Wastewater Pump Station Asset Performance Visualisation

Arush Kalra

Melinda Hodkiewicz
Mechanical Engineering
The University of Western Australia

Berwin Turlach
Mathematics and Statistics
The University of Western Australia

Vikesh Raikundalia & Desmond McEwan
CEED Client: Water Corporation

Abstract

The Water Corporation has recently approved and is currently implementing a new Asset Class Strategy with the objective of ensuring all assets, in particular, Wastewater Pump Stations across WA are safe, reliable, compliant and cost-effective. A previous study manually developed performance-based reliability measures through an amalgamation of ad-hoc processes. However, this method is laborious, slow and unrepeatable. The aim of this study is to develop a semi-automated process for generating these measures for all operational pump stations. This study presents a fresh approach to the acquisition, processing and visualisation of data stored in various databases within the corporation. The outcome of this study is to develop an intuitive Power BI interface accessible by Water Corporation personnel regardless of their technical background. The user-friendly graphical interface acts as a decision support tool for further investment and maintenance decisions undertaken by the Water Corporation.

1. Introduction

The Water Corporation is the principal supplier of water, wastewater and drainage services to over 2 million people throughout Western Australia. The corporation owns and operates over 1,000 wastewater pump stations (WWPSs). These pump stations have 10,000 unique configurations and have to be all covered by the corporations Asset Class Strategy. The objective of the Asset Class Strategy is to ensure the safety, reliability, compliance and cost effectiveness of all assets relating to the function of the pump station facility (Water Corporation, 2017a).

From 2006 to 2018, over 28,000 work orders were raised against WWPSs in the corporation's asset management database (SAP). The entries range from failures of critical components, such as pumps and motors, to scheduled preventative maintenance tasks. These datapoints provide an insight into the health of operational assets, from which reliability performance measures (time between failures, total downtime etc.) can be developed. These measures are important as they enable personnel to reach informed, data driven conclusions. Asset Management and Operations Support Software (AMOSS) database records high level information such as the make of pumps, switchboards and alarm systems installed at each WWPS in the field. This database is utilised to filter the reliability performance measures by component make. Additional knowledge of its asset base allows the corporation to maximise its utilisation of current assets before investing in new assets, quantitively determine the economic value of the various maintenance strategies currently in place and identify areas for improvement to the asset management process for WWPSs to maximise operational lifetime of its unique assets. For example, during the design of a new pump station, a reliability engineer is able to recommend a suitable component by analysing and comparing the performance of operational components. Planners are able to utilise the data to determine suitable maintenance intervals.

Traditionally, to determine performance measures, an individual needs to invest a considerable amount of their time to undertake the laborious data collection, cleaning and processing. Each individual makes assumptions throughout the process, effectively resulting in a series of ad-hoc processes that vary greatly based upon the individual's background. For example, the previous process involved the creation of a list of all functional locations by component make, often based on hearsay knowledge. As such, the potential for unexplained variances in the reliability performance measures generated increases. Due to the large number of data points, mistakes in data processing or calculations are common. As a result, decision-making personnel lack confidence in the performance measures generated.

The objective of this study is to improve the asset management process by developing a semi-automated process by which reliability performance measures are generated. This was achieved through the creation of a 'data pipeline', as illustrated in Figure 1. Data from AMOSS and SAP are the inputs into the pipeline which processes and simulates the data based on assumptions regarding data quality. Data quality was defined in terms of data readiness bands, as set out by Lawrence (2017).

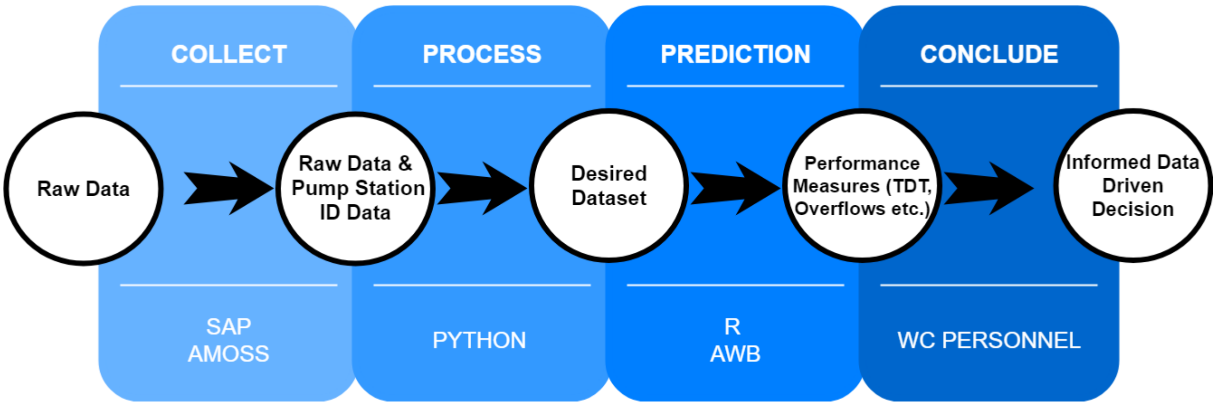

Figure 1 Data Pipeline

The focus of the study are WWPSs, in particular the following components: Power Supply, Switchboard, Level Sensor, Pump, Motor, Motor Starter, Pipe and Alarm System. The scope was narrowed to the most popular component makes as determined by Low (2018). Figure 2 illustrates a reliability model of components within a WWPS. The scope of the study was initially limited to Type 40 Pump Stations in the Perth Region. This limitation was later overcome by leveraging the AMOSS database to classify the type of WWPS.

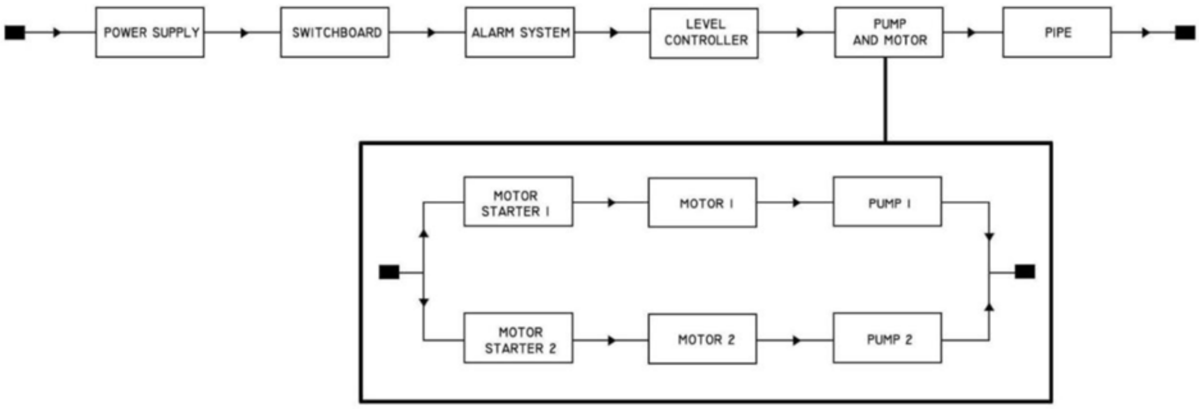

Figure 2 WWPS Reliability Block Diagram

2. Process

To aid the development of the data pipeline, a Python script was developed. The code's purpose is to automate the collection, processing and clean-up of the relevant data. Figure 2 illustrates detailed data flow within the pipeline, where the Python code acts as an intermediary between the blocks.

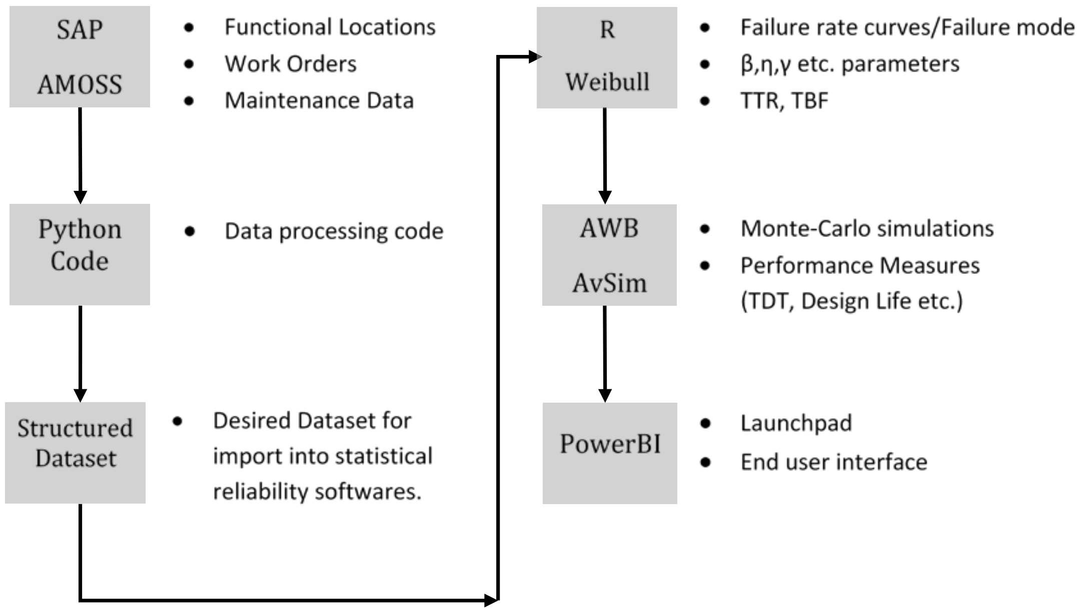

Figure 3 Detailed Data Flow

2.1 Data Acqusition and Data Cleaning

The first step is acquiring, merging and cleaning maintenance data from SAP and AMOSS databases. For example, each maintenance work order in SAP contains the functional location of the component, the type of maintenance activity (corrective or preventative), the time the work order is raised and how long it took maintenance personnel to fix the issue. Functional location of each asset (common identifier in both databases) was utilised to merge the two databases. This allows for maintenance work orders to be identifiable by component make. For example, all maintenance work orders relating to a Flygt motor can be filtered and reliabilty analysis undertaken.

However, the extracted data from SAP and AMOSS needed to be cleaned and refined for processing and further calculations. Several assumptions, such as minimum duration to minimum cost, were applied to remove data deemed unsatisfactory. Further, there were multiple instances where data in SAP was recorded incorrectly by maintenance personnel. These instances ranged from ommiting key fields to raising work orders against the component functional location instead of the pump station. Data entries with missing fields were ommitted, however, The ‘Superior FL’ data field in SAP was utilised to raise all component functional locations to their respective pump station.

2.2 Data Processing

The aim is to obtain time between failure values for each component across all pump stations. The calculation of the time values and discernment of the type of event (i.e. failure or suspension) is crucial for Weibull analysis and monte-carlo simulations. Reliability analysis via Availability Workbench can be undertaken on each component within the WWPS.

To achieve this, the Python code groups all events by pump station functional location. The data is then further sorted in ascending order based on the ‘Start Date Time’ associated with each work order. This sets up a clear timeline of events associated with each pump station and is utilised to calculate the time between failure value. ‘Maintenance Activity Type’ column is used to determine the nature of event, with failures denoted as ‘F’ and suspensions as ‘S’. ‘Start Up’ column is utilised to determine the age of the pump station and thus the time between failure associated with the first event for each pump station. Additionally, the WC records failure tasks in the ‘PM Operator Task’ column. Since each of these task codes correspond to a particular component, the code creates a data frame for each component based upon the task code. However, preventative maintenance activities (suspensions) are raised as a Generic Work Instructions. As such, the code creates another data frame, this time using the ‘Document’ column and then concatenates the two data frames to form a list of all events related to each component. Further, a data frame for each make (flygt pump, forrers pump etc.) is created. The Time Between Failures are then calculated for each component make and reliability analysis undertaken.

2.3 Data Visualisation

A Graphical User Interface (GUI) allows users to interact with a computer via graphical icons. The end product of this project is a Power BI GUI that displays reliability performance measures for each WWPS configuration. This is advantageous to the end user as this approach doesn’t require prior technical knowledge of the code and acts as a launchpad to the code. Wang and Tan (2006), outline six primary principles to be used as guidelines for developing GUIs for modern industrial automation software:

1. **User Familiarity –** an effective UI needs to provide its users with minimal constraints as they manipulate the interface.
2. **Consistency –** high UI consistency is beneficial as it results in an increase in productivity of the end user. Skills learnt in one operation can be easily applied to another.
3. **Minimal Surprise –** comparable operations should have comparable results to avoid unnecessary frustration for the end user.
4. **Recoverability –** the UI must possess some fault-tolerance capability.
5. **User Guidance –** a well design help system is necessary for first time users.
6. **User Diversity –** UI should be able to cater to a diverse user base.

3. Preliminary Results

Key performance measures such as Time Between Failures, Total Down Time, Mean Unavailabilty etc. were represented via Power BI. Figure 4 illustrates the data visualisation hierarchy implemented within Power BI.

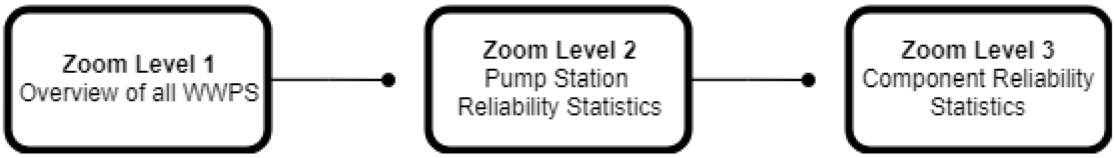

Figure 4 Data Visualisation Hierarchy

Zoom Level 1 represents an overview of all operational WWPSs owned by the corporation. The end user is able to access this overview via a map of WA or by utilising a time scale slider as shown in Figure 5. The user is able to utilise the drillthrough feature within Power BI to reach Zoom Level 2 for the selected pump station, with each circle representing a pump station.

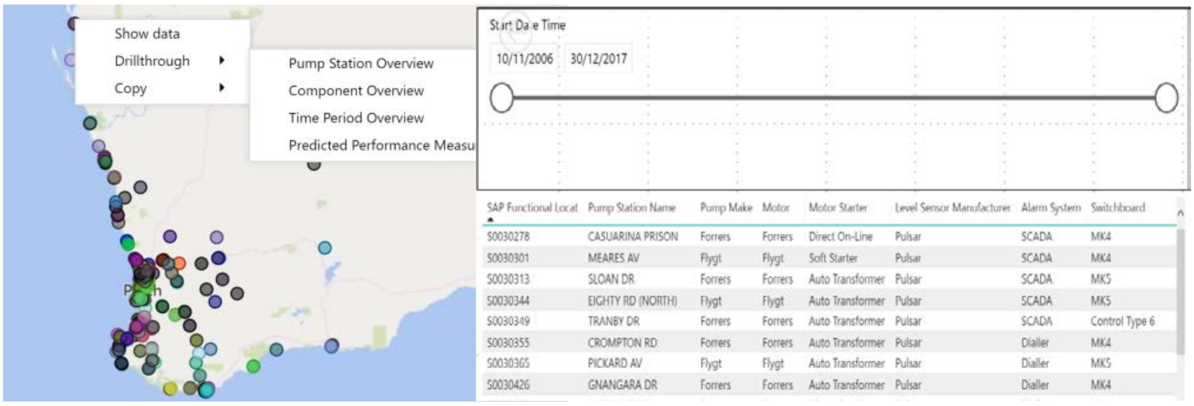

Figure 5 Zoom Level 1 (Map Overview and Time Slider)

Zoom Level 2, as shown in Figure 6, illustrates some performance measures at the Pump Station level. Further information such as, failed component, type of maintenance activity, mean downtime and more are also illustrated in Power BI. Future performance of each WWPS configuration is generated via monte-carlo simulation in Availability Workbench. For example, reliability measures such as total number of outages, total downtime and mean time to first outage are generated.

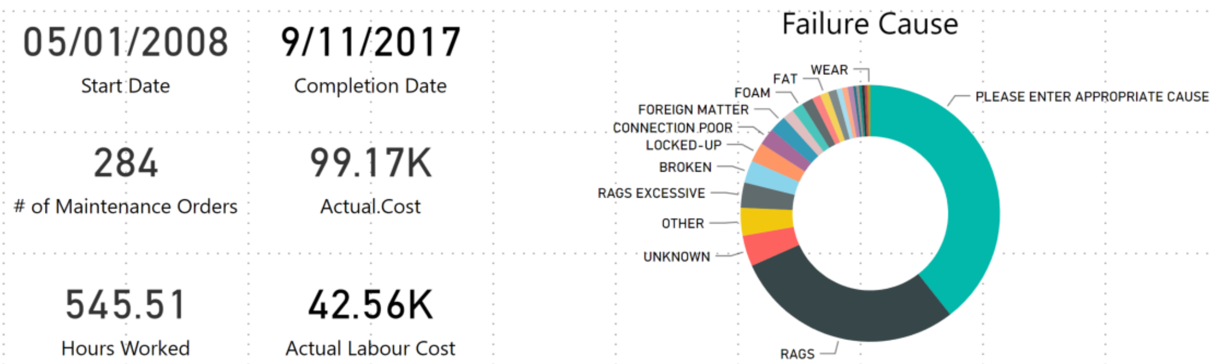

Figure 6 Pump Station Overview

Zoom Level 3 displays specific reliability performance measures by the component make. For example, the reliability rate over time (hours) of a level sensor can be displayed. Failure rate, total downtime, unreliability etc. are further performance measures displayed via Power BI for each specific component make. Comparisons of predicted component performance can also be made.

4. Conclusions and Future Work

The structured approach set out by the data pipeline and the code ensures the results are repeatable. The documentation in the code enable the results to be checked for accuracy. The Power BI interface is user friendly, allowing personnel to utilise the tool without needing to know the details of the code at the backend. Further work to be undertaken revolves around increasing the level of automation within the pipeline. For example, since Availability Workbench is a closed source software, automating the import and export of data has not yet been achieved. However, this does allow the reliability engineer to undertake discretionary changes regarding any component, thus enhancing the functionality and flexibility of the pipeline. Another area of improvement is the interface between the code and SAP/AMOSS databases. Currently, the user needs to manually download the databases as .csv files. Future work will eliminate this manual process by interfacing the database backend and the Python code via Structured Query Language.

5. Acknowledgements

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