Real-Time Dynamic Hydraulic Model of Water Distribution Networks

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Abstract: The impact of climate change and increasing urbanisation throughout the world has forced water utility managers to increase the efficiency of water resources. Reduction of real (or physical) water losses plays a crucial role in improving the efficiency of water supply systems. Considering these challenges, it will not be enough to rely only on traditional approaches to solve the problem of water losses. Therefore, more advanced techniques need to be developed and utilized. Recently, a framework for a real-time dynamic hydraulic model for potable water loss reduction was proposed. This paper focuses mainly on the three major components of the proposed real-time dynamic hydraulic model framework for potable water loss reduction, which have been developed recently. These are background leakage detection, pressure management, and water demand forecasting. A background leakage detection algorithm was proposed which, amongst others, permits the localisation of potential critical nodes or pipes with higher leakage flow in the network where such pressure management could be performed. More so, new controllers (algorithms) which perform pressure management by accurately setting the pressure, using either a pressure control valve or variable speed pump, have been constructed. In addition, background leakage flow is greatly affected by demand variations, a water demand forecasting model is constructed with the aim of annexing the demand variation for multi-period leakage analysis. Thus, a short-term water demand forecast utilising the Model Conditional Processor was constructed to forecast the following hour demand and the associated predictive uncertainty. Although each of these components have been tested independently, future work is ongoing for merging these components and integration within the dynamic hydraulic model framework.

Keywords: hydraulic model; pressure management; leakage detection; demand forecasting; water distribution network; water loss

1. Introduction

Climate change in countries like South Africa is predicted to mostly lead to a dryer climate. The primary effect of climate change is the disruption of the water cycle. Much of the impact of climate change is felt through the changing pattern of water availability. Thus, increased efficiency (saving water) of water resources can be obtained through water loss reduction approaches. Due to limited new water resources availability, this will mitigate the adverse effects of climate change on water

resources, thus, reducing the climate change vulnerability [1,2]. Another factor that drives the need for increased efficiency of water resources (especially for a water distribution network (WDN)) is the increasing urbanisation throughout the world [3]. This is because urban areas require extensive WDN infrastructure.

A critical part of saving water is to minimise the (real) water loss volumes due to existing infrastructure inefficiency. The maintenance and refurbishment of water infrastructure [4] are the costly first line of defence and should receive the highest priority from the government. The second line of defence is pressure management (PM). This is less costly; and has been demonstrated in the scientific literature to consistently reduce water leakage from pipes [5–7], reduce pipe burst frequency (hence ensuring less maintenance and refurbishing of the infrastructure) and possibly reduce water consumption (important in South Africa due to the high incidence of non-revenue water (NRW) use) [8]. Hence PM does not only save water, but also helps to solve socially related maintenance [9,10] and NRW usage problems. This could be achieved using the hydraulic models of WDNs.

A WDN hydraulic modelling is worthwhile in diagnosing network operation conditions. Unfortunately, most of the existing hydraulic models, which are primarily used for planning and water quality purposes represent the zero-inertia unsteady state by means of a succession of steady-states [11–14]. The steady-state nature of such a models limits their reliability and efficiency when WDNs is under partially failed conditions. This is because they do not enable the automatic adjustment of actuators which can enhance the performance of the WDN [15]. An example of such an actuator is a variable speed pump (VSP), pressure control valve (PCV), such as a pressure reducing valve (PRV), or a flow valve. Therefore, future WDN models should consider unsteady state conditions, such as the ones described in [14] in real-time applications in order to ensure that the implementation of measurement and logging technologies are used to provide higher credibility and simplify the modelling process [16]. To this end, Abu-Mahfouz et al. [15] proposed a framework for a real-time dynamic hydraulic model. Most pertinently, for reducing water losses, three major components of the dynamic hydraulic model framework are discussed in which recent research progress has been made: background leakage detection, pressure management and water demand forecasting. The background leakage detection involves the development of an algorithm for the selection of critical pipes and the nodes where such pipes are located in the network for possible pressure control in order to achieve water loss reduction. The pressure management (PM) entails the control of the excessive pressure at the nodes or critical pipes selected by the algorithm through the use of remote real-time control (RRTC). The water demand-forecasting [17] is also an important part that provides valuable information to the water distribution system operators for adjusting the water production, controlling the pumps, valves, and for leakage analysis and control. As water demand varies during the hours of the day, the base demand at each junction node of a WDN also varies, thus, affecting the background leakage flows across the node and pipe. The inclusion of this effect in the water distribution network modelling is important for a good leakage analysis and proper pressure management for water loss reduction. To this end, an appropriate demand-forecasting model is required in the dynamic hydraulic model framework with the aim of analyzing leakage flow for future demand variations in the WDNs. This is to facilitate planning and schedule maintenance of the system and appropriate pressure management in areas of high-water losses in the system. Therefore, this work aims to focus on developing a holistic system that addresses the issues of water loss through leakage detection, pressure management and demand forecasting at time-steps of 1 h, which are relatively small but sufficiently large to avoid interference due to the unsteady effects of home demands. Thus, the complete system is in progress.

The leakage reduction, pressure management and demand forecasting are part of the dynamic hydraulic model framework and are to work as a single entity or integrated to achieve a reduced water loss level in the system. Nevertheless, in this paper, the analysis and the application of these three components are first discussed independently and the results are presented, future work is ongoing for the merging of these components and integration in the dynamic hydraulic model framework. Therefore, the work is going to be expanded beyond this paper. These components are briefly introduced below.

1.1. Pressure Management

With the real-time monitoring of a pressure sensor becoming a possibility, advanced PM techniques which use this information can be considered. The cheaper option is to locate the pressure sensor adjacent to the actuator. However, the ability to keep the pressure constant where the consumer is located can only be attained when the pressure sensor is located at a remote node. This remote real-time control (RRTC) [18] is the PM technique studied. The goal of the RRTC is to attempt to keep the pressure constant at certain remote locations, by adjusting the setting of actuators in real-time [13,18,19]. The algorithm which calculates how the actuator settings should be adjusted is referred to as a controller. The development of the module to implement the controller and perform PM is highlighted. Research on a new PCV controller extending the work of [13,18,19] is described. Building on the PCV research, the development of new VSP controllers is discussed. Factors that determine the performance of some of the PCV controllers are also described.

1.2. Background Leakage Detection

Water losses occur in virtually all WDNs, although the volume of water loss varies from a particular WDN to another. Recently, the financial cost and environmental pollution caused by leaking pipes have been on the high side and have been a driving factor for the industrial need of efficient algorithms for water loss detection [20]. To address this problem, several methodologies for predicting leakage in water networks have been proposed [21–24]. Due to the complexity and disperse nature of water networks, with numerous nodes and pipes, localising the node(s) in WDNs and the exact leaking pipes connected to the node(s) where higher leakage flow occurs, is a strenuous task. Background leakage is pressure dependent, thus, controlling the excess pressure at some tactical nodes in the network is worthwhile in reducing the water losses. In this paper, an algorithm for detecting and localising critical pipes having higher diffuse leakage flow in WDNs is briefly discussed. The algorithm incorporates a pressure dependent background leakage model into a WDN hydraulic model for appraising the network leakage flow. The proposed algorithm has been tested and could be useful for water utilities to verify areas in the WDN where pressure management, discussed in the previous section, would be useful and indicate the potential pipes and nodes that could to be refurbished. The applicability of the proposed algorithm is demonstrated on a WDN and the results obtained are discussed herein.

1.3. Demand Forecasting

The pattern of water consumption varies during the day and week due to numerous factors. Thus, selecting an appropriate water demand forecast is required to continuously satisfy consumers with quality water in adequate volumes and at reasonable pressure [25,26]. In this case, a short-term water demand (STWD) forecast is researched. To solve water utility operational decision problems, several forecasting STWD models have been discussed in the scientific literature. A hybrid forecast, which is obtained from the combination of two or more deterministic models, can be considered as a promising STWD forecasting approach. Nonetheless, it is insufficient for the kind of operational planning decisions that water utilities make when future demand is uncertain [25–27]. To ensure reliable and robust decisions, the model conditional processor (MCP), originally proposed by [27], is utilised in this paper to generate a full predictive probability density instead of a single valued forecast. The MCP is a Bayesian method (i.e., uncertainty post-processor) used to estimate the predictive uncertainty, which is conditional on a set of predictions by one or more deterministic forecasting models. The MCP is selected based on the recent applications that have proven its validity and robustness [26–29].

2. Materials and Methods

2.1. System Architecture

Abu-Mahfouz et al. [15] proposed a framework for a real-time dynamic hydraulic model. The system consists of three major components; smart water network, active network management and real-time dynamic hydraulic model. The focus of this paper will be on the last component.

2.1.1. Smart Water Network

Several techniques and systems that can be further developed to address the problem of water loss are available. For example, leakage detection algorithms, smart PM and dynamic hydraulic models. However, to operate efficiently, these systems require an efficient network that enables the real-time monitoring and control mechanism. Internet of Things (IoT), wireless sensor networks (WSN) and other enabling technologies can be utilised to build the required smart networks to enable the real-time monitoring and control mechanism for these systems. Therefore, a low-cost general interface platform, called WaterGrid-Sense, has been developed. This enables the real-time monitoring and controlling of several types of WDN components such as water meters, pressure sensors, flow valves, pumps and PCVs.

2.1.2. Active Network Management

The required smart water network is dynamic and consists of large number of heterogeneous, resource constrained and application dependent sensors/actuators. Therefore, configuring and managing these networks is considered a challenging task. This motivates the need to develop a heterogeneous WSN management framework that will be used to manage the various aspects of the deployed smart water network. For example, monitoring, controlling, reconfiguring the network components, and ensuring the security and efficient operation of the network.

2.1.3. Real-time Dynamic Hydraulic Model

As discussed earlier, most off-line hydraulic models are steady-state in nature which may limit the reliability and efficiency of water networks. In these models, thousands of unknown parameters are approximated using a short-term sample of a sub-set of hydraulic data. Thus, the calibration results may not accurately represent the system conditions for the full range of operational conditions that can occur. A real-time dynamic hydraulic model that continuously considers the on-line hydraulic measurements will provide more realistic predictions. The dynamic model will use real-time sensed data to evaluate the current conditions of the network and automatically send control signals to various network components. This would adjust the network performance and make it more efficient [15].

The envisaged real-time dynamic hydraulic model consists of several components and techniques, which include; online data synchronisation and integration, data imputation, demand forecasting, PM and a leakage detection algorithm. We refer the readers to [15], for more details about these components. In the rest of the paper, we will focus mainly on three main components, as shown in Figure 1, PM, background leakage detection and the short-term demand forecasting.
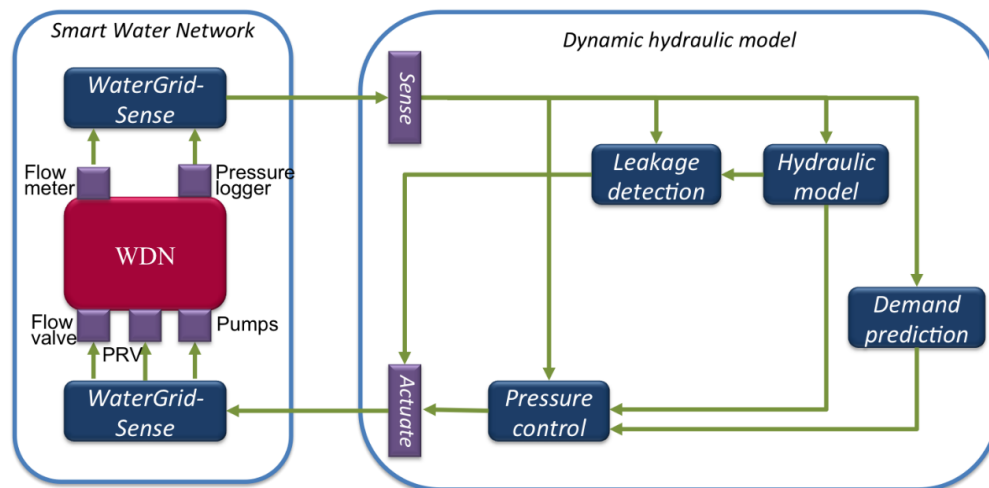
Figure 1. System architecture.

2.2. Pressure Management

The RRTC is usually attained by using an electronic programmable logic unit to implement the controller, inputting the pressure readings (Figure 1) at the remote node. The "pressure control" module (Figure 1) not only implements the controller but adds several additional features.

An inherent feature of a controller is that it uses currently known information about the WDN (at time t), to change the actuator setting (at time t), which will then be in effect from time t to t + T_c in the future. Here T_c is known as the "time-step" (typically of the order of minutes). In principle, information after time t should also be used to determine the actuator setting at time t. The "demand prediction" module (Figure 1) can predict future consumer water consumption. Used in conjunction with the "hydraulic model" module (Figure 1) which inputs consumer water consumption, the "pressure control" module is envisaged to be able to model the state of the WDN after the actuator setting is changed at time t. If the WDN is not subjected to changes that might cause harm to it, and the expected performance of the WDN is acceptable, the actuators are adjusted according to a control signal sent to them (Figure 1). Otherwise the changed settings should be modified. This process will be repeated until it reaches an optimal level.

Detailed results will be reported later for hydraulic model RRTC studies using the "pressure control" module. For these results, this module is used in isolation from the "demand prediction" module, which has been left as future work. For the "pressure control" module a computer program has been written which can perform RRTC in a hydraulic model of the WDN, by incorporating the engineering complexities of the actuators (adjusting the setting of a PRV or the speed of a VSP). A WDN with either one controlled PRV or one controlled VSP, and various controllers, can be considered.

The program was constructed in C++ programming language. It interacts with the hydraulic extended-period solver EPANET2 [18], via the EPANET2 programmer's toolkit, so that the controller can be simulated on a hydraulic model of a WDN. EPANET2 is by far the most used software in the WDN field; and has a public domain licence. In addition, EPANET2 has been a stable software since the year 2000 [30]. The program can read in any hydraulic model of a WDN specified by an industry standard EPANET2-formatted input file. As a consequence, the controller can be simulated on hydraulic models generated by many commercially available software packages, because these packages often support EPANET2-formatted input files.

The time-variation of the water demand factor and reservoir levels of the WDN are read at intervals T_c from an additional input file. Standard output files are currently: the time-dependent actuator setting, the time-dependent remote node pressure, as well as four files which provide detailed output related to the hydraulic solver, debugging, errors and checks on the correctness of the input file. The program is currently run from the command line.

2.3. Background Leakage Detection

The steps involved in the leakage detection algorithm is briefly described in the Algorithm 1 (Table 1). The algorithm incorporates a pressure-dependent background leakage model into a WDN hydraulic model to estimate the network flow, including leakage outflow at each node as well as at the pipe level. The allocation of the leakage flow is such that half of the total leakage flow from the pipe is lumped at each of its end nodes. Its mathematical formulations involving the solution of water distribution network hydraulic model and pressured dependent background leakage model is presented in [31]. As may be observed, the process involves the hydraulic analysis and the leakage computation. This is achieved by modelling the water network topology and solving the resulting model using a Newton-Raphson based methodology. When this analysis is being performed based on the supplied water network data, the leakage outflow (node and pipe level) and its threshold are estimated. This threshold is computed as the mean of the leakage flow in the pipes. The algorithm checks if the estimated background leakage flow in each pipe is relatively high (higher above the pre-defined threshold). Such a pipe is tagged as critical pipe; the algorithm then recommends that PM [23,24] could be performed in nodes of the network where the critical pipes are located. Alternatively, by selecting the critical pipes and the nodes where they are located, a pressure management zone may be created using this information where the pressure at the inlet of such zones checks for water loss reduction.

Thus, in most cases, any pipe in the network with a relatively high background leakage flow above a predefined tolerance is tagged as a critical pipe. Thus, areas of the network where such pipes are located need attention from utilities and must be verified to reduce water loss volume.

Table 1. Proposed leakage detection algorithm.

Algorithm 1. The Leakage Detection Algorithm
1: Start {
2: Load network parameters
3: Read network parameters and initialise
4: for node i = 1 to n_t, *(n_t: the number of nodes in the network)*
5: for pipe j = 1 to b, (b: the number of pipes in the network)
Run hydraulic analysis and compute leakage vector
Compute the background leakage threshold (tolerance)
if the pipe leakage vector < tolerance
Print "No leaking pipe"
else
Print "Leaking pipe"
Tag leaking pipe as critical pipe and report critical pipe ID
Display "PM recommended in areas where the critical pipe with ID. is located"
end if
6: end for j
7: end for i
8: Stop}

The details of the algorithm formulation encompassing the hydraulic and background leakage model for the system may be found in [31].

2.4. Demand Forecasting

As stated in Section 1.3, the MCP is an uncertainty post-processor that allows the combination of one or more forecasting models to produce a predictive probability density instead of a single valued forecast [27]. The MCP entails converting historical observations and the corresponding forecasted values into a normal space using the Normal Quantile Transform (NQT) in order to arrive analytically at an estimate of the joint distribution of the real and forecasted values and hence at a conditional

distribution of the real values given the forecasted ones [26–28]. However, in this paper, we are in the most favourable case since the conversion into and return from the Gaussian space and the problem of the tails fitting are not necessary. Thus in this paper, the observations and model forecasts generated by the autoregressive-moving average (ARMA) and feed-forward back propagation neural network (FFBP-NN) models are essentially Gaussian. In this paper, we demonstrate how to use the models' information to improve our knowledge on the future demand, in terms of variance of prediction errors, by building the probability density of the future demand conditional on the predictions generated by ARMA and FFBP-NN models through the MCP approach.

In this work, the predictive uncertainty is estimated based on a set of predictions by an autoregressive-moving average (ARMA) model and a feed-forward neural network (FFBP-NN) model [32]. The algorithm starts by selecting the training datasets that include subsets of the real observed values and subsets for the forecasted values of ARMA and FFBP-NN. Then the data-sets obtained are converted to the NQT space. The MCP prediction is estimated in the NQT space and reconverted in the real space. Predictive uncertainty in MCP could be evaluated by determining the possible variation around the forecasted values. Many values in the validation prediction sets are beyond the range of observation, and the predictions in the calibration set. Therefore, upper and lower tail models are developed to eliminate such values. For further details, we refer the reader to [32].

3. Results

3.1. Pressure Management

For both a PCV and VSP there are well-known relationships between the change of head over the device and the water flow rate in it, here referred to as "head-flow relationships". Controllers for a PCV which explicitly depend the head-flow relationship for its derivation were proposed and shown to often outperform a generic proportional controller which do not use the head-flow relationship for its derivation [13,18,19]. A new PCV controller which depends on the head-flow relationship for its derivation was very recently proposed [33]. This controller performs well when compared to the proportional controller. This was verified in a hydraulic model study using the program described above for two example WDNs studied, both of which have one controllable PRV. Four new VSP controllers, which are the first to depend on the head-flow relationship for their derivation, were constructed very recently [34]. Here a hydraulic model of an example WDN, with one controllable VSP, was studied. Most of the new controllers perform better than the proportional controller. Figure 2 shows that the consumer water consumption time-variation, and the time-variation in pump speed needed for RRTC, have a similar dependence in the WDN studied [34]. Here the nodal consumption is based on bulk measurements sampled at 1-h time steps, where the effect of the effect of pulses in the consumption disappears. If shorter time steps are needed, which is generally not the case in water distribution systems, this assumption should be removed to model the effect of pulses in the consumption, which are closer to the real operation of the network [35]. In fact, it has been argued in the latter case that a bottom-up approach with pulsed consumption is needed [36].

In contrast to the majority of controllers, most of the controllers which use the head-flow relationship for their derivation have the ability to respond to changing WDN conditions, for example, demand and reservoir level changes, through their dependence on the flow rate in the actuator. This enhances their ability perform well when WDN condition patterns change [19]. The drawback is that a flow meter must be present to measure the flow rate, or a hydraulic model must be able to estimate it. It was recently shown, for some of the PCV controllers, that this flow rate can be as uncertain to 15–20% without affecting the controlling ability [37]. This enhances the practical use and robustness of these controllers.

What are the factors that drive the deviation of pressure at the remote node from the constant set-point target pressure? It was found, to a reasonable approximation, that for some of the PCV controllers that depend on the head-flow relationship for their derivation, the deviation is proportional

to (a) the head-loss over the PCV, (b) T_c, and (c) the scale-independent rate of change of the flow rate in the PCV [37]. In fact, analytical formulae exhibit these factors, and enable a first attempt at predicting the deviation.
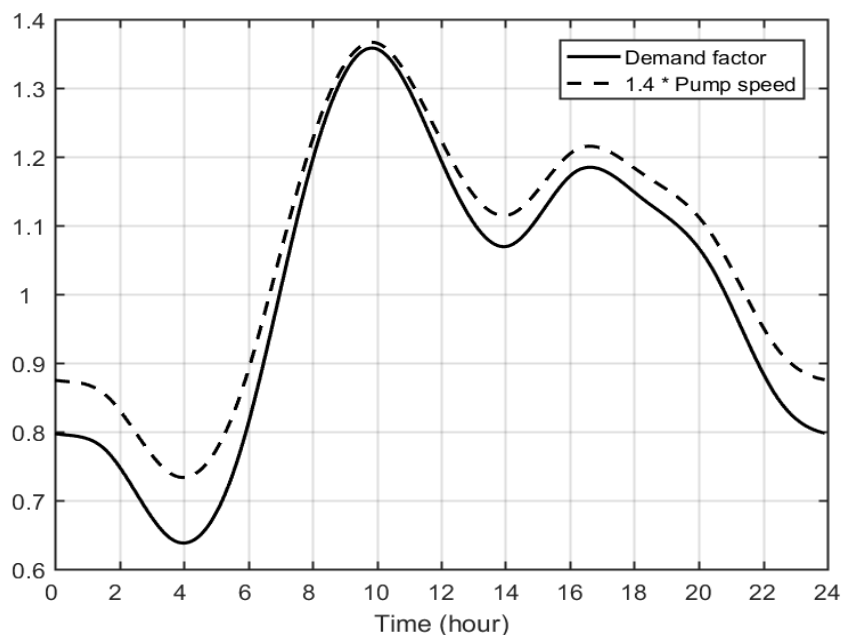

Figure 2. Demand factor (with daily average 1) over one day. Pump speed needed for PM over one day (scaled).

3.2. Background Leakage Detection

To test the applicability of the algorithm, the WDN shown in Figure 3a was used. The network consists of three reservoirs acting as the source or supply node (nodes 1, 69 and 70) and 67 demand nodes (nodes 2 to 68), interconnected by 108 pipes of varying lengths and diameters between 104 m to 2400 m and 150 mm to 600 mm respectively. Water is supplied by gravity from three elevated reservoirs (R1, R2 and R3) with a total head of 220 m. The base demand at the consumption nodes varies between 0 L/s to 30 L/s. Hazen-William's model is used for the head loss estimation. For the sake of simplicity, the same Hazen-Williams friction-loss coefficient of 120 was assumed for the pipes. Figure 3b relays the profile of the required flow and the leakage flow rate in each pipe. Pipes 83 and 84 have the highest background leakage flow while the least occurs in pipe 16. This is due to the fact that the pressure head at the end nodes of those pipes (node 39 and 64 for pipe 83) and (node 41 and 70 for pipe 84) is relatively high which increases the computed average pressure head in the pipes. This is also supported by the longer length exhibited by pipes 83 (2400 m) and 84 (2262 m) as against the 104 m for pipe 16. In addition, the leakage flow in pipes 23, 26, 28, 58, and 85 should also be monitored, as they are also relatively high.

In Figure 3c, the plot of the pipe leakage flow rate against the estimated background leakage threshold for the case study water supply network is presented. As may be observed, some of the pipes are characterized by relatively high background leakage flow (above the threshold) while some are with a lower leakage flow. The algorithm selects pipes 23, 26, 28, 58, 83, 84 and 85 whose background leakage flow is relatively higher and far above the threshold. These pipes are tagged as critical pipes for this network where PM is recommended. Alternatively, since the algorithm also specifies the nodes of the network where these pipes are attached, PM may be performed at these nodes.

The result presented in Figure 3d indicates the pipe(s) that has the biggest impact in terms of the water loss volume. As may be seen in Figure 3d, pipes 23, 26, 28, 58, 83, 84 and 85 experienced the highest water loss volume and may be considered as critical pipes. This is due to the relatively high-pressure head status at the end nodes of these pipes. While the leakage flow rate in the critical

pipes is relatively low compared to the required flow, those pipes still have more impact in terms of the water loss volume in the network. Therefore, PM in the areas surrounding these pipes will reduce the volume of water loss in the entire network.
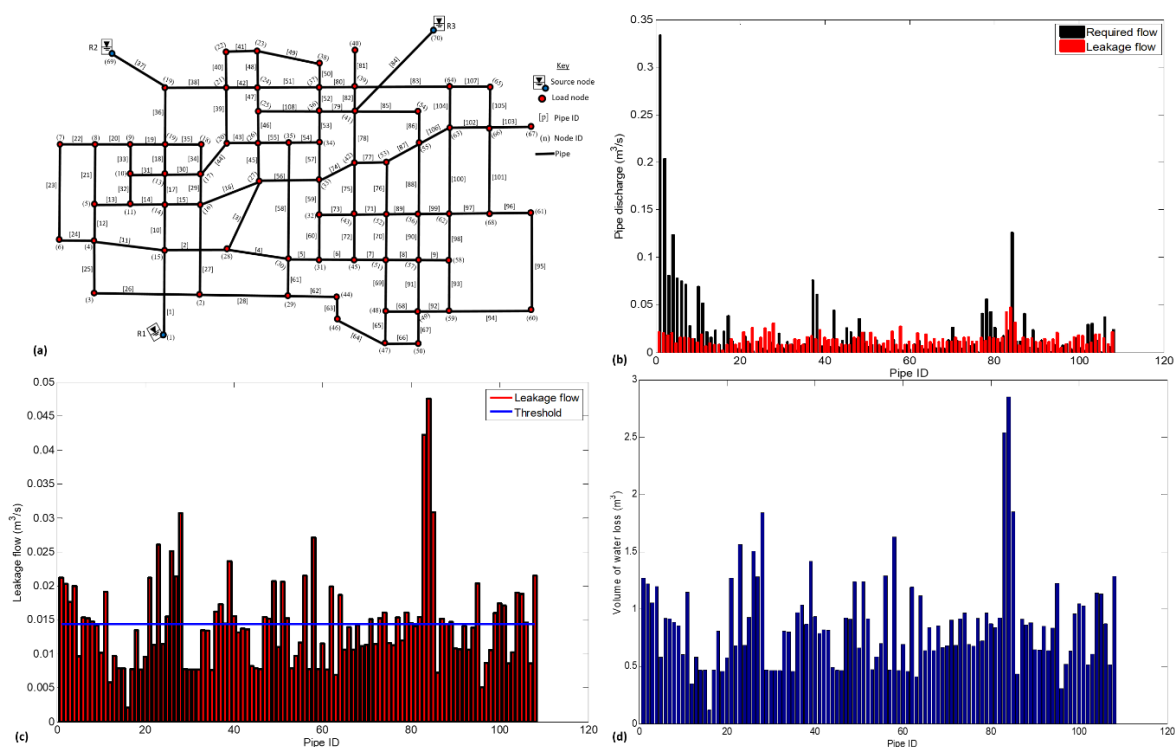

Figure 3. Results of the water network analysis: (**a**) The case study network; (**b**) Pipe discharge vs. pipe leakage flow; (**c**) The pipe leakage flow against the leakage threshold; (**d**) Volume of water loss in each pipe.

3.3. Demand Forecasting

This section tries to show that it is possible to predict the uncertainty connected to the forecast of future demand. To achieve this aim, the predictive performance of ARMA, FFBP-NN, hybrid model (combined forecast from ARMA and FFBP-NN) and MCP is assessed (see Figure 4a,b). This assessment is based on a 168 h (one week) long set of data sampled at hourly time steps estimated from observations by averaging eight weeks of observations. These averages were the only available data from a case study site located in a hydraulic zone in the small city of in south-eastern Spain, which has a population of approximately 5000 consumers. The number of data used for the calibration and validation sets are approximately 60% and 40% respectively, where the first 100 h are used for calibration. In addition, the MCP estimates the future expected value and its predictive uncertainty on the basis of the forecasts generated by ARMA and FFBP-NN (see Figure 4c). Lastly, to show that MCP accurately evaluates the expected utility value, the 5% probability acceptance limit plot is displayed (see Figure 4d).

Table 2 together with Figure 4a,b show that hybrid forecast outperformed those of ARMA, FFBP-NN and MCP, and this outcome supports what has been discussed in the scientific literature [25]. However, with such a best single valued forecast, reliable and robust decisions is not guaranteed [27]. Although Figure 4b shows that the predictive performance of MCP is slightly less compared with hybrid model, Figure 4c depicts that MCP generates the estimate of the full predictive probability density, which considers the expected utility function within a Bayesian Decision scheme [32]. Finally, the 5% probability acceptance limit plot shown in Figure 4d indicates that MCP can be reliably used to estimate the expected utility values to be maximised within a Bayesian Decision scheme [27,32].
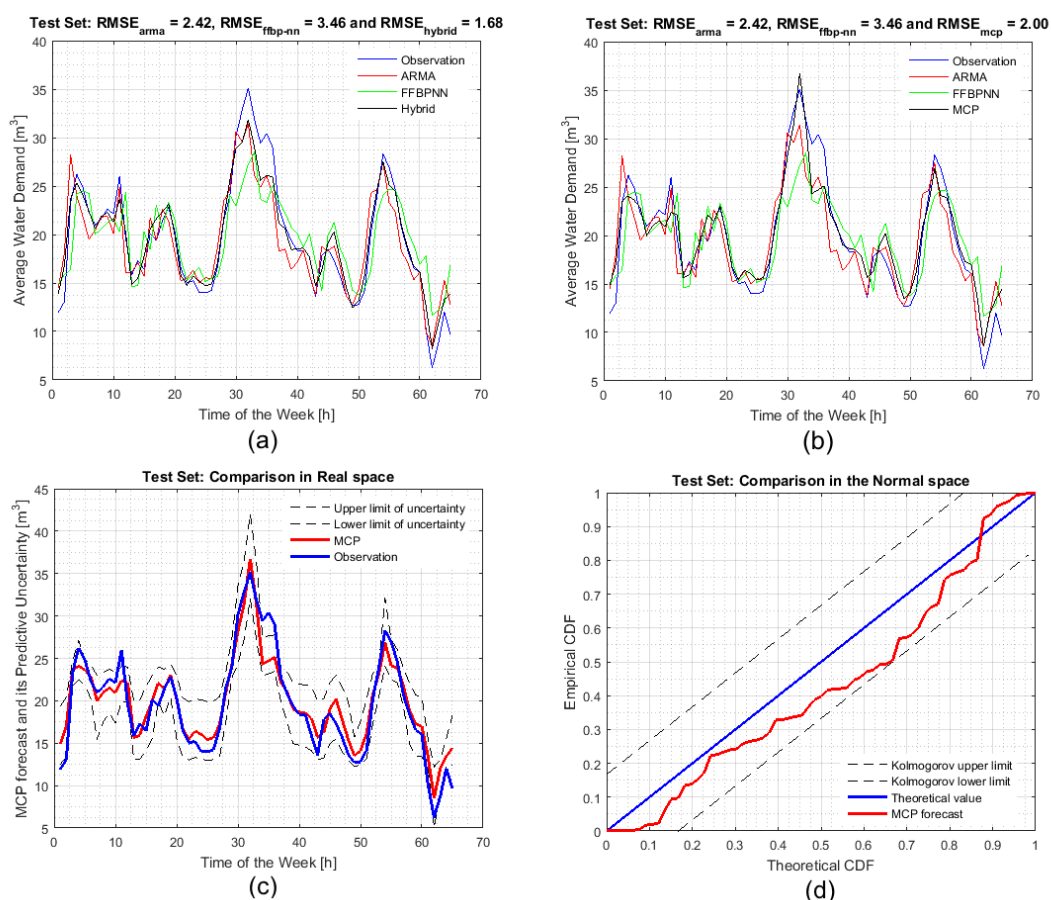
Figure 4. Outcomes of test dataset: (**a**,**b**) forecasting performance of autoregressive-moving average (ARMA), feed-forward neural network (FFBP-NN), hybrid model and the model conditional processor (MCP). In addition, (**c**) MCP forecast and estimation of its uncertainty and (**d**) 5% probability acceptance limit plot.

Table 2. Predictive performance assessment using forecasting statistical terms.

Forecasting Performance	RMSE	MAPE (%)	NS Efficiency
ARMA	2.42	10.3	0.84
FFBP-NN	3.46	15.7	0.68
Hybrid	1.68	7.36	0.93
MCP	2.00	9.29	0.89

4. Conclusions

The real-time dynamic hydraulic model is an effective way to mitigate the problem of water losses and improve the efficiency of water distribution network (WDN). The proposed framework [15] utilised various advanced systems, methods, and techniques to develop a real-time dynamic hydraulic model for potable water loss reduction. This paper focuses on three main components of the proposed framework which are: pressure management (PM), background leakage detection and demand forecasting. Although each of these components has been tested independently, an integration within the dynamic hydraulic model would improve the functionality of water supply systems. Thus, this work is still in progress and is going to be expanded beyond this paper.

New controllers which perform PM by accurately setting the pressure, using either a pressure control valve (PCV) or variable speed pump, have been constructed. The factors which determine the how well the pressure is set have been determined for some PCV controllers. This progress will improve the choice of efficacious controllers available for use in real-world real-time remote-control

applications, which will require the pressure to be set as accurately as possible. Although PM is economically feasible on its own for various scenarios [38], and integration of PM within a dynamic hydraulic model would be more expensive, the model offers additional functionality.

The proposed background leakage detection algorithm incorporates a leakage model into a WDN hydraulic model which allows the estimation of the background leakage outflow at the node and pipe level. The simulation results can be considered as evidence that the developed algorithm permits the detection of critical pipes in the network with higher leakage flow. The algorithm may be used by water utilities to assess the state of WDNs for PM and other related purposes, to address water loss reduction.

The model conditional processor (MCP) was utilised to generate a full predictive probability density instead of a single valued forecast to ensure reliable and robust decisions. The results confirm that MCP may expeditiously be utilised for real-time short-term water demand forecasting since MCP reveals the predictive uncertainty connected to its forecast, and such information could help water utilities evaluate the risk connected to a decision.

Author Contributions: All the authors have equally contributed to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

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