde was chosen because of its portability and easy usage which makes it ideal for large scale water quality research. Aside from the advantages, the sonde allows for only limited types of parameters to be analyzed. For instance it is not possible to analyze important parameters as BOD, COD and fecal coliforms, however, the available quality sensors can estimate the level of each gray-water streams' pollution. The parameters considered were: pH, oxidation-reduction Potential (ORP), Chloride, Nitrate and Conductivity. Three houses were investigated at Coimbra city and three analysis groups were established in each gray-water stream in order to get a representative concentration value.

Figure 5.5: Gray-water streams samples collection and analysis in Portugal

The household water consumption investigation was also performed. A volumetric water-meter (3/4") with pulsed output was installed in each house and a data-logger developed by "Liceu de Artes e Oficios de São Paulo" (LAO) was used to log consumption data every 15 seconds (Figure 5.6). In addition to the consumption information, the users had to register the moment of use in each hydraulic device in a time-sheet (i.e. sink tap, washbasin tap, toilet flush and wash-machine). With the consumption and time of use data it was then possible to estimate the water volume consumed in each device. Five houses were considered for investigation, but only four were used in analysis due to water-meter problems. Four weeks of water consummation was considered in this analysis.

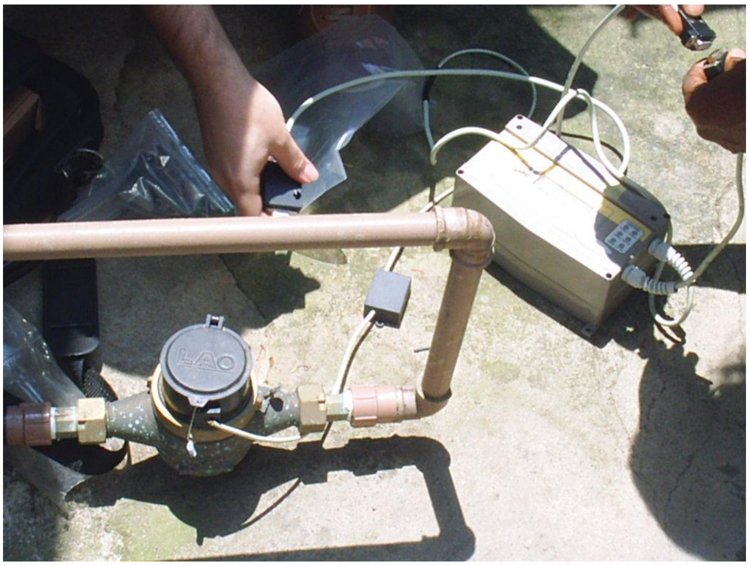

Figure 5.6: Water-meter and data-logger used for water consumption investigation in Brazil

5.2.2 Gray-water streams quality evaluation and discussion

Gray-water quality evaluation in Brazil

The evaluation of gray-water nutrients (i.e. Nitrogen, phosphorus and Potassium) contained in five households streams (i.e. washbasin - WBA, bath - BAT, laundry - LAU and kitchen - KTC) indicated that the highest concentrations were found in the kitchen and laundry streams (Figure 5.7). It has been observed that the general nutrients concentration values is compatible with the references presented in this work. However, the phosphorus concentration in the laundry stream was higher than in other studies in this field which could mean that the washing and cleaning products used were rich in phosphorus. The high quantity of phosphorus in urban waste-water may result in lakes or rivers eutrophication [VS96], so its quantity in cleaning products must be controlled. On the other hand, the high phosphorus [AGC05] and potassium [OCM01] concentrations would be suitable for irrigation reuse purposes.

Aside from the phosphorus, the clothes cleaning products also have a high quantity of sodium which results in a higher concentration in laundry streams (Figure 5.8).

In view of the irrigation reuse purpose, as the sodium concentration is higher in the reused effluent there is the risk of the soil becoming saturated with the substances

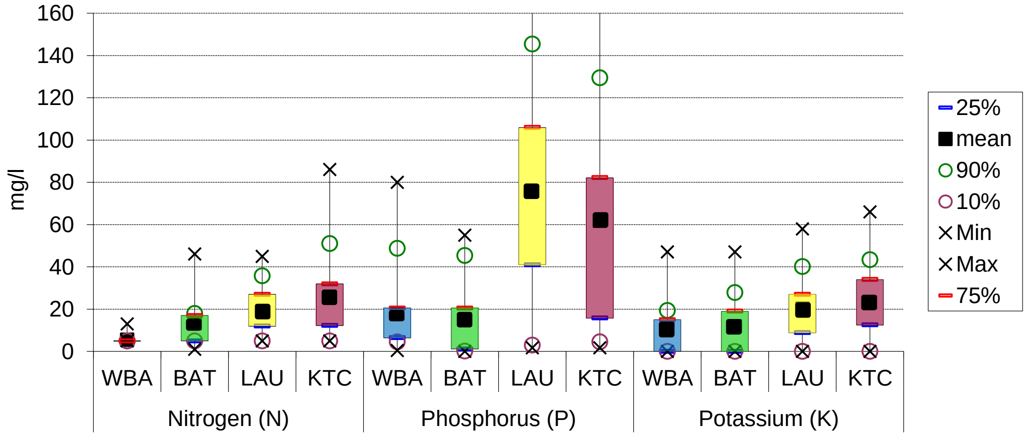

Figure 5.7: Nutrients concentration in the gray-water streams.

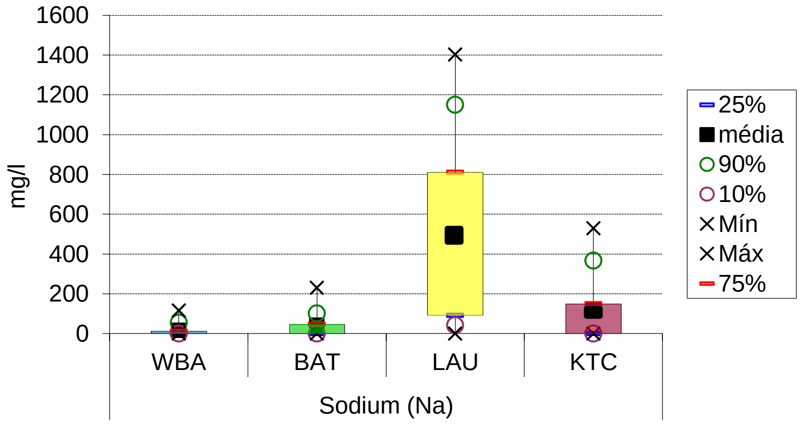

Figure 5.8: Sodium concentration in the gray-water streams.

discharged in the effluent [Meh03]. The estimation of Sodium Adsorption Ratio (SAR) indicates the risk of soil saturation and it is given by:

$$SAR = \frac{Na}{\sqrt{\frac{Ca+Mg}{2}}} \tag{5.1}$$

where Sodium (Na), Calcium (Ca) and Magnesium (Mg) is expressed by milliequivalents by liter ($mmol_c/l$). Through a process known as Cation Exchange the Ca and Mg act to displace the sodium contained in the soil [SLDD00]. The risk of sodium adsorption can be identified considering the following limits: low - SAR<10; medium

- 10≤SAR≤18; high - 18≤SAR≤26; very high - SAR>26. The calculated SARs for laundry streams indicated that the risk of sodium adsorption is very high for almost all samples analyzed (Table 5.5). Despite the laundry streams not be recommended for irrigation it would be suitable to toilet flush reuse.

Table 5.5: SAR values in each laundry streams samples

House-hold	SAR values ($mmol_c/l$) S1	S2	S3	S4	S5	S6	average
H1	8.6	9.3	124.9	82.4	16.3	0.0	42.4
H2	81.4	32.0	119.6	116.5	91.4	49.4	82.4
H3	30.0	0.0	0.0	110.7	11.4	42.8	29.8
H4	104.2	127.5	169.9	213.2	81.6	83.1	126.6
H5	81.1	11.1	41.1	10.2	52.9	8.8	31.9

The gray-water hardness concentration level is related to cleaner products with magnesium and calcium in its composition [SPdA04]. The hardness classification of waters are: 0 to 50 mg/l (milligrams per liter) is classified as soft; 50 to 150 mg/l as moderately hard; 150 to 300 mg/l as hard; and more than 300 mg/l as very hard [SMP94]. The washbasin CaCO3 concentration is highest of all and the average analysis indicates that it is a moderately hard stream (Figure 5.9). It is estimated that tooth paste and soap uses are the main reasons for washbasin hardness.

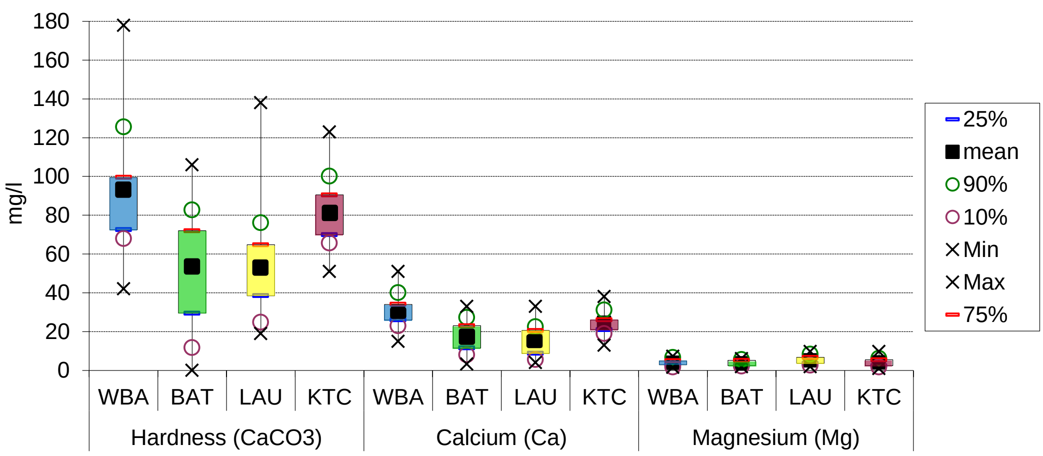

Figure 5.9: Hardness, Calcium and Magnesium concentration in the gray-water streams.

Regarding reuse, water hardness can cause encrustation and/or clogging in micro-irrigation reuse systems. Pipeline clogging risks is low when hardness (H) concentration is less than 150, medium for 150<H<300 and high when H>300 [PHS90].

Hardness concentration values for all gray-water streams do not indicate clogging risks for irrigation systems.

As can be seen in figure 5.10 the kitchen stream has the highest concentration of organic matter, suspended solids, BOD and COD. For this reason some authors ([Rap04], ([AJ03] and ([FKG05]) exclude this stream for gray-water reuse. However, if it is being considered for use, a biologic treatment is recommended to be used for the kitchen stream in order to maintain an optimum CQO:N:P ratios.

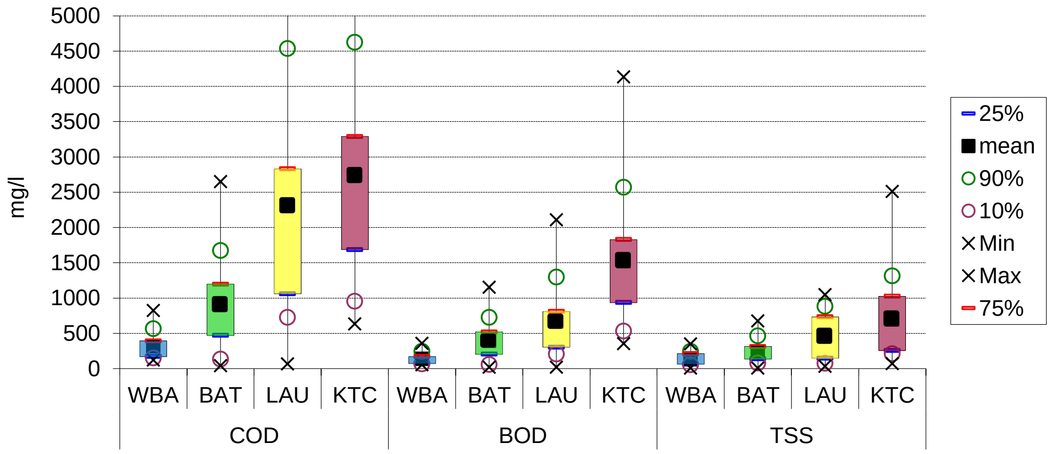

Figure 5.10: COD, BOD and TSS concentration in the gray-water streams.

The suspended solids concentrations are directly related to the organic matter present in the effluent. The total suspended solids concentration from households' gray-water streams is the outcome of washing clothes, cleaning dishes, hands, face, floor, brushing teeth, bathing and so on. Residues from fabrics, furs, hairs and fats which have blended with the cleaning products can be found in most gray-water streams. The TSS concentration depends on the quantity of water, dirtiness, amount and types of products employed.

Due to high TSS concentration levels a pretreatment is recommended for gray-water streams. However, due to low concentration levels found in the washbasin, some authors recommend a direct reuse in toilet flush [KAO$^+$]. Figure 5.11 presents a washbasin stream direct reuse example.

Figure 5.11: Direct washbasin stream reuse for toilet flush.

The fecal coliform concentration indicates the potential presence of pathogen microorganisms that may cause diseases such as typhoid fever, paratyphoid fever, bacillary dysentery and cholera [VS96]. The greatest fecal coliform concentration was found in the kitchen streams (Figure 5.12).

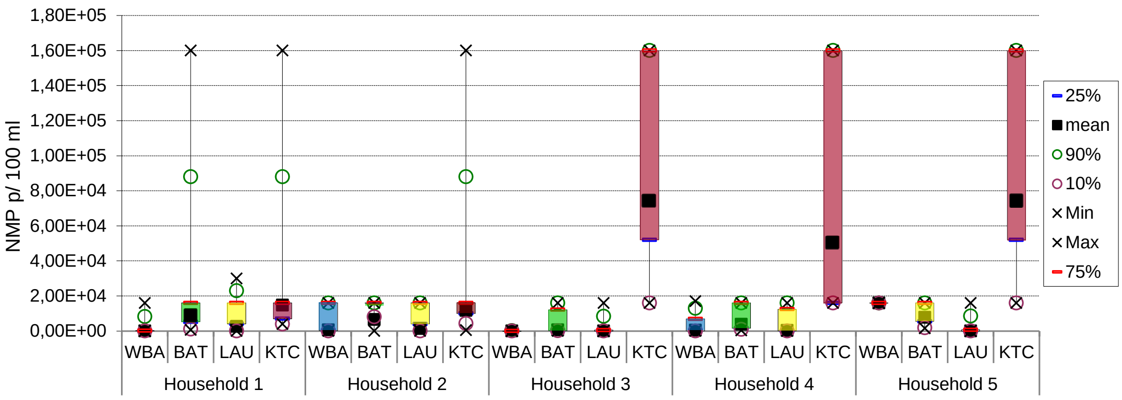

Figure 5.12: Fecal coliform concentration in the gray-water streams.

Bigger differences can be found in fecal coliform concentration presented at the household 5 washbasin streams in comparison with the others. It was identified that household 5 was usually occupied with five children. Additionally, during the period of investigation, the shower was not working for a few days, so it is supposed that the younger children's baths were being set up in the washbasin and/or the bath effluents were discharged there. This example demonstrates the influence of users' behavior and customs on gray-water variability. Table 5.6 presents the quality statistical analysis of the each analyzed parameter.

Table 5.6: Gray-water streams quality statistical analysis

Parameter	Stat.	WBA	BAH	LAU	KCH
Nitrogen (mg/l)	min	0.00	0.00	5.00	5.00
	max	13.00	46.00	45.00	86.00
	mean	1.00	13.26	19.07	25.70
Phosphorus (mg/l)	min	0.40	0.00	1.70	1.70
	max	80.00	55.00	231.00	275.00
	mean	17.99	15.11	75.72	61.81
Potassium (mg/l)	min	0.00	0.00	0.00	0.00
	max	47.00	47.00	58.00	66.00
	mean	10.74	11.81	20.26	23.22
Hardness (mg/l)	min	42.00	0.00	19.00	51.00
	max	178.00	106.00	138.00	123.00
	mean	93.03	53.50	53.27	80.73
Magnesium (mg/l)	min	1.50	1.00	1.90	1.90
	max	7.30	9.70	6.00	9.70
	mean	3.91	4.00	3.62	5.16
Calcium (ml/l)	min	15.00	3.20	4.00	13.00
	max	51.00	33.00	33.00	38.00
	mean	30.33	17.64	15.33	24.57
Sodium (mg/l)	min	0.00	0.00	0.00	0.00
	max	115.00	230.00	1402.00	529.00
	mean	15.30	41.21	497.23	119.50
COD (mg/l)	min	123.00	40.80	66.00	634.00
	max	824.00	2648.00	7376.00	7440.00
	mean	314.90	903.76	2312.60	2741.10
BOD_5 (mg/l)	min	53.48	17.74	18.86	352.22
	max	358.26	1151.30	2107.43	4133.33
	mean	136.91	392.94	660.74	1522.83
TSS (mg/l)	min	8.00	5.50	31.00	70.00
	max	349.00	673.00	1046.00	2511.00
	mean	140.43	245.81	449.23	697.23
Fecal coliform (Ufc/100ml)	min	1.00E+00	2.00E+00	1.00E+00	5.00E+02
	max	1.70E+04	1.60E+05	3.00E+04	1.60E+05
	geom-mean	2.30E+02	3.96E+03	2.14E+02	3.44E+04

Gray-water quality evaluation in Portugal

The evaluation of gray-water households' streams in Portugal indicated that the greatest concentrations of pollutants are to be found in the kitchen and laundry streams, the same as the experiments in Brazil and other studies have demonstrated. The Electrical conductivity (EC) concentration found in laundry streams was much higher than other gray-water streams due to the high sodium concentration found in the cleaning products (Figure 5.13 a)). For most situations, the higher the concentration of dissolved salts in fluids, the better the conductor, and the higher the electrical conductivity. A factor of 0.65 x EC may be used to estimate Total Dissolved Solids (TDS) at the gray-water [EF05]. An 18 hour laundry stream storage and measurement indicated that there is an increased concentration of EC in the analyzed gray-water (Figure 5.13 b)). Depending on the contamination level, a long term gray-water storage may result in significant quality degradation due to chemical and biological processes [Alm07].

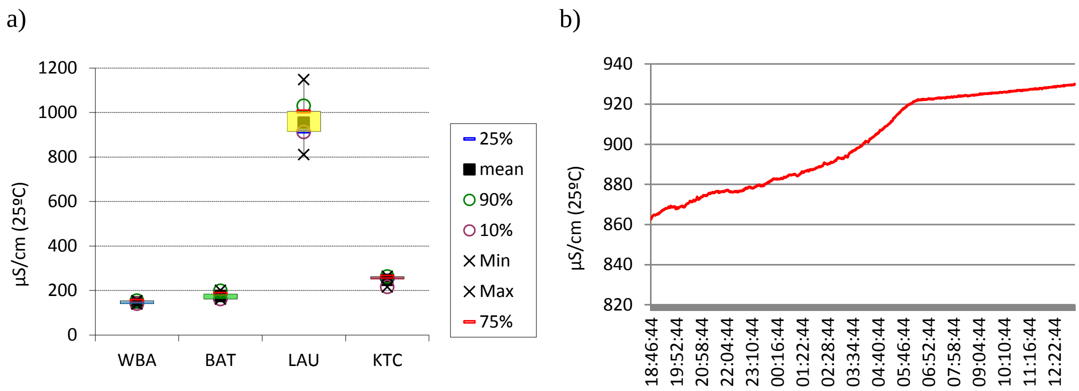

Figure 5.13: Conductivity concentration: a) gray-water streams, b) laundry steams storage.

A pH value indicates the amount of hydrogen ions that are present in an aqueous environment. The hydrogen ion concentration gives an indication of the acidity of a substance. The pH in the analyzed gray-water stream varies from 4 (minimum value in kitchen stream) to 10 (maximum value in laundry). The washbasin, bath and kitchen streams all have a fairly neutral pH while laundry streams are more basic (Figure 5.14 a)). Oxidation Reduction Potential (ORP) values are used much like pH values in determining water quality. The washbasin and bath streams have more oxidizing power than the kitchen or laundry streams (Figure 5.14 b)). ORP levels below 300 mV are to be avoided. Oxidizing is needed to convert any ammonia (NH_3) into nitrites (NO_2^-) and nitrates (NO_3^-). Ammonia can be harmful to water reuse due to the production of bad odors.

Although chloride ions (Cl^-) are not toxic to humans, they can increase the rate of corrosion on metals in the presence of water. Vegetation is also sensitive to the amount of chloride in the soil. The WHO (World Health Organization) has established 100 mg/l Cl^- as a maximum of chloride ions for water used for irrigation, while 250 mg/l

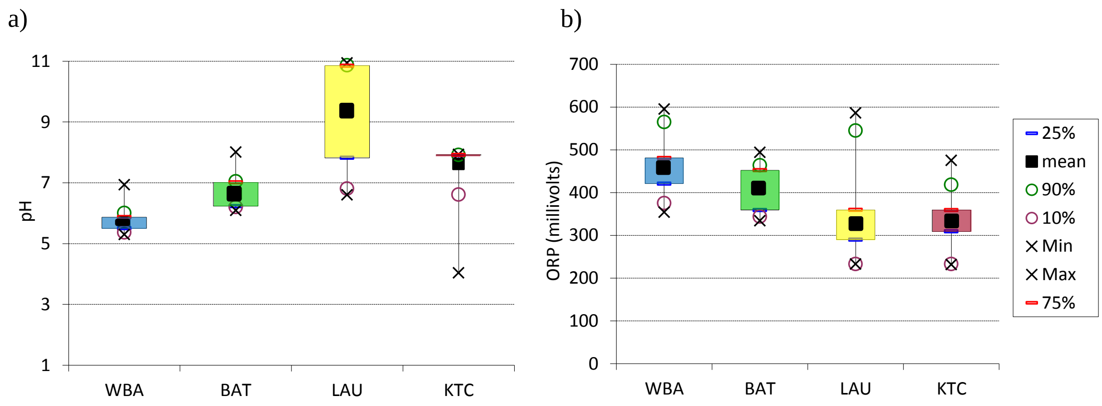

Figure 5.14: Gray-water streams concentrations: a) pH; b) ORP.

Cl^- is the maximum for drinking water. The Cl^- concentration found in the gray-water streams were lower than 100 mg/l (Figure 5.15 a)), so it is presumed not to be harmful for metals or plant irrigation. The nitrate (NO_3^-) concentration in gray-water is also not too high (Figure 5.15 b)) which means that the streams would be suitable for reuse in artificial lakes and ponds. Nitrates are nutrients for aquatic plants and algae, causing overproduction when present in excessive levels (eutrophication).

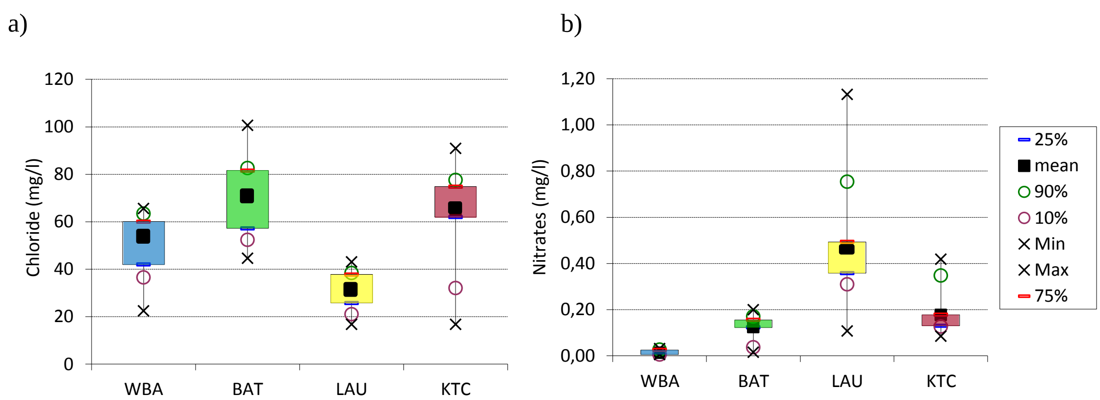

Figure 5.15: Gray-water streams concentrations: a) Chloride; b) Nitrates.

Table 5.7 presents the quality statistical analysis of each analyzed parameter. The general analysis indicated that the gray-water concentration for proposed parameters are in accordance with studies in this field [Baz05] and [EAHL02]. The process of collection and analysis of the gray-water streams in this work were very simple and would be feasible to replicate in many household settings. Other parameters would be analyzed using similar methods such as: Dissolved oxygen (DO), Turbidity and

COD.

Table 5.7: Gray-water streams quality statistical analysis

Parameter	Stat.	WBA	BAH	LAU	KCH
pH	min	5.30	6.09	6.60	4.04
	max	6.94	8.01	10.94	7.93
	mean	5.70	6.63	9.32	7.62
Conductivity (mg/l)	min	139.54	161.51	810.93	215.88
	max	153.96	201.61	1147.41	263.62
	mean	145.83	175.18	954.31	247.80
ORP (mg/l)	min	354.00	334.00	233.00	232.00
	max	595.00	494.00	586.00	475.00
	mean	458.43	409.42	328.77	334.89
Chloride (mg/l)	min	22.45	44.62	16.77	16.71
	max	65.61	100.64	43.11	90.93
	mean	54.05	70.89	31.63	65.18
Nitrate (mg/l)	min	0.01	0.01	0.11	0.09
	max	0.03	0.20	1.13	0.42
	mean	0.01	0.12	0.47	0.18

5.2.3 Water consumption analysis

The water consumption characterization of each device utilized is useful in identifying if the household gray-water streams' volume is enough for reuse purposes. Besides, the daily production of gray-water in each stream and the parameters concentration values are necessary to calculate the pollution loads used to identify a suitable treatment system. Four households were monitored in Brazil during four weeks in order to estimate the consumption characteristics. Table 5.8 presents the water consumption analysis for the four households.

Table 5.8: Households water consumption analysis

Water Consump.	Household1	Household2	Household3	Household4	mean
Number of users	5	3	3	1	3
Percapita tot (l/p/d)	91.52	233.92	108.74	55.61	122.45
Water loss (%)	0.7%	17.3%	29%	0.3%	12%
Real percapita* (l/p/d)	90.88	195.16	81.36	55.47	105.72

*values without water loss.

The *per-capita* water consumption (cpd) for the four households (122.45 l/p/day) is similar to the "cpd" for the Feira de Santana region (115 l/p/day), thus the information acquired was considered representative for all houses in the region. Water losses were identified in the monitored water supply systems , mainly with the 2nd and 3rd households, where 17% and 29% of the total consumption was wasted. This water loss volume was identified and counted for constant small flows (less than 0.4 l/s) during the overnight period (between 00:00 AM to 05:00 AM) and when water use was not registered by the users.

The water consumption inquiry survey performed in Feira de Santana city (Brazil) [Alm07] indicated that consumption *percapita* is directly correlated with income (Figure 5.16-a). Income is measured here as the minimum salary (MS). The four analyzed households demonstrated similar tendency (5.16-b), but it has been observed that the tariff is more closely related to consumption than income, as indicated in Chapter 2.

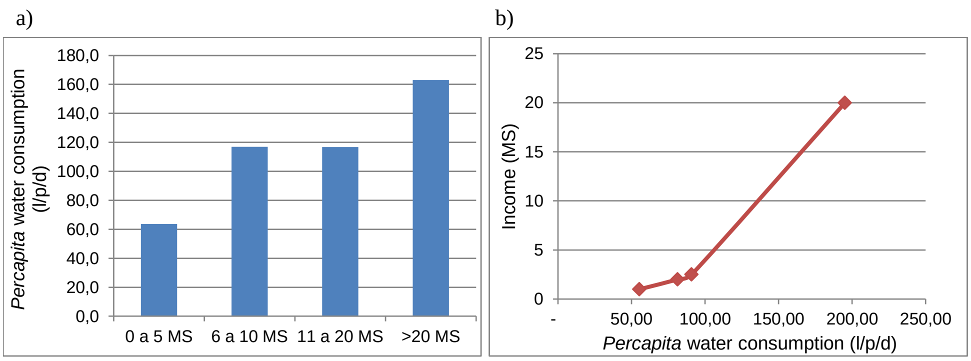

Figure 5.16: Relation between *percapita* water consumption and income.

It has also been observed that there is a reduction in water consumption during the weekends, most significantly on Sundays (Figure 5.17). This information can be useful to plan the estimations of water reuse necessities and treatment programs.

The water use identification was made using the relation between the water consumption signals and the time-sheet provided by the users. This analysis was only possible with household 2 because of the inconsistencies found between the information (signals and time-sheet) provided by the other households, making it difficult to compare and graph appropriately.

The household 2 water use evaluation indicated that the dishwashing and bath are the uses which consume the most water (Figure 5.18). Other studies have indicated that the toilet flush represents the major household consumption and its typical uses represent 20% to 30% of total consumption [MD99]. However, the newest toilet flush designs require less water which has decreased its representation regarding all others

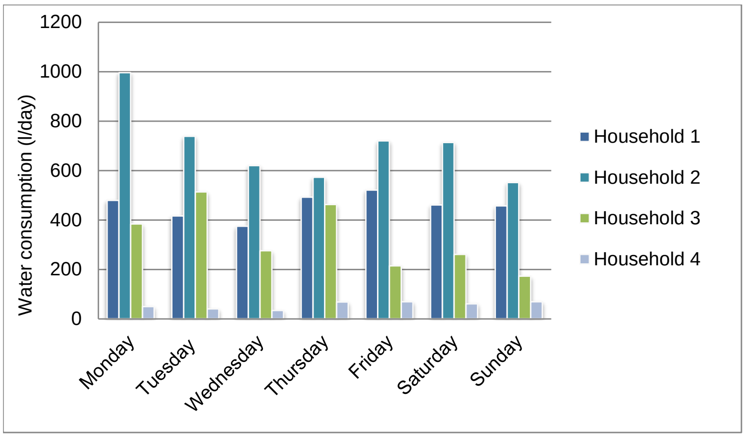

Figure 5.17: One week water consumption analysis.

uses.

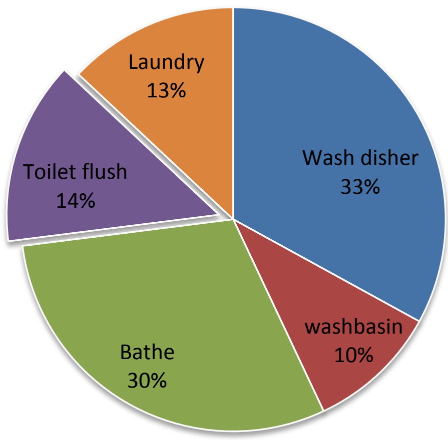

Figure 5.18: Household 2 water uses percentage.

Due to the low levels of pollution, the washbasin and bath streams are recommended for reuse in toilet flush. However, the uses' identification indicates that the amount of water used in washbasins and for bath is not enough to supply the toilet flush necessities. It demonstrates the necessity of further studies on reuse alternatives in order to achieve an efficient and safe reclamation.

5.2.4 Household water reuse evaluation

The pollution loads information is necessary to assist in the designing of a suitable effluent treatment system. In this work the quality and quantity of gray-water streams from four households was useful in estimating the pollution loads calculation. The quantity of the gray-water streams was calculated using a coefficient of affluence that represents the estimated percent of used water that goes to the sewer. The coefficient of affluence may vary from 0.7 to 0.9 [DR296], and in the houses of our experiment was 0.80. To estimate if the household's streams characteristics are suitable for water reuse, the pollution loads calculation of a limited number of parameters was instituted. These parameters were chosen because they are often cited in studies and water reuse standards, but they are also relevant indicators of contamination. The calculated household pollution loads are presented in Table 5.9.

Table 5.9: Gray-water streams pollution loads (per day)

Parameters	House-hold	Gray-water Streams			
		WBA	BAT	LAU	KTC
Volume (l)	H1	36.35	109.06	47.26	119.97
	H2	46.24	125.49	79.86	146.92
	H3	19.53	58.58	25.38	64.44
	H4	4.44	13.31	5.77	14.64
Nitrogen (g)	H1	0.15	0.98	0.98	1.54
	H2	-	2.05	0.29	3.13
	H3	-	1.02	0.79	2.46
	H4	-	0.50	0.11	0.63
Phosphorus (g)	H1	0.31	0.03	4.10	2.57
	H2	1.23	1.42	2.71	7.92
	H3	0.26	1.44	2.45	7.61
	H4	0.15	0.46	0.49	0.86
CBO_5 (g)	H1	3.12	11.65	24.64	183.39
	H2	5.41	61.48	34.60	272.44
	H3	4.68	46.60	31.33	115.15
	H4	0.72	4.90	5.21	20.39
TSS (g)	H1	2.35	22.40	23.89	70.88
	H2	3.09	14.58	10.00	32.37
	H3	4.44	27.03	15.37	76.96
	H4	0.87	3.12	4.15	9.53
Fecal coliforms (Ufc)	H1	2.15E+06	4.10E+07	1.65E+07	6.24E+07
	H2	6.29E+06	1.71E+07	4.30E+06	2.00E+08
	H3	1.19E+06	1.92E+07	1.43E+06	5.67E+07
	H4	3.63E+05	1.67E+06	7.70E+05	6.31E+06

Considering the pollution removal efficiency of the treatment processes presented in Table 5.4 (Section 5.1.3), the three treatment system was identified as being more suitable with regard to household pollution loads (Table 5.10). In Portugal, it was not found to fall within the standards for household gray-water reuse, so Table 5.11 presents a compilation of the standards presented in Appendix A in order to estimate the most used concentration parameters limitation.

Table 5.10: Gray-water treatments efficiency

Treat. n^o	Treatment system	Pollution remove efficiency				
		TSS	CBO_5	TN	TP	Fecal coliform
TS1	Screen+RBC+sand filtration+chlorination	82%	90%	-	58%	100%
TS2	MBR	99%	93%	63%	19%	99.9%
TS3	Wetlands	98%	99%	69%	71%	99.6%

Table 5.11: Gray-water standards limits

Water reuse purpose	TSS (mg/l)^1	CBO_5 (mg/l)^2	TN (mg/l)^3	TP (mg/l)^3	Fecal colif. (UFC/100ml)^4
Unrestricted: flushing toilet, laundry, air conditioning, process water, landscape irrigation; fire protection, construction, surface irrigation of food crops and vegetables (raw consumed) and street cleansing.	<20	< 10	<15	<0.5	<10
Restricted: Irrigation of gardens, where public access is controlled; subsurface irrigation of non-food crops and food crops and vegetables (consumed after processing).	<30	< 30	<15	<0.5	<200

1) China; 2) EUA and Brazil; 3) Spain; 4) Japan, Australia and Canada

The pollutant loads value and the removal efficiency of the treatment systems lead to the identification of the treated gray-water characterization (Figure 5.19). The new parameters concentration was compared with the standard limits presented in Table 5.11 in order to identify the most suitable treatment system for the data under examination.

It was observed that the treated gray-water stream from the washbasin presented a significant unrestricted water reuse potential considering the analyzed treatment systems. However, the phosphorus concentration values do not meet the standard limits. It was also observed that the treatment systems removal rate was not enough to achieve the suitable TP concentration for reuse. The treated gray-water TP values are below the standard threshold only for treated gray-water from the bath in household

Household	Gray-water stream	TSS (mg/l)			CBO_5 (mg/l)			NT (mg/l)		PT (mg/l)			Fecal coliform (UFC/100ml)		
		TS1	TS2	TS3	TS1	TS2	TS3	TS2	TS3	TS1	TS2	TS3	TS1	TS2	TS3
H1	WBA	11.6	0.6	1.3	4.3	3.0	0.4	1.5	1.2	3.6	6.9	2.5	0.00	592	2,369
	BAT	37.0	2.1	4.1	5.3	3.7	0.5	3.3	2.8	0.1	0.2	0.1	0.00	11,280	45,120
	LAU	91.0	5.1	10.1	26.1	18.2	2.6	7.6	6.4	36.4	70.3	25.2	0.00	4,543	18,173
	KTC	106.4	5.9	11.8	76.4	53.5	7.6	4.7	4.0	9.0	17.3	6.2	0.00	17,160	68,640
H2	WBA	15.3	0.9	1.7	7.4	5.2	0.7	0.0	0.0	14.2	27.4	9.8	0.00	1,730	6,920
	BAT	24.1	1.3	2.7	28.2	19.7	2.8	7.0	5.8	5.5	10.6	3.8	0.00	4,695	18,779
	LAU	38.1	2.1	4.2	36.6	25.6	3.7	2.3	1.9	24.1	46.5	16.6	0.00	1,183	4,730
	KTC	48.6	2.7	5.4	113.6	79.5	11.4	9.7	8.1	27.7	53.5	19.1	0.00	54,965	219,858
H3	WBA	22.0	1.2	2.4	6.4	4.5	0.6	0.0	0.0	3.0	5.9	2.1	0.00	327	1,309
	BAT	44.6	2.5	5.0	21.4	15.0	2.1	3.4	2.9	5.5	10.7	3.8	0.00	5,285	21,142
	LAU	58.5	3.3	6.5	33.1	23.2	3.3	6.2	5.2	21.7	41.9	15.0	0.00	393	1,573
	KTC	115.5	6.4	12.8	48.0	33.6	4.8	7.6	6.4	26.7	51.4	18.4	0.00	15,599	62,394
H4	WBA	4.3	0.2	0.5	1.0	0.7	0.1	0.0	0.0	1.7	3.3	1.2	0.00	100	400
	BAT	5.2	0.3	0.6	2.2	1.6	0.2	1.7	1.4	1.8	3.4	1.2	0.00	459	1,836
	LAU	15.8	0.9	1.8	5.5	3.9	0.6	0.9	0.7	4.4	8.4	3.0	0.00	212	847
	KTC	14.3	0.8	1.6	8.5	5.9	0.8	2.0	1.6	3.0	5.8	2.1	0.00	1,735	6,942

Meets with the unrestricted and restricted limits.
Meets only with the restricted limits.

Figure 5.19: Results of pollutant loads removal efficiency.

1. The phosphorus concentration found in laundry and kitchen gray-water streams were higher than those presented in the literature (Figure 5.20).

Although the TS2 and TS3 treatment systems were more suitable to SST and CBO_5 removal, a general analysis indicates that treatment system TS1 presented a better balance in the removal rate in order to achieve the standard threshold. Adding a disinfection process for the TS2 and TS3 treatment systems would be useful to improve fecal coliform removal [MSEHK07]. The MBR (TS2) is considered a good option for narrow spaces due to its compact structure and low sludge production. However, high installation costs make this economically available for buildings with more than 40 floors (160 households) [FH06]. The RBC (TS1) is a more economic option compared to the MBR, and is a good option for buildings with more than 7 floors due to the installation and maintenance costs. The most economic and ecologic option for gray-water streams treatment are the wetlands (TS3), however, it requires a significant area out-of-doors for the necessary flood area for gray-water treatment witch limit its use for households and small buildings.

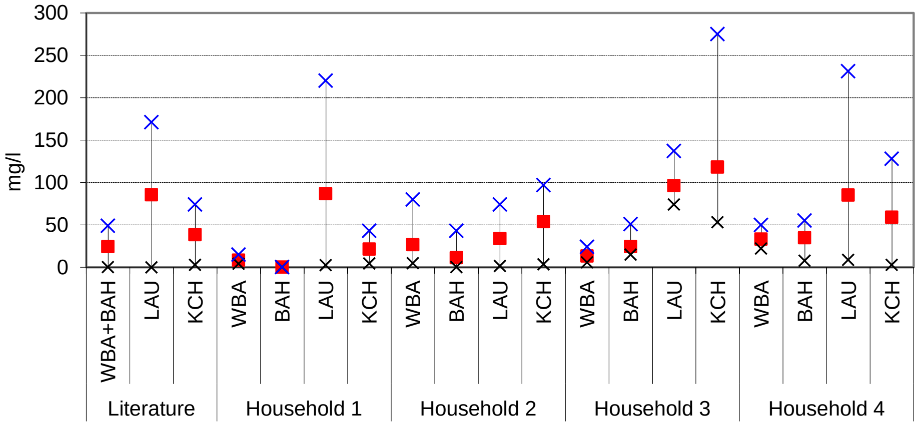

Figure 5.20: Households gray-water streams phosphorus concentration.

5.3 Conclusions

The general analysis of the gray-water streams' quality indicates that there are many variables contributing to its composition, and characteristics of the quality depend on the user's behavior, water supply quality and nature of cleaning products. The gray-water stream quality analyzed indicated that the kitchen and laundry streams present a greater concentration of pollutants than the washbasin or the bath. This result is in accordance with many studies in this field.

The water use identification and the gray-water streams quality allowed for the calculation of the pollutant loads. This information was needed to assess whether treatment systems are suitable in preparing household water for reuse. In this work three treatment systems were tested in order to evaluate the biological removal efficiency. In general, all the treatments analyzed are suitable for water reuse and meet most of the limits set by the standards for restricted and unrestricted reuse. However, changes in treatment processes are required to improve fecal coliform removal. For the Wetlands and MBR systems greater efficiency in removing coliforms is necessary to aggregate a disinfection process. The low phosphorus removal rate and the high concentration of this compound in the gray-water streams can explain why these systems do not meet the PT standards for almost all samples.

It is recommended for future works in this field that the implementation and maintenance cost analysis of the treatment systems be carefully in order to verify the feasibility of gray-water reuse compared to the water supply tariffs.

Considering the four houses which were analyzed, it is estimated that the implementation of the toilet flushing reuse system save about 15% of drinking water. Furthermore, if the water losses identified in household 2 and 3 were repaired, the water saved would be even higher, about 35% and 40% respectively. These figures demonstrate that the water loss reduction is as, or more significant in saving water, depending on the case, as the water reuse. Integrated studies on this field could have a significant impact on water conservation in many households.

Chapter 6

Conclusions and recommendations

GLOBAL warming, high water consumption and population growth trends suggest a worsening in water shortages, the scenarios presented for water availability have shown the necessity of alternative sources of supply for the future [Pro09]. Considering treated waste-water as a suitable alternative water resource, this thesis proposes and analyzes different techniques that improve both general and specific knowledge about water use and reuse. A fuzzy inference system (FIS) was utilized to estimate water reuse potential, as well as an automatic system for water use identification and a simplified method for household water reuse evaluation.

In response to questions about the reasons that drive agricultural and urban water reuse, an FIS was proposed to estimate water reuse potential. For agricultural reuse potential, the FIS was designed based on the information of a data set composed by 155 regions and for urban reuse was used the data provided by 183 cities. The analysis of the data-set indicated that environmental factors (i.e. features), including drought severity and water availability, and structural factors, including water exploitation index (WEI), water uses, population density, and waste-water treatment rate, are well correlated with water reuse. The features selected to compose the agricultural FIS were: drought, WEI and AGR/UWS-ratio (ratio between agricultural and water supply consumption). For the urban FIS, the features selected were: scarcity, demographic density and a waste-water treatment rate. Given the environmental and structural factors, the proposed FIS is able to identify whether the examined sample has reuse potential or not, with 96% accuracy in the case of urban reuse, and 90% accuracy in the case of agricultural reuse. The approach used to develop the water reuse potential model indicated that certain variables can serve as a warning to decision makers about the risks of water shortage and the consequent alternative water supply necessities. The decision parameters of the agricultural FIS rules indicate that the highest water reuse potential is verified for extreme and exceptional drought events in regions with WEI above 25%. For low droughts the WEI could affect the water supply when it reaches 45% or more. The AGR/UWS-ratio is the least representative feature for the analyzed model. The decision parameters of urban FIS rules show that the highest water reuse potential is verified for areas subject to high scarcity, demographic density above 300 and a waste-water treatment rate above 60%.

Studies on water reuse potential indicated that agricultural water reuse has the highest reuse potential in comparison to urban reuse due to high water consumption and lower water quality necessity. So, how to improve urban water reuse considering future water shortage scenarios? In this sense, the knowledge about quantity and quality of households waste-water gives valuable information for water reuse system designs. To identify the household water quantity accurately and automatically this piece proposes a water use identification system that uses transient flow rate and pressure signals. The approach of this work is focused at the signal signature identification, which is the first step of the full-blown system development. A simplified experimental facility was constructed to develop and test the data acquisition system tool for data processing. Water meters with pulsed out-put, pressure transducers, data acquisition cards (DAC), *cyble* sensors and a computer were used to compose the data acquisition system. A second experimental facility was also built to simulate a household water distribution system and was constructed in cross-linked polyethylene pipe-PEX. The system included five fixtures: sink, washbasin, shower, bidet and toilet flush. Two different tap mechanisms were installed: compression (threaded spindle) and cartridge (lever handle). The same pipe length was used for all fixtures in order to identify the signals' signatures. Many techniques presented in available literature can be used to process and classify signals, but in this work Fourier transform to convert the time domain into frequency domain signals, FS-GAIT as a feature extractor, and multiclass GDX and one-against-all SVM as classifiers were used. Fusion by majority vote was also used to improve OAA-SVM accuracy. The features' characteristics were extracted in the time and frequency domains and a feature selector was used to select representative features of the samples in order to improve the classification. The fusion by majority vote of the SVM classification results in the time domain presented the highest accuracies: 92% for the kitchen tap, 94% for the wash basin tap, 94% for the bidet, 100% for the shower and 100% for the toilet flush. This result indicated that each feature has a specific signature that can be recognized by the classifiers.

In a second phase the pipeline was constructed with different lengths to identify whether the pressure had any effect on accuracy. The results using the SVM classifier indicated that the differences in pressure actually improved the classification accuracy in the time domain for all five fixtures. The results were: 100% for the kitchen tap, 100% for the wash basin tap, 99% for the bidet, 100% for the shower and 100% for the toilet flush. A composition was also analyzed in order to test accuracies with two fixtures in use. The results were also good for pressure signals in the time domain: 99% for the kitchen tap and the washbasin tap, 97% for the kitchen tap and the bidet tap, 99% for the kitchen tap and the shower and 100% for the kitchen tap and the toilet flush. Further developments with the algorithm could be made to track the open/close fixtures, considering the transient's signals identification, in order to detect the usage time and flow rate and calculate the water consumption per fixture. The future expectation is to complete the fixtures composition and test the algorithm in a domicile instead of an experimental facility. It is estimated that the full-blown system development will be useful to manage water consumption in buildings using a computer or a mobile device. Besides, water use information will provide valuable contributions for developments in water reuse systems.

The developed acquisition system could also be useful for head losses and coefficient of simultaneity studies. In this sense, head losses in pipes, manifolds and water heaters, besides coefficient of simultaneity, was calculated for the PEX system. The results indicated that 12 mm and 16 mm pipes head losses values are compatible with the information provided by manufacturer diagrams, indicating that the data acquisition system is suitable for friction head loss analysis. In addition, the roughness coefficient calculated for these pipes is compatible with PVC roughness values which are considered a suitable result because both PEX and PVC are thermoplastic materials. The local head loss findings in the manifold without a lock-shield are more closely related to the T.A. curve (fully open) provided by the manufacturer diagrams when more than one output manifold is in use. As expected, the tankless water heater presented the greatest head loss of the entire PEX water pipe system. Regarding the coefficient of simultaneity calculation, the modified method presents values more compatible with the experimental facility data than that provided by the Delebecque method.

The household streams quality identification is also valuable in developing suitable water reuse and treatment systems. In this work, investigations about gray-water streams quality took place in Brazil and Portugal. The collection of gray-water streams from the kitchen, washbasin and laundry were assembled using plastic reservoirs connected at the stream out-puts. Plastic buckets were used to collect bath streams. The quality parameters analyzed in Brazil were: fecal coliforms, sodium, COD, phosphorus, total nitrogen, potassium, total suspended solids, calcium, hardness and magnesium. In Portugal, a multi-parametric sonde to test an on-site method analysis was used. The parameters in Portugal were: pH, oxidation-reduction Potential (ORP), Chloride, Nitrate and Conductivity. The general analysis of the gray-water streams' quality indicates that there are many variables contributing to its composition, and characteristics of the quality depend on the user's behavior, water supply quality and nature of cleaning products. The gray-water stream quality analyzed in all households indicated that the kitchen and laundry streams present a greater concentration of pollutants than the washbasin or the bath. This result is in accordance with many studies in this field.

To estimate whether the household's streams characteristics are suitable for water reuse, a pollution loads calculation of a limited number of parameters was instituted. These parameters were chosen because they are often cited in studies and water reuse standards, but they are also relevant indicators of contamination. Considering the pollution removal efficiency of the treatment processes, three treatment systems were identified as being more suitable with regard to household pollution loads: Screen+RBC+sand filtration+chlorination (SRSFC), MBR and Wetlands. Although the MBR and Wetlands treatments were more suitable to TSS and CBO_5 removal, a general analysis indicates that SRSFC treatment system presents a better balance in the removal rate in order to achieve the standard threshold. Adding a disinfection process for the MBR and Wetlands treatment systems would be useful to improve fecal coliform removal. Based on the analysis of four households, it is estimated that the implementation of the toilet flushing reuse system could save up to 15% of drinking water. Furthermore, if the identified water losses were repaired, the water saved could be even higher, from 35% to 40%. These figures demonstrate that water losses reduction is as, or more significant in saving water, depending on the case, as water reuse. Integrated studies on this field could have a significant impact on water conservation in many households.

The techniques and methodologies presented are suitable for large scale implementation and provide valuable information for efficient water use and reuse. However, improvements have to be made so that they can be used in a real environment. The main suggestions for future work in each suggested propose are:

1) Fuzzy inference system (FIS) for water reuse potential estimation

- In order to give more accurate results, the proposed FIS can be adapted to a narrower scope considering features of a small region or city
- Considering a narrower scope, FIS could add other factors to estimate the water reuse potential, such as the Rainfall Variability Index (RVI)
- Other tools could also be tested to identify the reuse potential, such as Bayesian network (BBN)

2) Automatic system for water use identification

- Wavelet transform could be used to provide new features for time domain transient signals because it gives time and frequency information simultaneously
- Some of the difficulties on water use identification could be solved by the use of an electronic or Self-Closing tap because they provide a more standardized start/stop work mechanism.
- More developments in tap work mechanisms also could be made in order to limit the flow rate into two or three levels as occur with toilet flush fixture.
- To disambiguate the hot water from the cold water usage, it could be proposed to use two pressure sensors, one at the cold water entrance and another at the hot water heater intake line. In this sense, the signals could be classified considering two independent systems.
- New developments with the algorithm could be made to track the open/close fixtures considering transient's signals identification in order to detect the usage time and flow rate (provided by water-meter) for water consumption quantification.

- As occurs in studies for electric loads disaggregation [KJ11], it is intended in the near future to produce a data set with water uses information using the data acquisition system developed in order to improve new water uses identification and disaggregation methods development.

3) Simplified method for evaluating water reuse applications in households

- It is recommended in future in-site waste-water quality characterization to apply sondes that cover a greater range of parameters for analysis
- Installation and maintenance costs of the recommended treatment systems for water reuse have to be evaluated in future works in order to compare with the water tariffs and estimate the economic advantages
- Integrated studies of household water losses and reuse are recommended to encourage water resources conservation

Appendix A

Quality limits of the water reuse standards

Table A.1: Water reuse standards for urban environment

Country	pH	TSS (mg/l)	Turbidity(NTU)	BOD_5 (mg/l)	NH_4N (mg/l)	PT (mg/l)	Fecal Coliform	Reuse purpose
Germany[1]	-	-	-	5 (BOD_7)	-	-	<10/ml	Toilet flush
China[1]	6-9	-	<5	<10	<10	-	<3/100ml	Toilet flush
	6-9	-	<20	<20	<20	-	<3/100ml	irrigation
	6-9	-	<5	<6	<10	-	<3/100ml	washing
EUA[1]	6-9	-	<2	10	-	-	ND (75%) 25 (max)	Unrestricted reuses[a]
	6-9	30	-	30	-	-	<200/ 100ml	Restricted reuses[b]
Japan[1]	5.8-8.6	-	-	≤ 20	-	-	10/100ml	Toilet flush
	5.8-8.6	-	-	≤20	-	-	-	Landscape irrigation
	5.8-8.6	-	≤10	≤10	-	-	-	Environmental (aesthetic settling)
	5.8 8.6	-	-	≤5	≤3	-	-	Environmental (limited contact)
Australia[1]	-	30	-	-	-	-	<10 (90%) 30 (max)	Unrestricted reuse
Brazil[2]	6.0-9.0	≤5	≤2	≤10	≤20	≤0.1	ND	Toilet flush
Spain[3]	5.5-9.5	10	<2	-	<15[c]	<0.5[c]	-	garden watering and toilet flush[d]
	5.5-9.5	20	≤10	-	<15[c]	<0.5[c]	-	Landscape, washing (streets, industries and cars) and firefighting[e]
Portugal[4]	6.5-8.4	60	-	-	-	-	<100/ 100 ml	irrigation
Canada[5]	-	≤20	≤5	≤20	-	-	≤200	Toilet flush

Source: 1)[LWO09], 2)[FIE05], 3)[dlPdlE07], 4)[IPQ05] and 5) [Can10].
ND: non-detectable
a) Toilet flushing, landscape irrigation, car washing and agricultural irrigation.
b) Irrigation of areas where public access is infrequent and controlled golf courses, cemeteries, residential, greenbelt.
c) Environmental quality standards (see article 245.5 from RD 849/1986)
d) *E.Coli* = 0 UFC/100ml and 1 egg/10L of *Nematodos Intestinales*.
e) *E.Coli* < 200 UFC/100ml.
Some unrestricted reuses and toilet flush demands a residual chlorine in amounts of ≥1 mg/l

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