QUANTIFYING PREVENTIVE MAINTENANCE EFFICACY:
A BALTIMORE CITY USE CASE

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Abstract

Existing preventive maintenance efficacy research heavily focuses on quantifying system degradation in deterministic, probabilistic, and policy-based models, yet in a data centric age they inadequately address data requirements, the linchpin for improving preventive maintenance and graduating to predictive maintenance. Using Baltimore City's public facility maintenance work orders, this study demonstrates the impact of data requirements on frequency, time and cost key performance indicators (KPI) and addresses omitted variable bias introduced by lack of condition-based data. Overall results show that maintenance cost has annually increased by $6,520 despite a sharp drop in 2018. Facilities in poor condition with persistently high repair needs present an opportunity for Baltimore to tailor its preventive maintenance strategy using condition-based data and separating money for a narrower definition of functional maintenance, potentially making better use of up to $14 million. Data requirements such as tracking corrective and preventive maintenance work for the same system and parts, combining facilities condition index (FCI) scores with work order frequency, prioritizing which facilities get preventive maintenance using return on investment thresholds, and enforcing data quality discipline compose the road map to these insights.

Table of Contents

Introduction

Whether paying a parking ticket, keeping the heat on, or using child care services, cities are exploring ways to become data-smart and more sustainable because their residents' lives depend upon it. Infrastructure is one key intersection of data and sustainability because it enables the operating needs of a society. Common to all cities, sustainability means keeping infrastructure in good working order while saving resources, and data is the feedback mechanism to know whether the maintenance program accomplishes these goals. If infrastructure maintenance programs are not able to accomplish their objectives, the local government cannot function and the most volatile members of our community are at high risk, such as Baltimore City schools. The remaining challenge is, therefore, getting more data and more information out of data, a simply spoken but prodigious task that depends on clear data requirements. Since proactive (preventive) and reactive (corrective) maintenance work order data is a common data collection requirement among infrastructure maintenance programs, it is a good opportunity to increase preventive maintenance value through data requirements development.

This study has a two-pronged focus: 1) frequency, time, cost and condition key performance indicators, and 2) a programmatic and policy level view of data requirements that enable efficacy. While there is ample research about the limitations of scheduled preventive maintenance, this study explores how, through data collection requirements, preventive maintenance can be expanded beyond schedules. Regression, descriptive statistical analysis and government personnel interviews are used to measure the history and likely future of preventive (PM) and corrective maintenance (CM) as an infrastructure health condition.

Analyzing frequency, the study demonstrates methods to examine rates of PM and CM to prepare for unplanned maintenance work orders. Analyzing time, the study presents seasonal impact on cost and frequency. Analyzing cost, the study illustrates how the FCI score can be used to target facilities that have the highest and lowest maintenance return on investment, demonstrating data features that help determine the best maintenance strategy and support better budget planning.

Background

Baltimore's Department of General Services (DGS) is responsible for "the vertical and fleet infrastructure for Baltimore City government, providing services to other Baltimore City agencies and enabling them to complete their missions and service delivery objectives."[1] Currently, DGS uses five publicly reported measures for the Facility Maintenance Division budget: 1) the Facility Condition Index (FCI) for a subset of buildings, 2) the percentage of work orders closed on time, 3) the preventive to corrective maintenance ratio, 4) customer satisfaction and, 5) total cost of ownership.[2] However, they want to improve these indicators for better budget planning and for a better understanding of how well PM is working. For example, of 638 buildings, only 40 have an FCI score. In other cases, there isn't enough data to determine PM efficacy by ratio, work order time or customer satisfaction, so DGS needs to mature its data collection and structure requirements.

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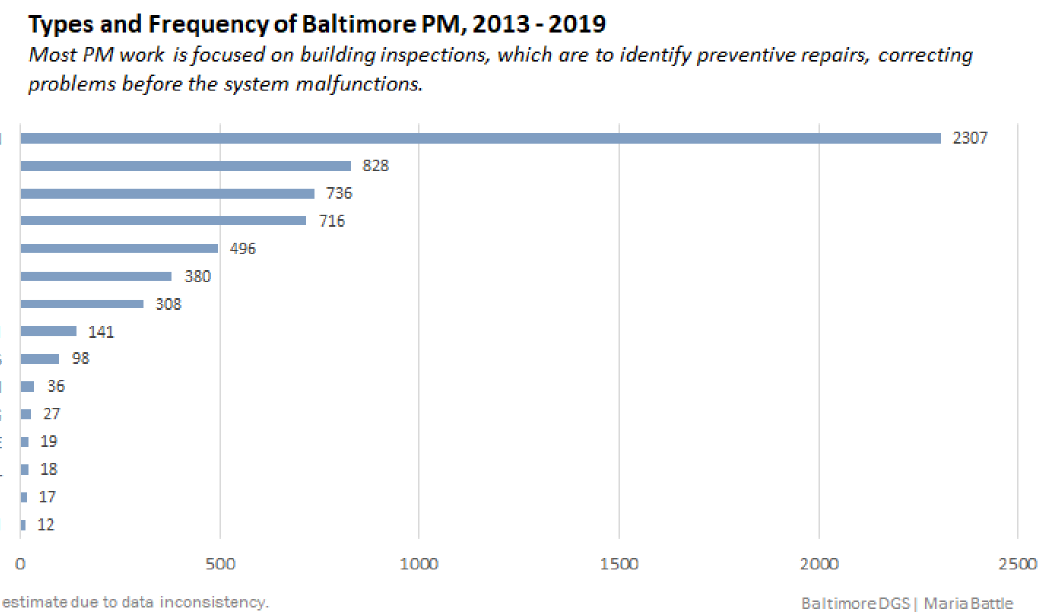
[1] "About Operations Data." *Data.world@brl1906*, January 9, 2019. Accessed February 5, 2019. https://data.world/brl1906/facility-maintenance-data-jan-2019.

[2] "About Operations Data", p. 1.

The history of Baltimore's facilities maintenance program starts before 2013, but in 2013 the program shifted from paper to electronic maintenance work order tracking for the first time. Although there have been smaller efforts to track PM prior to 2016, 2016 demarks the largest

Figure 1

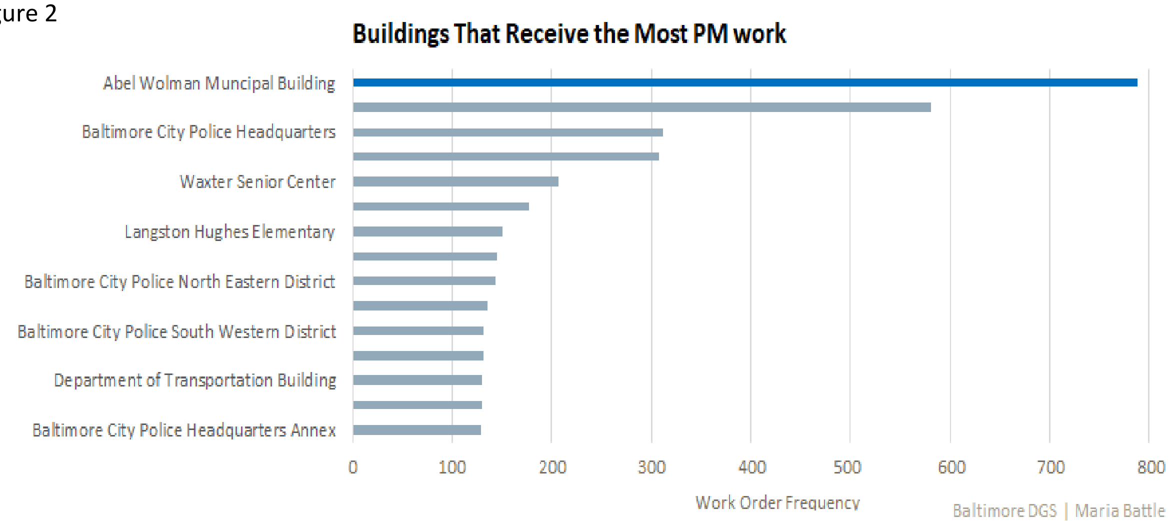


effort so far, focusing on HVAC inspections that will catch repairs before system malfunction.[3] Also, in 2016, DGS officially began implementing data tagging requirements to label work order data as PM or CM. Baltimore defines PM as time based, scheduled maintenance or manufacturer recommended maintenance practices on equipment and facilities to include changing filters or unit parts before system failure. They define CM as requested service to repair something that is broken or not functioning properly. Figure 1 enumerates PM categories, and descriptions of each can be found in the data.world@euclid46 Baltimore City Preventive Maintenance lab book. Work orders are entered into the Archibus system, an Integrated Workplace Management System (IWMS) platform with a SQL database.

[3] "About Operations Data", p. 1.

The data show DGS has provided maintenance service to an estimated 638 buildings between 2013 - 2019 which are functionally grouped as municipal, city government, judicial, office spaces, health departments, and multipurpose/community centers. Among all buildings, size has a high variance; for example, a sample of 40 buildings ranged between 400,000sf (Baltimore City Police Headquarters) and 200sf (a utility structure).[4] The Abel Wolman Municipal Building, a 181,630sf city government office building, receives the most PM work (figure 2). It also hosts as a public walk-in payment service for things like water, taxes, and citations.

Figure 2



One of Baltimore's key challenges is infrastructure investment. "As in many older cities, Baltimore's aging infrastructure and new capital investment needs require funding beyond available existing resources", and although Baltimore's resources are constrained, it has nearly

[4] The total number of buildings and square footage currently serviced was not provided for this study. DGS affirms that buildings are added and surplused from the data list. One estimate state only 100 buildings are currently maintained by DGS, but this list is unverified for the study. Only 42 buildings have recorded ages and FCI scores.

doubled its PM efforts in 2015, 2016 and 2018.[5] The DGS annual maintenance operating budget is roughly $35.2 million of which $11 million is budgeted for building repair expenses only. Baltimore repair expenditures were over budget by $8.7 million in 2017, then declined by over half in 2018 (figure 4, p. 17).[6] From 2013 - 2019, DGS spent $313 thousand on PM and $66 million on CM.[7] Cost increase among all maintenance types is unevenly distributed among buildings. Some have had relatively small or no increase and are relatively less expensive to maintain, such as Signet Bank, Department of Transportation Building, and the Northern Community Action Center. Other more expensive buildings increased between $400 - 600 thousand in 2017, such as Courthouse East and Baltimore City Police Northwestern District.

Baltimore is seeking ways to plan facility maintenance budgets better, which it must forecast two years in advance. It does not have a "formal" or specific facilities/system replacement fund. Surpluses of money are syphoned to a transparent side-account as a general pot from which emergencies are covered. Cost is also of interest because it is a KPI where Baltimore lacks data quality discipline. As the data show, many expenditures are unknown or generalized as "other".

Literature Review

Similar to a car owner's manual specifying an oil change every 10,000 miles, electrical systems, water pipes and HVAC system vendors recommend when to replace belts, gauges,

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[5] "Ten-Year Financial Plan." Bureau of the Budget and Management Research. September 15, 2017. Accessed April 28, 2019, https://bbmr.baltimorecity.gov/ten-year-financial-plan.

[6] Baltimore invested ~ $313k in PM prior to the 2018 CM decrease but work order data analysis during this time period could not determine whether this is cause and effect.

[7] DGS reports $6.6 million has been budgeted for PM of which $313 k in this dataset may be a part. This sum is unverified.

ducts, valves, etc. This scheduled maintenance is known as PM. “Preventive maintenance is the regularly scheduled work needed to keep buildings and their components operating at peak efficiency, prevent their breakdown, and extend their useful life.”[8] In contrast, repairs are to fix something broken or not operating properly, otherwise referred to as CM. System maintenance is typically categorized as either CM (reactive/unplanned) or PM (scheduled). “Preventive maintenance itself can be categorized into two classes: systematic preventive maintenance and condition-based maintenance (CBM).”[9] Recently, emerging technology has expanded infrastructure maintenance capability to use predictive maintenance (PdM), a technique to determine when maintenance is needed based on system conditions, i.e. real-time system stress factors not covered by scheduled maintenance. Some cities are implementing a PdM approach using common, off-the-shelf technologies like GIS and closed circuit TV, for example the City of Placentia, California Sanitary Sewer Maintenance Program.[10] The intent of PM is the same as PdM: plan system service, detect and prevent potential system failures, extend system life, and avoid unplanned maintenance. In practical terms, these criteria can be used to measure whether a PM or PdM maintenance plan is operationally and fiscally more effective than corrective maintenance.

Among CM, PM and PdM maintenance studies, the body of research generally falls into three approaches: deterministic, probabilistic, and policy-based optimization. Maintenance

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[8] J. Nobles, J. Alter, E. Bennett, V. Bombach, S. Delacueva, J Hauer, . . . L. Yang, “Preventive Maintenance for University of Minnesota Buildings,” 2002, 17.

[9] E. Deloux, B. Castanier, & C. Bérenguer, “Predictive maintenance policy for a gradually deteriorating system subject to stress,” *Reliability Engineering & System Safety 94*(2), 2009, 427.

[10] *City of Placentia Sanitary Sewer Preventive Maintenance Program*. Report. City of Placentia, California, 10.

optimization studies frequently appear in the 1970's, although researchers have applied operations research to system optimization since World War II.[11] In 1999, the Institute of Electrical and Electronics Engineers (IEEE) surveyed the growing body of knowledge on maintenance optimization.[12] Following IEEE, many others widely expanded PM because, while many organizations and businesses primarily use it, it has limited parameters of measurement and therefore has risks.[13] For example, it may not extend the system life, it may cause over/under maintenance, it does not calculate whether labor costs far more than parts, and it can be overall too expensive. The body of knowledge continues to explore predictive, and data driven preventive, methods to refine the assumptions of rigid and linear maintenance schedules that do not address interdependent complexities and system fail probability.[14] The challenge and reward of data driven preventive methods are to discover omitted variable bias in factory specifications, then use those variables to refine the way maintenance is conducted at programmatic, system, and component levels. Meeting this challenge would place Baltimore city on a path toward smart city modernization.[15]

[11] J. Ellenberg, *How not to be wrong: The power of mathematical thinking*, NY, NY: Penguin Books, 2015, 57.

[12] J. Endrenyi, "The Present Status of Maintenance Strategies and the Impact of Maintenance on Reliability," *IEEE Power Engineering Review,* 2001, 68.

[13] M. Vasili, T.S. Hong, N. Ismail, & M. Vasili, "Maintenance optimization models: A review and analysis," 2011, 1132.

[14] C. M. Lapa, C. M. Pereira, M. P. Barros, "A model for preventive maintenance planning by genetic algorithms based in cost and reliability," *Reliability Engineering & System Safety*, 2006, 237.

[15] R. Lea, "Smart Cities: An Overview of the Technology Trends Driving," March 2017, https://www.ieee.org/content/dam/ieee-org/ieee-web/pdf/ieee-smart-cities-trend-paper-2017.

Approaches

Common to most research approaches, deterministic reliability models focus on new ways to collect data about the system and its components in order to remeasure deterioration over time and stress.[16] Fine tuning these parameters offers additional data to scheduled maintenance, such as the system's expected lifespan given usage and other stressors. Predicting the rate of deterioration given certain parts and conditions would allow facilities maintenance staff to proactively replace a system rather than sink costs into maintenance. Without this prediction, system failure could present a surprising hazard, such as causing thousands of people to go without heat in the winter.

Probabilistic approaches attempt to address gaps in deterministic models such as random human error, delaying the maintenance schedule or not following other recommended practices.[17] For example, Lapa et al. address a deterministic assumption that maintenance intervals are evenly spaced.[18] They offer a genetic algorithm to explore performance rather than fixed interval maintenance. Considering maintenance on a system as a whole, they use a cost-reliability model to continuously fit maintenance schedules on a High-Pressure Injection System (HPIS) to study corrective maintenance probability, repair cost, outage times, PM costs, and probability of imperfect maintenance. Other probabilistic approaches to maintenance optimization have used Monte Carlo risk modeling and Markov continuous time studies to

[16] Vasili et al., "Maintenance Optimization Models," p. 1132.

[17] I. W. Soro, M. Nourelfath, & D. Aït-Kadi, "Performance evaluation of multi-state degraded systems with minimal repairs and imperfect preventive maintenance," *Reliability Engineering & System Safety,* 2010, 67.

[18] Lapa et al., "A model for preventive maintenance planning," p. 237.

optimize availability intervals.[19] They generally measure system performance as multiple, simultaneous states of degradation given a repair schedule, evidence that could both help maintain continuity of operations and offer a financial benchmark of diminishing return. Their theories establish that every system has an overall lifespan and good maintenance may prolong the system life to full potential while bad maintenance may speed up the deterioration process. Measuring PM efficacy in extending system life could assist budgetary decisions about where to apply more resources to a PM program.

Last, others have taken a policy optimization approach. Deloux et al. combine statistical process control (SPC) and condition-based maintenance (CBM): "CBM policy is used to inspect and replace the system according to the observed deterioration level. SPC is used to monitor the stress covariate….CBM approaches are usually more efficient than systematic preventive maintenance policies based on the a priori statistical knowledge of the system lifetime."[20] An emerging technology of condition based approaches in both PM and PdM within the past several years is the Internet of Things (IoT). Using sensors, IoT is a hybrid physical-digital maintenance solution to gathering system condition data. While expensive, this data driven approach has a good point: the better the data, the better the prediction.

Gaps

"Local governments reported that the greatest obstacles to preventive maintenance are

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[19] M. Ghavami, M., M. Kezunovic, "Probabilistic evaluation of the effect of maintenance parameters on reliability and cost," *2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, 2010, p. 6

[20] Deloux et al., "Predictive maintenance policy for a gradually deteriorating system," p. 425.

competition for limited dollars, insufficient staff hours available, and levy limits."[21] Considering this, previous research has a few gaps. First, the current body of knowledge does not widely discuss data requirements for optimization solutions, a key cost driver in implementing data driven solutions. This gap is understandable given big data did not previously exist; however, now there is a need to integrate data production into every system. Since data integration is nontrivial, a solution should not presume broad applicability if the implementer cannot generate, process and store certain new data to implement a new solution. A way to bridge this gap is for researchers to address how cities can be more resourceful with their current data capabilities. By extension, this gap points to a need to focus attention on PM programmatic evaluation in order to optimize data produced by maintenance tasks and create a transition plan from corrective maintenance to successful data-driven PM and PdM. The capability to capture a high volume of quality data with current resources is the linchpin of prevention and prediction.

Second, PM and PdM research largely discuss methods that seem most applicable to large, critical systems, e.g., nuclear reactors. To avoid calculation complications, many studies are system specific or use a system with few components which does not adequately address a wide variety of infrastructure. Third, many models require individual system reliability tests which are not scalable if volume is a challenge.

Two exemplar studies demonstrate data resourcefulness and data sharing that can show a path toward data-driven preventive maintenance programs and establish a framework for predictive maintenance indicators. The Evaluation Report for the Preventive Maintenance for

[21] *A Best Practice Review: Preventive Maintenance for Local Government Buildings,* 2000, 22.

University of Minnesota buildings measures the effectiveness of their PM program using variables such as the frequency of corrective work orders with building age and usage, whether overtime and corrective work orders increase or decrease after the PM plan is implemented, whether the cost of labor exceeds the cost of replacement parts, and the cost effect of categorizing work orders as preventively maintain, replace or run-to-fail.[22] Second, Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning uses a prediction method that can be broadly applied.[23] Relevant to facilities preventive maintenance, it describes a way to overcome data challenges that keep technicians and programs entrenched in a system of reactive response, and it offers a data driven solution to transition from a corrective to preventive program. It is an exemplar that prevention programs are systems with similar goals and challenges that can be overcome with data resourcefulness.

Theoretical Framework

This research focuses on operational decisions and facility conditions that are expected to decrease unplanned maintenance. To enable these operational decisions, policy optimization is explored through improving data collection. This research contributes to maintenance policy optimization by affirming the theoretical frameworks of the Preventive Maintenance for University of Minnesota Buildings study and the Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning study. It offers a resourceful way to measure PM efficacy using Baltimore City's work order data and policies. Further, this research expands the body of

[22] Nobles et al., p. 10.

[23] E. Potash, R. Ghani, J. Brew, A. Loewi, S. Majumdar, A. Reece, . . . R. Mansour, "Predictive Modeling for Public Health," 2015, 5.

knowledge to encourage and enable cities to publicly share their preventive maintenance solutions through civic technology. Open data production and contributions would offer many new economical solutions and methods.

A relevant, timely and economic solution for city PM is to seek policy optimization insights using the data that they already capture to the best of their current ability. This will reduce the risks of scheduled maintenance, strengthen budget planning, and identify near term, cost effective improvements that enable a city to develop more sophisticated methods if necessary. In routine maintenance work order data, city government data, and open data, we can use frequency of issues, cost/benefit, time, prioritization, and condition scoring to reveal additional key performance indicators. For example, we expect that the frequency, time and cost of corrective work orders should decrease after PM is implemented on a system, indicating that there are less emergencies and off-scheduled service requests. If they do not, we can examine conditions that influence these performance indicators.

We may also consider prioritizing facilities/systems based on one of three maintenance policies: preventively maintain, replace or run-to-fail. We can observe that facilities in good condition yield a return on PM investment by needing less repairs over time, needing less time for repairs and improving their overall condition score. Facilities whose performance indicate over-maintenance, a persistently high volume of repair work, and poor conditions may be better suited for replacement or run-to-fail when it becomes evident that PM will not correct these problems in a cost-effective way. By prioritizing PM on buildings that provide a return on investment, sunk cost can be avoided and savings can be applied to replacement.

Data and Methods

As a use case, a detailed analysis on Baltimore facilities CM and PM work order data from 2013 - 2019 is presented to study the relationship between time, cost, frequency and conditions as PM performance indicators and to discover additional data collection requirements that will strengthen the PM program and transition to a PdM program. As previously stated, the purpose of PM is to plan system service, detect and prevent potential system failures, extend system life, and avoid unplanned maintenance. By these criteria we may measure PM efficacy, and this study specifically focuses on avoiding unplanned maintenance. This study is based upon the FMDataset1-25-2019-share.xlsx dataset provided by data.world@brl1906, a free and open data repository.[24] A full and regularly updated data element dictionary, lab book and cleaned dataset can be found in data.world@euclid46. Baltimore City highly encourages civic participation in their open data.

Largely categorical, these data are an observational time series. Each of the 87,277 rows provides information about maintenance work orders divided among 638 buildings. Each work order is categorized as a corrective and preventive work type. The main features used to study corrective and preventive types are building name (`name`), preventive or corrective work type (`prob_type`), preventive maintenance category (`pmp_id`), dates and costs. Dates used in the study are `date_requested` and `date_completed` which include administrative time such as time to assign the order to a technician and invoice/receive payment. For analysis of only technician time, `date_assigned` and `date_completed` are recommended features. DGS advised that all cost features have a low accuracy confidence and should be joined to other

[24] https://data.world/euclid46/analysis-of-baltimore-city-preventive-maintenance

data in order to investigate beyond high level descriptive statistics.

There are several preventive maintenance categories in the `pmp_id` feature which DGS has added as data requirements developed.[25] These categories require normalization as described in the Baltimore FMD [lab book](#) on data.world@euclid46. More research is needed to refine this normalization. For this study, DGS recommended that any work order not labeled as PM should be considered CM.[26] Categories in the `prob_type` column distinguish PM work orders by using "PREVENTIVE MAINT", "PM" or "INSPECTION" in the label. All categories in the `pmp_id` column specify types of PM activities, such as "generator" or "HVAC". Where populated, these `pmp_id` categories help specify where `prob_type` uses a generic "PREVENTIVE MAINT" or other PM type label. DGS advised that they are trying to map values between `prob_type` and `pmp_id` to indicate when repairs are discovered during inspections and other PM activities (thereby generating more CM work orders). Analysis of this mapping has been reserved for a future study and were instead used to clarify and isolate particular PM categories between the two columns.

The University of Minnesota preventive maintenance evaluation report uses a facility condition assessment (FCA) database to understand the general condition of their buildings and adjust their expected level of maintenance effort and expected progress.[27] Following this and other established research about condition based preventive maintenance, this study correlates Baltimore FCI scores with work order frequency to categorically illustrate points at

[25] The absence of data in a given year does not necessarily indicate an absence of activity.

[26] DGS has not yet created a more specific/consistent categorical label for corrective work order activity.

[27] Nobles et al., "Preventive Maintenance for University of Minnesota", p. 9.

which facility degradation is associated with PM sunk cost. FCI scores were available for only ~40 buildings. The score is understood to represent a state of facility degradation at a given point in time. As the FCI score approaches 1 (100%), the facility's health declines and becomes a candidate for replacement. [28] It should be noted, however, that although FCI scores and maintenance frequency are used to demonstrate a correlation method, FCI scores are not in the FMDataset under study because they represent only one FCI assessment period. It is expected that FCI scores change over time. In addition, facility age which only represents age as of 2019, and building asset size help compose the FCI score among other unknown factors and could therefore pose potential multicollinearity. With additional research and data requirements, these could be interesting variables for regression analysis.

Findings

Research has well established that condition-based data improves scheduled maintenance. Before we consider condition data, let's explore the interpretation of KPIs without it.

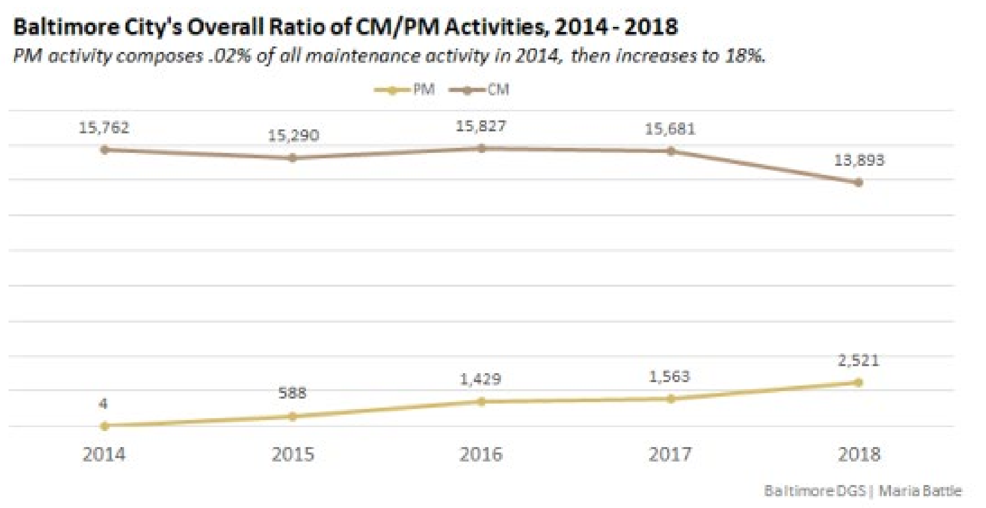
I. **Frequency, Cost and Time as Key Performance Indicators**

Cost and time are expected to covary with repair frequency, as increased work orders can require additional parts, labor, and personnel on the job. Likewise, PM is expected to decrease unplanned repairs that increase cost, time and frequency because it is assumed that proactive measures increase situational awareness and help address repairs before facilities malfunction/break. In the data, CM frequency was studied overall as a work order performance

[28] A general description of FCI inputs can be found at https://community.ifma.org/fmpedia/w/fmpedia/2459.

indicator of PM efficacy.[29] Between 2014 - 2018, CM frequency hovered around ~16,000 work orders, decreasing by 1,788 in 2018; however the proportion of maintenance dedicated to PM has increased from .02% to 18% (figure 3).[30] Likewise, a study of time showed time spent on work orders has decreased which is associated with a decrease in work order frequency, possibly indicating improved operational efficiency.

Figure 3



A study of cost shows that it has increased overall, except for 2017 - 2018 when costs dropped by half, the reason for which is undetermined by this study. Treating 2018 as an outlier, an OLS cost regression analysis between 2013 - 2017 shows that at the current rate, CM is likely to annually increase by $6,520.[31] By 2029, CM would cost $65,160 more than 2019 (figure 4).

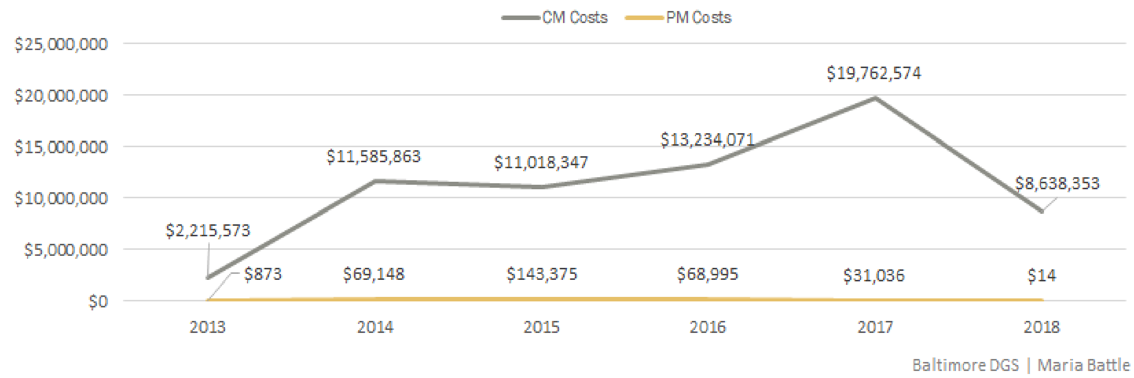
[29] Data was not cleaned for non-functional maintenance observations, e.g. snow removal, grass cutting, and deliveries. These observations need to be discussed with DGS to better understand their role in CM before they are not counted.

[30] Excluding the initial 2013 jump from ~3,700 CM work orders resulting from a paper to digital work order implementation.

[31] Compared to results that include 2018, Rsqared results are 12 points higher for costs between 2013 - 2017 and had a pvalue of .01. This study uses calendar years rather than Baltimore's July 1 - June 30 fiscal year.

Figure 4 **CM Costs Steadily Increase, Then Drop By Over Half**

Baltimore has invested ~$66 million in CM and ~$313k in PM.



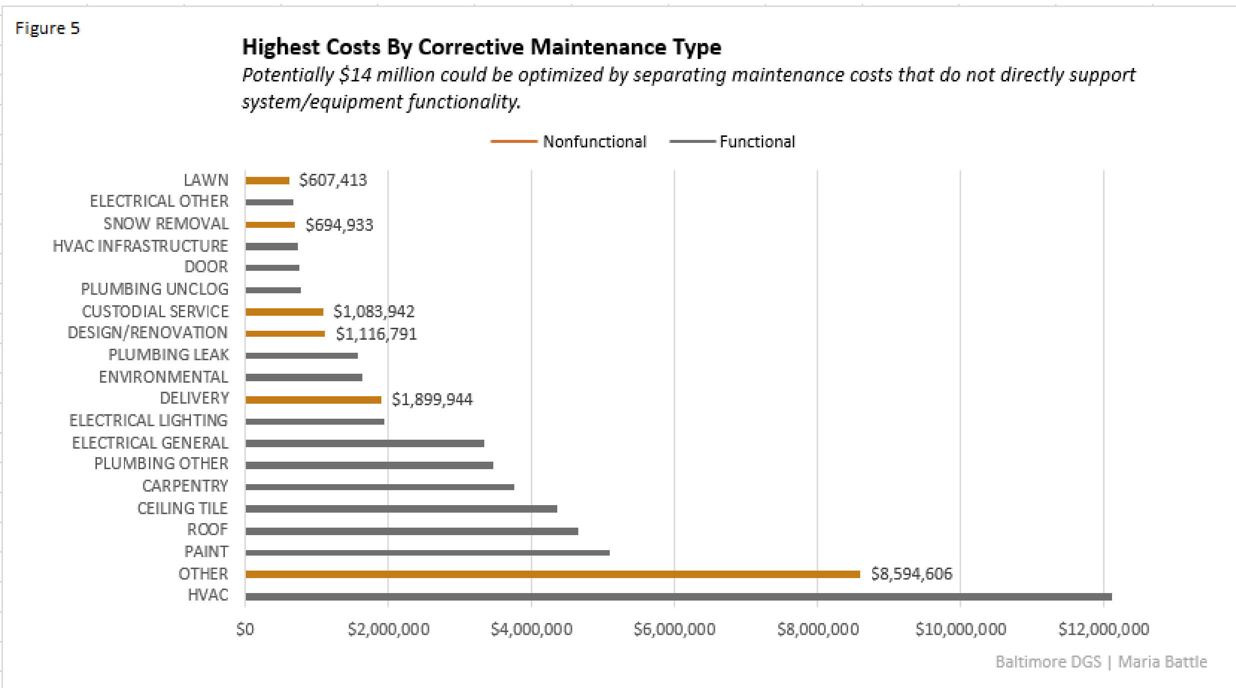
The effect of PM on CM frequency, time and cost are expected to have a direct relationship until additional variables are considered. For example, Baltimore uses PM activities to discover needed repairs, such as worn HVAC V-belts, before the system breaks. While this pro-action is an excellent practice, measuring its efficacy is subject to data structure and quality choices. These activities must be data-tagged differently than repairs made on broken or malfunctioning systems or else data analysis will show that preventive maintenance generally increases, rather than decreases, corrective maintenance. Likewise, CM for parts on the same system must be recorded. Additionally, adding and surplusing facilities from the area of responsibility can influence work order frequency, especially when there are inherited poor conditions and additional square footage combined with personnel attrition. Between 2014 - 2018, Baltimore has possibly averaged a 13% annual increase in the number of buildings they must service while personnel attrition increased and some buildings are not covered by the budget.[32] Even if Baltimore's repair frequency decreases, factors such as weather conditions,

[32] This calculation assumes that the unique building name count in any year is the total amount which is likely not accurate. Comparing building lists over time shows that some buildings may not be annually serviced.

consistency/accuracy of maintenance practices and building usage and age make the PM/CM correlation less direct. Future work order data collection requirements could control for these variables if they become data collection requirements.

Currently Baltimore does not distinguish maintenance activities that directly contribute to the function of the system/facility versus custodial services, repairs, service, and replacement/renewal/remodeling, and renovation. This also influences PM cost efficacy. Based

Figure 5



on the work order data alone, it appears Baltimore's broad definition of PM includes non-functional maintenance, such as "other", delivery, design/renovation, custodial services, snow removal, and lawn care, totaling $14 million over seven years (figure 5). Similar to Placentia, California's sanitary sewer preventive maintenance plan, the cost of non-functional maintenance could be funded through a capital budget, reserving the general operational budget for functional maintenance, giving system functionality first priority for replacement funding.[33]

II. Applying Facility Conditions Data to Frequency, Time and Cost

Two important ingredients of maintenance optimization are the chosen performance indicators and selected types of maintenance, and ideally they should be independent of non-related effects (such as changes to the operating environment) so that the benefits are seen in the PM performance area and not a related area like production, quality or inventory.[34] The method to optimize maintenance can itself show higher cost. Generally, to be preventive, work orders should capture component wear and tear conditions so it can be replaced before it causes system malfunction. These data should be tagged as preventive repairs as they are typically discovered during inspections or scheduled maintenance, and they should be distinguished from corrective repairs which are discovered and conducted due to system malfunction (see Appendix A, Terms and Definitions). For example, HVAC V-belt part ID, date installed, slack and cracks and worn or damaged sheave grooves should be part of the HVAC preventive repair work order. If a faulty V-belt has already caused a malfunction, such as extreme cooling, restricted air flow, water leaks, and compressor damage, it should be captured as a corrective repair work order.[35]

Weather patterns also influence maintenance budget planning and performance goals.

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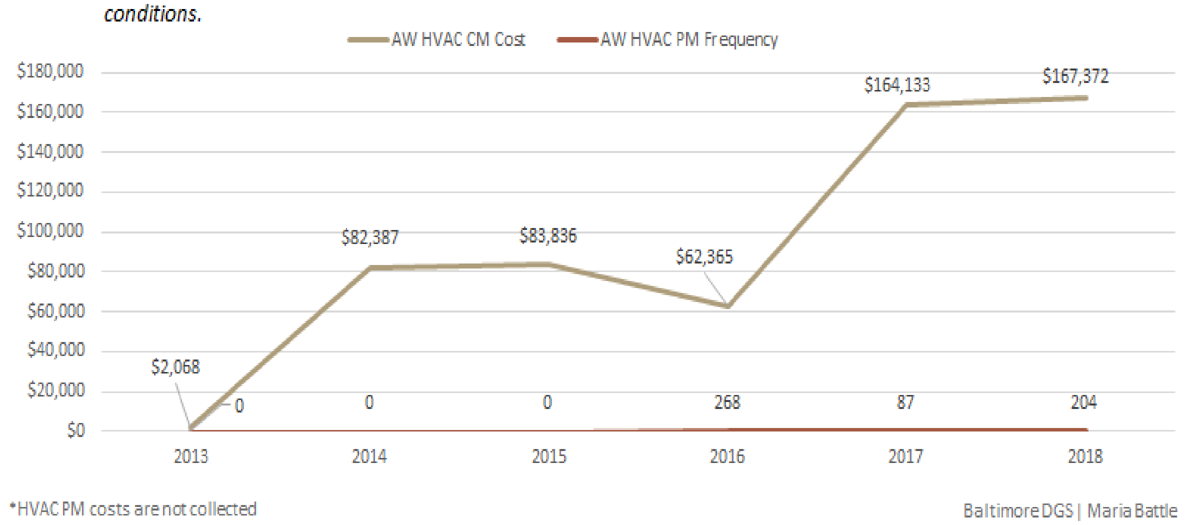
[33] "City of Placentia Sanitary Sewer Preventive Maintenance Program", p. 10.

[34] Erik Johansson, "Maintenance Optimization," February 10, 2013, http://www.lysator.liu.se/~ej/public_notes/public_notesse3.html.

[35] https://www.californiaac.com/vbelts.php

Currently, Baltimore measures PM effectiveness by not exceeding overall cost averages of prior years, but they want to improve this metric. Again, considering the Abel Wolman Building, it has the second most expensive HVAC CM total costs at $562,160.33. In 2017, costs increased by $100k (figure 6).[36] The average total cost for AWMB HVAC CM is $884; however, this average is

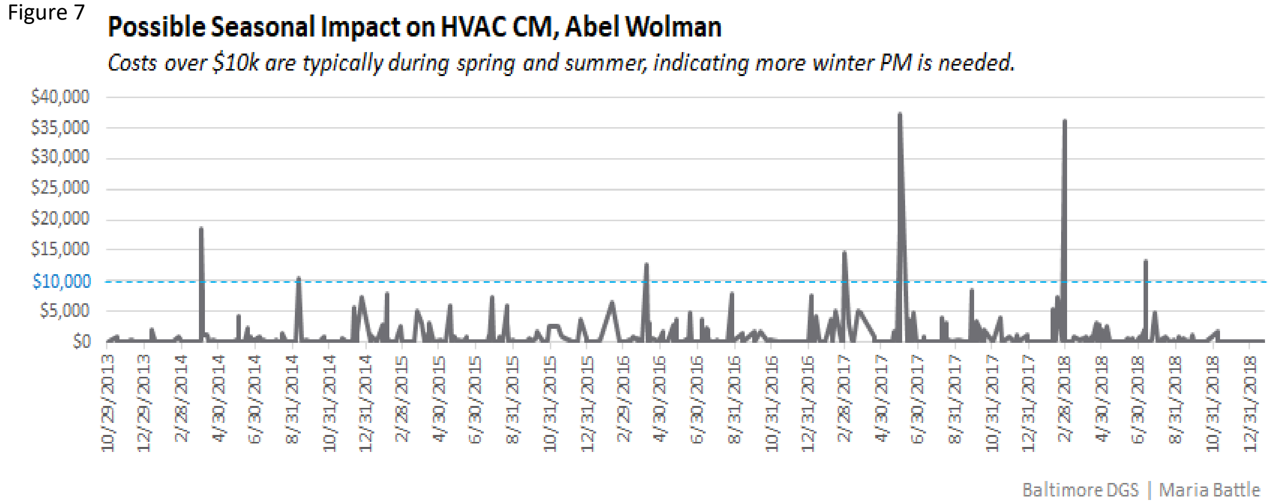
Figure 6 **Abel Wolman CM HVAC Costs Increase, Totaling $562,160**
Increases could be related to data collection and categorization choices, maintenance strategy, and facility conditions.



influenced by March/April and June/July seasonal cost patterns ranging from $10,360 - $37,118 (figure 7). In contrast, the median total cost is $10, demonstrating a wide spread. Baltimore could improve their measure of effectiveness by increasing preventive efforts on worn parts in the winter to keep spring and summer HVAC CM costs below $10,000. In addition, capturing which HVAC parts are annually worn by spring and summer with labor data would strengthen preventive maintenance with condition data. While the `pmp_id` HVAC inspection data show that V-belts (`eq_id`) are ordered every two years, inspection labor costs are not captured, and HVAC CM work orders don’t document component wear or repaired part numbers.

[36] Highest cost: MECU Building C at: $614,262.89. Regression analysis of AW HVAC CM cost over time had a .77 P-value due to many missing or zero values.

Figure 7



Currently Baltimore aims to provide schedule-based preventive maintenance for many facilities, but there are situations where a facility may not need or should not receive preventive maintenance. A facility manager's top maintenance decision about building components is prioritization. The University of Minnesota's proposed decision rubric is to divide facilities among three categories: preventively maintain, replace, or run-to-failure.[37] By using these three categories, maintenance activities and budget can be strategically prioritized. For example, established research has illuminated that scheduled maintenance has the potential for over-maintenance. A way to divide facilities among categories is to analyze whether it is more expensive to maintain than replace. In using the University of Minnesota's over maintenance cost test very broadly, Baltimore's data contained 5,293 work orders where the cost of labor exceeded the cost of parts, totaling $2,870,685 and signaling that some components may be cheaper to replace rather than preventively maintain. This test is not conclusive but demonstrates a method to identify possible overspending and over maintenance that could be investigated.

[37] "Preventive Maintenance for University of Minnesota Buildings," p.30

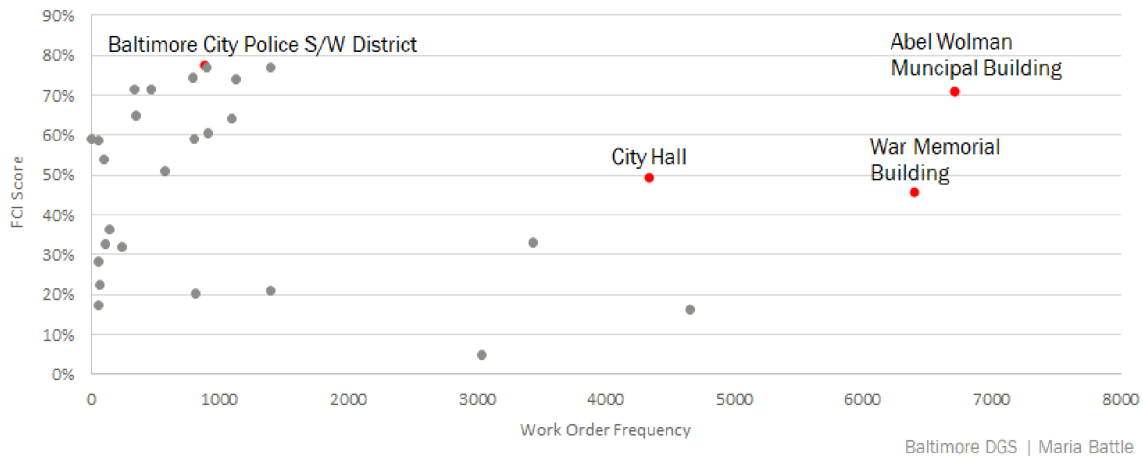
In addition to analyzing over maintenance, facility condition index (FCI) scoring can be used with work order data cost and frequency to determine the best maintenance category. In general, the FCI score is mathematically calculated as facility maintenance, repairs, and replacement deficiencies divided by the current replacement value of the facility. [38] Facility value and health are based on multiple variables including age, asset size, design, construction methods, and materials. Ranging from .1 - 1, as a building/system's deterioration increases, the index score approaches 1 (100% of the facility is deficient). When analyzed with work order frequency, FCI scores may be used to evaluate particular facility return on maintenance investment (ROI). For example, Baltimore has spent more than 6,000 work orders on the Abel Wolman Municipal building with a .7 FCI score, a disproportionate and expensive effort compared to Baltimore City Police Southwestern District with an FCI of .78 and 874 work orders. Controlling for other conditional factors, such as building usage, a continuously increasing CM work order rate, cost and FCI score may indicate replacement or run-to-fail of certain system components is a more cost-effective maintenance approach than preventive repairs and inspections. For example, data points over 2000 work orders that have an FCI score of .4 or higher, could be considered candidates for data quality evaluation and a new maintenance strategy (figure 8). Buildings that do not cross the threshold could be considered "within standards". More time and data collection will show how these predictors can be refined, such as whether FCI score improves as more PM is applied.

[38] https://en.wikipedia.org/wiki/Facility_condition_index

Figure 8

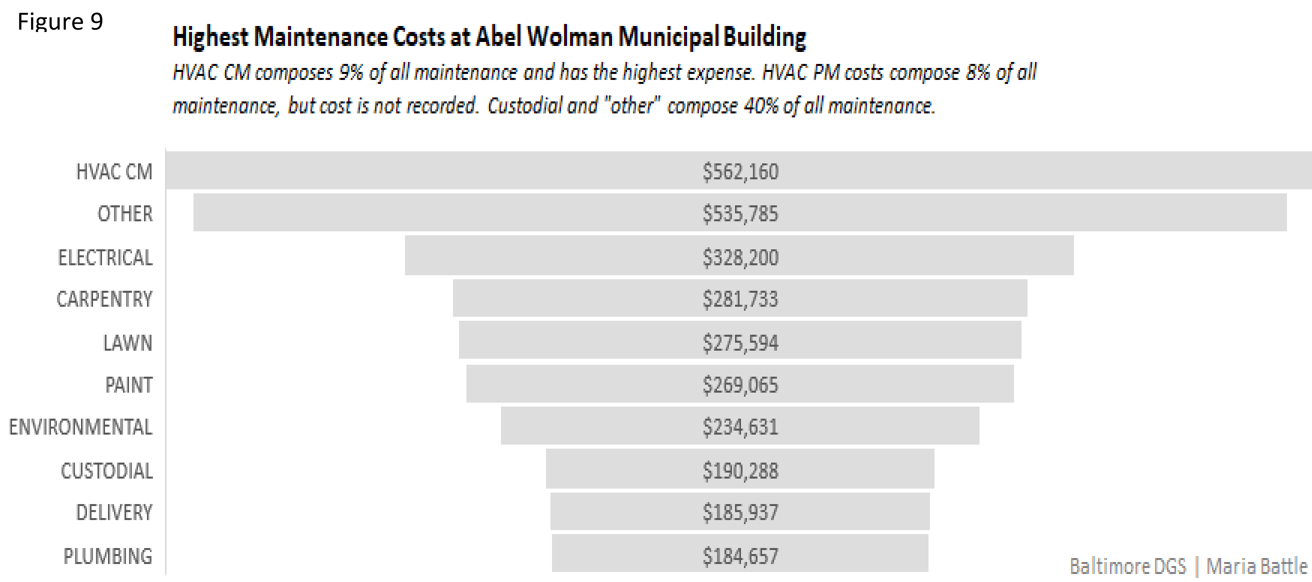
FCI Score May Be an ROI Indicator

Facilities with a persistently high FCI and CM frequency may be candidates for replacement or run-to-failure.



Using various conditions to increase situational awareness and information management requires a system that will help the facility manager make operational decisions. Due to time constraints and data limitations such as not linking CM and PM work orders to the same part number, cost, system, and time difference between PM and CM intervals, this study does not regress key variables across facilities to explore common contributing factors of PM efficacy. However, data requirements that enable correlation can be modeled from particular facilities. For example, the Abel Wolman building has a .7 FCI, 6,700 work orders, and the most expensive HVAC CM. This CM composes 9% of all this building's maintenance. Custodial services and "other" compose 40% of the maintenance work (figure 9), indicating a high personnel resource demand on those tasks. If the rate and cost of maintenance is too high, facility managers should evaluate the previously discussed factors together. First, evaluate the work order data input quality and structure. "Structurally, disordered data will give rise to the wrong data value and data service."[39] For example, one could examine what data has been tagged as corrective versus preventive repairs and whether costs are specified versus "other". Having the required data, the facility manager can then investigate over-maintenance and whether corrective repairs are decreasing wherever PM on the same parts is applied. Third, observe whether the queue of maintenance work is backlogged due to resource constraints. Finally, among other conditions previously discussed, the facility manager should check whether maintenance resources are being consumed by non-functional maintenance tasks. Having adjusted for these

Figure 9



factors, if corrective repairs and system malfunction continue to increase, run-to-failure or replacement may be a more cost-effective solution for the systems that generate the most problems. Baltimore has spent 41 days on average for each PM work order on this building. Shifting maintenance to run-to-fail and replacement for certain systems could free up this time for facilities and equipment that will improve with PM.

[39] Kyung Seok Ryu, Joo Seok Park, and Jae Hong Park, "A Data Quality Management Maturity Model." *ETRI Journal* 28, no. 2, 2006, 195.

III. Metadata Management

For operations to take more intentional control of preventive maintenance efficacy, data management is a key dependency. Data collection requirements can reduce operational ambiguity which in turn enable more accurate budget estimates and more effective policies. Operations teams must understand which of their activities to report, how they should report them, and understand the input system. Leadership must specifically communicate their requirements and enable operational feedback. Data requirements development should be considered in the maintenance program budget because it takes time, money and dedicated personnel to develop and implement them in a meaningful way for operations.

When considering which data requirements best fit the organization, at a minimum maintenance tagging or labels should specify the system, part number, system function, time of replacement, and type of maintenance. Unique features should not have duplicative meaning or labels, reducing the need for normalization and possible misinterpretation. Labels should have consistent semantics and syntax and be reserved for specific categories of desired efficacy outcome, which will enable data analysts to measure the effect of PM on CM consistently. This will enable each PM work order to correspond to a CM work order. In Baltimore's data, currently only 33% of the work order categories have CM data for its PM counterpart (Table 2, Appendix A).

Those entering data into the system should use the labels consistently between PM and CM work which may require training and a way to note and reconcile inconsistencies in the system. Consistent entry can be supported by providing drop down menus with tooltips to define the labels rather than allowing for free flow text. Table 2, Appendix A, is an example of data requirements that could strengthen Baltimore's work order data collection process, system, and analysis.

Conclusion

This research has focused on operational decisions and facility conditions that are expected to decrease unplanned maintenance. Work order frequency, time, cost and condition performance indicators make a case to consider three maintenance categories: preventive maintenance, replace, or run-to-failure. In order to prioritize maintenance work, the following data collection, situational awareness and analysis are needed.

1) Repairs discovered during PM should be clearly distinguished from repairs needed as a result of system malfunction/breakage. Each work order should have a part number, system ID, date or replacement, and notes about the current condition.
2) Every PM work order category should have a corresponding CM work order category for the same system and parts. Categories of work must be specific and syntactically/semantically consistent.
3) Combine facilities condition index (FCI) scores with work order frequency, time and cost to establish a condition-based return on maintenance investment.
4) Collect data about additional conditions that may affect the PM/CM correlation, such as weather, increased or surplused facilities in the area of responsibility, and inherited poor facility conditions, personnel changes, etc.
5) Separate maintenance budget resources specifically for maintenance that supports facility functionality and facility replacement. Inspect costs that indicate over-maintenance.

By taking a data requirements approach, we explore a pathway to transition from reactive maintenance to predictive maintenance with existing capabilities and data. Focusing on data requirements maximizes the use of existing data and resources before spending money on external solutions and validates whether there is a need to expand existing system capabilities. Data requirements support data transparency, increases civic participation and accountability and unifiy fiscal and operational goals.

Further Research

Baltimore City envisions that local governments can benefit from sharing their maintenance data requirements and preventive maintenance strategy through civic technology and research. There is a common desire to learn about successful optimization practices, and Baltimore can be at the forefront of this innovation.[40] This research could be expanded to discover more about the approaches of other local governments to similar problems.

Because the data for this research were limited, this study could be expanded as a data engineering project and civic technology effort. Mutually beneficial systems, information, and resources across Baltimore could be explored for API development. Using civic technology could help Baltimore share data needs with the public, enabling citizens to contribute solutions. For example, facility ages and size are part of real estate records in the Enoch Pratt Free Public Library. Since these records are not easy to search, a distributed effort would help off-load this burden. Additionally, an online choropleth of facility information, including pictures, age, and square footage would enable public data analysis.

[40] *Preventive Maintenance of Municipal Buildings*. March 2019. Project request for support from Department of General Services, City of Baltimore, Department of General Services, Baltimore.

Finally, a text mining analysis could be applied. In a separate dataset at data.world@euclid46, Baltimore's maintenance work orders contain free flow text descriptions that could provide additional context and expound on the work order purpose.

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Appendix A

Table 1: Terms and Definitions of Maintenance Work

Terms	Definitions
Corrective Maintenance (CM)	A maintenance strategy to categorize unplanned, unknown maintenance tasks, such as plumbing stoppages due to misuse.
Corrective Repairs	Repairs performed on a system after system malfunction, recurring as needed rather than on a fixed schedule. It includes emergency repairs.
Preventive Maintenance (PM)	A proactive maintenance strategy to plan system service, detect and prevent potential system failures, extend system life, and avoid unplanned maintenance. It does not include emergency repairs.
Preventive Repairs	Repair needs discovered during preventive maintenance tasks and addressed prior to system malfunction or breakage, usually recurring on a schedule or situational awareness of system conditions.
Run-to-failure	A maintenance strategy to intentionally not perform preventive maintenance and preventive repairs on a system. Only corrective maintenance and corrective repairs will be performed until the system is replaced.
Replacement	Complete replacement of a system or piece of equipment. This data should be separated from renewal, remodeling or renovation even though system replacement is often done during these activities.
Functional Maintenance	Maintenance the directly contributes to the function of a system or piece of equipment. Lawn service, deliveries, snow removal, etc. are not considered functional.

Appendix A

Table 2: Data Requirements Development

Maintenance Data Label	PM Work Order Count	CM Work Order Count	Data Requirements
Building Inspection	2,258	unknown	Make categorical labels specific in order to clearly correlate PM & CM work orders. How much did the frequency, time and cost of these inspections reduce CM work in these buildings?[41] This is unknown without tracking corrective work orders for this same category.
Generator	724	0	Track repairs for these systems, or if the system did not need any repairs between inspection periods, CM entries should clearly indicate "zero repairs" rather than zero. The absence of data and data labels have unreliable interpretation. Was any CM data collected for these repairs? Or did PM prevent 100% of repairs?
Fuel	381	0	
Plumbing	0	10,659	These systems need a PM plan or be distinguished from maintenance data. Decide which maintenance activities should be considered PM. Add PM labels for corresponding CM maintenance activities.
Electrical	0	10,289	
Roof	0	1145	
HVAC	848	12,217	This is better data collection. We can start analyzing the effect of PM on CM if data includes features such as square footage, age, work order duration, system ID, system & component condition, date replaced, and repaired part IDs. Adding these features would strengthen preventive maintenance analysis.
Elevator	736	1,038	
Extermination	11	1040	

[41] In Baltimore's case, building inspections were used to identify needed repairs. Therefore, we expect the data to be curvilinear. If the system is in poor condition, CM work orders could increase during PM inspections (up curve) until the system reaches a sustainable point of health, thereby gradually decreasing the likelihood the frequency of repairs (down curve).

About the Author

Awarded an MS in Government Analytics from Johns Hopkins University, Maria Battle is a data scientist and cyber security researcher at the Johns Hopkins Applied Physics Laboratory. She has worked in the cyber security sector and operations management for 24 years, starting in the U.S. Navy and U.S. Army as a communications expert, then managing operational services for Fortune 500 companies in the hi-tech commercial marketplace. In 2017, she become Chief Technology Officer of Secon-Delta, LLC and in 2018 served as the Director of System Security Engineering for the U.S. 2020 Decennial Census Technical Integrator contract.