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Maintenance 4.0 Opportunistic Strategy for Electric Buses

FERNANDO AGREDANO[1], HUSSEIN A. TAHA[2,3], SOUMAYA YACOUT[1]

[1] Department of Mathematics and Industrial Engineering, Polytechnique Montréal
2500 Chem. de Polytechnique, Montréal, QC H3T 1J4, Canada
luis-fernando.agredano-gonzalez@polymtl.ca
soumaya.yacou@polymtl.ca

[2] Department of Renewable Energy R&D, Solutions Serafin Inc
9301 Bd Ray-Lawson, Anjou, QC H1J 1K6, Canada

[3] Department of Electrical Engineering, Sohag University
Sohag Al Gadida City, Sohag Governorate 1646130, Egypt
hussein.taha@polymtl.ca

***Abstract-* In recent years, Industry 4.0 has reached different economic sectors. This innovation opens the door to developing new technologies and approaches to solving daily challenges in maintenance. In this paper, a maintenance 4.0 strategy is developed by using digital technology, the Internet of Things, and real-time data access. The objective is to increase the useful life and to decrease operational costs. The paper evaluates three different maintenance strategies by using a Monte-Carlo simulation approach to support Electric Buses' (EBs) maintenance management. One of those strategies uses the Maintenance 4.0 approach, and its results show operational maintenance's cost savings.**

***Key Words*: Maintenance 4.0, Monte-Carlo simulation, Electric Buses, Fleet Management.**

1 INTRODUCTION

Nowadays, the use of electric buses for public transport has increased significantly. The STM in Montreal is planning on increasing the number of electrical buses [*Bus électriques*, n.d.]. Every electric bus is composed of an integrated system [Taha et al., 2021]. In this system, part replacement is a time-consuming operation in which the high-voltage safety constraints have to be fulfilled and power voltage must be drained before the replacement [DGUV, 2012]. Therefore, the maintenance of electric buses must be done in a garage that has the necessary tools and equipment, and failure on the road is costly.

This paper uses a simulation approach to evaluate different maintenance strategies, which include a Maintenance 4.0 opportunistic one. The objective is to determine if the use of Maintenance 4.0 would result in any cost savings.

The Maintenance 4.0 approach comes from the fourth industrial revolution known as Industry 4.0 which emphasizes the use of digital technology, the Internet of Things, and real-time data access [Righetto et al., 2021]. More specifically, in the field of maintenance, it involves:

1. The use of sensors and other data sources and machine learning algorithms to analyze maintenance data and to recommend the best course of action for maintenance activities.
2. Data access by means of internet or cellular technologies.
3. Digital Twins (DTs) which are virtual replicas of physical assets that provide real-time information through sensors. The DTs simulate and optimize maintenance actions.

Presently, the maintenance strategy that is based on the health condition of a component is called condition-based maintenance (CBM). [Du et al., 2020] used proportional hazard models in which the condition is measured by vibration signals. The objective is to predict the spindle's remaining useful life. [Chen et al., 2020] used autoencoder (machine learning technique) to extract significant features and then use the Cox proportional hazard model in which the condition is represented by cumulative mileage, engine's age, and vehicle's age to estimate the RUL and to compensate censored data. Deep learning techniques were used to predict the time between failures. [Tong et al., 2022] propose an approach to optimize predictive maintenance by a combination of Neural Networks and proportional hazard models. All these papers proposed methods to improve remaining useful life estimation, time between failures estimation, and optimize predictive maintenance for single-component systems.

Opportunistic maintenance is based on replacing components that have not failed yet but meet specified criteria at scheduled or unscheduled downtimes of the bus. It is a maintenance strategy that is implemented in hierarchical multicomponent systems [Barde et al., 2016] [S. Barde et al., 2016], [Abdel Haleem & Yacout, 1998]. They later compared maintenance strategies including opportunistic maintenance in which opportunistic replacement's decision is based on age and according to safety limits. [Jiang et al., 2021] and [Y. Chen et al., 2022], both used condition-based maintenance to model the system's behavior and take maintenance actions when an opportunity arises. [Jiang et al., 2021] considered a series-parallel hybrid system with economic dependence. [Y. Chen et al., 2022] considered one system with identical and independent components. [S. R. A. Barde et al., 2019] used reinforcement learning to get the optimal opportunistic maintenance age-based policy. The condition of the components was not considered.

This paper proposes an opportunistic and age-based maintenance that takes into consideration the condition of the components. The data regarding the age and the health of the component is obtained from sensor's readings. The data is analyzed by machine learning algorithms to determine whether a certain component should be replaced or not. The main differences between the proposed strategy and those that are mentioned in the literature are the use of real-time data that give dynamic modeling capabilities instead of the static models obtained by the proportional hazard models. Moreover, our proposed strategy automates the decision-making process by building a digital twin and by using machine learning for finding the best maintenance action. As such, the main advantages of our proposed modeling strategy over the CBM strategies, specifically the proportional hazard models are:

1. It adapts to changes in health condition over time. This makes it useful for dynamic environments, which is required for electric buses in public transport.
2. It handles non-linearity, collinearity, and high-dimensional data by using the appropriate machine-learning techniques.
3. It provides real-time predictions.
4. Some machine learning techniques are able to handle incomplete data. They are useful for real applications in which the data comes from sensors.
5. It automates the decision-making process through Machine learning.

2 PROBLEM DESCRIPTION.

Without loss of generality, in this paper we consider only the driveline system of electric buses. This system is composed of four main components: 1) The electric Motor, 2) the wheels, 3) the tires, and 4) the transmission (Figure 1).

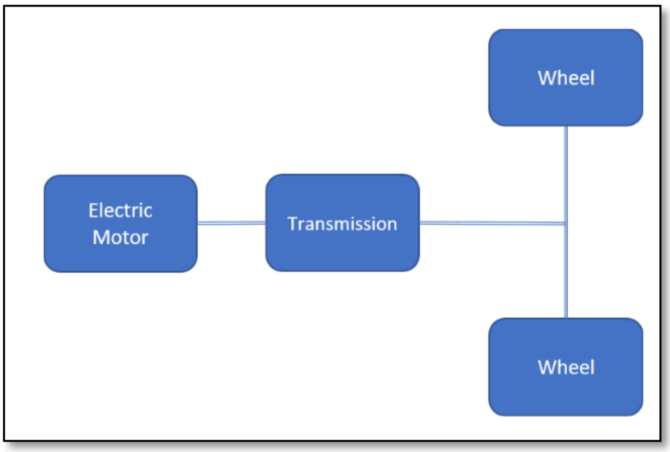

Figure 1. Electric Bus Driveline system layout

Three maintenance strategies are considered.

1. Corrective Maintenance Strategy in which a component is replaced only if it fails.
2. Opportunistic Maintenance Strategy in which a component is replaced if it fails. Other components are also replaced if their ages have reached a specified age control limit (ACL).
3. Opportunistic Maintenance 4.0 strategy. We assume that we have a real-time condition's indicator "Z_o" that represents the state or the health of the components. A component i, is replaced if it fails. The other components, o=1, 2, 3, are replaced if their ages have reached a specified age control limit (ACL_o), or if Z_o has reached a specified state control limit (SCL_o).

3. METHODOLOGY

3.1 Nomenclature.

- **i**: Component i^{th} that failed and that needs replacement, i = 1,2,3,4
- **Cc_i**: Cost of the i^{th} component.
- **WF_i**: Replacement Cost of the i^{th} component which will be replaced because an opportunity exists.
- **TF**: Tow Fees
- **RN_o** It's a flag to indicate if the o^{th} component needs to be replaced opportunistically. It takes the values 1 for YES and 0 for NO.

The maintenance cost associated to the failure of component i is computed by equation 1.

$$C = \sum_{i=1}^{4} Cc_i + \sum_{i=1}^{4} WF_i + TF \qquad (1)$$

Where C is the Maintenance cost associated with the failure of component i, Cc_i is the cost of the i^{th} component to be replaced, WF_i is the cost of manpower used of the replacement action, and TF is the tow fees.

3.2 Maintenance Strategies

Three maintenance strategies are compared:

1. Corrective Maintenance Strategy: In this scenario, a component is replaced only if it fails.
2. For the Opportunistic Maintenance Strategy, the cost saving of replacing more than one component results from the TF, which is charged once per event of failure. The decision to replace a component opportunistically is given by equation 2:

$$RNo = \begin{cases} 1, & If\ failure\ , \quad Lc_o > ACL_o \\ 0, & Otherwise \end{cases} \qquad (2)$$

Where Lc_o is the age (in hours) of the o^{th} component, o=1, 2, 3. The values of ACL_o, o=1,2,3 are obtained from equation 3. The Age Control Limit values for each component are obtained by minimizing the maintenance cost per unit time [Jardine et al., 2013]. This equation represents the optimal preventive maintenance time, t_p, when a fixed age strategy is used. In this case *ACL* is equal to t_p.

$$C(t_p) = \frac{Cp*R(t_p)+Cf*F(t_p)}{t_p*R(t_p)+\int_0^{t_p} tf(t)dt} \qquad (3)$$

In equation 3, $C(t_p)$ is the preventive maintenance cost per unit time if the component is replaced at time t_p, Cp is the cost of preventive action, $R(t_p)$ is the reliability at time t_p, Cf is the cost of corrective maintenance, and $F(t_p)$ is the probability of failure at time t_p. The goal is to find the time t_p that minimizes the cost of preventive maintenance of a component. We use equations 4 and 5 to compute Cp_i and Cf_i, respectively, for each component i, as follows.

$$Cp_i = Cc_i + WF_i \quad (4)$$
$$Cf_i = Cc_i + WF_i + \text{Tow Fees} \quad (5)$$

3. Opportunistic Maintenance 4.0 Strategy. The decision to replace a component is given by:

$$RN_o = \begin{cases} 1, & If\ failure \lor Lc_o > ACL_o \lor Z_o > SCL_o \\ 0, & Otherwise \end{cases} \quad (6)$$

Where *SCL* is the State Control Limits and Z_o provides information about the condition or the health of the o^{th} component of a system, o=1, 2, 3. In a generic form, this indicator is the output of a model that takes, as input information readings from sensors placed on the components 1, 2, 3, and 4 of the physical system, as shown in figure 2.

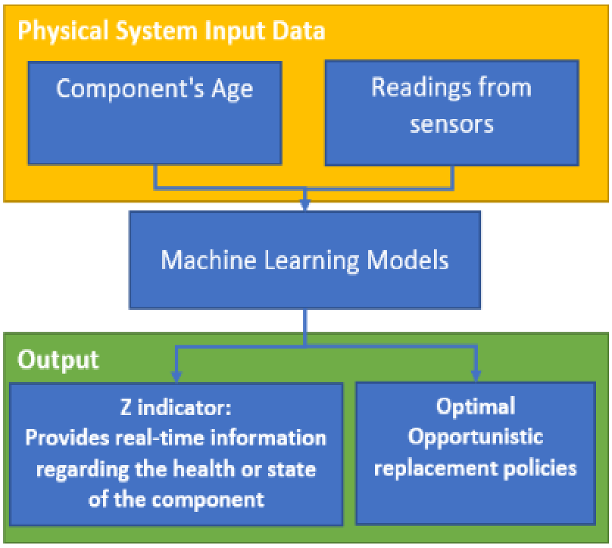

Figure 2. "Z" indicator Schema

In this paper, Z_o is a normalized real-time indicator. It takes values between 0 and 1. For example, if the $Z_o = 1$, it means that the o^{th} component is in a critical state, and if $Z_o = 0$, this means that the component is in a perfectly normal state.

4. Numerical Example

4.1 Monte-Carlo Simulation.

The Operational maintenance costs are the cost of each component, the cost of manpower to replace each component, and the tow fees of failure on the route [*Remorquage-Exclusif-Tarifs.Pdf*, n.d.]. The historical data about the component's failures are given in [S. R. A. Barde et al., 2019]. Based on real failure data, the authors developed the Weibull distributions representing the failures events of each component. The parameters of the Weibull distributions that represent the failure times of each component are shown in table 1. In this paper these parameters are used in a Monte-Carlo simulation to generate failure times for each component of the four components.

Table 1. Maintenance Information

Component	Electric Motor	Wheel	Tire	Transmission
Shape	1.005955	79.81	414.16	109.25
Scale (hours)	15,804.8	713.55	2365.08	996.88
MTTF (hours)	15,758.79	708.5	2361.8	991.7
Component Cost (Cc_i)	$50,000.00	$463.00	$704.00	$20,000.00
Replacement time	24 hours	2 hours	1 hour	24 hours
Manpower hourly rate	$14.25			
Manpower Cost (WF_i)	$342	$35.62	$14.25	$342
Tow fees	$2180.33			

The Monte-Carlo simulation is a method to solve mathematical and or technical problems using probabilistic models through the simulation of random variables when their probability density function is known. As, such, Monte-Carlo simulation is used to generate failures events for each of the fours components. For this purpose, the R programing language is used [Wang & Pham, 2006]. In this paper, the random variable is the time to failure of the i^{th} component according to their Weibull distribution function.
For simulation purposes, Z_o is computed as follows:

$$Z_o = VLc_o / TtF_o + Error \quad (7)$$

Where VLc_o is the age of the o^{th} component (in hours), TtF_o is the time to failure of the o^{th} component (in hours) that is generated by Monte Carlo simulation and the error is a random variable that follows a normal distribution with mean = 0 and standard deviation = 0.001, which purpose is to make the Z indicator more realistic by introducing random noise.

The Monte-Carlo simulation inputs are Weibull Distribution function parameters, the Costs, the Age Control Limits *(ACL)* for strategies 2 and 3 and the State Control Limits *(SCL)* for strategy 3.
In this paper, the simulation run length is 100,000 hours and the output is the average cost per unit of time, which is computed as:

$$AC = CC(T) / T \quad \text{(Equation 8)}$$

Where AC is the average cost per unit time, CC(T) is the cumulative maintenance cost of the system operating T hours, and T, is the run duration, which in this case is 100,000 hours.
Some necessary assumptions to perform the Monte-Carlo simulation are:

1. Buses run 24 hours.
2. At the beginning of each simulation run, all the components are as good as new.
3. The opportunistic maintenance and opportunistic maintenance 4.0 are done only at the failure of a component.

4. All components are replaced by new ones. No repairs are considered.
5. The Electric bus driveline is a series reliability system, one component's failure stops the entire system.
6. All the components in the system are statistically independent.
7. The tow fees are only applied once per failure event on the road. This means that if a component fails and it is decided to replace other component opportunistically , the tow fees remain the same $2180.33.
8. All the replacement parts are available when needed.

To make sure that simulation run is long enough , we perform a 100,000 hours' long run to compare the simulated mean times to failure (MTTF) versus the theoretical ones for each component [Abdel Haleem & Yacout, 1998]. During this run, no opportunistic maintenance was performed. From Table 2, we can observe that the MTTF values obtained from the simulation run are very similar to the theoretical ones, the only one that deviates slightly is the electric motor, due to the low number of failures during the simulation run, which is expected according to its Weibull parameters.

Table 2. Theoretical vs Simulated MTTF Values

	Electric Motor	Wheel	Tire	Transmission
Theoretical MTTF	15,758.79 hours	708.5 hours	2361.8 hours	991.70 hours
Simulated MTTF	13,799.5 hours	708.0 hours	2361.3 hours	992.03 hours
Error %	12.43%	0.04%	0.02 %	0.03%
Number of failures	7	141	42	101

4.2Numerical Results

The age, and the state control limits for each component are shown in Table 3

Table 3. Age Control limits and State Control Limits

	Electric Motor	Wheel	Tire	Transmission
***ACL* (hours)**	At failure	663	2325	975
SCL	0.8521	0.6992	0.4845	0.7318

Each maintenance strategy was run 30 times. The histograms of the average cost per unit time resulting from those 30 runs are shown in figure 3. A visual comparison is given in figure 4, which represents the average cost and their confidence intervals at 95% of confidence for each strategy, and finally, table 4 shows a numeric summary.

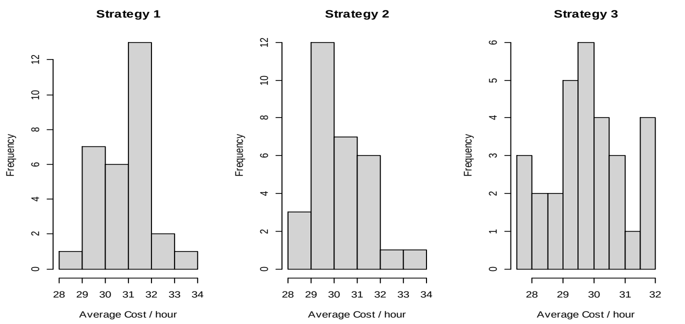

Figure 3. Histograms of the average cost per unit time per strategy

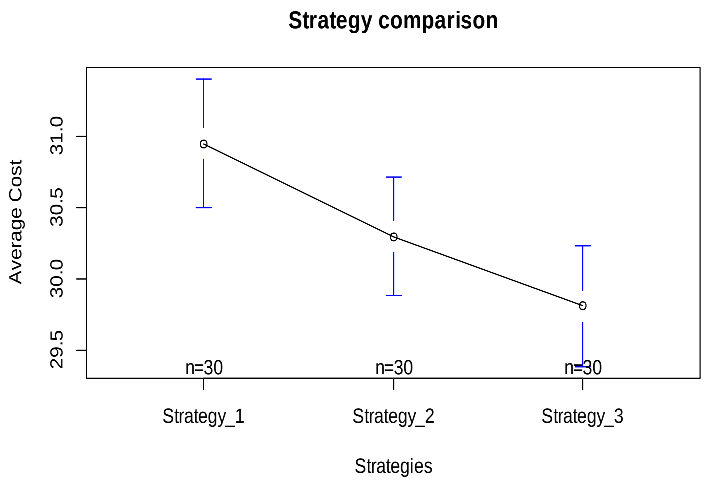

Figure 4. Average cost per unit time comparison

Table 4. Simulation runs summary

	Corrective Maintenance	Opportunistic Maintenance	Opportunistic Maintenance 4.0
Average Cost / hour	30.94514	30.29737	29.81227
Standard Deviation	1.207036	1.115832	1.131891

To validate that the average cost from strategy three is statistically lower compared to the other two strategies, we verify that the data follows a normal distribution by using the Anderson-Darling test. Then we perform a two-sample T-test for the means. With 95% confidence, we can conclude that the average cost/hour from strategy three is significantly lower than strategies one and two. The two sample T-test results are shown in Table 5, where AC is the average cost per unit of time.

Table 5. Two-sample T-test results

Strategy Comparison	P value	Alternative Hypothesis
3 vs 1	0.0002	$AC_{strategy3} < AC_{Strategy1}$
3 vs 2	0.0499	$AC_{strategy3} < AC_{Strategy2}$

We can observe that strategies two and three are better than strategy one. The cost saving when implementing strategies two and three is $0.647/hour and $1.1328 /hour, per bus respectively compared to the corrective maintenance.

If strategy two is implemented, when analyzing a horizon of 5 years, the savings will be around $32,100.00 per bus. In the same way, if strategy 3 is implemented, in a horizon of 5 years, the savings will be around $49,600.00 per bus.

On October 2022, the average number of available STM (Société de transport de Montréal) buses was around 1589 units [*Indicateurs de performance*, n.d.], this could represent a total saving of $51,006,900.00 and $78,814,400 .00 for strategy two and three respectively.

4. Conclusion

From the results, we can conclude that the best maintenance strategy is Opportunistic Maintenance 4.0. The fact that using sensor data for condition monitoring and machine learning techniques which adapt dynamically to new sensor data makes maintenance 4.0 promising advancement in maintenance management. The saving resulting from opportunistic maintenance 4.0 is not negligible for a five-year horizon maintenance plan. However, the results are highly dependent on the accuracy and precision of the Z_o indicator (the condition of the components). In practice, this indicator and the model used to estimate it should be carefully analyzed to obtain optimal results.

For future work, real data will be generated from the testbed that is constructed in the Intelligent Physical Systems' laboratory at Polytechnique Montreal.

Finally, a digital twin, will be developed to automatically estimate, and adjust over time, each component's failure probability function and degradation state in real time (Z) to develop adaptive maintenance actions, for maintenance management, especially for large number of vehicles in fleets.

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