INTELLIGENT WATER NETWORKS – THE EMERGENCE OF OPERATIONAL MODELLING AND REAL TIME DECISION SUPPORT TOOLS

Patrick Bonk (Innovyze), Ann Pugh (Innovyze)

ABSTRACT

Globally the Water Industry is buzzing with buzzwords: "Smart Water", "Innovation", "Big Data", "Analytics" – and the ever increasing list of acronyms: AMR, AMI, SWM and IWN to name a few – are leading many in the industry to 'paralysis by analysis'.

Simply stated: Telemetry, hydraulic predictions and other data collection processes are generating bigger/better but underutilized data sets. The intent of this paper is to methodically demonstrate ways in which Intelligent Water Networks are within every utility's grasp utilizing their existing skillsets, data sets, IT Infrastructure and software tools. The paper will discuss two main categories of technology pertinent to Intelligent Networks:

1. Time Series Analysis/Reporting:

An event detection "watch dog" accepts time series in real time from field providing web-based data access and diagnostics to all within a water organization.

2. Automated Hydraulic Model Projections.

Informed by live and predicted data the automated hydraulic model utilizes predictive capabilities flow, pressure, velocity, water quality and energy consumption may be modelled through all parts of network.

KEYWORDS

Intelligent Water Networks, Operational Modelling, Real-Time Decision Support Tools, Automatic Meter Readings, Predictive, Event Detection.

1 INTRODUCTION

Globally the Water Industry is 'buzzing with buzzwords': "Smart Water", "Innovation", "Big Data", "Analytics" – and the ever increasing list of acronyms: AMR, AMI, SWM and IWN to name a few – are leading many in the industry to 'paralysis by analysis'. An Intelligent Water Network is one that uses technology to gather and act on information in an automated fashion to improve the reliability, sustainability and efficiency of the network.

Overall, Intelligent Water Networks (IWN) are being driven by:

- Predictive decision support tools.
- The need to reduce the loss of knowledge when a workforce ages.
- The aim to design systems with less redundancy.
- Cost savings from increased energy efficiency and effectiveness of daily pump operations.
- Customer satisfaction relating to reliable, taste of water and cost of service.

The potential exists, with an increasing number of sensor readings from the field to leverage data in real-time providing utilities with the ability to:

- Understand how planned changes in the system will affect customers.
- Identify what events may be occurring in the system unnoticed.
- Quantify how the system can be operated more efficiently.
- Determine what impact each system is having on another.

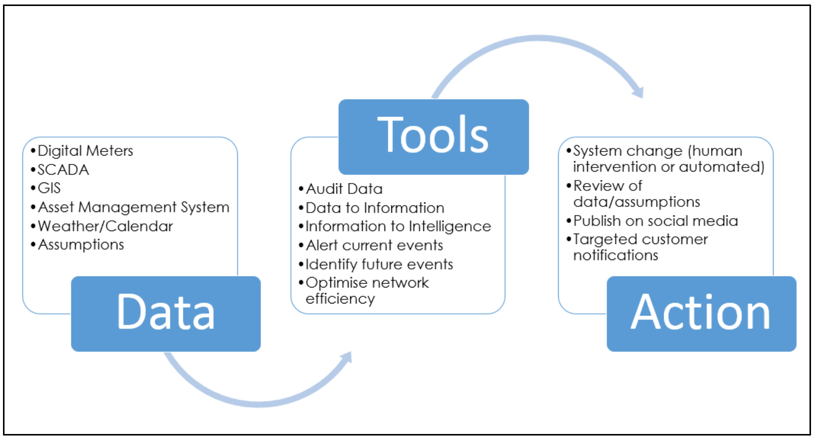

Figure 1: An illustration of an IWN through the flow of Data, through to the Tools used and Prospective Actions

Figure 2 articulates the 5 main layers comprising of an Intelligent Water Network. This paper will focus on the "Data Management and Display" and "Data Fusion and Analysis," layers 4 & 5 as shown in Figure 2 below.

Figure 2: The 5-layers to comprising an Intelligent Water Network

In summary these are:

- Physical:
  The "wet" assets – pipes, valves, tanks, taps etc. These objects have a function to deliver water, they do not collect data.
- Sensing and control:
  Have one "wet" end and one "dry" end. These objects measure the assets in the physical layer.
- Collection and communication:
  The first "dry" layer and contains the object that transmit and store the data (such as SCADA and AMI) but no significant data processing and no human interaction
- Data management and display:
  The first human layer. Data from different sources is compiled and analysed, with visualisation tools such as dashboards to provide context for the information.
- Data fusion and analysis:
  Large processing of data occurs in this layer to derive detailed insight into system performance.
  Includes tools such as hydraulic models, adaptive pressure management, pump/energy/chemical optimisation, decision support tools and near real time burst detection.

Simply stated: Telemetry, hydraulic predictions and other data collection processes are generating bigger/better but underutilized data sets. The "Big Data" era provides potential for a higher degree of integration between operations, planning and management. However, the current live data bottleneck caused by securing these live datasets combined with the use of 'small data' analysis software (spreadsheets, etc.) when the stale time series data is finally accessed, stifles innovation. When the skills sets of technical staff from all segments of the utility can access live data, the hydraulic networks will in effect be monitored by many more staff by way of stored logic and associated alert generation.

The intent of this paper is to methodically demonstrate ways in which Intelligent Water Networks are within every utility's grasp utilizing their existing skillsets, data sets, IT Infrastructure and software tools. The paper will discuss two main categories of technology pertinent to Intelligent Networks:

1. Time Series Analysis/Reporting:

An event detection "watch dog" accepts time series in real time from field providing web-based data access and diagnostics to all within a water organization.

2. Automated Hydraulic Model Projections.

Informed by live and predicted data the automated hydraulic model utilizes predictive capabilities flow, pressure, velocity, water quality and energy consumption may be modelled through all parts of network.

2 CREATING CONTEXT: THE IWN OZWATER15 WORKSHOP SESSION

VicWater (Victorian Water Industry Association) is the peak industry association for water corporations in Victoria, Australia. VicWater plays an important role in the Victorian Water Industry in influencing government policy, providing forums for industry discussions on priority issues to stakeholders, identifying training needs and the production of performance reports and industry guides.

The Intelligent Water Networks Program is a partnership between VicWater, 17 Victorian Water Corporations and the 'Department of Environment, Land, Water and Planning'. The IWN investigates new technologies and innovations to meet common challenges such as population growth, aging infrastructure and climate variability in a more efficient and effective manner.

The IWN Program held an innovation workshop for the OzWater15 (Adelaide, South Australia) conference attendees where the purpose of the workshop was as follows: "The key should be to share this information and experience across the industry so that we can all benefit and reduce risk aversion via collaboration."

The workshop format involved asking participants (Directors, Managers, Operators, Engineers) who had broken off into sub -groups the following 4 main questions (VicWater IWN, 2015):

1. Are there existing technologies that are stopping us from progressing?
2. Why are emerging technologies not business as usual?
3. What are areas for improvement for embracing new technology and innovation?
4. Are there existing innovations/technologies that are stopping us from progressing?

Overall the main them of the workshop was "Risk aversion via collaboration."

Figure 3: A figurative snapshot of the ideation exercises at the IWN's OzWater15 Workshop

Themes such as risk aversion, internal silos, knowledge loss, big data and technological challenges were all raised. These issues collectively confront many within the industry; yet water authorities across the world have the opportunity to capitalize on the continual advancements of the latest decision support tools.

3 REAL-TIME DECISION SUPPORT TOOLS

3.1 THE CURRENT TELEMETRY SITUATION

SCADA (Supervisory Control and Data Acquisition – systems used to control assets and collect data) data is collected by Water Organizations for a real-time and historical understanding of their network, the ongoing operation, maintenance, and critical design considerations. Many existing SCADA processes suffer from a "bottleneck effect" where large amounts of live and historic data (flow, pressure, tank level, pump/valve status) is being gathered and stored at great expense yet is being underutilized for the following reasons:

- Too many steps to obtain/report on data when only a small group have access to SCADA.
- Security concerns regarding access to SCADA system.
- To gain further fidelity is costly.
- Too much latency (time between signal sent and engineer access)
- Low confidence in data that is collected.
- Making sense of data can be prohibitively resource intensive as much of the analytical efforts remain manual and time series of interest may not even fit in Microsoft Excel or Access Databases

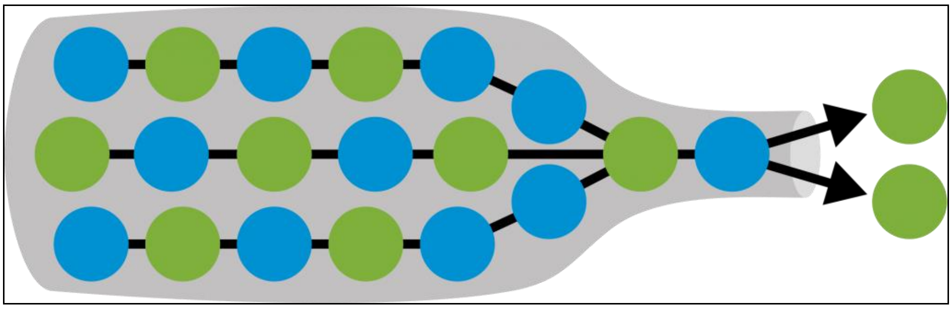

Figure 4: Data collection as a figurative bottleneck: Large amounts of data is collected yet remains underutilized across water organizations.

The data discrepancy that occurs between what is actually collected through to what could potentially be distributed among the spectrum of key stakeholders within an organization creates a "siloing" effect leading to the underutilization of resources.

Figure 5: An Image of the "Siloing" that occurs when Data Access is limited within a Water Organization

3.2 DATA NEEDS WITHIN AN ORGANIZATION

Further to the "bottlenecking" and "siloing" effect that occur from the stagnation of data from collection to utilization and the impact the lack of data distribution has, there also must be much consideration given to the unique needs and responsibilities of the multiple types of roles within a given organization.

Figure 6: Various Personas within a water organization illustrated to represent their unique data needs.

Roles will vary greatly depending on the size and type of organization, however roughly speaking, for the purposes of discussing the needs of roles working within a water organization, the stakeholder groups will include Operators, Engineers, Management and Directors/Board Level.

Table 1: Stakeholders within a water organization and their data needs.

Stakeholder	Data Need
Operators	- Updating operating manuals. - Predicted loss of system integrity - Asset Performance & live levels of service - Event Detection and Response - Optimized controls
Engineers	- System Design and Behaviour - Event Forecasting - Understanding Demand
Management	- Non-Revenue Water - Developing Key Performance Indicators - Collaboration amongst their team - Knowledge Management
Directors/Board Level	- Risk Management - Regulatory Compliance - Cost/Benefits Analysis

3.3 THE NUMBER OF TELEMETRY DATA END-POINTS ARE INCREASING

As part of an IWN, Automatic Meter Reading (AMR) and Advanced Metering Infrastructure (AMI) are predominant technologies being widely implemented. According to the "2014 Review of Smart metering and Intelligent Water Networks in Australia and New Zealand," conducted by Dr Beal of the Smart Water Research Centre; AMR data is being collected at increasingly growing rates.

The report captures the sheer scale of data being collected within Australia and New Zealand, stating that as of 2014, 10 Water Authorities within Australia; including Mackay (QLD), Water Corp (WA) and Yarra Valley Water (VIC) had over 10,000 telemetry endpoints within their respective networks (Beal, 2014).

The report further stated:

> *"The end points (number of meters, including sub-meters) ranged from less than 10 for a small pilot trial to over 57,000 in a previously un-metered region in Tasmania. The smaller projects with low numbers of end points were typically related to trial or pilot studies. In organizations where end points are different than the previous years, usually signifies the updated number of actual/planned meters to be rolled out." (Beal, 2014)*

Figure 7 shows a graphical image from the 2014 IWN report showing the number of end points for telemetry data in 2014 relative to 2013 for various utilities in Australia and New Zealand.

Figure 7: As of 2014, within New Zealand and Australia metered data points ranged from less than 10 to upwards of 57,000 end points (Beal, 2014).

3.4 DATA SAMPLING: A NECESSITY FOR 'BIG DATA'

Data sampling is "a statistical analysis technique used to select, manipulate and analyze a representative subset of data points in order to identify patterns and trends in the larger data set being examined." (TechTarget, 2016)

Traditional methods such as spreadsheet work are no longer effective or even plausible to be able to receive, handle and manipulate the massive amounts of data inputs being taken in by an organization from their telemetry feeds. Web-browser based tools now exist to automatically pull data from the source incoming telemetry database for rapid manipulating into predetermined statistical patterns to interrogate and determine significant trends and correlations in the data.

3.5 CASE STUDY 1: 'A MILLION DATA POINTS'

Innovyze was approached by a client from a large Water Authority in Victoria with the request to demonstrate the value of data sampling for a large amount of timeseries data. The same data set included: 1 sensor with 1second reads over a period of a year providing a massive amount of measurements: 31.6 million data points.

The vast number of data readings was provided by the client within 30 Microsoft Excel spreadsheet files. Figure 8 shows a screenshot of the error messages received when attempting to plot the respective data within the provided spreadsheets. Based on the amount of data alone – little to no analysis was able to be carried out within the said spreadsheet files.

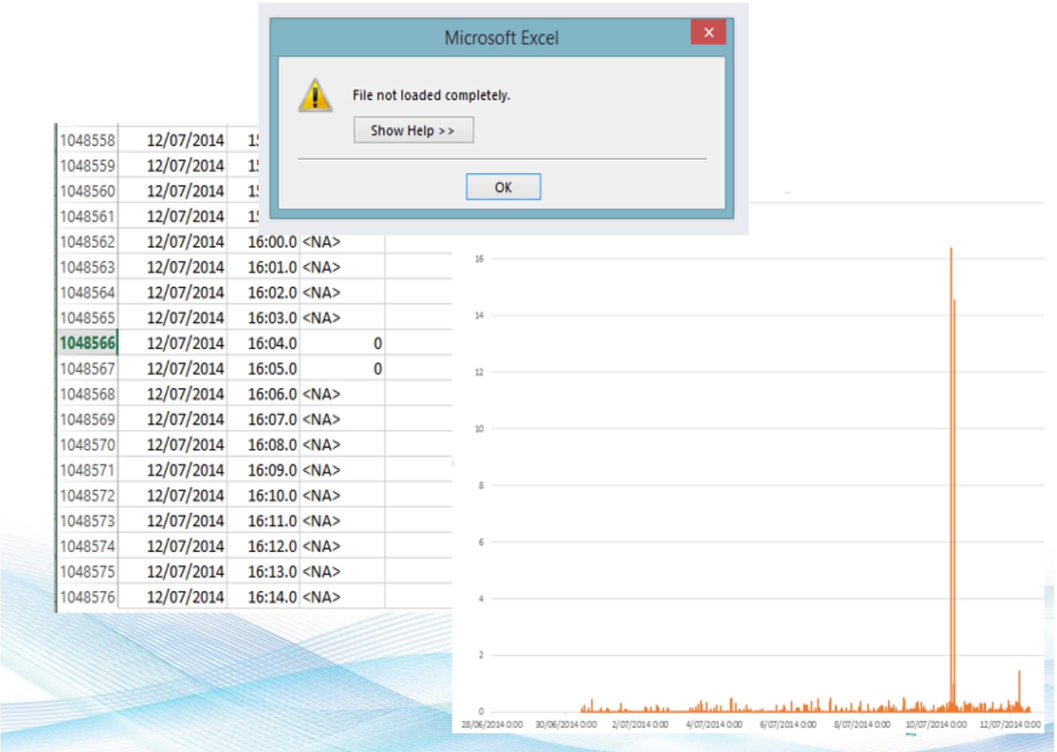

Figure 8: Screenshot of 1 of 30 Microsoft Excel spreadsheet files provided to Innovyze by Australian client.

Innovyze responded to the request from the client by uploading the data to a timeseries database connected to one of its web-based, sampling and built-in querying decision support tools. The following are a series of screenshots from the demonstration to client, showing the software's ability to seamlessly handle the large amounts of data.

In particular the software demonstrates an ability to sample based on either open/high/low/close over multiple data intervals and sampling periods for the data set with 31.6 million data points (1 sensor, 1 second reads, 1 year of data).

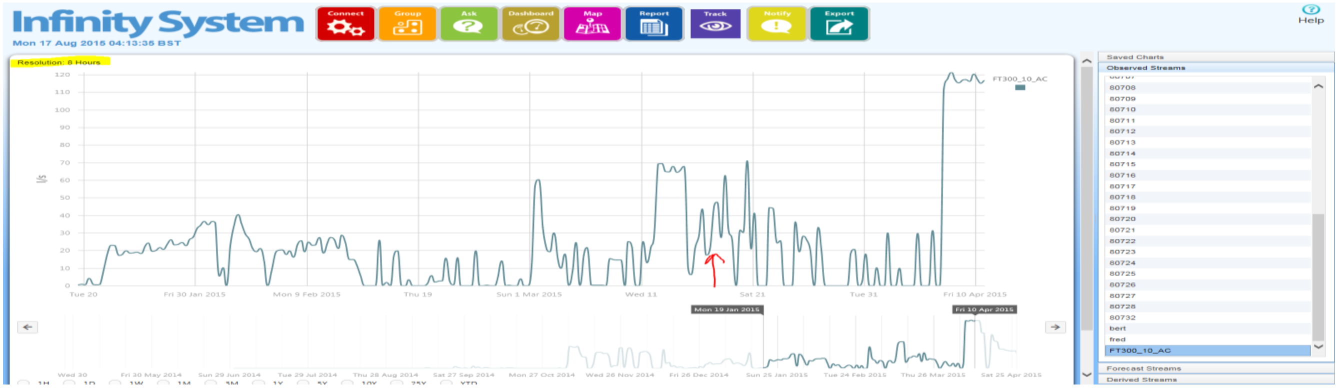

Figure 9: Screenshot of 3 Month Duration, Sampled at 8 hour Intervals (Y Axis: 0-120 l/s).

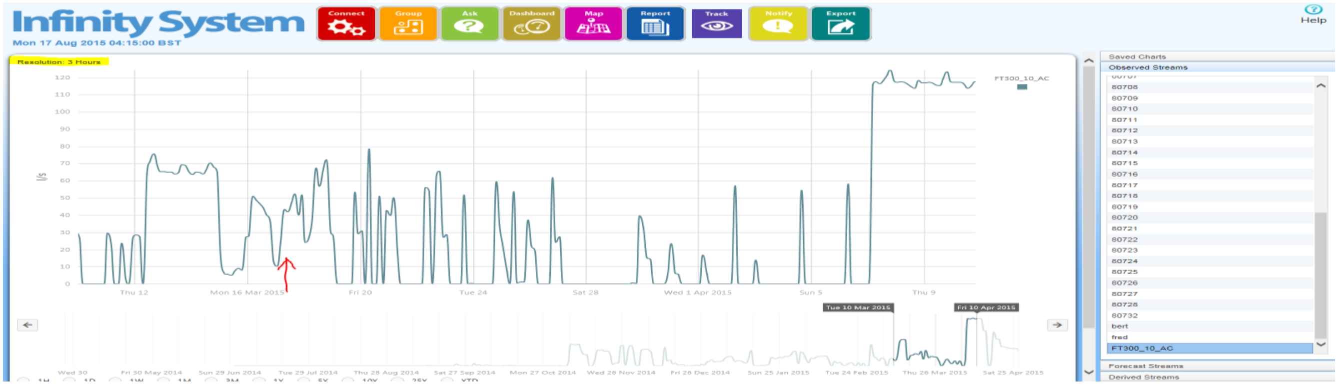

Figure 10: Screenshot of 6 Weeks, Sampled at 3 hour Intervals (Y Axis: 0-120 l/s)

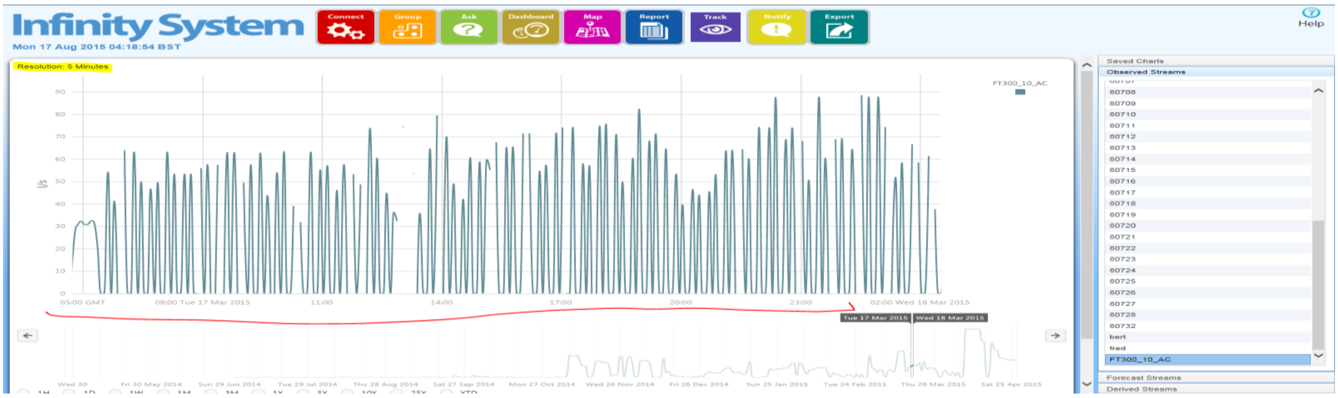

Figure 11: Screenshot of 5 Days, Sampled at 5-Minute Intervals (Y Axis: 0-90 l/s)

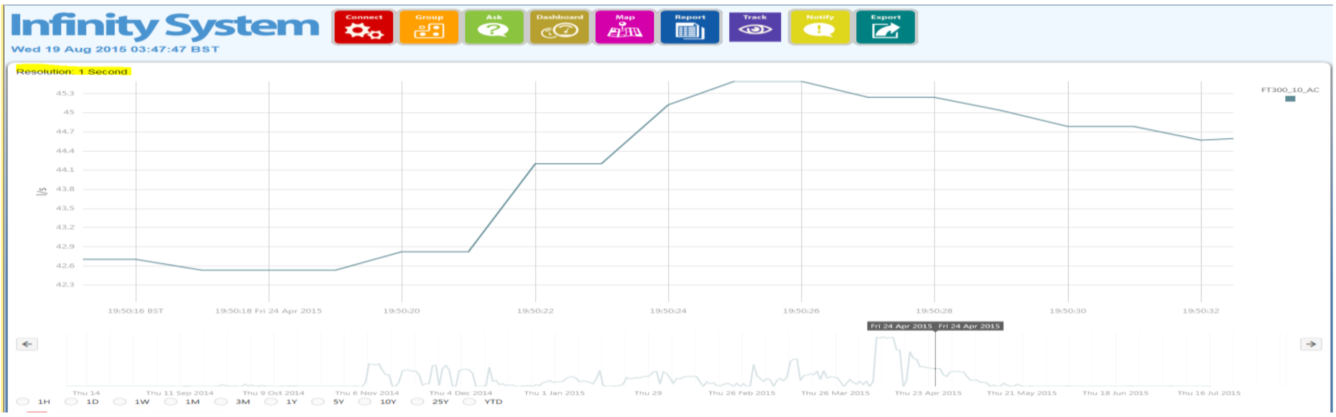

Figure 12: Screenshot of 20 Seconds of data, Sampled at 1-Second Intervals (Y Axis: 42.2-45.3 l/s)

3.6 CASE STUDY 2: A “WATCH DOG” PIPE BURST SCENARIO

Innovyze approached a valued client; a Council within the Northern New South Wales area to demonstrate a web-based, geospatial, event detection “watchdog.” Upon hearing a description of the off-the-shelf software solution the respective Council put forward a pipe burst scenario that went undetected by their current SCADA system and was detected by the public which had the potential to create a PR problem.

The following are key points to paint a picture of the pipe burst scenario:

- The pipe burst went unnoticed for 4-hours
- Happened on a Saturday
- Detected by public
- Using a $ per litre lost approach - $1,000 potentially saved if response time was cut to 2-hours

What was “seen” by Operations? When Council retroactively looked at the burst scenario of what was seen by the Operators:

- Tank Level dramatically dropped but went unnoticed while within normal operating bands.
- When Tank Level was flagged, the cause was thought to be potentially due to a faulty pump (insufficient means of determining the “why”)

3.6.1 ANALYTICAL ANALYSIS OF PIPE BURST

Once the data had been uploaded to the web-based, event detection tool, Innovyze conducted a review of the historical data from the aforementioned burst scenario. Normal operations for 5-days of flow data was provided. Reviewing 5 days of flow data leading up to the burst to gain a sense of standard system behaviour, Figure 13 shows a snapshot of the flow data for a typical day ahead of the burst incident.

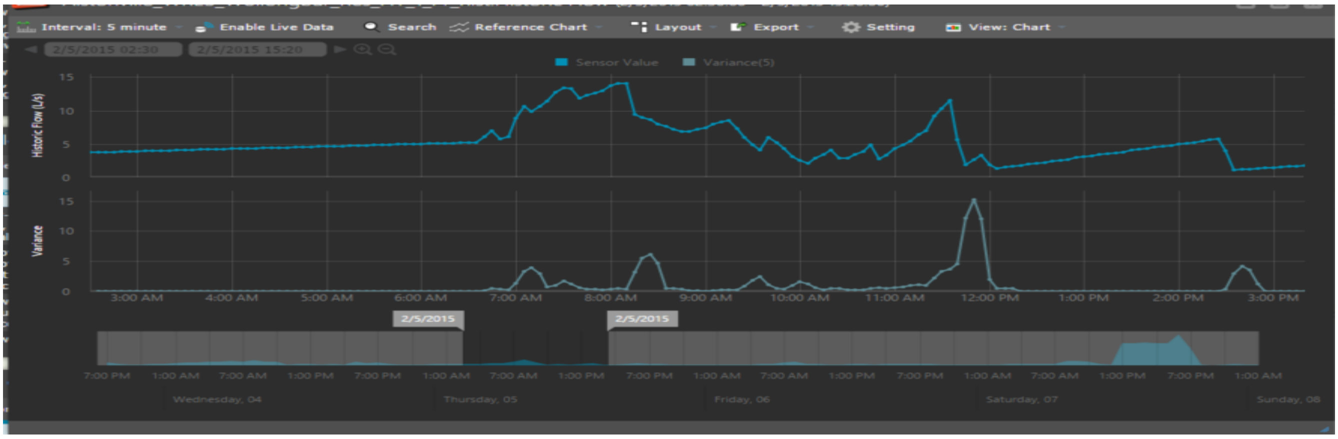

Figure 13: Screenshot of 3 Days, Sampled at 15-Minute Intervals (Y Axis: 0-120 l/s)

In the above figure, the top flow timeseries in blue is the sampled flow data (high value, 5 minute interval) wereas the bottom flow series in light green is a derived timeseries utilizing the following variance function shown in Equation 1:

$$\operatorname{Var}(X) = \sum_{i=1}^{n} p_i \cdot (x_i - \mu)^2, \tag{1}$$

A brief review of the 5-days leading up to the burst with the above variance timeseries (Var,5) revealed that for normal system behaviour the Variance did not exceed a value of 15.

Whereas when utilizing the same variance equation (Var, 5) through to the pipe burst incident the derived variance timeseries drastically spiked to a value upwards of 600 indicating a burst had occurred.

Figure 14 shows a snapshot of the measured burst incident (blue timeseries, top) and its respective impact on the derived variance timeseries (light green, bottom) used to trigger the alert within the watchdog, event detection tool.

Figure 14: Screenshot of 3 Days, Sampled at 15-Minute Intervals (Y Axis: 0-120 l/s)

As shown in the above figure, the burst was detected within 10 minutes as opposed to what was an event that went unnoticed for 4-hours eventually being discovered and called in by the public. A large historical dataset was not required to determine the exceedence value that triggered the alert, used within the software's data searching mechanism as part of the "Watch-Dog" event detection tool.

3.6.2 APPLICATION OF WEB-BASED "WATCH-DOG"

The early response of the pipe burst scenario was significant using this particular web-based, geospatial, event detection tool because of the following:

- The web-based "watch dog" picked up the burst within 10 minutes and generated automatic emails; cost savings of greater than $1,000 for this particular burst scenario.
- The respective Shire Council had recently implemented SCADA but the data historian pulled data from SCADA on a daily basis at midnight creating a scenario where all but those in the control room had to wait a day to use the SCADA that was being collected.
- Existing IT infrastructure, software systems residing on current desktop and skillsets were used to build the search, track and scheduling mechanism that successfully detected the burst from a historic timeseries.
- Built in Queries and Search functionality; therefore scripting or SQL syntax skills are not required
- "Off-the-Shelf" package with a setup Wizard for simple implementation process
- No specialist implementers required to setup SCADA alerts
- Timeseries data accessed by all (secure – read only access)
- Accepts any time series as data source (incl. surge detection – AQDBC)
- The live data feed received connects to existing hydraulic planning models for continuous calibration providing. With the up-to date calibration the potential now exists to model "what-if" scenarios on actual field events.

4 PREDICTING SYSTEM BEHAVIOUR: OPERATIONAL MODELS

4.1 PROGRESSING FROM PLANNING MODELS

Limiting the broad discipline of network modelling to water supply for the purposes of the scope of this paper, planning models as we know them are not fit for use by a utility's operations team for decision support. The main vulnerability with regards to the quality of a hydraulic model for use as an operational decision support tool is that it is typically calibrated to a particular (often peak use) day of the year. An average day, theoretical-current year scenario is then derived from said respective peak day which can mislead the un-initiated into believing the average day scenario is indeed a calibrated average day.

The true purpose of the aforementioned scenarios is to look into the future developing various scenarios to cater to the effects of population growth, future levels of service, type of water use and prospective impacts of climate change for a given planning horizon. Key aspects to the recipe that comprises a hydraulic model for planning purposes includes:

4.1.1 INGREDIENTS TO A PLANNING MODEL:

Planning models are calibrated to current day scenarios and are built with static control assumptions and are mainly used to devise "what if" scenarios to right-size infrastructure for a given time horizon. The following table summarize the types of model inputs as well as their respective data sources that are used to build, run and calibrate a standard planning model.

Table 1: Main Ingredients to a Hydraulic Model for Planning Purposes

Type of Model Input	**Data Source**
Infrastructure	GIS, Design Drawings, Pump & Curves
Demand (Historical, Theoretical)	Billing Data Sets & Source Outflows
Controls (fudged, historic, static)	SCADA Historian, Asset Registers, Anecdotal Data
Model Settings	Typical Model Run Period – 1-3 Days
Planning Model Notes: - Often built using incomplete data sets - High Degree of simplification and assumptions - Factors of safety built into design assumptions - Starting point to develop master planning 'horizons' - Demand, boundary conditions and a mode of control from one day in the past	

4.2 OPERATIONAL MODEL PREDICTIONS

4.2.1 PURPOSE OF AN OPERATIONAL HYDRAULIC MODEL:

The purpose of an Operational Hydraulic Model is to understand the future state of the network with a known degree of trust. Projection runs provide a glimpse of the future state of the network that provide the ability to optimize energy use to maintain desired system pressures and chemical dosing costs associated with water treatment. Predicting the future state of the system allows action to be taken prior to an undesirable event occurring.

- Known hydraulics and water quality at every asset and customer point
- Allow scenarios to be trialed and assessed allowing for an optimized system response.
- Test responses or plan optimized maintenance.
- Predict future state of network with known degree of trust
- Allow a platform to rapidly test responses to predicted.
- Run models and generates alerts automatically.
- Make adjustments to network by testing responses before the event itself occurs.

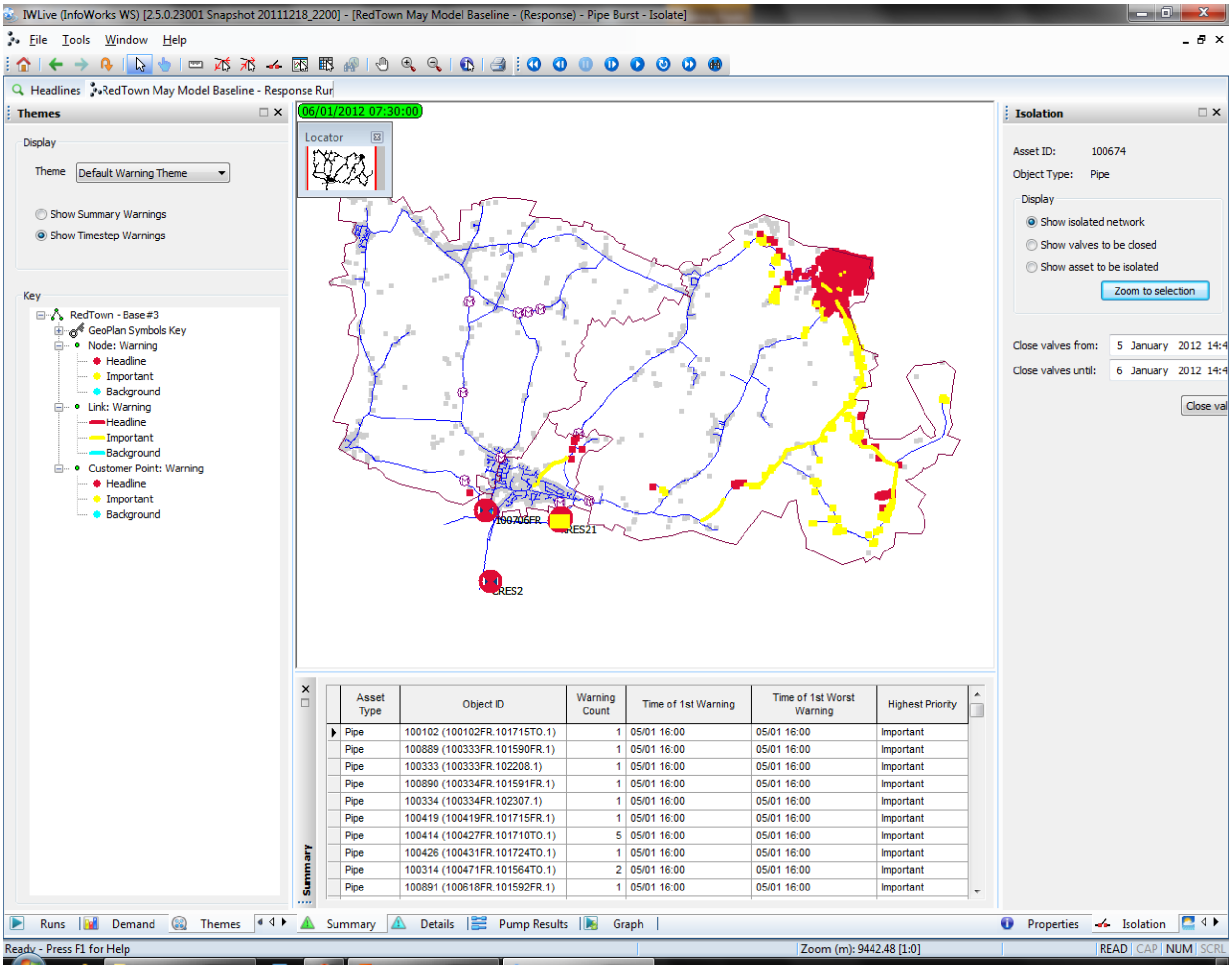

Figure 15: Operational Model snapshot forecasting a drop in pressure due to morning peak demand.

4.2.2 INGREDIENTS TO AN OPERATIONAL HYDRAULIC MODEL:

Operational models are automatically updated and ready to action with a response run to test the outcome of a potential system adjustment. The following is a summary of the ingredients for an operational model with the intent to demonstrate how the core elements of a planning model remain when an operational model is built and brought online with live telemetry and predictive forecast capabilities.

Table 2: Main Ingredients to a Live Operational Hydraulic Model

Type of Model Input	Data Source
Infrastructure	GIS, Existing Hydraulic Planning Model
Demand (Live)	Re-predicted 'just-in-time' for every scheduled live model run Near-term error correction and weather influence used
Controls (Live)	Actual Valves Open/Close Pump on/off – Pump Schedules, System Response (tank level data) Set-points taken directly from live SCADA feed
Model Settings	Model runs kickoff at present time, run through a hindcast for verification and into a forecast period for alert generation Model runs automatically; frequency of runs pre-defined.
Operational Model Notes: - Models are up-to-date and ready to action for live and predictive decision support - Prediction inputs consist of demand forecasts and live updated control settings. - Verification to provide level of trust in current model predictions. - Controls (reservoir levels, pump/valve status are automatically updated from live data.	

An operational model differs from a planning model in the main following ways:

- Automatically verified against telemetry data.
- Considers fluctuations in demand based on weather, day of the week/time of the year and utilizes regression for weather driven forecasts.
- Controls are updated automatically
- Used to predict and avoid service failures
- Model is maintained as mission-critical; continuous verification provides a known degree of trust
- Provide an up-to-date calibrated model for the planning purposes.

4.2.3 DEMAND FORECASTING: 'A LOOK INTO THE FUTURE'

Transitioning from utilizing Billing Data for a snapshot in time to devise future growth scenarios within planning models, demand forecasting involves the analysis of patterns from historical demand data to identify seasonal and weekly influences in daily water demands. The predictive ability of the operational model is predicated on the model utilizing demand feeds that automatically adjust to fluctuations in demand from weather, events and conditions in the network.

Differences in temperature are multiplied by a regression factor and added to the predicted daily demand. Meaning that if the weather forecast is hotter than average, the predicted demand will be increased. If the weather forecast is not available, the demand forecast tool will use the average weather value for that day to improve the standard demand forecast.

The only prerequisite for sub daily demand forecasts is 12-months of historic flow meter data from the flow meters that make up district metered/demand managed areas.

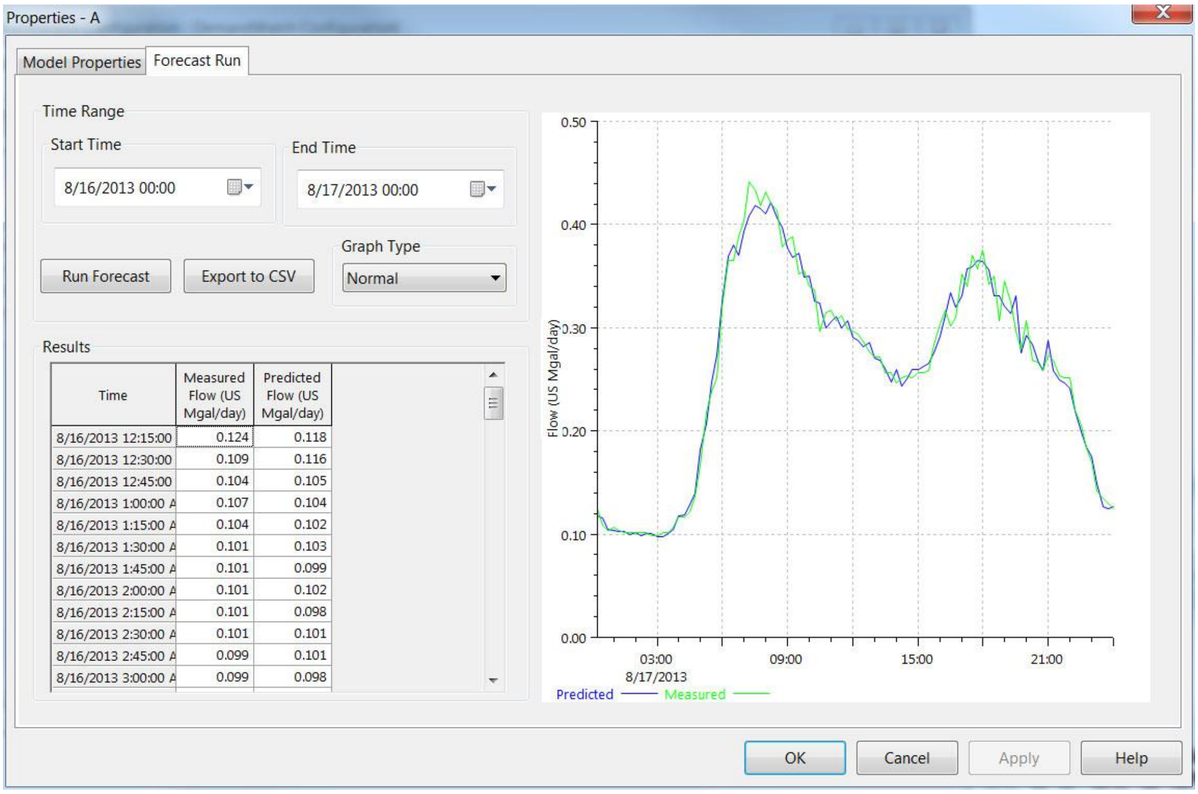

Figure 16: Demand Prediction verified against Observed Data as it's measured in real-time.

The following is a brief overview of considerations within a given demand analysis to generate forecasts:

- Supplies a flow prediction in time steps ranging from one minute to many hours at any flow-metered point in the network (typically at DMA boundaries)
- Demand prediction is generated at a given point in time
- The user may wait a set period of time to verify how well the model is predicting from the observed telemetry as it enters the model in real-time.
- Demand predictions based on mean day of week with consideration to season of the year.
- Short-term error correction and weather influence allows adaptive predictions that "tail off" for each projection run.
- Demand forecasts are sub-daily.

Below is a screen shot of two demand predictions vs observed data shown in an Australian water authority's SCADA viewer (flow through a major PRV). The following screenshot, Figure 17 was taken from a test-run where runs were completed to understand how a prediction made at 9am each day might vary if re-predicted every 30 mins, temperature being the variable.

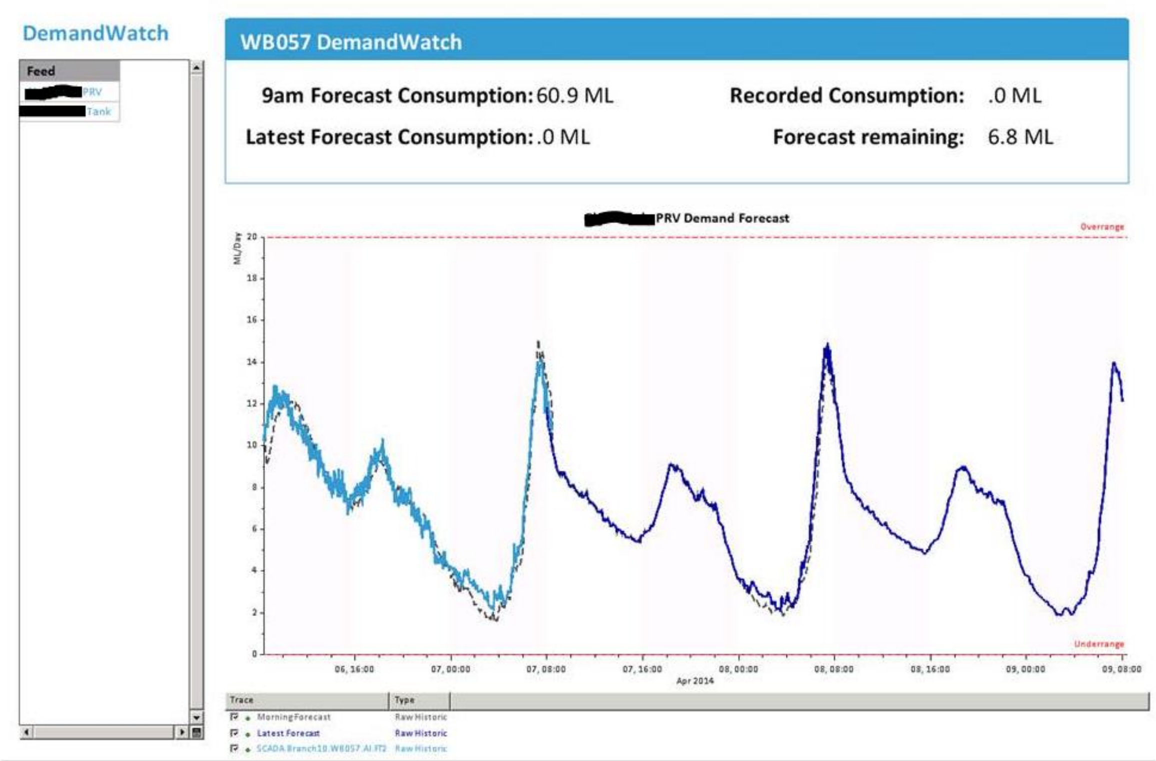

Figure 17: Demand Predictions vs. Observed Data in an Australian Water Authority's SCADA (PRV flow)

The Figure above shows the Demand Analysis and Forecasting tool runs during the simulation period will use a near perfect demand set due to the persistence (short term error correction) having corrected the initial prediction as the observed data became available.

- A forecast that is made at 9am is saved for the whole day and is displayed as a light grey dashed line, this will help to see how good the long term predictions are.
- The dark blue the latest forecast, every 30 minutes the demand forecasting tool will empty the history and then predict the next 24 hours.
- Live data is show in light blue.

4.2.4 THE NEED FOR AUTOMATIC SIMULATION RUNS AND LIVE CONTROLS

Traditional simulation software is limited by the need to manually:

- Start the simulation
- Interpret the output to find adverse conditions in the network
- Compare modelled against observed times-series at every measured point for model verification.
- Manually update the models controls for when the operators change a set-point or status of an asset.
- Manually scale base demands and leakage according to the most recent flow meter data.

A team of round the clock modelling practitioners would be required to perform the aforementioned tasks if the automation capabilities were not available within the operational models.

4.3 MODEL VERIFICATION AS THE SOURCE OF TRUST

The verification process; carried out automatically provides a degree of trust that may be continually checked within a live hydraulic model as a critical predictive decision support tool. Projection simulations may be commenced at a point in the past so that verification is performed from beginning of simulation until the last known telemetry value. One may wait for further observed data to be available for a second verification if the initial verification was not conclusive and an adverse condition was being predicted by the model.

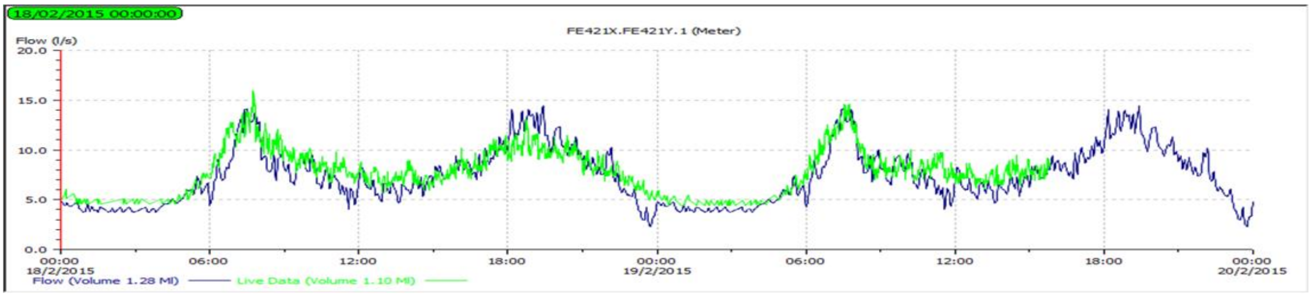

Figure 18: Graphical representation of automatic verification against telemetry data in real-time

The verifications may be carried out either manually or automated.

Root mean square error calculated as:

$$\sqrt{\frac{\sum\left(S(t)-L(t)\right)^2}{n}} \qquad (2)$$

Where:
S(t) = simulated data value at timestep t
L(t) – live data value at timestep t
N = number of timesteps during simulation.

Percentage Difference between model and live values calculated as:

$$100x\frac{\sum\left|S(t)-L(t)\right|}{\sum\left|L(t)\right|} \qquad (3)$$

Where:
S(t) = simulated data value at timestep t
L(t) = live data value at timestep t

4.3.1 FUTURE PREDICTION AND OPTIMIZATION - OPERATIONAL MODEL OUTPUTS

Operational hydraulic modellers need to spend their time responding to projected adverse conditions to develop optimal responses to adverse conditions that develop in the network. Skillsets pertinant to identifying adverse conditions in the network from simulation results may now be templated and automated by being stored away as alert logic embedded within the software. This logic is then automatically applied to every new projection in order to generate alerts. Alerts trigger alert emails to appropriate staff.

Verification Warnings are user defined to hightlight when the live data deviates from the model predictions. Simulation warnings are user defined summary results for the simulation include:

- Threshold Warnings (absolute and % threshold).
- Duration Warnings (absolute and % threshold)

Three priority levels:

- Headline
- Important
- Background

Figure 19 shows a visual representation of how a respective timeseries would be statistially interogated based on exceedences for a given Time Duration and Threshold Level (i.e Pressure values). The aformentioned exceedence are pre-defined by the user and generated automatically by the live operational model.

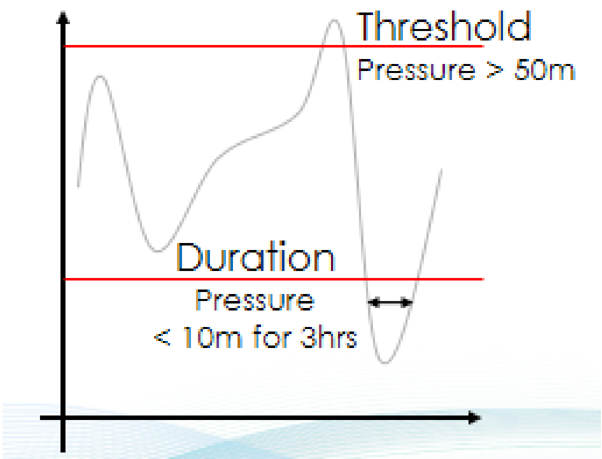

Figure 19: Threshold and Duration (automatic) Predictive Warnings

4.4 OPERATIONAL HYDRAULIC MODEL CASE STUDY1: SOUTH EAST WATER

South East Water, in 2014 after an extensive technology trial adopted a real-time predictive modelling tool for their potable water system. The business aspirations included (Sourghali, 2016): “Optimized and efficient operations, rigourous and supported decision making, improved accuracy of supporting systems and common understanding across the business.”

To this point, the South East Water team have made the following observations with regards to the adoption of live models:

1. Planning models differ from Operational models for the following key reasons (Sourghali et. Al., 2016):

- Operational models require accurate and complete data sets.
- Operating rules in operational models need to be reflective of every day operation by automatically updating from SCADA.
- Planning models are designed for sizing assets with ‘peak summer demand’ conditions which is not always appropriate for operations when flow conditions are low and network water quality is of concern.

2. Realistic future demand forecasts are imperative, stating the necessity of short term demand forecasting (Sourghali et. Al.,2016):

“The predictive component also includes an error correction – as the demand forecasting model is running 24/7 it compares its predictions with the observed data and applies a correction to match the recorded observation. This is necessary to ensure that the operators are seeing a forecast system that closely resembles the current operation.

The error correction decreases over the forecast period so that ultimately the long term future forecast matches what was observed and derived from the training period. Therefore if we enter a different climatic cycle it may be necessary to retrain the demand model, or to be using multiple forecasts to assess different possible scenarios.”

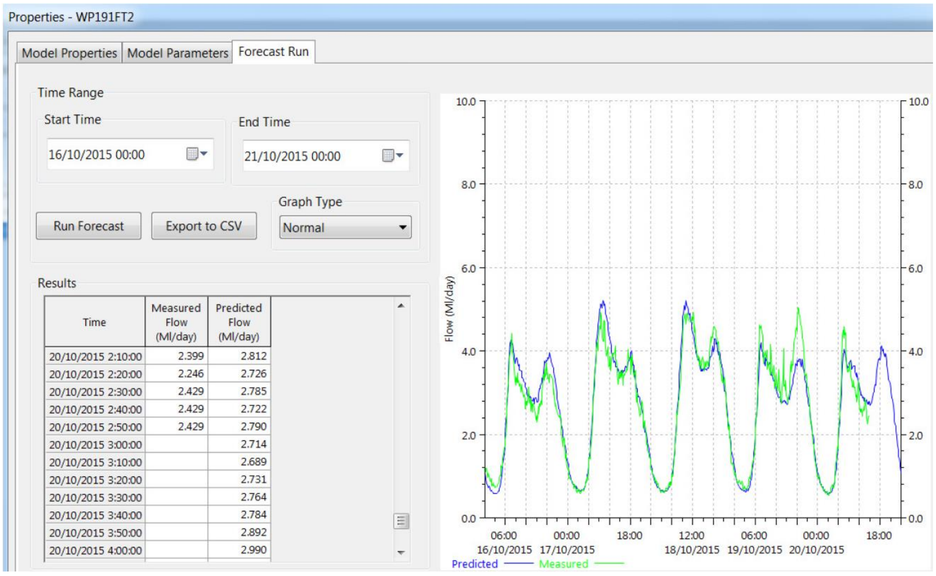

Figure 20: South East Water – Comparison of Demand Prediction to Live Observed Data. (Sourghali et. Al, 2016)

South East Water concluded the following when considering the future implications of the impact live predictive models will have to their team (Sourghali et. Al, 2016):

“Real time predictive modelling has the potential to provide optimized operational decision making and provide a common, shared understanding of how the network operates – at all times, not just during a calibration period.”

4.5 OPERATIONAL HYDRAULIC MODEL CASE STUDY 2: YARRA VALLEY WATER

Yarra Valley Water has identified Operational Live models as the next generation of their hydraulic modelling practices. Yarra Valley Water have recently completed a successful technological trial and have identified the following benefits in progressing their hydraulic models with the Live Operational approach.

Key Benefits (Fernando et. Al., 2016):

1. Operational Decision Support Tool
2. Continual Audit and Calibration of Hydraulic Models (and SCADA)
3. Enhanced Communication and Collaboration

Yarra Valley Water completed a successful technology trial that confirmed the live models ability to receive live telemetry feeds and run verifications to gain a level of trust in prospective forecasts.

The success factors for the Technology Trial were as follows (Fernando et Al., 2016):

- Successful connection to telemetry
- Validation of configuration files
- Projections of future conditions generated
- Observed data and forecasts can be compared and statistically analysed
- Mapping layers can be utilised

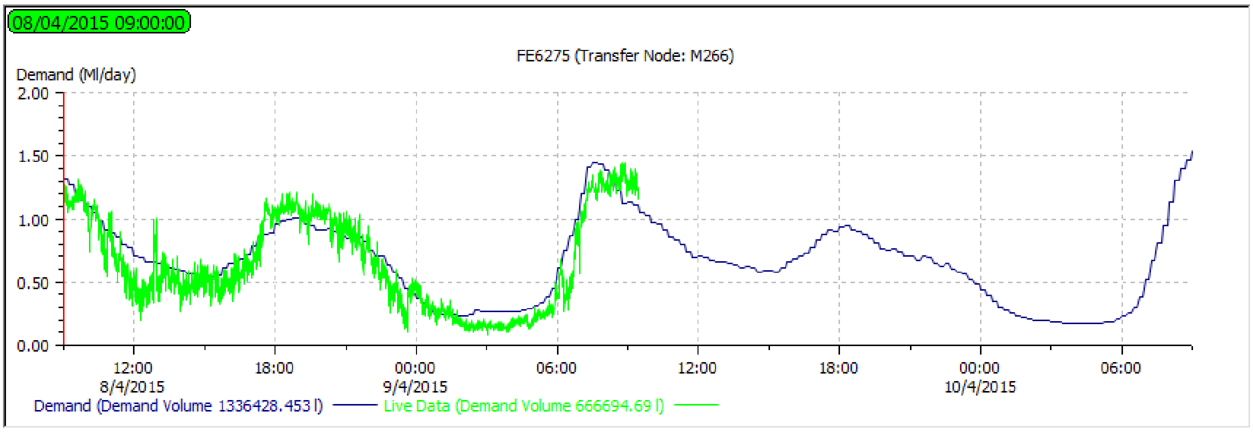

Figure 21: Yarra Valley Water - Model Prediction vs. Actual Flow (Fernando et. Al, 2016)

Yarra Valley Water anticipates benefitting from the ability to utilize their live models to assess network issues and respective solutions through the use of remote controlled assets enabling the swift response (Fernando et Al., 2016). Upon completion of their Live Modelling with Remote Controlled Assets technology trial, Yarra Valley Water stated the following:

"The complexity of water supply systems can make it difficult for even the most experienced operator to determine the best course of action in a given circumstance, particularly with respect to accurately determining the outcomes of their actions. Although it is not suggested that the water supply system can be operated without a qualified operator, live modelling is a powerful support tool which ensures the right decisions are being made. Having accurate and up to date models which are continually validated by live data means that we are able to trust the model predictions and share the operational knowledge of a few individuals across the whole business." (Fernando et. Al, 2016)

5 CONCLUSIONS

5.1 INCREMENTAL FIRST STEPS TO AN INTELLIGENT WATER NETWORK

Hydraulic models and retrospective time varying hydraulic and water quality measurements (typically taken from SCADA) are widely used and well understood in most water utilities across New Zealand and Australia. Planning models contain all of the same attributes as live operational models. Accordingly, the majority of skillsets, data sets, IT infrastructure and software tools required for Intelligent Water Networks are already in place.

If one assumes the project cost of rebuilding a master planning model every 3-5 years for a population of 250,000 people is approximately $500,000, reallocating these funds into development and maintenance of live hydraulic operational/master planning models will allow both optimized planning and operations without increasing model centric expenditure.

5.2 A COMPELLING FUTURE – WHAT HAS NOT YET HAPPENED?

Simply stated: Telemetry, hydraulic predictions and other data collection processes are generating bigger/better but underutilized data sets. The "Big Data" era provides potential for a higher degree of integration between operations, planning and management. However, the current live data bottleneck caused by securing these live datasets combined with the use of 'small data' analysis software (spreadsheets, etc.) when the stale time series data is finally accessed, stifles innovation. When the skills sets of technical staff from all segments of the utility can access live data, the hydraulic networks will in effect be monitored by many more staff by way of stored logic and associated alert generation.

Advancements in computer processing and hydraulic model simulation speed will allow operational models to be run in "sensitivity analysis" mode (simultaneous predictions) where the key inputs remain live; however factors of safety, alternate modes of control (e.g. system feeds from an alternate source) and alternate predictions (e.g. demand forecasts using varied error correction settings and weather feed sources) to provide numerous potential futures from which optimized operational decisions. This approach has already been adopted by meteorologists globally to communicate the probability of certain future rainfall intensities.

ACKNOWLEDGEMENTS

Victoria Intelligent Water Networks for conducting the Intelligent Water Networks workshop at OzWater 2015. Results of the workshop that were publicly distributed were used in Section 2 of this paper as a way of articulating the common challenges that are faced across the industry. Workshop questions were excerpted from the Workshop Summary Notes distributed by the Victoria Intelligent Water Networks upon conclusion of the respective workshop.

REFERENCES

1. Beal, Dr. Cara., 'The 2014 Review of Smart Metering and Intelligent Water Networks in Australia and New Zealand,' Smart Water Research Centre and Water Services Association of Australia.

2. Fernando et. Al., (2016) 'Live Modelling with Remote Control Assets,' Yarra Valley Water.

3. Sourghali, V., Pugh, A. (2016) 'The Vision and the Journey for Predictive Modelling,' South East Water and Innovyze.

4. Anon, (2016). Search Business Analytics [Online] Available at: http://searchbusinessanalytics.techtarget.com/definition/data-sampling [Accessed August 8, 2016]