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DECISION SUPPORT TOOLS FOR PREVENTIVE MAINTENANCE INTERVALS AND REPLACEMENT DECISIONS OF ENGINEERING ASSETS.

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Abstract – **Prognostic models for maintenance decisions have inherent limitations due to quality & quantity of historical data, assumptions made, and time required in validating models. In this paper, Preventive Maintenance (PM) Intervals, Failure events, cost and maintenance records from Computerized Maintenance Management System (CMMS) are analyzed for reducing downtimes and Operating Expenditure (OPEX). The proposed methodologies for maintenance intervals and replacements with acceptable level of confidence are articulated to asset maintenance of a City Council of Australian Local Government organisation as a case of improved decision making under limited information.**

Keywords – **Decision Support, Preventive Maintenance Interval, Weibull Analysis, Risk Ranking, Degradation Modeling**

I. INTRODUCTION

Asset management decisions have significant influence on operating and capital expenditure of any big organisation similar to city council. Illustrative example from Australian Local Government organisation is considered in this study for unstructured and at times insufficient field data resulting a risk based informed decision making in maintenance and replacement of engineering assets for reduced costs and risks along with enhanced performance.

Issues and challenges in wastewater treatment plants and sewer pressure mains of the city council assets are studied and analyzed in this research project. Failure modelling, non-destructive wall thickness assessment and parametric survival curves are proposed to better estimate capital investment needs and more accurate replacement timelines.

II. METHODOLOGY

Balancing Risk, Performance and Cost is now a globally accepted trend in good practice asset management in line with, ISO55000, ISO standard for asset management. This study is performed on two groups of assets where decisions are more influenced by cost in one set of assets and risks in the other set of assets.

In the evolution of maintenance strategy, the domain of traditional reliability engineering sits between Corrective Maintenance (CM) and Preventive Maintenance (PM) whereas Prognostics and Health Management (PHM) positions between PM and CM[1]. Prognostics is the key enabler that permits evaluation of system reliability by predicting failures more accurately and providing informed risk based decision making in maintenance of assets and capital expenditure. Prognostic modelling is able to better predict remaining useful life [2, 3]. It is able to develop health management roadmap of assets through a general path model [4. 5]

Park, Tin and, Jeong proposed a framework for modelling the likelihood of failure of underground pipeline assets [6]. Chattopadhyay and Kumar estimated parameter for degradation using parametric modelling approach [7]. Chattopadhyay discussed issues and challenges of balancing cost, performance and risk in life cycle management of capital intensive assets [8]. Beebe extensively covered predictive maintenance of pumps using effective condition monitoring approach [9]. Rahman and Chattopadhyay proposed optimal service contract policies for outsourcing maintenance services [10]. Chattopadhyay and Yun developed 2D models and analyzed warranty costs for reducing risks of failures [11].

Techniques of fault diagnosis for Condition Based Maintenance (CBM) are more mature in research for life cycle management of industrial products/systems compared to that of PHM method, which has been significantly growing in recent years. International Standard ISO 13381-1 provides a comprehensive guidelines for performing failure prognostics of engineering systems [12]. Prognostics is defined as an estimation of time to failure and associated risks of one or more known and potential failure modes. A sound methodology is used for generating Weibull parameters of failure data and is applied in risk based decision making in maintenance.

Historical data available from City Council's CMMS was used for analysis and illustrative example of this paper.

INSTRUMENT ASSETS

Instrument assets of various types (asset classes) were considered from Waste Water Treatment Plants (WWTP) of the city council in Australia. Analysis showed that primary impacts of low and/ or non-availability of these instruments were increased costs, followed by reduced performance. Business risk resulting from failure of these assets was not significant.

Figure 1 shows that 14 out of 73 classes of assets contributed significant portion of total maintenance cost. Further distribution of cost for Reactive Maintenance (RM), Preventive Maintenance (PM) and Total

Maintenance was analysed for broad objectives of asset management actions and is provided in Table 1.
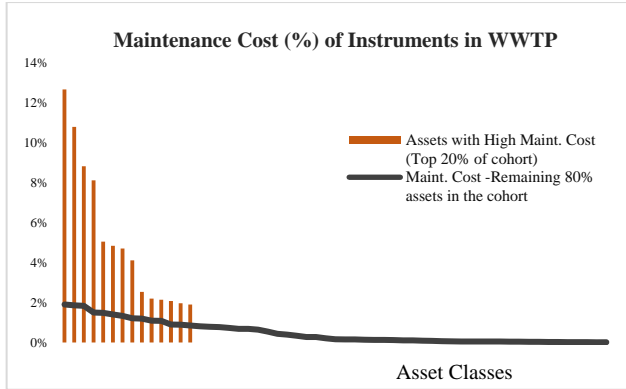

Fig. 1. Distribution of Maintenance cost among Instrument asset classes

TABLE 1
MAINTENANCE COST DISTRIBUTION AND OBJECTIVE IDENTIFICATION

Asset Class	RM	PM	Total Cost	PM/ Total	RM/ Total	Objective
Dissolved Oxygen Analyser	3	2	1	52%	45%	< PM, < RM
Actuator	1	N	2	9%	85%	< RM
Flow Meter	2	7	3	20%	79%	< RM, < PM
pH Meter	9	1	4	82%	16%	< PM, < RM
Level Sensing Element	4	N	5	19%	80%	< RM
Level Transmitter	5	N	6	24%	66%	< RM
Turbidity Analyser	6	9	7	28%	68%	< RM, < PM
Solenoid Valve	7	8	8	42%	57%	< RM, < PM
UV Intensity Sensor	11	11	9	47%	46%	< PM, < RM
Pressure Transmitter	8	N	10	35%	65%	< RM
Nutrient Analyser	N	5	11	85%	15%	< PM
Flow Switch	N	3	12	87%	13%	< PM
Orthophosphate Sensor	N	6	13	92%	8%	< PM
Chlorine Residual Analyser	N	12	1	57%	40%	< PM

Analysis is conducted based on relative costs for Reactive Maintenance, Preventive Maintenance and Total Maintenance Cost. Actions are classified into four categories or groups, as shown in Table 2.

TABLE 2
RANKING OF HIGH MAINTENANCE COST CLASSES

Group	Action
1	Reduce cost of PM
2	Prioritize PM cost reduction over RM cost
3	Prioritize RM cost reduction over PM cost
4	Reduce cost of RM

For each of the 14 instrument asset classes, Time to Failure (days), Frequency of PM and Cost of RM & PM were analysed from CMMS data.

Recommendations from Original Equipment Manufacturer (OEM) on maintenance scope used to overrule any other considerations during initial years of operation of plant. As maintenance management system, personnel skills and asset knowledge matured, the asset owners looked for feasible opportunities for further improving decision making of maintenance schedules including capital investments. Key considerations were eliminating unnecessary PMs, incorporating lessons learnt from performance data and reducing OPEX, wherever possible, through rationalisation of PM.

A failure prediction model was proposed using Weibull analysis for asset class behavior. Each valid RM Work Order is counted as a failure event in this analysis using available data from 01-July-2013 to 27-Feb-2017. Time between two consecutive failure events (TBF) in this period is extracted for each asset of any particular asset class. Assets having identical functions, specification and similar failure modes are pooled together in this analysis.

III. RESULTS FROM INSTRUMENT ASSETS

A typical case of a Flow Meter is considered here for an illustrative example. As the range of TBF varied between 2 to 638 days for 38 failure events of Flow Meter, a normalized parameter T* was used. This approach was taken due to unavailability of failure data prior to 01-July-2013.

$$T* = T + \text{Stdev}(\sum TBF) \quad (1)$$

$$\text{Median Rank} = \frac{(f(i) - 0.3)}{(f(n) + 0.4)} \quad (2)$$

Weibull curve for Flow Meter was generated by plotting $\ln(T*)$ against $\ln(\ln\left(\frac{1}{(1 - Median\ Rank)}\right)$. The resulting Weibull plot is provided in Figure 2.
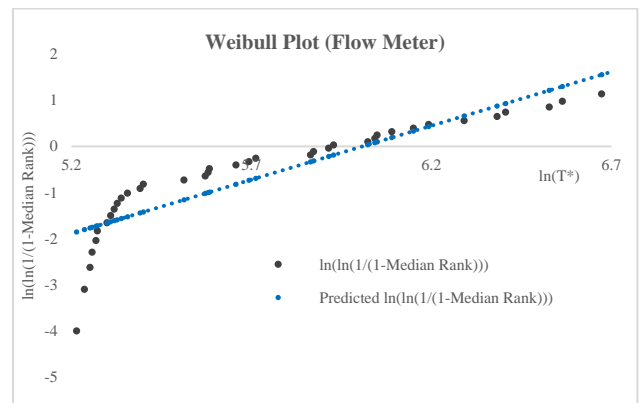

Fig. 2. Weibull Plot for Flow Meter

Regression analysis of defect data was carried out to obtain shape parameter β. Characteristic life α for the asset group was estimated as follows:

$$\alpha = e^{-\beta} \tag{3}$$

Probability of Failure (P-F) curve for the asset class was developed as shown in Figure 3. From this curve, time to reach a target reliability of 95% is extrapolated for desired interval for PM.
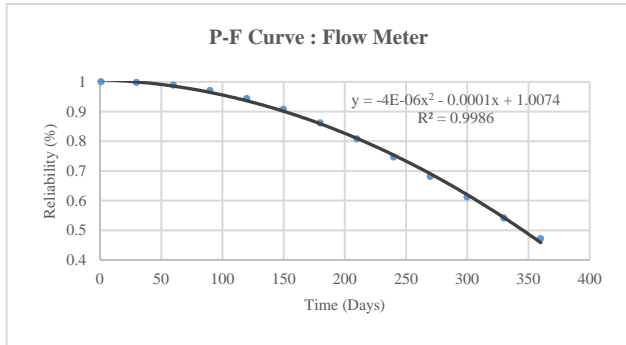

Fig. 3. P-F Curve for Flow Meter

Table 3 provides findings from analysis of 14 classes of assets across four categories. The proposed maintenance frequency is decided based on lowest possible cost considering a minimum threshold of 95% reliability.

TABLE 3
PROPOSED PM INTERVALS FOR DIFFERENT GROUPS
OF ASSET CLASSES

Group	Asset Class	Estimated Threshold for 95% Reliability (days)	Existing Maint. Frequency	Proposed Maint. Frequency
1	Nutr. Analyser	75	1 W	1 M
	Flow Switch	523	1 Y	1 Y
	Orthoph. Sensor	160	1 W	3 M
	Chl Res Anlyser	184	2W, 1 Y	6 M, 1 Y
2	Diss O2 Anlyser	214	1 M	6 M
	pH Analyser	205	2 W	3 M
	UV Int Analyser	188	2 M, 6 M, 1 Y	6 M, 1 Y
3	Flow Meter	113	1 Y	6 M
	Turb. Analyser	152	1 Y	1 Y
	Solenoid Valve	269	1 Y	1 Y
	Actuator	232	1 Y	9 M
4	Level Sensing Element	238	1 Y	1 Y
	Lev Ind. Trans.	185	1 Y	1 Y
	Pr. Transmitter	203	1 Y	1 Y

Above analysis provided a basis for rationalisation of PM. For asset classes in Groups 1 and 2, there is a marked reduction in expected maintenance expenditure by extending maintenance intervals.

For Groups 3 and 4, analysis showed a need for increase in frequency for Flow Meters and Level Sensing Elements to provide desired reliability. Although there was a marginal increase of PM cost, the reason behind this is consideration of risks associated with failures along with the fact that more frequent PM picked up early warning signs of potential failure of assets and therefore avoiding high RM costs.

It was recommended for a trial of the new maintenance intervals for a period of 18-24 months, append CMMS data, re-run analysis and fine tune P-F curve to further enhance confidence of decision making in risk based asset management.

In the initial attempts to model failures, β obtained from analysis was less than 1 for all asset classes, apparently indicating infant mortality. However, knowing the physical assets have been in service for quite some time without drastic failure events and due to absence of good CMMS data, the analysis was re-run with standard deviation of failure times (T*).

Figure 4 shows the actionable defects across the asset classes as on date and are: calibration drift, component failure, decommissioning, wear and material failures. In the subsequent iterations, further analysis on impact of defect data needs to be considered for more accurate decision making of PM intervals.
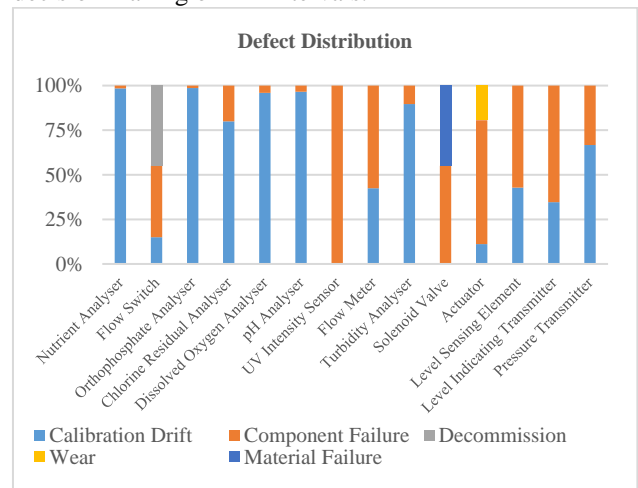

Fig. 4. Distribution of actionable defects

SEWER PRESSURE MAIN

The Sewer Pressure Main (SPM) consists of 12 pipe line assets with diameters ranging from 375mm to 750mm. Oldest pipe has clocked 41 years in service, most recent sectional replacement was done 6 years ago. Lengths of pipe sections vary from 4m to 2.12 km. Material of construction are Ductile Iron-Cement Lined (DICL), Cast iron (CI), Mild Steel-Cement Lined (MS-CL) and Asbestos Cement (AC). There are limited or no maintenance data and failure records for the SPM. Due to operational and budget constraints and challenges of terrain, it was not possible to conduct assessment and gather asset condition data with reasonable level of confidence. However, primary impact of failure is found as operational and business risk followed by costs. The only information available or assets was from the run performed using a free-swimming foam ball with acoustic sensor data, for locating leaks, any gas and air pockets.

During this test, no pipe leaks were identified. There were two major types of findings as shown in Figures 5 and 6. First one was the location and length of localised air, gas

pockets and gas slug pockets. The other one was information on pipe wall anomalies. In case of the latter, the location and the qualitative size of the anomaly was identified, however, a differentiation on type of anomaly, i.e wall thinning, crack etc. could not be quantified from the available data. Therefore, this exercise provided a qualitative baseline information of pipeline condition.
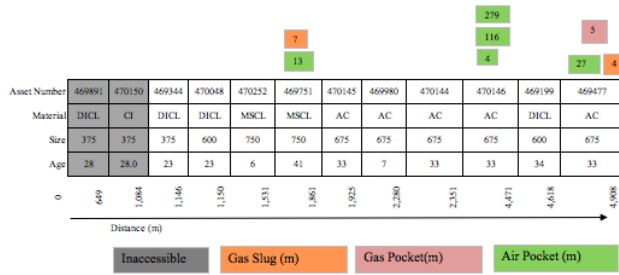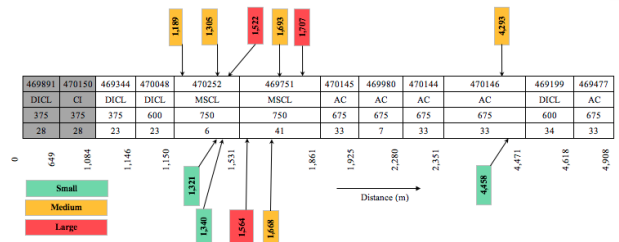

Fig. 5. Location of gas / air pockets

Fig. 6. Distribution of pipe wall thickness anomalies

IV. RESULTS FROM SEWER PRESSURE MAINS

Table 4 summarizes available limited information on these assets as used for degradation modeling and replacement decisions.

TABLE 4
CURRENT CONDITION OF SPM SYSTEM

Asset Number	Description	Size	Material	Measured Length	Construction Date	Age (Years)	Anomaly Type	Anomaly Length (m)	Anomaly Size	Anomaly Qty.
469891	Pressure Main	375	DICL	649	30-Mar-89	28				
470150	Pressure Main	375	CI	435	30-Mar-89	28				
469344	Pressure Main	375	DICL	62	9-May-94	23				
470048	Pressure Main	600	DICL	4	9-May-94	23				
470252	Pressure Main	750	MSCL	381	10-Mar-11	6				
469751	Pressure Main	750	MSCL	333	27-Aug-76	41	Air	13.00	Medium	2
							Gas slug	7.00	Small	2
									Large	2
									Medium	2
									Large	1
470145	Pressure Main	675	AC	64	15-Feb-84	34				
469980	Pressure Main	675	AC	355	9-Jul-10	7				
470144	Pressure Main	675	AC	71	15-Feb-84	34				
470146	Pressure Main	675	AC	2120	15-Feb-84	34	Air	4.00		
							Air	116.00		
							Air	279.00		
469199	Pressure Main	600	DICL	147	3-Aug-83	34			Medium	1
									Small	1
469477	Pressure Main	675	AC	147	9-Dec-83	34	Air	27.00		
							Gas slug	5.00		
							Gas Pocket	4.00		

Each asset is assigned a score using a scale of increasing severity from 1 to 5. Variables considered are age, transport volume and condition. For condition, the scores are derived from the type, length, size and number of anomalies recorded. Current degradation factor is modelled as follows:

$$\text{Current Degr. Factor} = \exp\left(-\frac{\text{overall score for asset}}{\text{Total Overall Score}}\right) \qquad (4)$$

Overall score is allocated using the product of three individual scores and is presented in Table 5.

TABLE 5
FACTORS USED IN DEGRADATION RANKING OF ASSETS IN SPM

Asset Number	Age Score	Volume Score	Condition Score	Overall Score	Current Degrad. Factor
470146	3	5	3	45	0.72
469751	4	2	4	32	0.79
470145	3	1	3	9	0.94
470144	3	1	3	9	0.94
469199	3	1	3	9	0.94
469477	3	1	3	9	0.94
470150	3	1	2	6	0.96
469980	1	2	3	6	0.96
469891	3	1	1	3	0.98
469344	2	1	1	2	0.99
470048	2	1	1	2	0.99
470252	1	2	1	2	0.99

Relative performance of each asset compared to parametric curve from its current state of degradation till end of expected service life (60 years) is calculated using the relation developed by Park H et. Al [6]

$$S(t) = \exp(-\exp(-3.6095\mu)\, t^{3.6095}) \qquad (5)$$
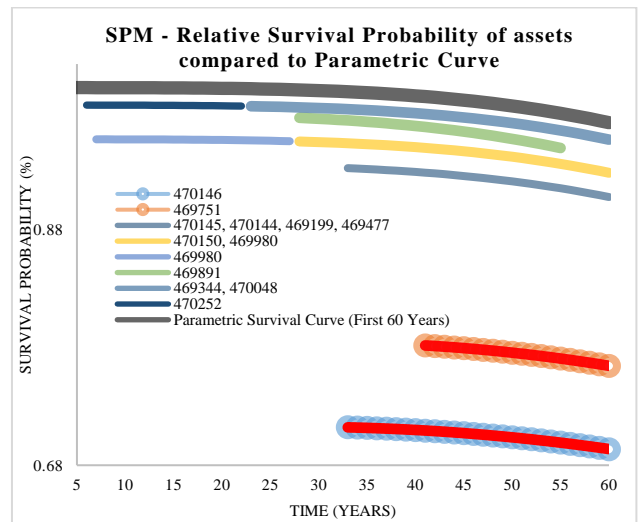
Failures are modelled for $\mu = 5.0647$

Fig. 7. Relative survival probability of SPM assets

From current condition ranking and relative survival probability using parametric curve (Figure 7), two assets, i.e. 470146 and 469751 were allocated top priority for replacements in a 10 year planning window. The asset replacement cost is estimated accordingly and is provided in Table 6.

TABLE 6
REPLACEMENT PRIORITY OF SPM ASSETS

Asset Number	Current Deg. Factor	Priority	Unit Rate of replacement ($/m)	Asset Replacement Cost ($, FY 2016-17)
470146	0.72	**1**	1,200	2,544,461
469751	0.79	**2**	420	139,852

V. CONCLUSIONS

In the absence of good quality maintenance data, consideration by the council in the recent past was to rely on OEM recommendations and executive judgements based on experience of maintenance team for maintenance decisions including planning and budgeting. This research has developed risk-based decision models and used pool data to deal with limitations of failure and maintenance history. Through rationalization of PM intervals, primary objective of reducing maintenance costs was achieved. This has significant potential for further enhancing asset performance and utilization of engineering assets. Findings from this pilot study along with information more accurate asset condition, further enhanced risk analysis and improved option engineering helped in enabling informed maintenance decisions including preventive maintenance intervals and level of interventions. Implementation of research findings resulted in reducing asset capability gaps through timely investments of required capital. Further analysis with new and better quality data over a period of time is recommended for calibration of these models in two to three years' time.

ACKNOWLEDGMENT

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