Predicting throughput time

ESCF OPERATIONS PRACTICES:
INSIGHTS FROM SCIENCE

Predicting Throughput Time

European Supply Chain Forum

TU/e
EINDHOVEN UNIVERSITY OF TECHNOLOGY

DEPARTMENT OF INDUSTRIAL ENGINEERING & INNOVATION SCIENCES

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CONCISE SUMMARY OF THIS BEST PRACTICE

Availability of machines is very important in achieving operational excellence. In Aerospace, this need is especially high, to make sure that airplanes can keep up with flight plans and passengers, as well as cargo, can get to their destination in time. However, machines have to be maintained from time to time. Then, it helps to have a good estimate of when the maintenance activity will be ready. This enables the maintenance department to take appropriate measures, such as keeping the optimal number of spare parts in stock and optimally planning for down time of the machine. This operations practice describes how Fokker Services implemented a technique for predicting the throughput time of their maintenance activities on airplane engines. It shows that they managed to improve their throughput time prediction, which potentially means a higher customer satisfaction can be achieved. Moreover, the techniques that they use to predict the throughput time of a repair, can also be used to predict the expected time until the next repair or maintenance action is necessary. We expect that – with the advent of Internet of Things – such 'data-driven condition based maintenance', will not just be important for Fokker Services, but for all companies that maintain expensive machinery.

KEY TERMS

Throughput time prediction, Spare parts, Performance visualisation

RELEVANT FOR

Equipment vendors, seeking to optimize service levels.

Predicting Throughput Time

Aerospace is an important part of the world's infrastructure. With airplanes, it has become commercially viable to explore the world, to transport goods faster and to meet face to face when large distances have to be crossed. One of the players in this market is Fokker Services. Fokker Services mainly focuses on airplane parts, electrical systems and landing gear. The maintenance and repair of these parts is also done by Fokker Services.

When a part has to be repaired, a process is started where a part visits different statuses. From the intake and inspection of the part until shipping of the repaired part and sending the invoice, Fokker Services is involved in the process. Based on the inspection, a part is quoted for a repair or replacement price. At the Material step, the right materials are ordered and collected so that the Assembly can take place. After repairing and assembly, testing takes place to make sure the part is ready to be installed in the airplane again. In figure 1, this process is visually displayed. As can be seen, for certain customers, certain steps can be skipped and after the testing period, it can happen that a part has to return to Quoting or Material.

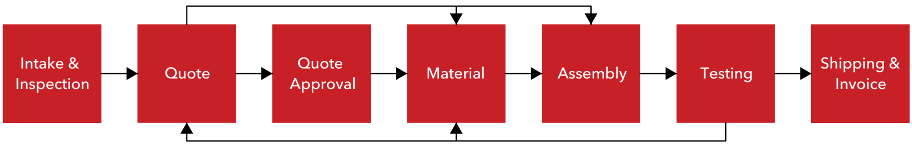

Figure 1: The repair process

For the customers of Fokker Services, it is of crucial importance that flight hours can be met and that, in case of a broken part, a repaired part is delivered as soon as possible. Besides the goal of minimizing the duration of the repair time, Fokker Services also wants to inform the customers of the lead time of the repair. When customers know the waiting time for repaired parts, they can optimize their planning for that. Therefore, to keep customers satisfied, it is important for Fokker Services to know exactly how long a repair will take. Besides keeping the customer satisfied, knowing the lead time more precise can also help Fokker Services with their own capacity planning.

Data analytics

Within Fokker Services, a data analytics team is active that has the ultimate goal of predicting which parts in an airplane will break when. Through predictive modeling and in cooperation with Eindhoven University of Technology, several projects are undertaken to achieve this goal. This best practice focuses on predicting the throughput time of repairing a part. At this moment, the estimation of the throughput time is mostly done by the managers in the repair shops. Unfortunately, for several reasons this estimation is often far from reality, as is described in the frame below.

PRESENT WAY OF ESTIMATING THE THROUGHPUT TIME

At this moment, the estimation of the throughput time is done by the shop manager. A faulty part enters the repair shop and after the inspection, materials need to be collected or ordered. This takes time and when the material has arrived, the planning department decides when the part will be repaired. The estimation of the durations of these tasks is based on experience and gut-feeling. Besides that, the planning department naturally allows for slack to ensure a larger probability of finishing tasks in time. This way of estimating throughput times results in rescheduling and a relatively large variety in the realized time.

By making the estimation data-driven, shop managers do not have to estimate the throughput time themselves anymore and a more precise estimation can be made. To develop such a method, Claessens (2016) improved on the throughput time prediction method of van Dongen, Crooy and van der Aalst (2008) by first predicting the likely path that a repair will take and subsequently predicting the throughput time for that path.

A TECHNIQUE FOR PREDICTING THROUGHPUT TIMES

Van Dongen, Crooy and van der Aalst (2008) use non-parametric regression to predict the remaining throughput time. This requires a large sample size because the data will supply the model structure as well as the model estimates. The predictions are made after each activity occurs, based on the information that is known at that time. For example, before the intake not much is known about an airplane engine that must be repaired, although the type and the age of the engine that must be repaired may already be a good indicator of the necessary repair time. After the intake, more is known, including whether any parts must be replaced that are difficult to obtain and how long the intake itself took. This information can be used in a new regression to improve the prediction of the remaining throughput time.

AN IMPROVED TECHNIQUE FOR PREDICTING THROUGHPUT TIMES

Where the approach of van Dongen, Crooy and van der Aalst (2008) takes the dataset as a whole, Claessens (2016) discovered that it is often possible to distinguish between different cases in a process, which behave differently with respect to their throughput time. For example, figure 2 shows a distribution of throughput times of patients in a particular ward in a hospital. It clearly shows that there are multiple distributions, which in this case depend on the diagnosis of the patient. If the throughput time of each patient would be predicted similarly, all patients would get an average prediction of about one-and-a-half years, while actually at least two groups can be distinguished, one with an average throughput time of only a few days and one with an average throughput time of around two years. First predicting the group that the patient will be in and then predicting the throughput time accordingly will improve the accuracy of the prediction for all patients.

In the hospital example it is easy to see that there are different groups of cases with different throughput time distributions and the group that the case is in can easily be derived from a known variable (in this case the diagnosis of the patient). Claessens (2016) shows that a similar approach can also be used in less obvious situations.

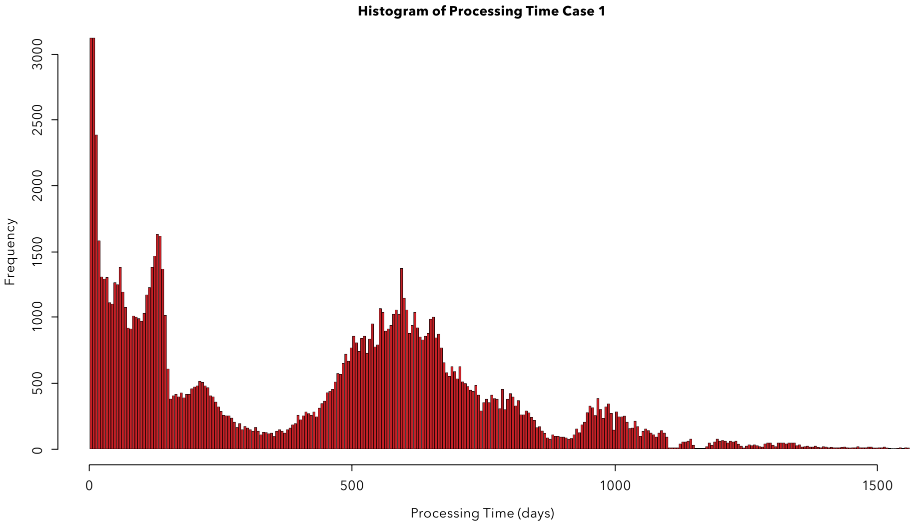

Figure 2: A distribution of processing times of patients

Figure 3 illustrates the general idea of the approach of Claessens (2016). The approach uses machine learning to create a two-stage prediction model. The first stage predicts the category that a new observation (e.g. a patient or an airplane engine) is likely to be in. For each category a regression model is learned and the second stage predicts the throughput time of the observation based on the regression model that belongs to the predicted category. This two-stage prediction model is trained in such a way that the overall throughput time prediction most accurately corresponds to the actual throughput time based on past observations.

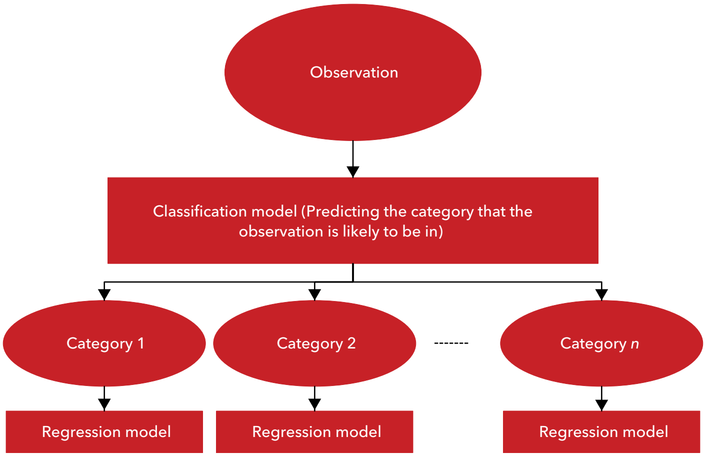

Figure 3: The approach of Claessens

Choosing the relevant data for this model is very important as it should keep the model simple but effective. Claessens makes a selection of the available data, dividing the data in general variables and variables that are specific for Fokker Services. When looking at the general variables, besides the age of the order (i.e. the time the order has already been in progress), which is always added as basic information, there are three categories of predictor variables. 'Attribute predictors' are attributes of the order itself, such as the type of the order and the priority of the order. 'Process predictors' are properties that describe how the order is moving through the process, such as the current activity that is being performed on the order and the previous activity. 'Operational predictors' are properties of the resources that are executing the order, such as the work in progress, the processing time and the utilization (the probability that a resource is busy).

The Fokker case

Where the idea of Claessens is applicable to many companies, his main goal was to develop his idea for Fokker Services. In some ways, the market of Fokker Services is very special. The goal of estimating throughput time in the best way possible and therefore, minimizing delays, is a challenging one in the airplane market. This is because of the lifespan of an aircraft relative to the speed of technological progress. So, when a part fails, it is relatively challenging to replace or repair the part

PRESENT PERFORMANCE

Now, Fokker Services bases the throughput time estimation on the Standard Turn Around Time, Standard TAT for short. If the Standard TAT is likely to be exceeded for any reason, a First Promise Date (FPD) is given. As mentioned before, the estimation of such a date is done by the shop managers, and therefore, unfortunately, not very precise. In table 1, the performance goal of the Standard TAT and FPD is given. This goal is defined by Fokker Services. The actual performance is also mentioned.

Name	Target performance ($P(X \leq x)$)	Actual performance ($P(X \leq x)$)
Standard TAT	80%	60%
FPD	95%	71%

Table 1: the actual and target performance

MODEL PERFORMANCE

The model of Claessens (2016) eventually provides some clear insights regarding the Standard TAT and the FPD.
First, in figure 4, the performance of the prediction of the Standard TAT is displayed. As mentioned, the legacy method on average predicts a throughput time of 13 days, which is correct only 60% of the time, while the goal is to reach a performance of 80%. Now, the new method gives two measures. The first one is a prediction at the same performance as the legacy method. This prediction is on average 15 days and, consequently, worse than the prediction made by the legacy method. The explanation for this difference is a lack of input attributes at this point. The process information is unknown for example, and therefore the model does not perform satisfactorily yet, while shop managers can estimate such attributes based on experience. However, the benefit of the new method is that a prediction at the desired level of performance (80%) can also be made, which on average is 20 days.

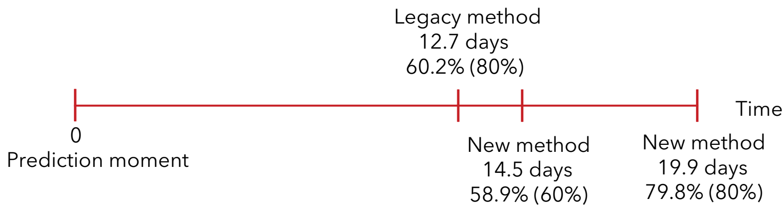

Figure 4: The performance of the prediction of the standard TAT

Because the model updates itself at every status, the quality increases in a later stage and can therefore easily be used to predict the FPD as well. Figure 5 shows the performance of the prediction of the FPD. As the FPD is predicted at the moment at which the Standard TAT is not met, the moment at which the prediction is made varies.

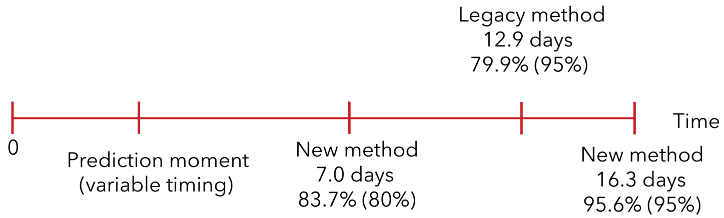

Figure 5: The performance of the prediction of the FPD

Conclusions can now easily be drawn. The legacy method gives an FPD of 13 days on average, which is correct 80% of the time. With the new method, the prediction at the same level of performance is greatly improved and only 7 days on average. When the goal of the 95% performance for the FPD is reached, the average number of days goes up to 16. This is a few days longer than the legacy method, but does secure the desired 95% performance.

IMPLICATIONS

When looking at the results, the model outperforms the current method in almost all cases. The problem with the current predictions, that for the standard TAT as well as for the FPD the service levels are not met, can be solved by the new model. The real power of the new method lies in predicting the throughput time of running cases, which it can do substantially better than the legacy model. Another benefit of the new model is that it can keep the prediction up-to-date and at the desired level of performance at all times without requiring any human intervention.

BENEFITS

Two major benefits of the new method for predicting throughput times can be identified. The first one is performance related. Since the prediction can be done multiple times and does not incur extra costs, the predictions become more precise over time and are quickly more precise than the legacy method. Furthermore, the shop managers will not have to spend time anymore on making the predictions. Instead, they can use their time to check the orders that have an unusual predicted throughput time. Maybe, a vendor does not deliver spares on time or there is a problem in a specific stadium of the repair process. The shop manager now has the time to identify and sort out these problems.

MODEL EXTENSIONS

At Fokker Services, the model of Claessens (2016) has contributed to the actions that are undertaken to create a better service for the customers. At this moment, Fokker Services is implementing the model with two adjustments.

First, the new model calculates the net throughput time. This means that delays that are created by external parties are not taken into account. However, because of supply chain management thinking, Fokker Services decided to include delays that are caused by the vendors of the materials in the model. This way, the total throughput time can be calculated as well. As Fokker Services has little influence on the time that the vendors need, this might not seem very logical. However, without an estimate of the delays that are caused by the vendors, the net throughput time that is communicated towards the client can never be precise. Also, by including vendor delays, the data can tell how the vendors perform and in the future, decisions on the choice of the vendor can be made based on this information.

A second adjustment is the degree of visualisation. The Data analytics team noticed that the shop managers would not just accept the statement that the predicted throughput time of an order changed, they want to know why. Not just out of curiosity, but also to have the chance to find out if something could be changed about the problem that caused the delay. Therefore, visualisation also became an important part of the project. For example, for every status that the system has, an estimate is provided of the time that an arbitrary part stays in that status.

A future vision

Where the idea of Claessens (2016) predicts the throughput time of a part that is already under maintenance, Fokker Services also wants to know when parts break. Similar techniques to the ones described above can be used to do data-driven predictions on when parts are likely to break or need maintenance.

Fokker Services has a strong head start with making data-driven predictions of that kind, because as can be seen in figure 1 (on the first page), the process of repairing also entails a testing phase.
In the testing phase, test data is generated on 309 data points. With these 309 data points, Fokker Services should have ample data to determine the expected number of flight hours of the tested part.

The next step would be to retrieve information on these data points while the part is actually in the airplane and in use. This way, based on the measured data points, a prediction could be made and continuously updated of the number of flight hours before the part should be maintained again. For Fokker Services as well as for the airplane industry, this is an interesting development, because it enables better planning of maintenance activities and increases safety.

We expect that – with the advent of Internet of Things – such 'data-driven condition based maintenance', will not just be important for Fokker Services, but for all companies that maintain expensive machinery.

References

- Claessens, T.R. (2016), “Predicting Throughput Time”, Master Thesis, Eindhoven University of Technology, The Netherlands.
- van Dongen, B.F., Crooy, R.A., & van der Aalst, W.M.P. (2008). Cycle time prediction: When will this case finally be finished? In *OTM Confederated International Conferences “On the Move to Meaningful Internet Systems”* (pp. 319-336). Springer, Berlin, Heidelberg.

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Editorial

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