# Design of a Workflow Optimization System for Urban Water Utility Maintenance

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***Abstract*—The Water Distribution System (WDS) in the District of Columbia is one of the most complex in the world, spanning 1,440 dense urban miles. Providing water to 700,000 residents and 16.6 million annual visitors, the system consists of approximately 40,000 valves, 9,500 fire hydrants and 130,000 service connections. Originally developed in the 1800s, the median age of pipe in the WDS has reached 78 years. Ruptures in water main pipes carrying over 200 psi of pressure can buckle roadways, flood streets and cause widespread service disruptions. In winter months, this can create icy conditions which are extremely hazardous. The District's water utility reports approximately 500 water main breaks per year. Since the implementation of a priority system designed to expedite processing of high-impact emergency failures, the utility's operational data has identified high response times for incidents classified as low priority. The average is approximately 84 days, nearly six times higher than emergency incidents. The scheduling phase of the workflow is responsible for 98 percent of the total delay, indicating the need for a streamlined scheduling methodology. Emergency incident volume increases twofold in winter months, with sporadic failures caused by temperature fluctuations. This has forced the utility to increase reliance on contracted crews by 20 percent, and indicated an urgent need for weather-dependent failure forecasting tools.**

**A queueing model of the utility's workflow was used to derive standard scheduling protocols for groups of low priority incident types. Results indicate that achieving performance goals is feasible without additional resources. Recommended workflow configurations and operational improvements reduced the low priority response time to 12.4 days. Additionally, an Artificial Neural Network (ANN) was trained and deployed to generate main break forecasts for scheduling purposes. Validation tests using the utility's observed main breaks reported $R^2$ = 0.88 and $R^2$ = 0.86 for the weekly and daily models, respectively. The prediction model is coupled to the workflow to predict surges in failure volumes and allow for a proactive workflow response.**

***Keywords*— *Water Distribution System; Failure Prediction; Workflow Optimization; Main Breaks; Water Utility; Priority System; Artificial Neural Network.***

## INTRODUCTION

The water utility that serves our nation's capital is DC Water. Its multijurisdictional service area spans across three states: District of Columbia, Maryland, and Virginia. In Maryland and Virginia, the organization treats wastewater that flows from the Potomac River into the District. Its Distribution and Maintenance Branch (DMB) is tasked with maintaining the District's vast and complex water distribution system. It does so by reactively responding to reported failures, resolving customer concerns and undertaking infrastructure renewal projects. Performing large-scale repairs in a dense urban environment carries inherent challenges. To minimize property damage, environmental impact and customer inconvenience, the DMB uses a priority system with five levels with priority five being the most urgent and priority one the least. Freezing temperatures in winter months add a dynamic element to the priority system. Minor water leaks initially classified as low priority can escalate, causing dangerous icy conditions.

## I. CONTEXT

The DMB is responsible for repairing various WDS asset types which includes water mains, water meters, property service lines, service valves, manholes, and hydrants. Among priority four and five incidents, water main incidents are single-handedly responsible for 47 percent of the annual failure volume. Meters and service lines form the largest block of lower priority incidents with 44 percent and 21 percent compositions, respectively.

DMB's internal requirements state that priority five incidents shall be responded to within 24 hours while priority four incidents may be held up to 48 hours. Incidents classified as priority one through three must be assessed within 15 days [1]. Low priority incidents experience the largest performance gap according to operational data provided by the utility. Response times for these incidents in the 2014 to 2016 period are lognormally distributed with a sample mean of 83.9 days. The distribution fit is shown in figure 1.

A significant performance gap exists between the target mean from DMB's performance goals and the sample mean derived from its operational data. Improving low priority workflow efficiency is therefore the utility's primary concern.

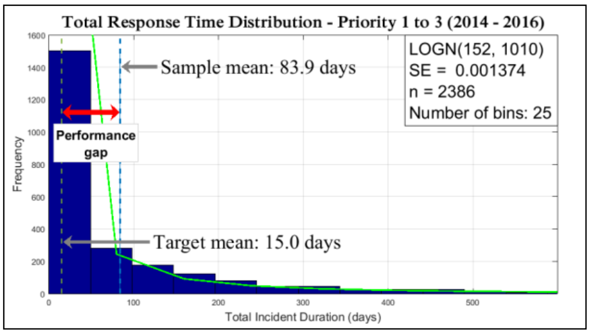


**Figure 1 - Low priority performance gap**

The response workflow for low priority incidents is fundamentally different from their high priority counterparts. Additional measures are taken to minimize inconvenience and cost as it relates to all stakeholders. For example, before initiating a water main repair the DMB must request a designated crew from the Distribution and Control Branch

(DCB) to close the required valves and isolate the circuit. This requires a minimum 48 hour notice to all affected customers. The utility is not required to provide notice when addressing emergency failures.

Low priority work orders are therefore scheduled cautiously with process dependencies taken into account. Due to the multiple coordination processes involved, work orders can stay open for weeks at a time. The utility seeks to reduce the backlog of work orders that have been open for over 60 days by 90 percent in the fiscal year 2015. It also seeks to maximize the use of in-house repair crews. DMB staff consists of one general foreman, three crew foremen, and eight repair crews. Currently, its annual reliance on contractors remains at 20 percent. Contractors are primarily used during high volume seasons when in-house crews are unavailable.

## II. STAKEHOLDER ANALYSIS

Primary stakeholders involved are the DMB staff, DC Water, and the ratepayers. Under new leadership since 2010, DC Water has made a rebranding effort which involves a new name, logo and website. Among the efforts was a push to improve public image and provide greater value to customers [2].

Given this new posture, tensions exist between the organization's leadership and unionized staff. Process changes proposed as a result of this study must not undermine the interests of staff. They must take fairness of dispatch into account and provide suggestions which benefit both stakeholders.

Ratepayers in the District are also vital stakeholders that expect consistent, quality service from DMB and wish to minimize rate increases. High response times inconvenience ratepayers who want complaints resolved as soon as possible. In light of increasing utility bills as a result of infrastructure renewal projects, customers hold higher expectations with regard to service quality. DMB seeks to address this tension by reducing response times.

## III. PROBLEM AND NEED STATEMENTS

The cost of living in the District of Columbia is the highest in the country according to a 2014 report by the Bureau of Labor Statistics (BLS). The costs of essential utilities are among the highest in the nation [3]. Furthermore, DC Water has reported an annual increase of 13.7% in the cost of water service to D.C. residents and visitors in the fiscal year 2017. This has prompted the organization to prioritize minimization of service cost under the constraint of maintaining industry-wide quality standards [4].

The DMB aims to achieve the greater organization's objectives of cost reduction and quality compliance by way of optimizing day-to-day operations. To this end, the DMB has suggested several internal areas of improvement that directly impact cost and quality of service to ratepayers [5]. Suggestions were evaluated against the current performance of the branch using historical operational data and the following problems and needs were identified.

### A. *Problems*

Low priority incidents are subject to large delays (μ = 84 days, σ = 142 days) that reduce service quality and incur unnecessary costs by underutilizing staff.

Response times are increased due to unanticipated failure surges and the subsequent 20% reliance on contracted crews incurs unnecessary cost.

### B. *Needs*

There is a need to develop and standardize scheduling workflow for low priority work orders of various failure types.

There is an additional need to acquire a main break forecasting ability to dictate crew schedules in winter months.

## IV. METHOD OF ANALYSIS

Two systems were developed to address the needs mentioned in the previous section: a Workflow Optimization System (WOS) and a Failure Prediction System (FPS). Inputs and outputs to each model can be seen in figure 2 and the following sections describe each system in detail.

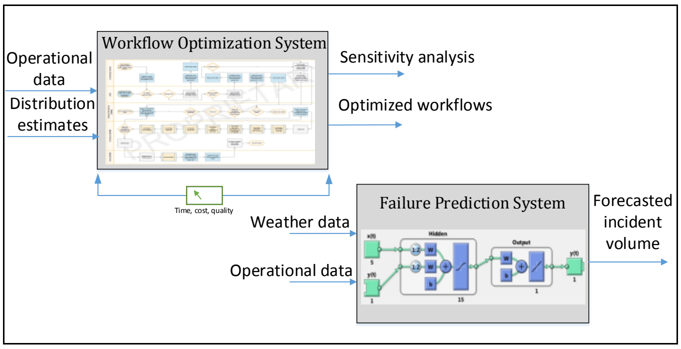


**Figure 2 - Solution Models**

### A. *Workflow Optimization System (WOS)*

WOS is a comprehensive model of the utility's response workflow, with separate processes for emergency work orders and low priority work orders. Resources are shared between the two parallel workflows. Due to the focus on low priority work orders, their corresponding response process is modelled in greater detail than the emergency response process. Figure 3 depicts the simulation with embedded submodels.

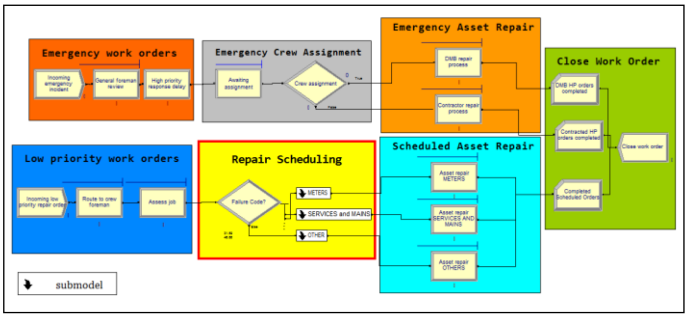


**Figure 3 - Workflow Optimization System**

Operational data provided by the sponsor was utilized to derive probability distributions that model process durations and other random variables such as interarrival times. Processes for which there is no available time data were modelled using estimated distribution types and parameters. This process was guided by expert opinion provided by DMB staff and analysis of free-text fields containing remarks and date stamps corresponding to each work order.

Process dependencies were identified to obtain the ideal process sequences. For example: coordination of staffing, materials, and equipment for a meter replacement is a process which can only be performed after tree removal is authorized or rejected by the Urban Forestry Administration (UFA). Depending on the UFA's assessment, the DMB must either perform a typical meter replacement or re-route water supply plumbing in order to bypass the meter embedded within tree roots. Staffing, materials, and equipment are all dependent on the UFA's decision.

Three replications of a 365 day simulation were run to model a typical year and generate the required statistical precision. Work order output statistics passed verification testing with simulation values within reasonable proximity to the utility's historical data. A summary of simulation output averages compared with the DMB's recorded averages is provided in Table I.

TABLE I
SIMULATION OUTPUT VERIFICATION

| Block | Distribution | WOS Average | DMB Average | % error |
|---|---|---|---|---|
| Asset repair meters | N(0.146, 0.17) | 0.1595 | 0.146 | 8.46% |
| Asset repair services and mains | -0.001 + EXPO(0.247) | 0.2471 | 0.2466 | 0.20% |
| Asset repair others | -0.001 + EXPO(0.161) | 0.1631 | 0.160 | 1.90% |
| Emergency interarrival | -0.001 + LOGN(0.796, 3.57) | 430 | 529 | 23.02% |
| Low priority interarrival | -0.001 + WEIB(0.21, 0.538) | 962 | 869 | 9.67% |
| Total work orders | - | 1392 | 1398 | 0.43% |

Simulation output errors are within acceptable ranges of 10% for repair durations and 30% for number of work orders. Error tolerances were established using variance observed in historical operational data. The scheduling delay time cannot be verified due to lack of recorded data. Therefore, WOS is run using workflow configurations derived by analyzing process dependencies and parallel processing opportunities.

### *B. Failure Prediction System (FPS)*

A Failure Prediction System was developed to provide daily and weekly main break volume forecasts. Two Artificial Neural Networks (ANNs) have been trained using a four-year set of historical weather and operational data, allowing each model to generate time series main break volume forecasts. These are to be used by the DMB's general foreman to set crew schedules in peak volume periods.

A validation accuracy requirement of $R^2 = 0.60$ was established after consulting the sponsor, faculty advisors and subject matter experts. Practicality, feasibility, precision and recall were taken into account when deriving the desired performance target. The coefficient of determination target evaluates the accuracy of the validation test which uses data not utilized in the training or testing set.

An analysis was performed by acquiring historical weather data and plotting it alongside water main break data over an eight year period [6]. Weather data was recorded at DCA airport, whose close proximity to the District (less than five miles) allows it to be used in this study. It contains daily statistics such as minimum, maximum, and average temperatures.

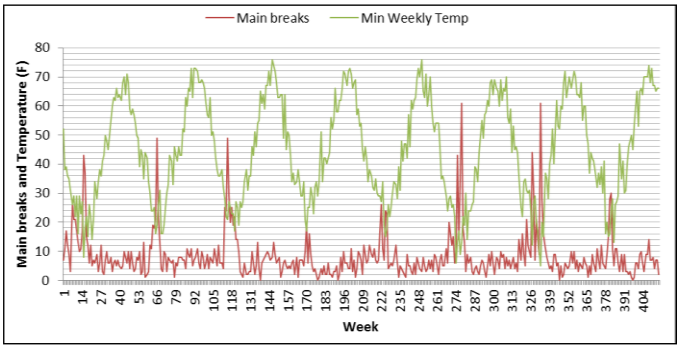


**Figure 4 – Ambient temperatures and main breaks (8 years)**

Figure 4 contains a plot with minimum ambient temperature and cumulative main break time series plotted using weekly time steps. Qualitative analysis of the time series suggests that high cumulative weekly failures are correlated with large temperature deviations and minimum temperatures.

A Nonlinear Autoregressive with Exogenous Input (NARX) model is employed to utilize two time series: main break volume and various ambient temperature statistics. NARX models are designed to predict a series y(t) using past values of y(t) and another series x(t), which is the exogenous input. The function approximation method used to implement the NARX model is an Artificial Neural Network (ANN). Inspired by biological neural networks, ANNs adjust weight and bias values dynamically to learn nonlinear relationships between input and output variables.

The ANN employed in this solution is a Time Delay Neural Network (TDNN) which uses time-series data to predict sequences given past states and inputs. The input series x(t) can contain multiple elements. Past values of output series y(t) are used in TDNNs as inputs into the model and the number of required delay states is an adjustable property of network architecture. The weekly model architecture depicted in figure 5 utilizes two delay states per input, one hidden layer and five input elements.

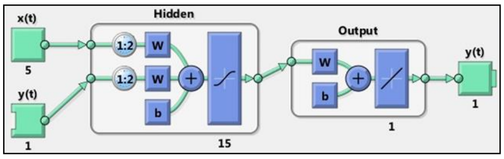


**Figure 5 – Time delay neural network architecture**

Use of delay states to predict an output series is highly applicable to this problem given the soil-pipe temperature lag present in the WDS domain. Water mains buried as deep as 15 feet underground can take several days to react to temperature fluctuations, causing a delayed response.

Both ANNs were designed, trained and tested using the Neural Network Toolbox (NNT) provided in MATLAB®. Architecture modification, data normalization, selection of weather inputs, and modification of parameters was guided by past studies, expert opinion, statistical methods and analysis of preliminary results.

A multilinear regression analysis determined the ideal input parameters for the weekly model. These inputs include weekly minimum temperature, standard deviation of weekly temperature, average daily temperature difference, and two additional nonlinear combinations. Regression analysis of model output following testing and training can be seen in figure 6 below. Overall, the prediction model obtained an $R^2$ value of 0.96.

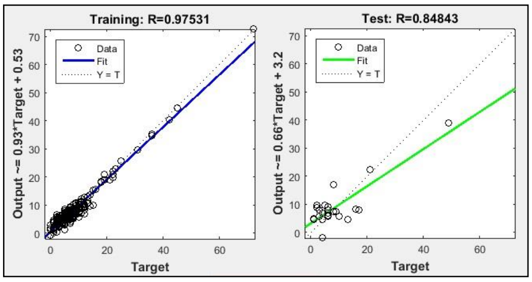


**Figure 6 - Prediction model output regression**

Data used to train and test the weekly model consisted of 246 weekly time steps and was divided randomly with 66 percent and 44 percent used for training and testing, respectfully. Despite the existence of an eight year data set, DMB suggested use of post-2012 data, citing concerns of poor quality in earlier periods. The four year data set contains noticeable variance in both series during each peak (as depicted in figure 4), suggesting that it provides a practical tradeoff between error minimization and generalization.

To improve generalization while minimizing mean square error (MSE), Bayesian regularization was selected as the training algorithm. Initial training with the default Levenberg-Marquardt algorithm generated unsatisfactory results. The algorithm reported high accuracy for the large training data set ($R^2$ = 0.92) but low accuracy in the testing and validation outputs (average $R^2 \approx 0.59$) which is a sign of overfitting. This is caused by the algorithm's emphasis on local minima and MSE minimization. Bayesian regularization demonstrated higher accuracy under the same conditions across both training and testing data segments. This is due to the algorithm's ability to ignore noise and improve generalization with the use of additional parameters and adaptive weight minimization. Note that this algorithm does not use a validation set.

The model's testing performance with the smaller data set is critical to determine its feasibility as a forecasting tool. Time series output of the weekly model in figure 7 from weeks 100 to 130 demonstrates its performance when compared to target values extracted from the utility's historical data. Random division of the training and testing data points is also visible in the response plot.

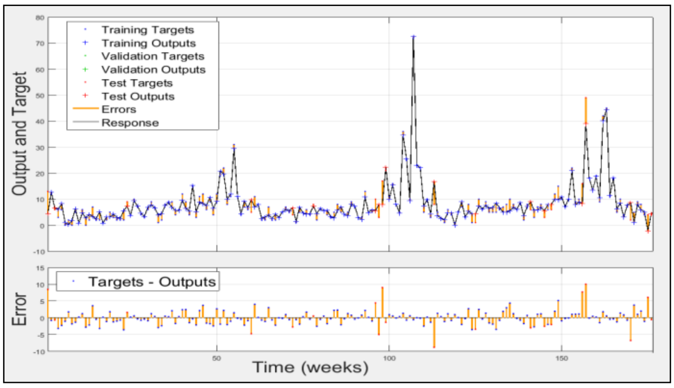


**Figure 7 – FPS weekly time series response**

The error histogram indicates that the errors are normally distributed with negligible error bias. The FPS ANN models may be deployed as part of an application capable of forecasting weekly and daily failure volumes using weather forecasts as inputs. Forecasts from such an application can be used to proactively set winter repair crew schedules.

## V. RESULTS

### A. *Workflow Optimization System (WOS)*

The simulation was developed with a number of modelling assumptions and constraints. Low priority incidents assigned to contractors are omitted due to negligible 3.4 percent historical utilization prompted entirely by complexity of repair. Further, the repair process is not modelled due to variation in circumstances involving each repair. Use of quantitative data is limited to 2015 records due to it being the latest complete year with the most reliable data [6]. It should be noted that in 2015, a water meter rehabilitation project undertaken by DMB caused a 225 percent annual increase in meter incidents, 90 percent of which are low priority.

#### *i. Design of Experiment*

TABLE II
DESIGN OF EXPERIMENT

| INPUTS | | | | | OUTPUTS | | |
|---|---|---|---|---|---|---|---|
| **Workflow Type** | **Failure Code** | **Process** | **Distribution** | **Num. Replications** | **Workflow Response Time (days)** | **Resource Utilization** | **Completed Scheduled Orders** |
| All | All | Site assessment | N(1.5, 0.05) hours | 3 | 12.36 | 0.38 | 930.33 |
| All | All | Site assessment | N(1.0, 0.15) hours | 3 | 8.14 | 0.31 | 949.67 |
| Low Priority | Meters | UFA investigation delay | Expo(12.0) days | 3 | 12.13 | - | 947.33 |
| Low Priority | Meters | UFA investigation delay | Expo(8.0) days | 3 | 10.68 | - | 972.00 |
| Low Priority | All | Parts delay | Logn(1.8, 0.05) days | 3 | 12.42 | - | 952.67 |
| Low Priority | All | Parts delay | Logn(1.0, 0.05) days | 3 | 12.35 | - | 924.33 |

In the design of experiment outlined in Table II, improvements are proposed for restrictive processes to determine the overall effect on the DMB's workflow and reduce response times. Distributions modelling current DMB practices are designated by the light blue row entries of Table II.

By reducing the average site assessment time by 0.5 hours, the response time for low priority incidents is reduced by over four days, the number of completed scheduled work orders has increased, and the crew foreman utilization is reduced. This proposed change is implemented by encouraging more detailed recordkeeping from investigation crews belonging to DCB. The next proposed change is to decrease the average wait time for the Urban Forestry Administration (UFA) to investigate a proposed tree removal. Currently, the DMB holds off on submitting investigation requests to the UFA until multiple requests have accumulated. Results indicate that if the DMB were to individualize UFA investigations, the low priority response time and the amount of completed orders would both improve. Lastly, this experimental design measures the effects of improving the average parts procurement delay by one day by optimizing parts inventory using historical data, an effort currently under way.

*ii. Scheduling Workflow*

There is currently no recommended scheduling workflow for low priority incidents. Among the three crew foremen, each utilizes a unique scheduling methodology with no status system, recorded data or accountability. A standard response process exists but is not widely used, according to the sponsor [6]. This workflow, depicted in figure 8, contains series blocks consisting of scheduling processes which ultimately lead to the work order being dispatched to a repair crew. The swim lane corresponding to the crew foreman's responsibilities contains each scheduling process.

The workflow does not effectively address low priority work orders. Time-sensitive processes such as coordination of permits (II) and utility markings (I) are initiated early which runs the risk of their expiration and subsequent repetition. Utility markings are only valid for a period of seven days and an emergency work permit is valid for 72 hours. Scheduling a service disruption (IV) is a downstream process which carries an average delay of 8.0 days, requiring the first two processes to be repeated given an average delay. Utility lines are marked within two hours for an emergency incident, but the same process takes an average of 1.2 days for a low-priority incident. Due to larger delays associated with external processes, low priority work orders must be scheduled methodically.

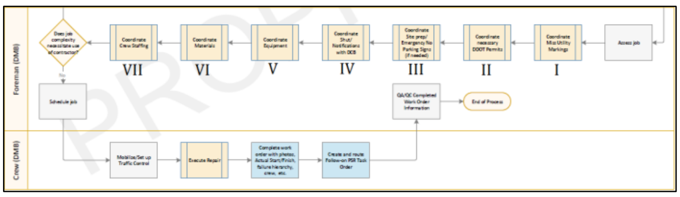


**Figure 8 - Current DMB scheduling workflow [8]**

Low priority incidents were grouped into three categories: meters, services and mains, and others. Categories were based on total duration, incident count and unique properties of each incident type. Among this group, water meter incidents were found to be the largest single category of low priority work orders, as depicted in figure 9. They are also subject to the largest delays. The scheduling delay is responsible for 99.23 percent of the total duration of meter incidents.

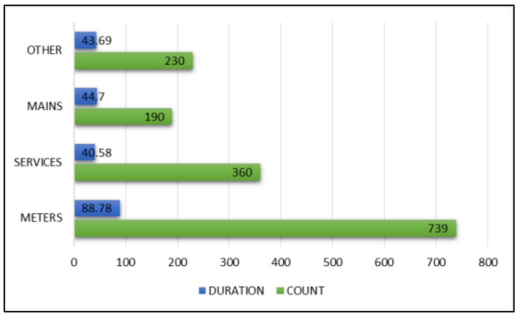


**Figure 9 - Low priority incident count and duration (2015)**

Analysis of free-text remarks fields which contained scheduling information exposed the schedule-heavy nature of meter incidents. 46 percent of meters incidents belonged to problem codes associated with lack of access, 8 percent of which involved the asset being embedded in tree roots. A comprehensive scheduling workflow was therefore developed for scheduling meter incidents due to the large impact of scheduling delays and the sheer volume of meter incidents. The derived workflow is depicted in figure 10 below.

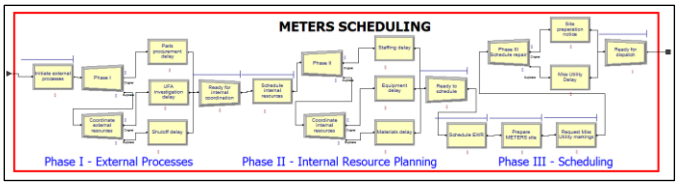


**Figure 10 - Meters scheduling workflow**

Scheduling workflow was divided into three phases: external processes, internal resource planning, and scheduling. Phase I consists of processes with the longest estimated durations and the least number of dependencies. Phase II consists of internal resource coordination involving staffing, materials, and equipment. Lastly, phase III consists of short-duration time-sensitive scheduling processes such as request utility markings, prepare site, and schedule emergency work order with DDOT. Services and mains were combined into a single workflow due to 86 percent of these incidents being associated with leaks which require similar scheduling practices. Lastly, a generalized scheduling workflow was generated for the remaining failure types.

*B. Failure Prediction System (FPS)*

FPS forecasts were generated for a period of four weeks and compared with the utility's actual weekly main breaks during the month of February 2017. The result is illustrated in figure 11. The "actual" time series represents recorded main breaks in February, 2017 and the "forecasted" series contains FPS output for the given weather forecast [9]. R-squared for this validation test was 0.875.

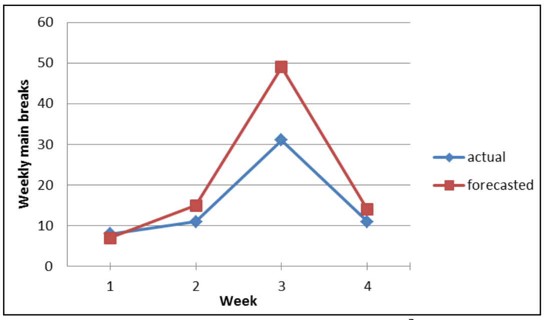


**Figure 11 - FPS forecast validation ($R^2$=0.875)**

The only modification to the daily model is the addition of eight more delay states. The weekly model only used two delay states as the previous two week's temperature and failure data is sufficient to account for soil-temperature lag. A daily forecast requires a larger quantity of delays to account for lag due to the short-term nature of the model.

The daily model was validated against 2013 data which was not used in training or testing cycles. It reported an $R^2$ of 0.86 for an eight day forecast performed on the third week of January. Daily forecasts are generally less accurate than weekly forecasts due to increased precision demanded by the model and low input-output correlation.

## VI. BUSINESS CASE

Utility Maintenance Consulting Services (UMCS) is a water utility consulting service whose focus is to provide forecasting tools that allow water utilities to predict emergency failures. In addition, WOS will be customized based on the customer's needs to enhance operational efficiency. This will be done by deriving optimum workflows, dispatch methods, and schedules for the customer. The product utilizes weather and historical repair data.

Customers will subscribe to the UMCS service on an annual basis with a five-year contract. There are 605 water utilities nationwide that lack an ability to forecast incident volume [insert link here]. The annual subscription will provide the typical water utility customer with easy access to optimized scheduling and maintenance procedures in addition to forecasting main break failure tools, translating into reduced operational costs, utilization of contracted crews, and improved customer satisfaction.

For example, DC Water has 523 high priority failures per year with an average of $10,000 per repair in addition to 769 incidents of utilizing contracted crews in the past four years. At a cost of $10,000 per incident, the total sums to $12,920,000. The subscription price is 8% of the total which is $1,033,600 per year.

Subscribing to the UMCS service will reduce the utility's reliance on contracted crews. For example, during the first year, DC water can reduce its use of contracted crews by 15% which translates into savings of $1,153,500. This amount in savings is still greater than subscription price and carries other benefits of allowing DC Water to provide high quality services in efficient manner and reduce the backlog of work orders. Further business case analysis for UMCS indicates that the break-even point will be reached after the first year with 93% ROI, first 5 years with 393% ROI, and 10 years with 1209% ROI.

## VII. CONCLUSION AND RECOMMENDATIONS

Despite the lack of historical resource utilization data, the utility has observed periods of low crew utilization due to low volume of work orders that are ready for dispatch. Implementation of proposed changes expedites dispatching of low priority work orders, thereby increasing repair crew utilization which averages 0.92 in WOS.

The utility's goals are achievable with the current set of resources by means of FPS-guided resource scheduling, minor operational changes and implementation of proposed workflows. Results highlight the sensitivity of average low priority response times to the quality of initial investigative reports, UFA communication protocols, and configuration of scheduling workflows. The latter parameter has the largest single impact on backlog volume and low priority response time. The large disparity between simulation response time (12.4 days) and actual response time (83.4 days) with all other variables held constant indicates that current scheduling practices are far from ideal.

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