ABSTRACT

Machine maintenance is a challenging operational problem, where the goal is to plan sufficient preventive maintenance to avoid machine failures and overhauls. Maintenance is often imperfect in reality and does not make the asset as good as new. Although a variety of imperfect maintenance policies have been proposed in the literature, these rely on strong assumptions regarding the effect of maintenance on the machine’s condition, assuming the effect is (1) deterministic or governed by a known probability distribution, and (2) machine-independent. This work proposes to relax both assumptions by learning the effect of maintenance conditional on a machine’s characteristics from observational data on similar machines using existing methodologies for causal inference. By predicting the maintenance effect, we can estimate the number of overhauls and failures for different levels of maintenance and, consequently, optimize the preventive maintenance frequency to minimize the total estimated cost. We validate our proposed approach using real-life data on more than 4,000 maintenance contracts from an industrial partner. Empirical results show that our novel, causal approach accurately predicts the maintenance effect and results in individualized maintenance schedules that are more accurate and cost-effective than supervised or non-individualized approaches.

Keywords First keyword · Second keyword · More

1 Introduction

Machine maintenance constitutes an intricate operational problem. The challenge is to avoid machine failures and costly overhauls, while simultaneously minimizing the cost of preventive maintenance (PM). Moreover, maintenance is often imperfect in practice since it does not restore the machine to a state as good as new. In fact, a broad spectrum of maintenance effects have been studied in the literature, ranging from perfect maintenance, which restores the system to a state as good as new, to worst maintenance, where maintenance causes the machine to fail [Pham and Wang, 1996].

Existing approaches in imperfect maintenance rely on strong assumptions regarding the effect of PM. First, the effect is modelled as either deterministic or stochastic assuming a certain probability distribution. These assumed effects,

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however, might not correspond to the actual effect. Second, the effect is typically assumed to be machine-independent, i.e., identical for all machines. In reality, the effect of the same type of PM intervention could be very different for different machines. For example, changing a gear would likely have a different impact on a brand new machine compared to the exact same maintenance intervention on an old, worn down machine.

This work relaxes both assumptions by proposing a completely data-driven maintenance policy that learns the effect of maintenance conditional on a machine’s characteristics. The benefit of this approach is that it allows (1) to flexibly learn the maintenance effects from observational data (instead of assuming a certain deterministic or stochastic effect based on expertise), and (2) to design a machine-specific PM schedule based on these learned effects.

These benefits are achieved by framing maintenance as a problem of causal inference. We argue that the challenge in maintenance is that, for each specific machine, we only observe one outcome for the maintenance frequency that was administered in practice. We never observe the counterfactual outcomes – what would have happened if that machine received more or less maintenance in the past. Therefore, we never know whether the optimal maintenance frequency was prescribed. This is exactly the aim of causal inference, i.e. to predict each individual machine’s potential outcomes in terms of failures and overhauls for different levels of PM. By learning a model that predicts the number of overhauls and failures given the PM frequency, we can optimize the PM schedule to minimize the total estimated cost. Essentially, we propose using observational data to learn a machine-specific digital twin for maintenance that predicts what would happen if a machine is prescribed a certain maintenance schedule.

This work contributes by proposing a novel prescriptive framework for maintenance that prescribes maintenance based on the estimated effect of PM on the machine’s number of overhauls and failures. To this aim, we frame maintenance as a problem of causal inference. Consequently, we leverage state-of-the-art machine learning methods for causal inference that learn models to estimate a machine’s potential outcomes for different PM frequencies from observational data. Moreover, we formulate a prescriptive policy that uses the potential outcomes to decide on the optimal PM frequency so as to minimize the total cost of failures and interventions. Empirically, we contribute by demonstrating the excellent use of the presented prescriptive framework on a dataset consisting of more than 4,000 maintenance contracts of industrial equipment provided by an industrial partner.

## 2 Related work

Machine maintenance has been studied extensively in operations research, with a wide variety of proposed maintenance policies [Wang 2002, Ding and Kamaruddin 2015, de Jonge and Scarf 2020]. Although most existing work assumes that maintenance restores the system to a state that is as good as new, maintenance is typically imperfect in reality. In fact, different maintenance effects have been studied in the literature, ranging from maintenance that restores the system to a perfect state to maintenance that makes the system’s state worse [Pham and Wang 1996]. Consequently, developing maintenance policies that incorporate imperfect maintenance is an important research problem.

### 2.1 Imperfect maintenance

Existing work models the effect of imperfect maintenance as either stochastic (based on a known probability distribution) or deterministic [Pham and Wang 1996, Chukova et al. 2004]. Stochastic effects include the \((p, q)\) rule, where maintenance is perfect with probability \(p\) and minimal with probability \(q = 1 - p\) [Nakagawa 1979a, Brown and Proschan 1983], as well as its age-dependent variant \((p(t), q(t))\) [Block et al. 1985]. Other work assumes a deterministic effect. Improvement factor models assume that maintenance decreases the system’s failure rate by a deterministic improvement factor [Malik 1979]. Similarly, in virtual age models, imperfect maintenance decreases the system’s age or its failure intensity with a deterministic factor \(q\) where \(0 < q < 1\) [Kijima 1989, Tanwar et al. 2014].

Conversely, instead of making assumptions regarding the effect of maintenance, our work proposes to learn the effect of PM from data. Data-driven approaches have recently gained importance in the maintenance literature [Bousdekis et al. 2021]. Condition-based maintenance is a recent paradigm where maintenance is optimized based on the machine’s state or its characteristics [Gits 1992, Alaswad and Xiang 2017]. Especially relevant to our work are recent, predictive maintenance approaches that learn a predictive model from data to decide on the appropriate maintenance interventions [Swanson 2001, Carvalho et al. 2019].

Similar to the general literature on imperfect maintenance, existing condition-based approaches that do consider imperfect maintenance assume either a deterministic or stochastic maintenance effect. There exist three broad categories of condition-based approaches that account for imperfect maintenance [Alaswad and Xiang 2017]. A first category considers minimal maintenance with a deterministic effect, in which a system has several deterioration stages and imperfect maintenance returns the system to the previous stage. A second category considers stochastic effects where the maintenance effect is governed by an assumed probability distribution. Finally, in improvement factor models,
imperfect maintenance decreases the system’s hazard rate with a (deterministic) factor between zero and one. To the best of our knowledge, no existing condition-based approaches aim to learn the effect of maintenance from data.

Finally, this work focuses on a provider of full-service contracts

2.2 Prescriptive analytics and causal inference

Instead of assuming a certain PM effect, this work uses data-driven models to learn the effect of maintenance using techniques from causal inference. Causal inference aims to estimate the effect of a certain cause from data, e.g., the number of failures resulting from a certain maintenance frequency compared to not applying any maintenance. Ideally, estimating maintenance effects would be done by conducting a randomized controlled trial: assigning different levels of maintenance to a collection of (similar) machines and comparing the outcomes [Rubin, 1974]. However, in practice, this approach can be prohibitively expensive or even unfeasible. In maintenance specifically, it would be challenging to randomly assign various levels of PM to different machines. Therefore, we need to rely on historical, observational data of machines and their maintenance.

The challenge of working with observational data is that this data is biased due to existing maintenance policies that were applied [Rubin, 1974]. For example, as a result of an existing policy, machines more prone to failure might have been more likely to receive maintenance in practice. This phenomenon, called selection bias or confounding bias, can result in biased estimates of the counterfactual outcomes if ignored. Therefore, specialized tools have been developed in the causal inference literature to tackle exactly this problem and learn causal effects from observational data, i.e., in the presence of selection bias [Yao et al., 2021]. Specifically, our work is related to learning potential outcomes for continuous-valued interventions [Imbens, 2000, Hirano and Imbens, 2004, Imai and Van Dyk, 2004, Schwab et al., 2020, Bica et al., 2020], e.g., the number of PM interventions per running period.

Causal inference has been applied to a variety of applications, such as personalized medicine [Berrevoets et al., 2020], economic policy design [Athey and Wager, 2021], or marketing [Varian, 2016, Devriendt et al., 2018]. Moreover, it is related to prescriptive analytics [Verbeke et al., 2020, 2022], which has recently gained importance in operations research [Bertsimas et al., 2019, Bertsimas and Kallus, 2020]. In this work, causal inference is used to predict a machine’s potential outcomes for different levels of maintenance and decide upon a personalized maintenance schedule. To the best of our knowledge, this is the first application of causal inference for maintenance optimization.

3 Problem overview

This work aims to solve the problem faced by a provider of full-service maintenance contracts. The service provider is responsible for maintaining the client’s asset at a predetermined price [Deprez et al., 2021]. Therefore, for each contract, the service provider needs to decide on a usage-based PM schedule, prior to contract start, based on information such as the type of machine it concerns and/or the machine’s age at contract start.

In this work, we assume the service provider conducts a single type of PM intervention and needs to decide on the frequency of these interventions. Planned PM aims to prevent two types of events. The first, overhauls, are unplanned, comprehensive maintenance interventions during which large parts of the machinery need to be replaced. From the viewpoint of the full-service maintenance provider, these are the most costly type of event. The second, machine failures, result in an urgent need for maintenance as the machine stops running until corrective maintenance occurs. This again incurs a cost to the service provider that is smaller than the cost of an overhaul, but larger than the cost of PM.

The overall goal is to find each contract’s optimal PM frequency that minimizes the combined cost of planned PM, overhauls and failures, from the perspective of the service provider. Although planning more PM interventions is likely to result in less overhauls and failures, it also comes at an increased maintenance cost. This means the PM frequency is a trade-off between costs resulting from planned PM on the one hand and costs resulting from overhauls and failures on the other hand. Due to heterogeneity in the contracts, maintenance might need to be planned more frequently for some machines. Therefore, it is important to consider the contract’s characteristics when deciding on the PM frequency. To this aim, the service provider has access to information on past contracts including how often maintenance was applied as well as the number of overhauls and failures that were observed.

Formally, each contract is defined as a tuple \((X, T, O, F)\). Here, \(X \in X \subset \mathbb{R}^d\) denotes the characteristics of the machine and contract. The treatment, the PM frequency or the number of preventive maintenance interventions that will be applied per running period, is denoted as \(T \in T \subset \mathbb{R}^+\), \(O \in O \subset \mathbb{R}^+\) and \(F \in F \subset \mathbb{R}^+\) are the contract’s number of overhauls and failures per running period. We adopt the Rubin–Neyman potential outcomes framework [Rubin, 2004, 2005] and denote the overhauls \(O\) and failures \(F\) per running period given maintenance frequency \(t\) as \(O(t)\) and \(F(t)\).
Figure 1: Causal diagram depicting the relations between the different variables. $X$: Machine and contract characteristics, $T$: Preventive maintenance, $O$: Overhauls, and $F$: Failures.

The objective is to decide on the optimal maintenance frequency $t_i^*$ that minimizes the total cost per running period. We assume a usage-based maintenance cost similar to Faccio et al. [2014]. A machine $i$’s cost per running period given PM frequency consists of the combined costs of PM, overhauls and failures:

$$c_i(t_i) = c_t t_i + c_o o_i + c_f f_i.$$  

Here, we assume that the individual costs of preventive maintenance, overhauls and failures ($c_t, c_o, c_f \in \mathbb{R}^+$) are deterministic and known.

To assist the full service-provider’s decision-making, a data set is available with information on $n$ past contracts $D = \{(x_i, t_i, o_i, f_i)\}_{i=1}^n$. For each of the past contracts, only one potential outcome was observed for $O$ and $F$: $o_i(t)$ and $f_i(t)$. The other, counterfactual outcomes are never observed. This is known as the fundamental problem of causal inference [Holland, 1986]. The challenge in causal inference is to predict, for a new contract, all potential outcomes by learning from this historical data.

Because past decisions regarding the PM frequency were made according to an unknown existing policy, there is selection bias in the data. This means that contracts that were likely to receive relatively little PM are different from machines that were likely to receive relatively much PM. For example, the service provider might have known from experience that a certain type of machine would be likely to fail often when not receiving frequent PM and, because of this, prescribed more maintenance to those machines in the past. Therefore, learning a predictive model for estimating potential outcomes from observational data needs to adjust for selection bias in this data to obtain unbiased estimates.

4 Methodology

Our methodology consists of a predict-then-optimize framework, see Figure 2 for a high-level overview. To estimate each contract’s cost for a certain PM frequency $c_i(t_i)$, each machine’s potential outcomes need to be estimated, i.e., its number of overhauls $o_i(t)$ and failures $f_i(t)$ for a PM frequency $t_i$, given its characteristics $x_i$. Therefore, the first step is to learn a machine learning model for estimating potential outcomes from historical, observational data on similar full-service contracts $D$. In a second phase, these estimated outcomes can be used to optimize the PM frequency and resulting total cost.

The rest of this section is organized as follows. First, estimating potential outcomes from observational data requires two standard assumptions. These are put forward in Section 4.1. Second, we estimate the potential outcomes by learning a predictive model from observational data. For this, we use a state-of-the-art methodology called SCIGAN [Bica et al., 2020], which is described in Section 4.2. Third, in Section 4.3 these predictions are used to assign each machine’s optimal PM frequency that minimizes the total estimated cost.

4.1 Assumptions

The challenge in estimating potential outcomes from observational data is dealing with selection bias. Learning unbiased estimates of the potential outcomes from observational data requires making three standard assumptions: consistency, overlap and unconfoundedness [Imbens, 2000; Bica et al., 2020]. Given these assumptions, adjusting for machine characteristics $x_i$ allows to account for selection bias in observational data and obtain unbiased estimates. The first assumption is consistency, i.e., a machine’s potential outcome given observed treatment $t$ is the observed outcome.

**Assumption 4.1. Consistency.** $Y = Y(t)$ for all $t \in T$.

The second, overlap or positivity, ensures that each possible contract $x_i$ has a non-zero probability of receiving each frequency of PM interventions $t_i$. 

4
| Feature         | Value |
|-----------------|-------|
| Machine type    | 2     |
| Age             | 10.2  |
| Running hours   | 2,000 |
| Contract type   | 1     |

Figure 2: Methodology overview. We present a high-level overview of our methodology. Machine characteristics $x_i$ are used to predict the potential outcomes in terms of overhauls $o_i(t)$ and failures $f_i(t)$. Based on these estimates, the total cost for different levels of maintenance can then be estimated. Finally, the PM frequency is chosen to minimize the total expected cost.

Assumption 4.2. Overlap. For all $x \in \mathcal{X}$ with $p(x > 0)$ and $t \in \mathcal{T}$: $0 < p(t|x) < 1$.

The third, unconfoundedness or no hidden confounders, ensures that there are no unobserved variables influencing both the treatment assignment $T$ and a potential outcome $O(t)$ or $F(t)$.

Assumption 4.3. Unconfoundedness. Potential outcomes $O(t)$ and $F(t)$ are independent of the PM frequency $T$ conditional on machine characteristics $X$: $\{O(t), F(t) \mid t \in \mathcal{T}\} \perp \perp T \mid X$.

4.2 Predicting preventive maintenance effects

First, we need to predict each machine’s potential outcomes $o_i(t)$ and $f_i(t)$ given a PM frequency $t_i$ based on characteristics $x_i$. Therefore, we aim to find models $g_o : \mathcal{X} \times \mathcal{T} \rightarrow \mathcal{O}$ and $g_f : \mathcal{X} \times \mathcal{T} \rightarrow \mathcal{F}$ defined by parameters $\theta_o, \theta_f \in \Theta$ and obtain unbiased estimates of the potential outcomes $g_o(t, x) = \mathbb{E}[O(t) \mid X = x]$ and $g_f(t, x) = \mathbb{E}[F(t) \mid X = x]$.

In this work, $g_o$ and $g_f$ are learned using SCIGAN, a recently proposed machine learning approach for predicting potential outcomes given a continuously-valued treatments [Bica et al., 2020]. SCIGAN achieved state-of-the-art performance across a variety of settings. $g$ is learned in two steps. First, a generative adversarial network (GAN) is trained to model the distribution of the potential outcomes: the generator is trained to generate counterfactual contracts that cannot be distinguished from factual, observed contracts by the discriminator. In a second phase, the GAN is used to augment the observed training data with generated counterfactual samples. This way, the augmented data set contains all potential outcomes, including both the factual outcomes and the generated, counterfactual outcomes. Because of this, selection bias is no longer a problem and, using this augmented data set, a predictive model $g_o$ can be trained to predict the potential outcomes in a supervised manner. For this, we use a neural network. More specifically, we use a multilayer perceptron (MLP).

4.3 Optimizing the maintenance cost

The optimal PM frequency is a trade-off between costs resulting from planned PM on the one hand and costs resulting from overhauls and failures on the other hand. However, using the potential outcomes $o_i(t_i)$ and $f_i(t_i)$, it can be seen that the overhauls and failures can be written as functions of the PM frequency $t_i$. Therefore, the predicted potential outcomes can be used to directly estimate the costs incurred at different PM frequencies. This is achieved by rewriting all terms in Equation (1) (PM, overhauls and failures) as a function of the PM frequency $t_i$:

$$
c_i(t_i) = c_t t_i + c_o o_i(t_i) + c_f f_i(t_i).
$$

Each machine’s optimal PM frequency $t_i^*$ is found as the level that minimizes the expected cost: $t_i^* = \arg \min c_i(t)$. To account for heterogeneity in the contracts, this optimal PM frequency is optimized for each specific machine.

5 Results

We validate our methodology empirically using real-world data on full-service maintenance contracts. The goal is to decide on the optimal PM frequency, prior to the contract start, to minimize the total cost resulting from preventive maintenance, overhauls and failures.
| Variable                                         | Domain                          |
|-------------------------------------------------|---------------------------------|
| **Machine information**                         |                                 |
| Type                                            | \{1, \ldots, 7\}               |
| Age at contract start                          | [0, 39]                         |
| Running hours at contract start                 | [2500, 110000]                  |
| Running hours during contract                   | [0, 186000]                     |
| Average running hours per year                  | [300, 8500]                     |

| **Contract information**                         |                                |
| Type                                            | \{1, 2\}                       |
| Duration (days)                                 | [180, 5850]                     |

| **Preventive maintenance per running period**    |                                 |
| PM frequency                                    | [0, 20]                         |

| **Outcomes per running period**                  |                                 |
| Number of overhauls                             | [0, 128]                        |
| Number of failures                              | [0, 185]                        |

| **Average costs (in €)**                         |                                 |
| Preventive maintenance                          | 73                              |
| Overhaul                                        | 207                             |
| Failure                                         | 104                             |

Table 1: **Data overview.** Overview of the available contract information on machine and contract characteristics, preventive maintenance interventions, overhauls, and failures.

5.1 Data

Our data set contains more than 4,000 full-service maintenance contracts. For each contract \(i\), we have information \(x_i\) on the machine, the contract itself, and maintenance-related events (see Table 1). Events are presented per running period, which is a set number of running hours. For reasons of confidentiality, the exact number of running hours per period is not presented. Costs are averaged over all events and re-scaled for reasons of confidentiality.

The data is preprocessed as follows. Categorical variables are encoded with dummies and \(x_i\) is standardized. The PM frequency, overhauls and failures that occurred throughout the contract are converted to the number of events per running period. Even though a contract’s exact number of running hours is not known in advance, an estimate is typically available.

5.2 Semi-synthetic setup

A good estimator should accurately predict both the observed outcome, the number of failures that did occur at maintenance frequency \(t_i\), as well as the unobserved outcomes, the number of failures if the machine had received less or more maintenance. In practice however, not all potential outcomes are observed, which makes evaluation of causal models hard. Because of this, we rely on semi-synthetic data to evaluate our model. This approach is commonly used in both causal inference [see e.g., Berrevoets et al., 2020] and maintenance [e.g., Deprez et al., 2021].

Potential outcomes \(o_i(t)\) and \(f_i(t)\) are generated based on the observed characteristics \(x_i\). For the overhauls, we have:

\[
o_i(t) = 7 \sigma \left( v_o^T x_i - \frac{1}{10} \sigma (w_o^T x_i) t + \epsilon_o \right)
\]

where \(v_o, w_o \sim \mathcal{U}((0, 1)^{d \times 1})\) and \(\epsilon_o \sim \mathcal{N}(0, 1)\). The 7 rescales the average number of overhauls to roughly same number in the original data. For failures, we similarly have:

\[
f_i(t) = 9 \sigma \left( v_f^T x_i - \frac{1}{10} \sigma (w_f^T x_i) t + \epsilon_f \right)
\]

with \(v_f, w_f \sim \mathcal{U}((0, 1)^{d \times 1})\) and \(\epsilon_f \sim \mathcal{N}(0, 1)\).
Figure 3: **Semi-synthetic data.** We show the observed outcomes in the training and validation set with dots and potential outcomes in the test set with a line. The average potential outcomes and cost are shown with a bold line.

![Figure 3](image)

**Figure 4: Simulating selection bias.** (4a) We show the distributions that govern the PM frequency for different machines. As these distributions depend on the machine’s characteristics, certain machines will more frequently have more maintenance, resulting in selection bias. Moreover, higher values of \( \lambda \) imply more diversity in the distributions and, consequently, more selection bias. (4b) We show how the PM frequency is distributed among the different machines in reality and as a result of different values of \( \lambda \). Larger values of \( \lambda \) result in more selection bias with a value of 30 resulting in a PM frequency distribution close to the original.

Using the semi-synthetic setup, the test set contains the potential outcomes for all possible values of \( t_i \in T \) using these equations. Conversely, the training and validation sets include only one observed outcome for one observed \( t_i \). The training, validation and test sets respectively consist out of 50%, 25% and 25% of the data. Hyperparameter optimization is based on the mean squared error on the observed outcomes in the validation set. An illustration of a generated data set is shown in Figure 3.

On the other hand, we want to evaluate our policy for different levels of selection bias. For this, we control the level of selection bias in the semi-synthetic data using an approach similar to Bica et al. [2020]. Selection bias is simulated by assigning PM frequencies from a beta distribution as follows:

\[
t_i \sim 20 \text{Beta} \left( 1 + \frac{\lambda \delta_i}{10}, 1 + \lambda \delta_i \right)
\]

(5)

where \( \delta_i = \sigma(w_b x_i) \) with \( w_b \sim \mathcal{U}(0, 1)^{d \times 1} \). \( \delta_i \) ensure that treatment assignment is based on observed features \( x_i \). This way, \( \lambda \) controls the level of selection bias. \( \lambda = 0 \) results in Beta(1, 1) or the uniform distribution, which implies random maintenance assignment. Higher values of \( \lambda \) imply more selection bias with \( \lambda = 30 \) resulting in a maintenance distribution similar to the observed distribution. An illustration of the observed distribution and generated distributions for different values of \( \lambda \) is shown in Figure 4.

### 5.3 Evaluation

Evaluation is done using three different metrics. First, we evaluate the ability of the machine learning model to accurately predict a contract’s potential outcomes. This is measured using the mean integrated square error (MISE) [Silva, 2016; Schwab et al., 2020]:

\[
\text{MISE} = \frac{1}{n} \sum_{i=1}^{n} \int_{0}^{m} (y_i(t) - \hat{y}_i(t))^2 \, dt.
\]

(6)
Table 2: Methodologies overview. Our proposed, individual policy, SCIGAN–ITE, prescribes the PM frequency based on the individual treatment effect (ITE) estimated using SCIGAN. This proposed approach is analyzed using an ablation study and compared with two variants. The first, MLP–ITE, does not account for selection bias. The second, SCIGAN–ATE, is a general policy based on the average treatment effect (ATE) and is not individualized towards each individual machine.

| Methodology      | Selection bias? | Individualized? |
|------------------|-----------------|-----------------|
| SCIGAN–ITE       | ✓               | ✓               |
| MLP–ITE          | ×               | ✓               |
| SCIGAN–ATE       | ✓               | ×               |

Second, we want to evaluate the accuracy of the prescribed maintenance frequencies. To this end, we consider a variant of the policy error (PE) \[\text{Schwab et al., 2020}\] that compares the prescribed maintenance frequency with the ideal level:

\[
\text{PE} = \frac{1}{n} \sum_{i=1}^{n} \left( t_i^* - \hat{t}_i^* \right)^2 .
\] (7)

Third, we evaluate the prescribed maintenance frequency in terms of costs using the policy cost ratio (PCR) that compares the costs of the estimated optimal maintenance frequency with the ideal level:

\[
\text{PCR} = \frac{1}{n} \sum_{i=1}^{n} \frac{c_i(\hat{t}_i^*)}{c_i(t_i^*)}.
\] (8)

For all metrics, a lower value indicates better performance with 0 being the optimal value for MISE and PE and 1 for PCR.

Our proposed maintainancy policy uses SCIGAN to learn the individual treatment effects (ITE) and will be referred to as SCIGAN–ITE. We benchmark this policy to two other policies (see Table 2). First, a policy based on a neural network (MLP) that learns \(o_i\) and \(f_i\) given \(x_i\) and \(t_i\) in a completely supervised manner without adjusting for selection bias (MLP–ITE). This allows us to assess whether there is a benefit of adjusting for selection bias. Second, the average policy (SCIGAN–ATE) sets a single optimal \(t^*\) for all contracts based on the average (instead of the individual) maintenance effect. This allows to validate the benefit of an individualized policy tailored towards each specific machine.

5.4 Empirical results

In this section, we present the results of the semi-synthetic experiments based on more than 4,000 maintenance contracts, as put forward in Sections 5.1 to 5.3. The goal is to answer two research questions. First, does an individualized approach outperform a general approach? Second, does a causal, prescriptive approach outperform a supervised, predictive approach? We aim to answer these for the observed maintenance frequency (Section 5.4.1) and assess the different policies’ sensitivity to varying levels of selection bias (Section 5.4.2).

5.4.1 Results for the observed PM frequencies

We present the results for the different methodologies given the maintenance frequency \(t_i^*\) that was observed in practice in Table 3 and Figure 5. For both failures and overhauls, SCIGAN more accurately predicts the potential outcomes in terms of MISE compared to MLP, the supervised approach. Moreover, the individualized, prescriptive approach (SCIGAN–ITE) most accurately prescribes the optimal PM frequency compared to the supervised (MLP–ITE) and non-individualized approach in terms of policy error. Finally, SCIGAN–ITE also results in lower costs compared to both MLP–ITE and SCIGAN–ATE. The improved performance of SCIGAN–ITE compared to MLP–ITE illustrates the importance of adjusting for selection bias when learning from observational data. Moreover, the relatively worse performance of the average approach, SCIGAN–ATE, indicates the benefit of an individualized, machine-dependent policy for imperfect maintenance that takes into account machine characteristics.

5.4.2 Results for different levels of selection bias

We compare performance for the SCIGAN–ITE and MLP–ITE for different levels of selection bias in terms of \(\lambda\) (see Equation 5). SCIGAN achieves good predictive performance in terms of MISE for the entire range of operating
### Table 3: Empirical evaluation.
We compare performance for the different policies over five runs. We evaluate each model’s ability to predict the potential outcomes $o_i(t)$ and $f_i(t)$ (MISE), as well as each policy’s ability to accurately prescribe the maintenance frequency (PE) and minimize costs (PCR). For all metrics, a lower value is better.

|        | MISE |         | PE   |         |
|--------|------|---------|------|---------|
| Overhails |     | Failures |      |         |
| SCIGAN | 7.71 ± 0.60 | 14.16 ± 1.68 | SCIGAN–ITE | 2.40 ± 0.46 | 1.07 ± 0.01 |
| MLP    | 10.25 ± 1.33 | 18.27 ± 3.65 | MLP–ITE       | 4.30 ± 1.25 | 1.11 ± 0.02 |
| SCIGAN–ATE | 8.77 ± 1.07 | 1.24 ± 0.04    |

Figure 5: Evaluating the policies’ decisions. We compare the accuracies and costs of each policy’s prescribed decisions in terms of the difference between the prescribed and ideal maintenance level (left), as well as the policy cost ratio (right). Results are shown for one representative iteration.

Figure 6: Results for varying levels of selection bias. We show results for different levels of selection bias in terms of $\lambda$ (Equation 5). Although SCIGAN–ITE performs similar to a MLP–ITE for lower values of $\lambda$, it has better performance for stronger levels of bias in terms of MISE, PE, and PCR.

### 6 Conclusion

This work proposes a novel prescriptive maintenance policy that accounts for imperfect maintenance effects by learning a machine-dependent maintenance effect conditional on the machine’s characteristics from observational data. This is achieved by relying on state-of-the-art machine learning methodologies for causal inference. The benefit of our approach is that, unlike existing approaches, our methodology does not need strong assumptions regarding the maintenance effect, but is instead able to learn from observational data using flexible machine learning models. We validate our approach with semi-synthetic experiments using real-life data on more than 4,000 full-service maintenance contracts. We find that our proposed approach outperformed both a supervised approach and non-individualized approach in terms of both accuracy and cost of the prescribed preventive maintenance schedules. Moreover, our work highlights the importance of dealing with selection bias when learning from observational data. These findings show that our proposed approach offers a powerful and flexible policy for individualized maintenance.
Causal inference requires strong assumptions, as does the proposed methodology proposed in this work. The first, overlap, implies overlap between distributions of machine’s receiving different levels of maintenance. Overlap can be tested [Lei et al., 2021] and characterized [Oberst et al., 2020] from data. Moreover, recent work has looked at characterizing uncertainty in regions where overlap is violated [Nethery et al., 2019] [Jesson et al., 2020]. The second assumption, unconfoundedness, is untestable in practice [Imbens, 2000]. It can however be assessed by people with domain-knowledge that are in charge of making maintenance decisions. The relevant question is whether all relevant variables regarding past maintenance decisions are included in the data. If there are unobserved confounders, adequately adjusting for selection bias might not be possible, which would result in biased estimates of the potential outcomes. Recent work has suggested the possibility of sensitivity analyses to assess the effect of hidden confounders [D’Amour, 2019] [Franks et al., 2019]. Finally, quantifying ignorance regarding the potential outcomes due to possible violations of these assumptions has been proposed [Jesson et al., 2021].

In terms of future work, it would be valuable to consider different types of maintenance interventions in terms of intensities and costs. Similarly, it would be useful to include more complex costs in this framework, such as stochastic costs or costs that need to be predicted from maintenance or machine characteristics. Moreover, it would be interesting to incorporate more flexible timing of maintenance interventions in our methodology and consider sequences of different maintenance interventions. Sequences of treatments have also received attention in the literature on causal inference [e.g., Robins, 1999] [Hernán et al., 2001] [Bica et al., 2019]. Finally, it would be interesting to look at ways of more closely integrating the predictive model in the decision-making step, e.g., by using predict-and-optimize [Elmachtoub and Grigas, 2022] or cost-sensitive approaches [Vanderschueren et al., 2022].

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