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Universitat Politècnica de Catalunya

Doctoral Programme:

AUTOMATIC CONTROL, ROBOTICS AND COMPUTER VISION

Doctoral Thesis Proposal:

DEMAND MODELLING AND CALIBRATION FOR HYDRAULIC NETWORK MODELS

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Contents

1 Abstract

Water distribution network models are used by water companies in a wide range of applications. A good calibration of these models is required in order to increase the confidence of the applications' results. The aim of this doctoral thesis is to develop an adaptive water distribution model which both calibrates its parameters and discerns between faults and system evolution. In previous projects, nodal demands were the major uncertainty within the model parameters. A demand calibration methodology was developed during the master project. The results obtained were promising, although the work done fulfils only a small part of the whole application. In order to accomplish the remaining tasks, further work must be done. First, system identifiability will be performed in order to determine the number of required sensors that make the system observable. The identifiability study will lead to sampling design methodologies and network reduction (skeletonization). Once the model is identifiable, two calibration techniques based on non-linear least squares and artificial intelligence techniques will be studied and adapted for the final application. A methodology for distinguishing between faults and parameter evolution will be developed too. All the subprocesses will be assembled in an open source software which combines the simulating engine from EPANET with the computational power from MATLAB, becoming a full calibration and monitoring application for water networks. Finally, at least two real scenarios will be monitored through the proposed application.

This thesis proposal sets the basis for the thesis development, presenting the work done on the subject, organising the future tasks and proposing a working plan.

2 Thesis goals and contributions

The principal aim of the doctoral thesis is to develop an adaptive on-line model for demands in water distribution networks. This model will calibrate its parameters on-line, and will be able to discern between system evolution (e.g. changes in demands) and faults (e.g. leakages, obstructions). This type of model may be used for water management and prognosis.

The secondary objectives involved in the generation of the adaptive model are:

- System identifiability: Determine the minimum number of measurements that have to be taken in order to make the system demands identifiable.
- Sampling design: Determine a sensor distribution methodology for both fault detection and demand calibration.
- Network skeletonization: Develop a process that reduces the model's elements keeping its behaviour unchanged, according to the use of the model.
- Network calibration: Once the system is identifiable (thanks to network skeletonization and sampling design), a methodology for calibrating the network's demands is developed.
- Fault versus parameters' evolution identification: The methodology is applied in order to discern between demands' evolution and faults.
- Software development: An open source software package[1] combining the EPANET water simulation engine with MATLAB will be programmed. The package will include all functionalities developed during the doctoral thesis. This software will allow the user to develop his own functions.
- Different networks are used in order to verify the adaptability of both the methodology and software.

[1] First version of the software available at `http://sac.upc.edu/training-benchmarks/simulador-de-xarxes-de-distribucio-daigues`

3 State of the art

A model is a representation of reality, like a map. There are maps with scales 1:25000 that allow walking through the mountains and know where the water sources are so that you are not thirsty. When the trip is longer and you take the car, you zoom out and need a map with scale 1:500000 where the sources are not present anymore. Nevertheless rivers let you know, when you cross them, that you are on the right way. Often the modellers have to sacrifice some precision in order to have a model that can be manipulated and constructed with a reasonable time and computational cost. This simplification must be compatible with the use of the model. In a water distribution company, the reality is a model of a network formed by pipes, nodes, demands, pumps, valves, tanks and reservoirs. Physics explains very precisely the behaviour of each element [84].

The current approach for monitoring urban water distribution networks is a combination of measurement via the supervisory control and data acquisition system (SCADA) with simulated models using hydraulic analysis software. An ideal water distribution network that could be whole monitored through instrumentation with a flow meter located in every pipe and a pressure probe at every node would have prohibitive costs, outweighing the potential benefits. In contrast, instrumentation employed in real-world networks is highly sparse, often consisting of pressure and flow measurements at pump stations and reservoirs only. Computer models are used to fill in the large gaps in data provided by the SCADA system [22].

3.1 Models

3.1.1 Dynamic models

Some models try to characterise transients in pipes, valves and pumps. Kapelan et al. [35] used inverse transient models for leakage detection. Vítkovský et al. [80] used these dynamics for leakage detection and calibration of roughness. Both used genetic algorithms. But the transient analysis may interest itself in order to know the behaviour of a network in these transients [42]. These models need a lot of data for calibration and are computationally expensive. Nevertheless, when the number of pipes, pumps and valves increases, the network tends to work steadier and the transients lose importance. A first main simplification has to do with time. The dynamics of each element have to be compared to the sample time of the system. Of course when the modeller gives up modelling the transient of some elements, some information is lost. Most applications in computer supervision and control in huge networks work with steady-state models concatenated in an extended period simulation (EPS) [14] [84].

In EPS models' dynamics come from the tanks, which are linear elements with mass balance equations. Calibrating such elements is not a hard issue because the number of tanks is not huge and moreover they are well described, specified and monitored by

level sensors. Some of these elements fulfil quality purposes like disinfection. Models of residual chlorine are of distributed parameters. An approach for their estimation is presented in [67]. The chlorine in tanks is often monitored as it is in a source of a network. Chlorine decay in pipes is normally more difficult to know. The number of pipes in a network makes impossible an exhaustive monitoring. Modelling and calibrating this behaviour is very useful when supervision of quality is required. As it is described in [59], [11] and [48] a good hydraulic model is necessary. This hydraulic model for pipes is where a huge effort in calibration is being employed. The flow and head-loss in a pipe have a non-linear relation depending on length, diameter, and roughness. There are different approaches (Hazen-Williams, Darcy-Weisbach, Manning) for this roughness. Determination of roughness or the constant for head-loss relation has focused a great effort.

3.1.2 Steady state models

The steady state models are the most used in water companies for design, supervision and control. In this work, the calibration effort is focused on these models. Steady state models are formed by a set of elements which represent the real network components. The interconnection of these elements allows obtaining an accurate estimation of variables as pressure, flows, chlorine concentration, etc. if the model is well calibrated. All the elements of the model have some parameters that have to be estimated. An exhaustive description of all the elements can be found in the EPANET users guide [68], a fully equipped, extended period hydraulic analysis package. It is free and almost a standard in the water industry. Nevertheless, other packages like Piccolo or Infoworks use similar if not identical model and some even use EPANET as simulation engine.

3.2 Calibration of models

Shamir and Howard [74] state that calibration "consists of determining the physical and operational characteristics of an existing system and determining the data [that] when input to the computer model will yield realistic results". The AWWA Research Committee on Distribution [3] used the word "verified" in place of "calibrated" but described a process of calibration: "System simulation is considered verified during preliminary analysis for design when calculated pressures are satisfactorily close to observed field gage readings for given field source send-out and storage conditions. If simulation is not satisfactory, the possibility of local aberrations, such as open boundary valves, is investigated. In the absence of other expected causative factors, the assumed local arterial network loads are adjusted until computed and observed field pressures are within reasonable agreement for various levels and extremes of demand, pumping, and storage".

Global calibration problem is very well presented by Savic et al. [73]. Methods are classified depending on their dynamics (static/transient) and depending on the optimization

methods (prove/explicit/implicit). Demand allocation and validation or correction of gross input data errors are important precursors for calibration. For the purpose of this paper [73], they are considered outside the scope of calibration.

The first conclusion extracted is that a high degree of interest in this topic has been shown by researchers, but it has been considerably less covered by practitioners. A number of questions have to be answered, such as: (1) What parameters can be calibrated with confidence? (2) What is the acceptable level of discretisation of calibration parameters and what is the acceptable level of agreement between measurements and model outputs? (3) How to parametrise the model when insufficient data are available? (4) What objective function type to use?

Ormsbee [49] suggested a seven-step general calibration procedure as follows: (1) Identification of the intended use of the model; (2) determination of initial estimates of the model parameters; (3) collection of calibration data; (4) evaluation of the model results; (5) macro-level calibration; (6) sensitivity analysis; and (7) micro-level calibration.

One of the most important issues in model calibration is the determination of the purpose of the model (pipe sizing for master planning, extended-period simulations for planning studies, subdivision layout, rehabilitation studies, energy usage studies, water quality models and flushing programmes).

In [50], Ostfeld et al. described a challenge on a simulated network and data that allows comparing different solutions. Interesting references have been extracted from this work and future work is well pointed. A calibration problem is inherently "ill-posed or under-constrained" as there are more unknowns than there are equations. Mathematically there are an infinite number of solutions which will provide good matching between measured and modelled data. The calibration process typically alters system demands, fine-tunes pipes' roughness, and modifies pump operation characteristics until satisfactory matching is attained between measured and modelled data. Once such a solution is achieved, how can one tell that the system is really calibrated? A possible way to address this issue is to extend the model's calibration matrix from data matching to, for example, the model's ability to successfully predict the resultant pressure and flows associated with an independently applied demand pattern and operating conditions, and to effectively predict the resultant pressure and flows associated with random abnormal/failure scenarios. In [86], Walters et al. used 90 pressure measurements for calibrating a 1000 pipes network by means of genetic algorithms. Results are well evaluated though there are 2 meters of difference in some pressure estimations. In [21], Datta and Sridharan described the direct problem that deals with the calculation of the pressure and flow distribution over the network, which corresponds to the given resistances and the consumptions and solves the inverse problem of determining resistances (Hazen-Williams coefficients) by means of weighted least squares (WLS) method using sensitivity analysis.

In [81], [82] and [83], Walski presented a methodology to adjust both demands and roughness in a pipe network using fire flow test. It was a global C-factor that was

adjusted during calibration. Water use estimates were adjusted using a global multiplier, although in a few cases individual C-factors or water use estimates were modified. In [82], the author described the importance of good data collection. Both consumptions and roughness were estimated by Reddy et al. [65] using WLS method based on the Gauss-Newton minimization technique. Bhave in [10], presented an iterative method under Savic's classification [73] that seems more like an explicit one where the network is divided in zones and the total demand in each zone is corrected while the resistances are adjusted too.

Walski presented in [81] formulas to assist the user in deciding whether to adjust roughness or water use and by how much. They are based on fire flow test. To correct for inaccuracies in input data it is necessary to first understand the sources of these inaccuracies. These can be grouped into several categories: (1) Incorrect estimate of water use; (2) incorrect pipe carrying capacity; (3) incorrect head at constant head points (i.e., pumps, tanks, pressure reducing valves); or (4) poor representation of system in model (e.g., too many pipes removed in skeletonizing the system). The major source of error in simulation of contemporary performance will be in the assumed loadings distributions and their variations. On the other hand, Eggener and Polkowski [27] state: "the weakest piece of input information is not the assumed loadings condition, but the pipe friction factor". The certainties of a previous model must be stated so that the effort in calibration is in the good direction.

In projects developed by the doctoral candidate's research group (PROFURED, RTNM, EFFINET), the experts assessed that one of the main causes of uncertainty in the models, and consequently in results, were the nodal demands [54]. The present work focuses in calibrating these demands, which cause the major prediction errors in the studied cases in the projects named before.

3.2.1 The unknown inputs: Demands

Demands are not physically in the network like nodes or pipes. They are inputs because they are the driving force behind the hydraulic dynamics occurring in water distribution systems [84]. Of course water is going out so common sense show them as outputs of the system. They are estimated as parameters but very complex ones. Finally from a control point of view they are nothing but disturbances that have to be rejected for a good service. Anywhere that water can leave the system represents a point of consumption, including a customer's faucet, a leaky main, or an open fire hydrant. Three questions related to water consumption must be answered when building a hydraulic model: (1) How much water is being used? (2) Where are the points of consumption located? and (3) How does the usage change as a function of time?

Determining demands is not a straightforward process like collecting data on the physical characteristics of a system. Some data, such as billing and production records, can be collected directly from the utility but are usually not in a form that can be directly

entered into the model. For example, metering data are not grouped by node. Once this information has been collected, establishing consumption rates is a process requiring study of past and present usage trends and, in some cases, the projection of future ones. Ideally, if individual meter readings are taken for every customer, they should exactly equal the amount of water that is measured leaving the treatment facility. In practice, however, this is not the case. Although inflow does indeed equal outflow, not all of the outflows are metered. These "lost" flows are referred to as unaccounted-for-water (UFW). Leakage is frequently the largest component of UFW and includes distribution losses from supply and distribution pipes, trunk mains, services up to the meter, and tanks. The amount of leakage varies depending on the system, but there is a general correlation between the age of a system and the amount of UFW. Newer systems may have as little as 5 per cent leakage, while older systems may have 40 per cent leakage or higher. Leakage tends to increase over time unless a leak detection and repair program is in place. There are some methodologies to study the UFW by means of the minimal night flow [40] and the DMA performance. If better information is not available, UFW is usually spread uniformly around the system (in spatial and time terms). If UFW is reduced, then the utility will see higher peaking factors because UFW tends to flatten out the diurnal demand curve.

Although water utilities make a large number of flow measurements, such as those at customer meters for billing and at treatment plants and wells for production monitoring, data are usually not compiled on the node-by-node basis needed for modelling. The modeller is thus faced with the task of spatially aggregating data in a useful way and assigning the appropriate usage to model nodes. The most common method of allocating base demands is a simple unit loading method. Most modellers start by determining base demands to which a variety of peaking factors and demand multipliers can be applied, or to which new land developments and customers can be added. Base demands typically include both customer demands and unaccounted-for-water. Usually, the average day demand in the current year is the base from which other demand distributions are built. Ideally, the process of loading demand data into a model from another source would be relatively automatic. Cesario and Lee in [19] described an early approach to automate model loading.

Water usage in municipal water distribution systems is inherently unsteady due to continuously varying demands. For an extended period simulation to accurately reflect the dynamics of the real system, these demand fluctuations must be incorporated into the model. The temporal variations in water usage for municipal water systems typically follow a 24-hour cycle called a diurnal demand pattern. However, system flows change not only on a daily basis, but also weekly and annually. As one might expect, weekend usage patterns often differ from weekday patterns. Seasonal differences in water usage have been related to climatic variables such as temperature and precipitation, and also to the changing habits of customers, such as outdoor recreational and agricultural activities occurring in the summer months.

Demands in a scenario are not the result of real-time measurements, but instead consist

of educated guesses that can be derived from a number of sources such as typical usage by consumers, customer billing records, and required fire fighting loads. To be effective a real-time modelling technique must acknowledge and accommodate the disconnection between mean demand estimates that change gradually and real demands. These two objectives (the time and spatial distribution) that have been described in [22] by Davidson and Bouchart are the aim of this work. So the calibration of demands will use both information coming from outside the network (billing records) and from inside the network (installed sensors).

The adjustment of demands is a typical inverse problem based on optimization. Aksela in [2] used a weekly consumption calculated and measured for classification of different households. This classification allows an estimation of the curves using Gibbs sampling and combined Gaussians. Davidson and Bouchart in [22] and Cheng and Zhiguo in [20] described how to estimate demands using head and flow measurements by means of explicit methods based on least squares (LS). Both formulate the problem for networks where the number of measurements and the number of parameters to estimate are similar. Combination of both demand estimation stages is required in order to have a method that converges.

3.2.2 Optimisation methods

Methodologies for calibration based on optimization (implicit) can be classified by the criteria like in [73]. The three considered criteria are the so-called A, D and V-optimality: the first two are concerned with parameter uncertainty, as they maximise the information content of a design (A-optimality minimises the average parameter variance by minimising the trace of the inverse information matrix; D-optimality maximizes the determinant of the same matrix), while V-optimality is concerned with prediction uncertainty (minimises the average prediction variance). Bush and Uber in [15] derived sampling design models from the D-optimality criteria, but were not directly solved as the D-optimal problem. The sampling design problem is presented in section 3.4.

Sensitivity is used for the resolution of the optimization problem like in [65] and [21]. The same sensitivity matrix has been used by Pérez in [53] for defining static network identifiability as establishing a minimum number of network observations (real and/or pseudo measurements) in order to solve the steady-state calibration problem (single loading condition).

The other basic calibration question about model prediction uncertainty and how it can be reduced may still be an elusive goal for researchers [73]. Describing calibration accuracy in terms of the ratio of observed to predicted head losses is superior to examining accuracy in terms of observed minus predicted pressures because the former provides guidance as to what parameters need adjustment, and the latter become meaningless for systems with fairly flat hydraulic gradients [83]. Information concerning the uncertainty in parameter estimates is contained in the a posteriori parameter covariance matrix [65].

Individual parameter confidence limits can be directly determined from the WLS algorithm [88]. Walski in [81] stated than an average difference of ±1.5 m with a maximum value of ±5.0 m for a good data set and the corresponding values of ±3.0 m and ±10 m for a poor data set would be a reasonable target. Cesario and Davis [18] stated that models can be calibrated to an accuracy of 3.5-7 m. This conclusions were obtained in the early 80s. In section 3.6 more detailed information about uncertainty is found.

3.2.3 Least Squares

The most used methodology for solving the inverse problem is the least square formulation [87], like in [42] [21] [65] [58] [41] [22] [33] [20]. The influence of different choice of weights in the WLS case is investigated and a systematic procedure is given for the selection of suitable weights in [65] and [21].

The non-linear least squares problem is a non-convex problem with multiple optima for the objective function, and it is generally solved as an iterative procedure. To be certain that the minimum found is the global minimum, the process should be started with widely differing initial values of the parameters. When the same minimum is found regardless of the starting point, it is likely to be the global minimum.

3.2.4 Global optimization methods

The calibration problem has multiple extrema due to the non-linear equality constraints. In these cases it is necessary to pose multi-extremal (Global) Optimization Problem (GOP) where the traditional optimization methods are not applicable, and other solutions must be investigated. One of these typical GOPs is the automatic model calibration or parameter identification. One of the approaches to solve GOPs that has become popular during the recent years is the use of the so-called genetic algorithms (GAs) [31] [47]. Preliminary results of this thesis have used GAs for the comparison with LS results. Other GO algorithms are used for solving calibration problems as well [26] [39], but GAs seem to be preferred. In [75] the authors suggested that many practitioners are unaware of the existence of other GO algorithms that are more efficient and effective than GAs. It is possible to distinguish the following groups:

- Set (space) covering techniques.
- Random search methods [60].
- Evolutionary and genetic algorithms (can be attributed to random search methods) [5] [86].
- Methods based on multiple local searches (multi-start) using clustering [78].
- Other methods (simulated annealing, trajectory techniques, tunnelling approach, analysis methods based on a stochastic model of the objective function) [66].

In [53], Pérez studied the properties of the calibration problem for roughness and demands and stated it as a signomial one. Most literature on water networks calibration that do not rely on least squares propose GAs [50].

3.3 Network reduction

Generally, water network models are automatically generated from Geographic Information System (GIS). This direct translation generates a model with a huge number of elements which do not have any impact on the network behaviour. The main aim of a reduced model is to preserve the non-linearity of the original network and approximate its operation accurately under different conditions. There are different methods for reducing the complexity of the model, such as skeletonization, decomposition, usage of artificial neural networks (ANNs) metamodels and variables elimination.

Skeletonization is the process of selecting for inclusion in the model only the parts of the hydraulic network that have a significant impact on the behaviour of the system [84]. The level of skeletonization depends on the intended use of the model. The reduced models have been called "surrogate networks" or "grey boxes" [74]. Eggener and Polkowski [27] did the first study of skeletonization when they systematically removed pipes from a model to test the sensitivity of results. Brandon [12] suggested three heuristic rules that can be used to carry out the skeletonization process: (1) relatively small demands along any pipe are added to the node at the end of the pipe; (2) pipes with small diameters are eliminated, and the area that is fed by them is represented by a single node; and (3) a group of adjacent nodes with similar pressures is reduced to one node. Hamberg and Shamir [32] proposed an approach for reducing the size of the models for the preliminary design phase based in a step-wise combination of the system elements. Saldarriaga et al. [69] skeletonized the network using the resilience concept. In [84] Walski et al. proposed an automated skeletonization process consisting in:

- Removing simple pipes: Pipes are removed from the system based on size or other criteria without considering of their effects on demand loading or hydraulic capacity.
- Removing branch pipes: Dead-end branches not containing tanks are trimmed back to a node that is part of a loop. This type of removal has no effect on the carrying capacity of the remainder of the system.
- Removing pipes in series: Pipes connected in series are replaced by an equivalent pipe which produces the same head-loss. Removed nodes split their demands between the two nodes at the ends of the resulting pipe. A cut-off may be considered in order to not remove nodes with large demands.
- Removing parallel pipes: As in the previous case, an equivalent pipe replaces the parallel ones. New pipe's parameters have to be calculated. No effect on demands is produced in this process.

- Removing pipes to break loops: Pipes with the lowest carrying capacity are removed for breaking loops. This action produces a loss of the system capacity.

Non-pipe elements can also be removed but with some considerations [84]. Using these basic steps, automated skeletonization reduces the network until a stopping criteria defined by the user is achieved. This stopping criteria is chosen depending on the use of the model.

Swamee and Sharma [77] proposed a simplification of the network by decomposing it in subsystems with one input in order to reduce the computational cost on the design of the water distribution system (WDS). Deuerlein [25] introduced the network reduction process as a decomposition of the network graph according to its connectivity properties.

Anderson and Al-Jamal [4] presented a parameter-fitting approach. They reduced the network by calculating two parameters' vectors representing the nodal demands and the links conductances. An objective function was formulated for maximizing the accuracy of the simplified network. Rao and Alvarruiz [64] captured the domain knowledge of hydraulic simulation model using ANNs for predicting the consequences of different control settings on the performance of the WDS. Broad et al. [13] presented a systematic methodology using metamodels and ANNs. The purpose of the metamodels is not to approximate the entire simulation model, but to obtain a relationship among variables that contribute to the fitness (e.d. energy consumption).

Variable elimination is based on a mathematical formalism. Some of the system variables can be eliminated from the system of non-linear differential equations that represent the mathematical model. Martínez et al. [45] presented an extended version of [79], proposing an algorithm involving linearisation, Gaussian elimination and a reconstruction of a reduced non-linear model. Paluszczyszyn et al. [52] presented an implementation of the latter algorithm for integration of the model reduction module with an on-line optimization strategy.

3.4 Sampling design

Calibration accuracy should be judged both by the model's ability to reproduce data, and by a quantitative measure of the uncertainty in calibrated parameter values. This uncertainty depends on the sampling design, including the measurement type, number, location, frequency, and conditions existing at the time of sampling [15].

Reviewed literature defines the sampling design as the procedure to determine [36]: (1) what WDS model predicted variables (pressures, flows, both, etc.) to observe; (2) where in the WDS to observe them; (3) when to observe (in terms of duration and frequency); and (4) under what conditions to observe.

In general, a sampling design may have one of several purposes [43]: Ambient monitoring, detection, compliance, or research. Model calibration is considered research sampling,

where the objective is to identify accurately the physical parameters of the system. A sampling design, $\mathbf{x}$, is a set of specified measurements $\mathbf{y}$, at particular locations and times, along with the experimental conditions under which measurements are made [15].

Walski [81] proposed one of the first sampling designs by suggesting to: (1) Monitor pressure near the high demand locations; (2) conduct fire flow tests on the perimeter of the skeletal distribution system, away from water sources; (3) use as large as possible test flow at the fire hydrant; and (4) collect both head and flow measurements.

Ligget and Chen [42] impressed the importance of sensitivity in inverse problems for two primary reasons. First, the need for the measurements to be made at a location where they are sensitive to the desired calibration parameters. Second, the degree of confidence that one has in the result depends on the sensitivity.

Different approaches for solving the optimization problem have been developed. Usually, the main objective of finding the best locations for sensors is combined with other objectives (i.e. devices' cost). GAs, sensitivity matrix analysis or heuristic methods are some of the methodologies used.

Yu and Powell [89] formulated the meter placement problem as a multi-objective optimization by seeking the best solution in terms of estimation accuracy and metering cost. They developed a method employing dynamic analysis of the covariance matrix of state variables and the decision-trees technique.

Ferreri et al. [29] ranked the potential location of the sensors according to their overall relative sensitivity of nodal heads with respect to roughness coefficients. Bush and Uber [15] proposed three general sensitivity-based methods derived from the D-optimality criterion to rank the locations and types of measurements for estimating the roughness coefficients of a WDS model using pressure measurements, tracer concentration measurements and a combination of both. The authors outlined that the proposed methods, although suboptimal, may have some advantages over purely statistical methods that lack a physical basis. Del Giudice and Cristo [24] compared these three sensitivity-based methods for selecting the worthwhile pressure and flow sensors location in water distribution network for calibrating roughness coefficients. Ahmed et al. [1] developed a sensitivity-based heuristic method (also derived from the D-optimality criterion), to study the uncertainty caused by measurement and estimation errors in water distribution networks.

Piller et al. [58] formulated the SD as an optimization problem which minimizes the influence of measurement errors in the state vector estimation subject to the constraint that the Jacobian matrix is of maximum rank. A greedy algorithm was used, which selected at each iteration the optimal location of the sensors.

Some of the mentioned approaches used an iterative selection of the sensors, adding at each iteration one sensor to the set of already located ones. However, Kapelan et al. [36] demonstrated that the optimal set of locations for n monitoring points is not always a superset of the optimal set for $n-1$ monitoring points.

Meier and Barkdoll [46] introduced genetic algorithms in sampling design to find the combination of fire-flow test locations that, when analysed collectively, stresses the greatest percentage of the hydraulic network, so the roughness parameters of grouped pipes can be calibrated. Lansey et al. [41] developed a sensitivity-based heuristic sampling design procedure for WDS model calibration to identify preferable conditions for data collection, accounting for uncertainty in measurements and its impact on both model parameters and predictions.

De Shaetzen et al. [23] proposed three sampling design approaches. The first two were based on the shortest path algorithm, and set sensors' locations depending on the distance between the source and the set of potential sensors nodes. The third approach solved the optimization problem based on maximization of Shannon's entropy, locating sensors in the nodes with highest pressure sensitivity on roughness changes. The sampling design cost was also taken into account.

Kapelan et al. [36] [37] presented a multi-objective sensitivity-based method for sampling design where both uncertainty and SD cost objectives where minimized. Model accuracy was maximized and formulated as the D-optimal criterion, the A-optimal criterion and the V-optimal criterion. SOGA/MOGA (Single/Multi Objective Genetic Algorithms) were used and compared, leading to the conclusion that the advantages in MOGA outweigh its disadvantages. The Jacobian matrix used was calculated prior to the optimization model run by assuming the model parameter values. Opposed to this deterministic approach, Behzadian et al. [9] tried to overcome this latter assumption by introducing parameter uncertainty using some pre-defined probability density function. Results in studied cases [35] [37] assessed that the calibration accuracy based on prediction uncertainty (V-optimality) is preferred over parameter uncertainty (D-optimal and A-optimal criteria). Similarly, D-optimality is preferred over A-optimality.

Recently, Kang and Lansey [34] posed the sampling design as a multiobjective optimization problem where the objective functions represented demand estimation uncertainty, pressure prediction uncertainty and demand estimation accuracy. The optimization problem was solved using MOGA based on Pareto-optimal solutions.

Not all sampling design approaches are addressed to parameter calibration. Pérez et al. [55] proposed a sampling design based on a leakage detection methodology. One sensor was located at each iteration of the procedure with the objective of minimizing the maximum number of nodes with the same binary signature (which cannot be isolated separately).

3.5 Identifiability

The inverse problem is often ill-posed. The ill-posedness is generally characterized by the non-uniqueness of the identified parameters. The uniqueness problem in parameter estimation is intimately related to identifiability [88].

Observability and identifiability terms are sometimes confound. System observability determines if the state of a system i.e. the system variables (head, flow) can be estimated. On the other hand, system identifiability resolves if the parameters of the system (consumptions, roughness's coefficients) can be calibrated. In conclusion, observability refers to system state (dynamic variables) while identifiability refers to system parameters (assumed constant in a certain time horizon).

An important contribution to the solution of the observability problem was made by Krumpholz et al. [38] who formulated necessary and sufficient conditions for observability in power-system state estimation in terms of meter location and network topology. According to their analysis a network is observable if and only if it contains a spanning tree of full rank. Bargiela [7] formulated the same problem for water systems.

Pérez [53] classified the identifiability as static and dynamic. Carpentier and Cohen [16] performed the study of identifiability for the static problem using graph analysis based on Ozawa [51]. The idea is that some operations in graphs are equivalent to operation on equations.

Conditions of identifiability for non-linear dynamic systems can be found in the literature. Walter and Pronzato [85] used the state space formulation by means of the dynamic information of the system. For the linear case, the invertiability of the matrix of the equations set was studied by Sorenson [76].

The complexity of the transient equations in dynamic identifiability makes their use difficult for real networks. The extended period identifiability is based on quasi-static equations, which allows to use simpler equations related from one time step to the next one by reservoir equations. Pérez [53] studied the extended period identifiability based on the sensitivity matrix rank in both linear and non-linear cases. The author stated that if many measurements are taken in the same conditions they will not add any information (not increase the rank of the sensitivity matrix) but could be useful for filtering the noise in the measurements.

3.6 Uncertainty

In the calibration of water distribution systems, inaccuracy of the input data causes the results to be inaccurate too. Therefore, it is important to give not only the estimated values of the calibration, but also an indication of how reliable these estimations are. Generally, sampling design, identifiability and other design and modelling processes involve the use of a calibration technique. In this section a review of how researchers treat the uncertainty in their approaches' results is presented.

Bargiela and Hainsworth [8] presented and compared three methods for confidence limit analysis:

- Monte Carlo simulation: Uncertainty in model predictions is calculated by a series of simulations where the input parameter's vector has random variations.

- Optimization-based approach: The confidence limits of the estimated values are calculated by means of an optimization problem with the linearised network equations as constraints.
- Sensitivity-based method: Analysis of the sensitivity matrix generated from the linearised network equations.

The authors select the latter approach as the better one due to the improvement on the computational requirements keeping similar results as the other methods.

However, most of the reviewed bibliography [88] [21] [65] [15] [1] [58] [41] [44] [36] [37] [9] [33] perform the quantification of the parameter and prediction uncertainties based on linear regression theory, a method known in the literature as the FOSM model (First-Order Second-Moment) [6]. A first-order approximation of the parameter covariance matrix $Cov(\theta)$ is defined as

$$Cov(\theta) = \sigma^2 \cdot J \cdot J^T \tag{1}$$

where σ^2 is the variance in measured parameters, and J is the matrix of the sensitivities of the measures relative to the estimated parameters θ, which can be estimated analytically or by a numerical approximation as used in [1]. Uncertainty in the parameter values is indicated by parameter variances in the ith diagonal element of the covariance matrix.

The prediction covariance matrix $Cov(P)$ can be also estimated to obtain the variance of the model prediction:

$$Cov(P) = J_P^T \cdot Cov(\theta) \cdot J_p \tag{2}$$

where J_P is the matrix of the sensitivities of the predicted values relative to the estimated parameters θ.

The uncertainty of an estimation as a whole (not separated individually) is evaluated using the trace, the determinant or the maximum singular value of the covariance matrices.

3.7 Fault detection and isolation

The evolution of demands that will be estimated on-line may hide leakages and non accounted for water [28]. There are methodologies based on models [61] [40] [35] [62] [56] [63] [80] that together with other methodologies (like acoustic methods [30] search) improve the performance of the networks, detecting and isolating the leakages.

The prediction of demands in a network based on models [17] may be useful for detecting tendencies that together with prognosis methodologies allow to distinguish among these two scenarios. Our research group has a long experience in leakage localisation that has lead to the need of a good calibration of demands [54]. In this thesis the need of detecting leakages when demand calibration is carried on will be taken into account.

4 Preliminary results

Some previous work related with water distribution systems has been done by the doctoral candidate during the participation in the research group's projects. Studies on leakage detection and isolation methodologies [48] [57] [71] are one of the main research topics of the group. The methodologies' results depend on the water distribution network model reliability. A study of the effect of demand calibration on leakage detection was performed [54] to assess this dependency. This study led to the conclusion that demands are one of the major sources of uncertainty in water distribution network models. That fact encouraged the doctoral candidate in studying the calibration of demands.

A master's thesis [70] based on demand pattern calibration was presented. In this work the calibration problem of estimating the nodal demands of a huge network was solved by adding some *a priori* information. The patterns of behaviour of the nodal demands were calibrated assuming that the type of contract of each node was known. A conference article with the master's thesis results has been submitted for the CCWI'13 conference. No uncertainty studies were performed because only synthetic data was used. Some problems with null head losses were ignored, but skeletonization of the network as a precalibration process was suggested. The sampling design was supposed to be known, but better results can be achieved if a sampling design methodology is developed, and additional identifiability studies are performed.

Furthermore, real data from two water companies are available. These real data have already been used for the application of a leakage isolation methodology in a real case. A journal article with the results of this real case will be submitted during this year. The data will be used for the verification of the thesis results.

Additionally, an open-source water simulation software is being developed. An application for pressure control [72] on water distribution systems is already available[2].

[2] `http://sac.upc.edu/training-benchmarks/simulador-de-xarxes-de-distribucio-daigues`

5 Working plan

Development of the thesis will be divided in 8 tasks, as seen in table 1:

- Task 1: State of the art study and thesis proposal writing.
- Task 2: Identifiability study and development of sensor distribution methodology. From the existing studies, generate a formulation for the particular case of demand calibration.
- Task 3: Numerical conditioning of the problem and simplification of networks. Formulate conditions of well-posed problems. First results suggest that simplification of network will be required.
- Task 4: Calibration methodology development and optimization solvers comparison. Starting from least squares methods used in preliminary results, develop a calibration methodology that guarantees convergence.
- Task 5: Study of the evolution of demands versus leakages for on-line decision support system.
- Task 6: Software development and case study applications.
- Task 7: Stage in other research centre (unknown date).
- Task 8: Thesis writing.

An estimation of the publications produced are listed with the timing on table 1:

1. Preliminary results in demand calibration.
2. Leakage isolation methodology.
3. Identifiability of the system and sampling design.
4. Network reduction for numerical conditioning.
5. Calibration methodology.
6. Software and case studies.

The research is supported by the Polytechnic University of Catalonia through the FPI-UPC grant. No extra resources apart from the access to bibliography and software programming tools are required.

Tasks	2012		2013				2014				2015		
Task 1			1,2										
Task 2					3								
Task 3					4								
Task 4								5					
Task 5													
Task 6											6		
Task 8													

Table 1: Working plan

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