DIGITAL TWINS: PROBLEM SOLVING WITH DATA DRIVEN AND PHYSICS BASED MODELS FOR THE PAST, PRESENT AND FUTURE STATE OF NETWORKS

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Prediction, Analytics, Energy Optimisation, Incident Response, Water Loss

EXECUTIVE SUMMARY

The past, the present and future conditions at the level of the asset can now be applied with digital twins to solve key problems and meet objectives for a given water network. Aiming to address where, when, why and how; the technological focus of this paper will be around the emergence of digital twin use cases where combinations of data driven and physics based models are being used within cohesive workflows that have been enabled through advancements in the respective platforms via cloud computing for increased scalability and deploying against previously unavailable computing resources.

INTRODUCTION

The past, the present and future conditions at the level of the asset can now be applied with digital twins to solve key problems and meet objectives for a given water network. A digital twin of a water network or plant, in short is a virtual replica of a physical asset, updated in real-time via two-way data connection to represent the live characteristics of a network or plant. Trust in these systems has reached a point where predictive alerts actively support predictive responses to planned and emerging incidents with “What-if” scenarios, and even inform the operation of networks with real-time AI recommendations. Figure 1 relates its application to common network objectives to the time horizon on which the problems are solved. Aiming to address where, when, why and how; the technological focus of this paper will be around the emergence of digital twin use cases where combinations of data driven and physics based models are being used within cohesive workflows that have been enabled through advancements in the respective platforms via cloud computing for increased scalability, deploying against previously unavailable computing resources. Mitigating trade-offs between model types; physics-based models and data driven models are ever more an ‘AND’ proposition instead of solely an ‘OR’.

HIGHLIGHTS

- The past, the present and future conditions at the level of the asset with analytics models.
- Trusted predictive decisions for incident management, reduction of water loss & energy.
- Combinations of data driven and physics based models within cohesive workflows.
- Mitigating trade-offs between model types via platform enabling scalability and compute power.

METHODOLOGY & TECHNOLOGY OVERVIEW

From data integration, analytics, visualisation through to the user’s interaction with the digital twin, data driven and physics based models compose the analytics layer as outlined by SWAN’s (Smart Water Network Forum) Digital Twin Architecture, shown in Figure 2.

Data Driven Models – Real-time Workspaces for End User & Predictive AI Recommendations:

A data modelling application with workspaces open to the end user’s expertise and unique data needs to inform operational and network performance decision making. The cloud hosted applications, with an example workspace shown in Figure 3 were designed to be utilised on a daily basis includes mapping, geospatially located sensors, alert mechanisms and workspaces the user can build based on the needs of specific persona types within an organization. Informed by a data modelling application, the platform allows users to establish real-time direct connections over manual downloads & spreadsheet work, streamline & standardise their network performance calculations & incorporate long term seasonality considerations and larger data sets into their analysis. Data driven models have progressed to a point where predictive AI, utilising a form of Model Predictive Controls (MPC) provide predictive recommendations and control schedules, shown in Figure 4 for actuatable elements – an operational plan for how operators can run a given asset and at what setpoint to run them (Abdul Gaffoor, 2020). The AI can abstract out any process schematic (Water, Wastewater network and treatment plants) into a real-time predicative model that accounts for changes to weather, how the environment changes, system changes – real time over a point in time (Abdul Gaffoor, 2020).

Predictive Physics Based Operational Models – "What-If" Incident Management:

Predictive decision support tools provide a future state of networks with a degree of trust for event detection, demand forecasting, and network simulation to optimize pressure management areas (PMAs). Why a physics based operational model? Sensors are not available in all parts of a network – visibility and understanding of the network during an incident requires supplementation via these respective models. Figure 5 shows model theming to indicate pressure gradients and areas of impact for affected customers due to a network incident. The model includes asset data, live controls, automatic simulation settings and incorporates demand predictions via machine learning utilising historic flows, weather forecasts and provides the user the ability to evaluate "what if" operational scenarios: What are the implications of changing a control within the system? What valves to close for this incident? What areas of network to isolate to minimise disruption?

Figure 6 briefly describes how the user interacts with the data driven and physics-based models relative to the time horizon in which they are conducting the analysis and addressing the respective problem/use case when utilising the software.

USE CASES & OUTCOMES

The outlined technology was applied to the following successful use cases.

Australian Metropolitan City–Pressure & Incident Management, Reduction of Water Loss & Pipe Breaks

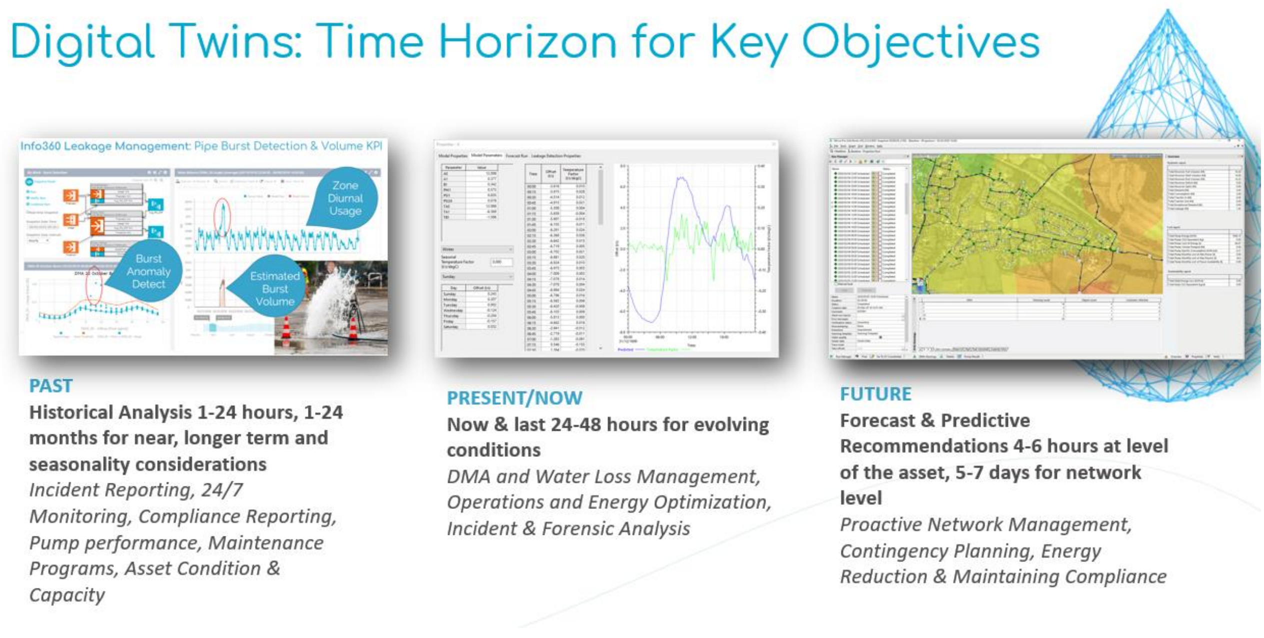
The deployment and implementation of a digital twin solution coupling data driven and physics based operational models for optimised results and actionable decisions around key identified challenges as part of the project included: Aging infrastructure causing pipe breaks as age related issues have been identified as on the rise, proactive management for reduction of water loss with a NRW target of 10% for 2030, consistently and consciously manage pressure transients and extreme pressure events with age related degradation of the network occurs, reduce data overload of multiple data acquisition tools and system via improved data organisation and consistency and address the dynamic between human knowledge of the network and what can be stored and accentuated within the digital twin. User interactions with the software's outputs include having a real-time and predictive continuous map view of water network (flows, pressures, tanks levels, pumps, PRVs, and PMAs/DMAs, etc.), simulate "what-if" interventions and user built workspaces with alerts based on demand predictions from machine learning model and KPIs (i.e infrastructure leakage index ILI).

United Utilities, UK – Predictive AI Recommendations for real-time network optimisation

United Utilities conducted a pilot project to reduce energy use through pump optimisation, improve resilience of network and increase visibility on the complex operational decisions being made based solely on human judgement and experience. The Oldham District Metered Zone was selected for the study as it had relatively high remote control capabilities and a high degree of instrumentation at sites (i.e flow meters, power meters at pump stations, level sensors at service reservoirs (Abdul Gaffoor, 2019). The Oldham Zone, the 5th most populated area in the Greater Manchester Region, supplies 55 MLD, services 19 DMAs, 5 of 10 pump stations remotely controlled and 4 out of 10 service reservoirs monitored. Figure 7 shows an overview of data sources ingested (SCADA, meters, billing, social media), Figure 8 shows how the AI platform interacts with the components of United Utilities network. Table 1 provides a summary of return on investment of the minimum, maximum and average savings scenarios for the 12-week study (Abdul Gaffoor, 2019).

CONCLUSION

The past, the present and future conditions at the level of the asset can now be applied with digital twins to solve key problems and meet objectives for a given water network. Trust in these systems means critical decisions are now being made with multiple kinds of analytical models. Combinations of data driven and physics based models are being used within cohesive workflows that have been enabled through advancements in the respective platforms via cloud computing for increased scalability, deploying against previously unavailable computing resources. Utilities and Councils can now deploy and expose both physics based and data driven models to more use cases and respective outputs from the models can be used by multiple types of personas and stakeholders within a water organisation.



Digital Twins: Time Horizon for Key Objectives

PAST

Historical Analysis 1-24 hours, 1-24 months for near, longer term and seasonality considerations

Incident Reporting, 24/7 Monitoring, Compliance Reporting, Pump performance, Maintenance Programs, Asset Condition & Capacity

PRESENT/NOW

Now & last 24-48 hours for evolving conditions

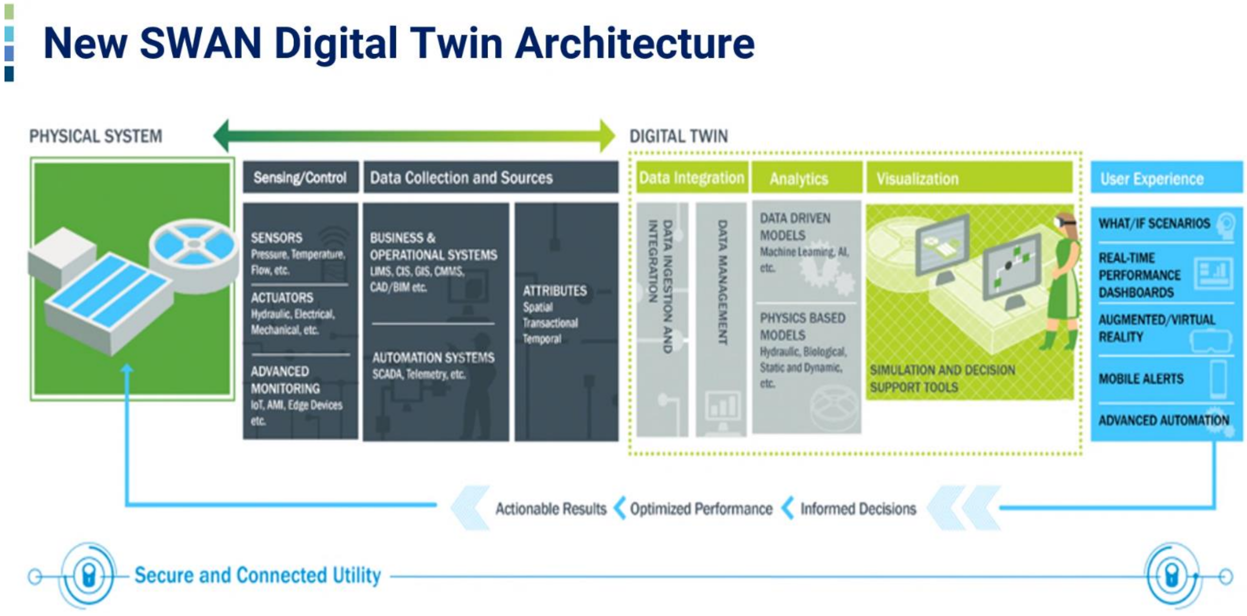
DMA and Water Loss Management, Operations and Energy Optimization, Incident & Forensic Analysis

FUTURE

Forecast & Predictive Recommendations 4-6 hours at level of the asset, 5-7 days for network level

Proactive Network Management, Contingency Planning, Energy Reduction & Maintaining Compliance

Figure 1 relates the time horizons of past, present and future states of the network to common network objectives and problems solved utilising digital twins.



New SWAN Digital Twin Architecture

PHYSICAL SYSTEM

DIGITAL TWIN

Sensing/Control

SENSORS
Pressure, Temperature, Flow, etc.

ACTUATORS
Hydraulic, Electrical, Mechanical, etc.

ADVANCED MONITORING
IoT, AMI, Edge Devices etc.

Data Collection and Sources

BUSINESS & OPERATIONAL SYSTEMS
LIMS, CIS, GIS, CMMS, CAD/BIM etc.

AUTOMATION SYSTEMS
SCADA, Telemetry, etc.

ATTRIBUTES
Spatial
Transactional
Temporal

Data Integration

DATA INGESTION AND INTEGRATION

DATA MANAGEMENT

Analytics

DATA DRIVEN MODELS
Machine Learning, AI, etc.

PHYSICS BASED MODELS
Hydraulic, Biological, Static and Dynamic, etc.

Visualization

SIMULATION AND DECISION SUPPORT TOOLS

User Experience

WHAT/IF SCENARIOS

REAL-TIME PERFORMANCE DASHBOARDS

AUGMENTED/VIRTUAL REALITY

MOBILE ALERTS

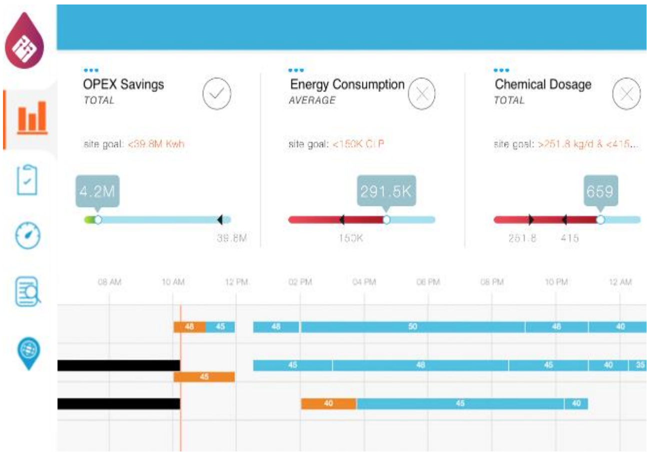
ADVANCED AUTOMATION

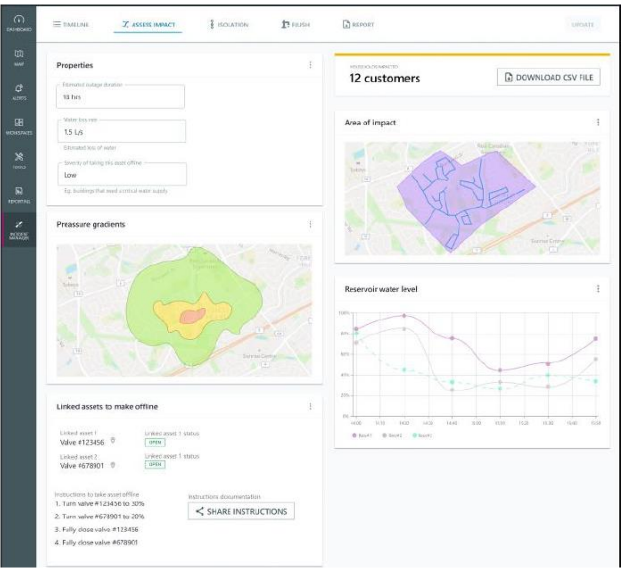
Actionable Results ‹ Optimized Performance ‹ Informed Decisions

Secure and Connected Utility

Figure 2: SWAN Digital Twin Architecture incorporating the aspects of Data Integration, Analytics, Visualisation and User Experience.

Figure 3: Workspaces, designed to be utilised on daily basis, are informed by a data modelling application allowing users to establish real-time direct connections and scalability of analysis.

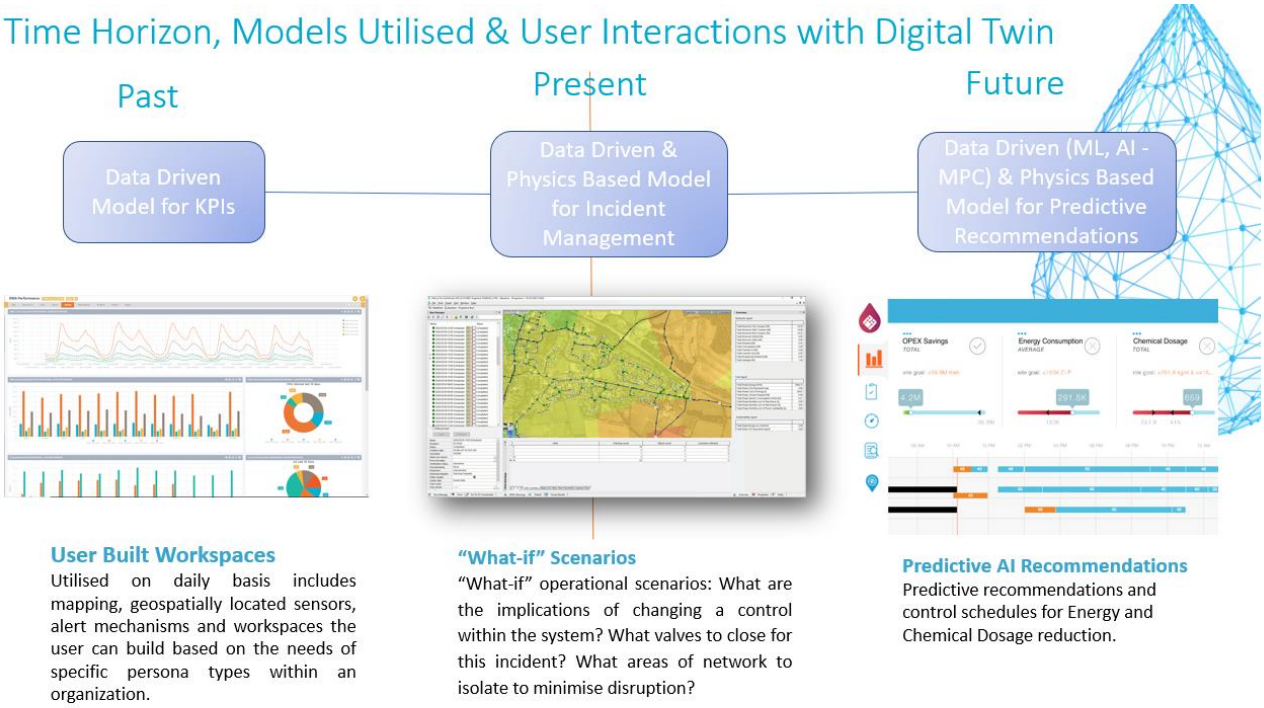




1. Turn valve #123456 to 30%
2. Turn valve #678901 to 20%
3. Fully close valve #123456
4. Fully close valve #678901

Figure 4 Predictive Controls (MPC) provide predictive recommendations and control schedules to meet operational objectives such as energy use and chemical dosages.

Figure 5 Operational interface for incident management and impact assessment.



User Built Workspaces

Utilised on daily basis includes mapping, geospatially located sensors, alert mechanisms and workspaces the user can build based on the needs of specific persona types within an organization.

"What-if" Scenarios

"What-if" operational scenarios: What are the implications of changing a control within the system? What valves to close for this incident? What areas of network to isolate to minimise disruption?

Predictive AI Recommendations

Predictive recommendations and control schedules for Energy and Chemical Dosage reduction.

Figure 6 shows how users interact with the data driven and physics-based models relative to the time horizon in which users are conducting their analysis.

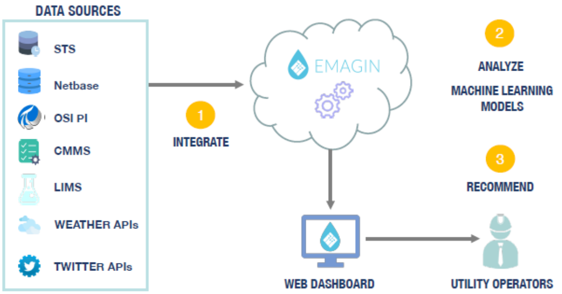


Figure 7 Data sources that informed the predictive AI model for the United Utilities study.

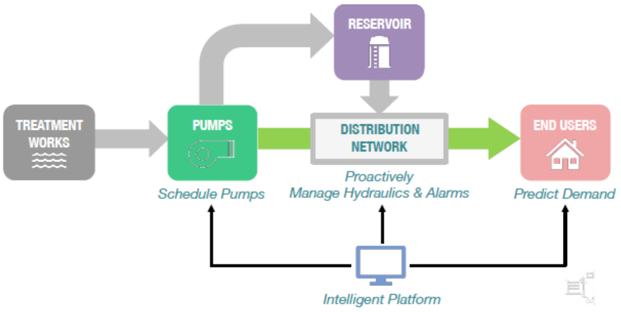


Figure 8 Schematic of key elements of the AI Platform utilised for the United Utilities study.

Table 1 Overviews the outcomes and benefits (Min, Avg, Max.) demonstrated with United Utilities for the 12-week study.

	MIN	AVG.	MAX.
Baseline Annual Operational Cost (£)		**230,367**	
Optimized Annual Operational Cost (£)	192,326	**180,148**	125,823
Savings (%)	17%	**22%**	45%
Savings per Annum (£)	38,041	**50,219**	104,544
Normalized Savings (£/ML)	2.1	**2.8**	5.7
Payback Period	7 months	**5 months**	2 months