Performance Evaluation of IoT-enabled Predictive Maintenance

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***Abstract*—Predictive maintenance (PdM) is gathering both researchers' and practitioners' attention in the Industry 4.0 era. Enabling technologies, such as IoT and AI make it feasible to operate PdM that was impossible in the past. However, only general benefits of PdM are presented and pragmatic issues, such as characteristics of failures that suite for PdM, are not addressed. This study evaluates performance of maintenance policies by using an agent-based modeling. This study identifies that the performance of PdM is comparable to preventive maintenance when variations of failure is small and that performance of PdM does not deteriorate significantly when the accuracy of prediction is low. These findings benefit practitioners when they select a maintenance policy.**

I. Introduction

Predictive maintenance (PdM) is gathering both researchers' and practitioners' attentions in the Industry 4.0 era. One reason for this trend is because Internet of Things (IoT), an enabling technology of the Industry 4.0, makes it feasible to collect data about factory machines. In addition, artificial intelligence (AI) technology, such as deep neural network, makes it accurate to predict remaining useful life (RUL) of machines.

PdM is considered to be an effective maintenance policy compared to other policies because it can reduce both unplanned stoppages and unnecessary maintenances. Although, the effectiveness of PdM is relatively obvious, it is mainly discussed qualitatively not quantitatively. This is not sufficient because to introduce IoT and AI technologies, companies need to invest resources into new systems and they need to justify the investments[1]. This study tries to quantify the effectiveness of the PdM by using simulation.

For the quantitative analysis, we compare number of expected failures and maintenances. By comparing the cost of both failures and maintenances, we can identify the areas in which each of the maintenance policies is preferable. We also execute sensitivity analysis to evaluate the impact of characteristics of failure on maintenance policy decision making. We assume equipment failure is stochastic and follows the Weibull distribution. We also assume equipment with increasing failure rate (IFR), which means rate of failure increases as the equipment is used longer.

II. Related research

A. Types of maintenance

This subsection introduces types of maintenance policies we evaluate in this study. Maintenance is categorized into two main types, corrective maintenance(CM) and preventive maintenance(PM). In CM, restoration of equipment is executed after equipment is failed. This maintenance is straight forward and acceptable when the cost of failure is negligible. However, as the size of equipment becomes large and complex, the cost of failure including costs incurred when manufacturing process is stopped becomes non-negligible.

PM, in contrast, is designed to keep equipment running by maintaining condition of it before failures happen. This PM also has two sub-types. One is predetermined periodic preventive maintenance, in which maintenance operation is executed periodically, and the other is condition-based maintenance, in which condition of the equipment is continuously monitored and maintenances are executed before failures are expected to happen. In periodic preventive maintenance, the timing is decided based on the past failure history data of the equipment.

Broadly speaking, these two types are categorized in preventive maintenance, but in some literature the periodic preventive maintenance is simply called preventive maintenance and condition-based maintenance is called predictive maintenance [2]. In this study, we also follow this definition and compare performance of these maintenance policies: corrective maintenance (CM), preventive maintenance (PM), and predictive maintenance (PdM).

B. Predictive maintenance enabled by IoT

In PdM, data collection about equipment and algorithms to predict RUL are crucial. However, data collection is not always easy. If the equipment has rotating parts, such as propellers or tires, it is difficult to attach sensors and continuously collect data of them, even though there are needs to collect the data[1].

Weight of the sensor system also becomes a constraint. For example, sensor data of aircraft, such as vibration, strain and temperature are crucial to detect degradations, but to apply sensors and harness the wire from sensors to the aircraft information system increases weight of the airplane, therefore, implementing aircraft PdM system is not simple[3].

These are constraints of PdM, but wireless technologies make it feasible to collect data in these difficult situations. There are battery-less sensor systems in which tiny sensors are attached to the parts, and the sensor data is collected by using radio wave[4]. By using this kind of system, condition data of rotating parts and weight-sensitive equipment can be collected and used for PdM.

C. Literature review

The same as our study, there are literatures that assess the impact of the Industry 4.0 on PdM. O'Donovan et al. reviewed literatures in this field and clarified the approaches and application areas[5]. Lee et al. investigated how data collected by the cyber physical system (CPS) is used for PdM[6]. Lu also reviewed studies about PdM in the Industry

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4.0 era and foresaw that the use of PdM would increase in the future [7].

In addition to the literatures to study trends in PdM in the Industry 4.0, there are studies that propose RUL prediction algorithms in PdM[8][9]. In these studies, algorithms such as deep neural network, are proposed and evaluated their effectiveness using a real-life data. In this study, we use their findings when selecting parameters of our simulation.

One implication of this study is to help practitioners to select an appropriate maintenance strategy by comparing the pros and cons of possible policies. There are studies that have the same purpose. Wang et al. proposed a method to help selecting optimum maintenance strategies based on a fuzzy AHP[10]. They assumed a maintenance selection process as a multi choice decision analysis problem and showed its effectiveness using a real power plant operation data.

There are studies that utilize simulation for an optimum maintenance strategy selection. Li et al. assumed that equipment consists of several parts with different failure timing distributions and proposed a method to select a maintenance strategy based on highest steady-state availability[11]. Their assumption is valid considering the structure of the ordinal equipment, but their model becomes complex when it is applied to real machines. Lee et al. also proposed a method to select optimum maintenance strategies by simulation[12]. They utilized the queuing model and proposed a method to evaluate maintenance strategies based on the interruption time of the maintenance operation. One of their assumptions is that occurrence of failure events is statistically distributed, which is the same as our study. However, their focus is to evaluate maintenance interval of the PM and is not applied as it is to our problem situation.

These studies also help practitioners to select an appropriate maintenance policy, but they do not evaluate the impact of failure with different characteristics. Our study, on the other hand, quantifies the impact of different characteristic failures that practitioners may face in the real situation. In this regard, our study is different from existing simulation studies.

III. Evaluation framework

To quantitatively identify the conditions where each of the maintenance policies is preferable, we analyze sensitivity of parameters that characterize failure and maintenance. The settings for analysis are as follows.

1) Variations in the RUL of equipment
Since equipment is usually assembled from parts and it is not used equally, it is presumable that the equipment RUL has variations. These variations affect effectiveness of the maintenance policies. This study clarifies the relation between RUL variations and maintenance policies to help decide an appropriate maintenance policy.

2) Prediction accuracy in PdM
Even using the latest algorithms, prediction errors are unavoidable. If the prediction is longer than actual RUL, unplanned equipment stoppage will happen, and if the prediction is shorter than actual RUL, on the other hand, maintenance is executed unnecessarily. In both cases, unnecessary cost is incurred. This study clarifies relation between prediction accuracy and maintenance policies to avoid these costs.

3) Maintenance interval in PM
This does not directly affect the effectiveness of PdM, but it is critical to know the difference in performance between PM and PdM. If the difference is not significant, the decision not to implement PdM could be reasonable. Therefore, relation between performance of PM in the different interval and maintenance policies is analyzed in this study.

4) Cost
In maintenance, cost is incurred in both cases when unplanned stoppages happen and when maintenance operation is executed. They are not mutually exclusive. Maintenance policies are decided to minimize the total cost, but costs of failure and maintenance are not equal in all the cases. Therefore, this study evaluates the impact of costs on the maintenance policies by changing the cost ratio between failures and maintenances.

TABLE I
Simulation parameters

Parameters	Description
Number of agents	Machine:200, Controller:1
Simulation period	5 years（365 × 5 days）
Weibull distribution	Use 2 for alpha and 470 for beta as default values. These values are from existing literature[14].
Percentage of failure prevention	This value is used when deciding a period in PM. Use 80% as a default value.
Accuracy of PdM	This value is the accuracy of RUL prediction. Use between 70% and 105%.

IV. Evaluation

A. Failure and simulation models

The same as existing literatures, this study assumes the Weibull distribution model for failure. Probability density function (f) and cumulative distribution function (F) are expressed as follows.

$$f(x) = \frac{\alpha}{\beta}(\frac{x}{\beta})^{\alpha-1}exp[-(\frac{x}{\beta})^{\alpha}] \quad (1)$$

$$F(x) = 1 - exp[-(\frac{x}{\beta})^{\alpha}] \quad (2)$$

Alpha and beta in the equations are called the shape parameter and the scale parameter, respectively. The shape parameter defines variation of failures, and the scale parameter defines average time when failures happen.

To simulate machines with different RUL, we use an agent-based simulation. In addition to agents for machines, we implement a controller agent to collect numbers of failure and maintenance and to calculate expectation values of them. Table I shows parameters used in the simulation.

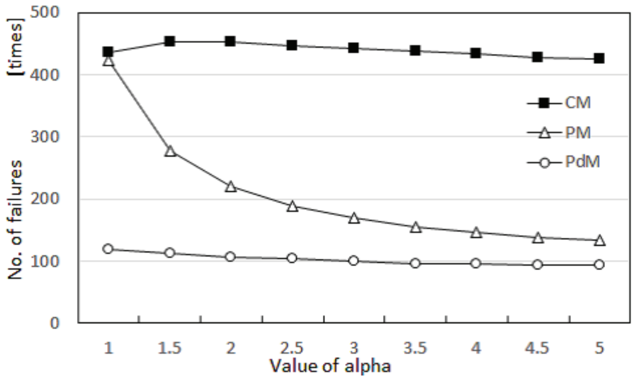

Fig. 1. Number of failures (shape parameter)

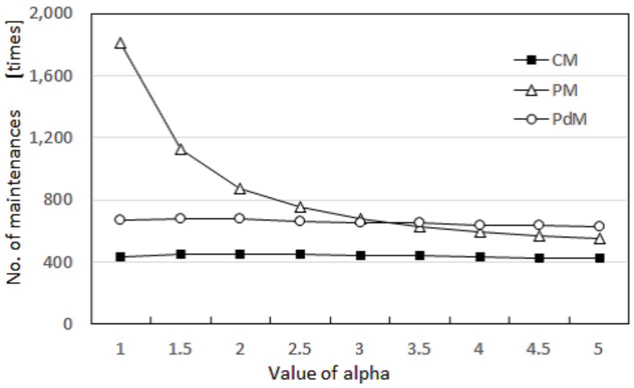

Fig. 2. Number of maintenances (shape parameter)

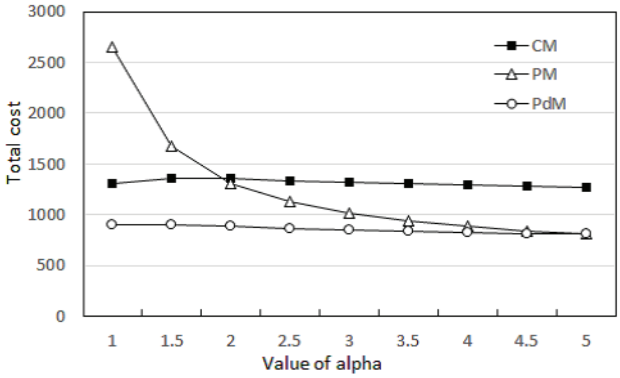

Fig. 3. Total cost (failure/maintenance = 2, shape parameter)

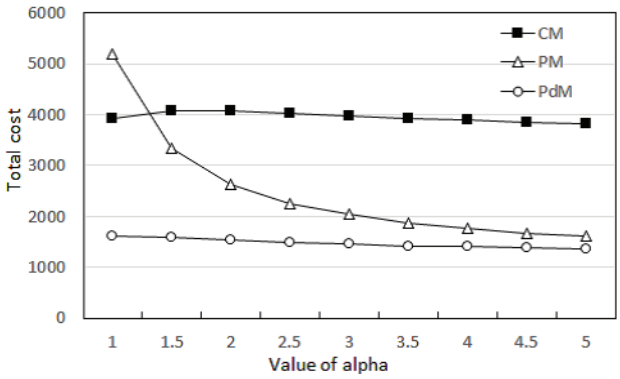

Fig. 4. Total cost (failure/maintenance = 8, shape parameter)

B. Variation in the RUL of equipment

Failures of equipment occur stochastically. The variation of failure is dependent on variations of failures of consisting parts, how the equipment is used etc. This variation is expressed by the shape parameter in the Weibull distribution. This study calculates number of maintenances and failures by changing value of the shape parameter from 1 to 5.

Fig.1 and Fig.2 show the result of the simulation. The effect of the shape parameter is large in PM but less in CM and PdM. It is envisaged that cases that unplanned stoppages happen before the fixed interval maintenance increase when the shape parameter is small (variation is large) in PM. However, in both CM and PdM, the effect of shape parameter is small because failures happen in CM and failures are predicted in PdM regardless of the interval of the failures.

Next difference in cost is evaluated. Costs are incurred in both failure and maintenance. The more frequent maintenance is carried out, the fewer failures we expect. In this case, you can decrease cost of failure, but the cost of maintenance increases. They are in the trade-off relationship.

In general, cost of failure is larger than cost of maintenance, but the extent is dependent on the situation. Therefore, we run the simulation by changing the ratio of these two costs from 2 to 8 and analyze the total cost. When two is set, cost of failure is two times more than that of maintenance.

Fig.3 and Fig.4 show the result of the simulation. In PM, the larger the shape parameter (less variation), the less cost is expected compared to other policies. This is intuitive because the shape parameter gives no impact on CM and PdM. This result implies that CM might be preferable to PM if the variation of the failure timing is large. In addition, the cost difference in PM and PdM is not large when the shape parameter is large, which means companies do not necessarily need to implement PdM in this case.

C. Prediction accuracy in PdM

PdM is effective in both avoiding unplanned equipment stoppages and unnecessary maintenances. However, the effect is not obvious if the accuracy of the RUL prediction is not high. This subsection assesses the impact of prediction accuracy on expected number of failures and maintenances.

For evaluation, we run simulation by changing the prediction accuracy. At the initial settings, accuracy of the prediction is uniformly distributed from 50% to 105% of RUL. Then we change the range in both less time and more time sides. For example, if the accuracy improves 20%, the range is from 60 % to 104 % of RUL.

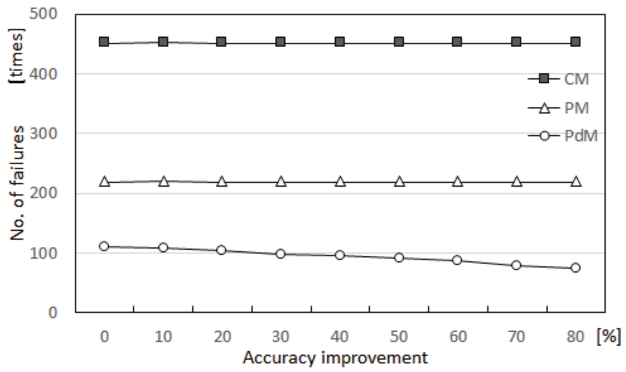

Fig. 5. Number of failures (prediction accuracy)

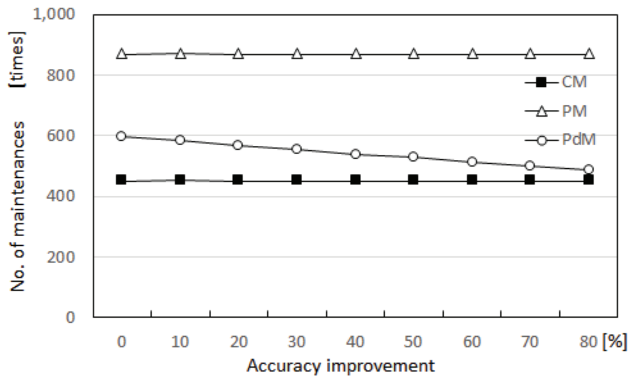

Fig. 6. Number of maintenances (prediction accuracy)

Fig.5 and Fig.6 show the result of the simulation. Numbers of CM and PM are shown as a reference. In both cases, the numbers decrease as the accuracy improves. However, the improvement is not significant.

Next impact of prediction accuracy and variation of failures(shape parameter) is analyzed. Fig.7 and Fig.8 show the result. In number of failures, we can observe a slight difference when the shape parameter is changed, but for maintenance, the difference in the parameters gives almost no impact.

D. *Maintenance interval in PM*

To understand the difference between PM and PdM, the impact of maintenance interval is evaluated. PM intervals are calculated by setting a failure prevention coverage percent in this study. For example, 50% of failures are avoided if we choose an interval value calculated by 50% coverage. For sensitivity of the interval, we analyze by changing percentage from 50% to 90%.

Fig.9 and Fig.10 show the result. Numbers of CM and PdM are shown as a reference. The number of failures decreases as the percentage of failure prevention increases, but the number of maintenances takes the opposite trend. This is intuitive because a high prevention coverage means less chances of failures but also more chances of unnecessary maintenances. Next, total cost is analyzed in the same manner.

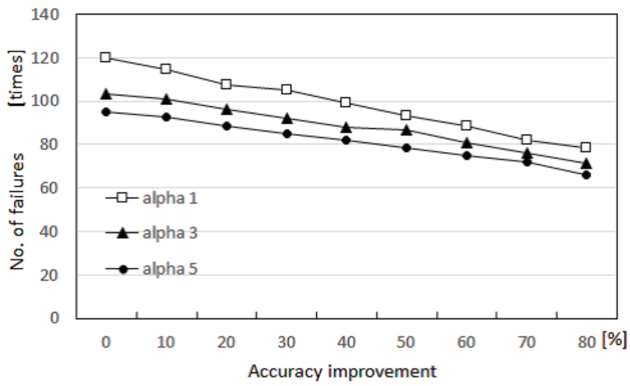

Fig. 7. Number of failures (prediction accuracy and shape parameter)

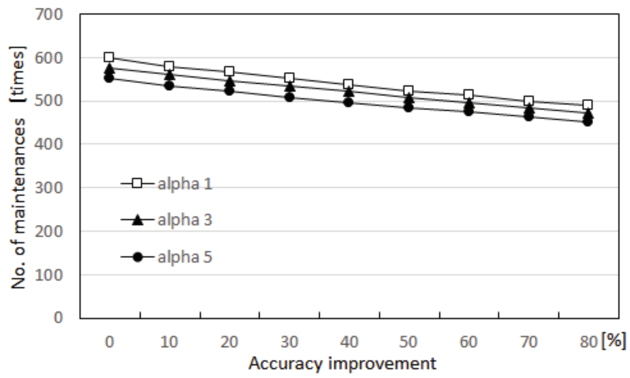

Fig. 8. Number of maintenances (prediction accuracy and shape parameter)

Fig.11 and Fig.12 show the result of the simulation. Costs of CM and PdM are shown as a reference. Since numbers of failures and maintenances take different patterns each other, the trends of total cost are different in each of the failure/maintenance cost ratio. When the ratio is low, total cost increases as the failure prevention coverage increases. But when the ratio is high, total cost decreases as the coverage increases. In addition, there are cases when cost of PM is

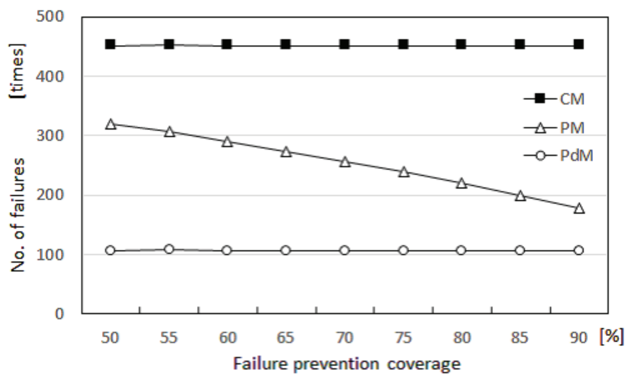

Fig. 9. Number of failures (maintenance interval)

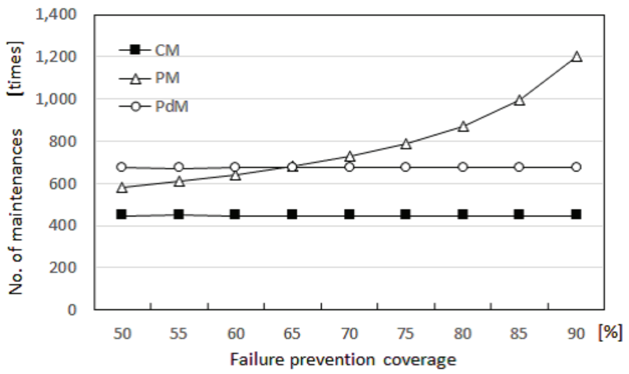

Fig. 10. Number of maintenances (maintenance interval)

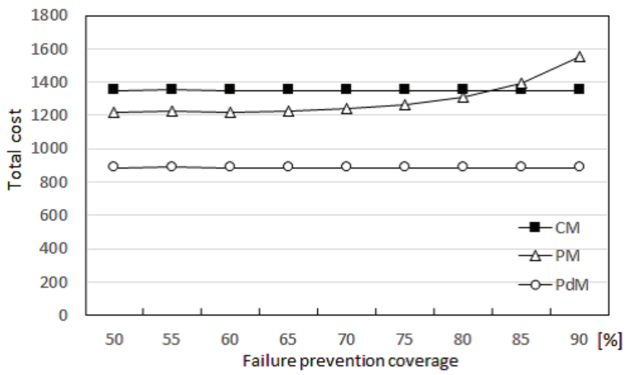

Fig. 11. Total cost (failure/maintenance = 2, maintenance interval)

lower than that of PdM in this simulation setting.

V. Summary

The Industry 4.0 sheds the new light on PdM because enabling technologies of the Industry 4.0, such as IoT and AI, make this maintenance policy feasible. PdM is believed to be more efficient compared to other maintenance policies, but it is claimed qualitatively and the conditions where PdM is

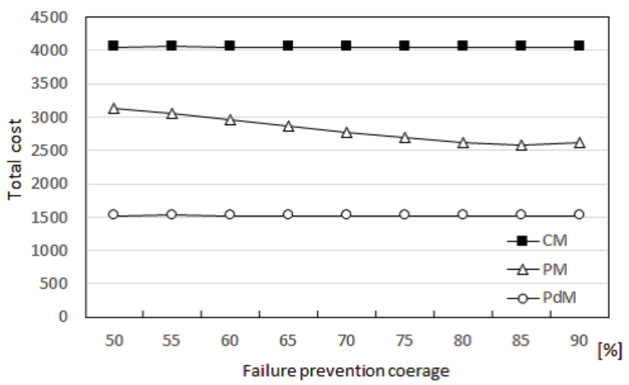

Fig. 12. Total cost (failure/maintenance = 8, maintenance interval)

preferable is not quantitatively assessed. Considering this situation, this study evaluates performance of PdM qualitatively by using a agent-based simulation. The failure we assume is IFR and is modeled using the Weibull distribution.

We evaluate the performance in three perspectives: impact of variation of failures, impact of PdM prediction accuracy, and impact of PM maintenance interval. From the failure variation analysis, we find that the performance of PdM is stable regardless of the failure variation. We also find that the cost of PdM is equivalent to that of PM when variation is small, which means PdM might not be necessary in such a situation.

From the PdM prediction accuracy analysis, we find that high accuracy can reduce both failures and unnecessary maintenances but that the impact of the accuracy improvement is not significant. From the maintenance interval of PM analysis, we find that cost ratio between failure and maintenance affects total cost of maintenance and that there are cases where PM with a shorter interval is preferable to other policies.

With these analyses, we find that combination of failure/maintenance patterns and maintenance policy affects performance of maintenance, such as expected number of failures and maintenances. These findings are crucial in deciding which maintenance policy to select in the real-life situation.

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