

A Digital Twin Proof of Concept to Support Machine Prognostics with Low Availability of Run-To-Failure Data

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Abstract: The present research illustrates a Digital Twin Proof of Concept to support machine prognostics with Low Availability of Run-to-Failure Data. Developed in the scope of the Industry 4.0 Lab of the Manufacturing Group of the School of Management of Politecnico di Milano, the Digital Twin is capable to run in parallel to the drilling machine operations and, as such, it enables to predict the evolution of the most critical failure mode, that is the imbalance in the drilling axis. The real-time monitoring of the drilling machine is realized with a low-cost and retrofit solution, which provides the installation of a Raspberry-Pi accelerometer, able to enhance the extant automation. Relying on a joint use of real-time monitoring and simulation, the Digital Twin implements a random coefficient statistical method through the so-called Exponential Degradation Model, eventually demonstrating to increase the prediction precision as monitoring data arrives. The Digital Twin Proof of Concept is described according to the entire process from data acquisition to Remaining Useful Life prediction, following the MIMOSA OSA-CBM standards.

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Keywords: Digital Twin, Fault diagnosis and control, Condition-Based Maintenance, Remaining Useful Life prediction, Random coefficient statistical method, Decision support.

1. INTRODUCTION

In recent years, traditional manufacturing industries are experiencing a tremendous shift motivated by the disruption of digital technologies within their factories. This new trend, known as Industry 4.0, relies on the adoption of technologies such as the Internet of Things (IoT), Big Data, Cloud computing and Artificial Intelligence (AI) to create a smart factory (De Carolis et al. (2017)). Within this trend, attention is also shifting to the creation of synergies between the physical world and the cyber one by means of Cyber-Physical Systems (CPSs). They ease the fast interconnection across the organization, from the field to the top management, taking decentralized decisions based on the data acquired and analyzed (Jazdi (2014), Lee et al. (2015)). In such a technological landscape, a "tool" that paves the way in the CPS integration is the Digital Twin (DT), (Qi and Tao (2018)). The concept of DT first started in the aerospace industry and it was initially defined as the digital's counterpart of a physical system. Nowadays, the concept of DT is spreading fast in manufacturing. Moving in this direction, the DT took the role of monitoring the overall lifecycle of products (Abramovici et al. (2016)) or production systems (Rosen et al. (2015)). It is indeed defined as "an integrated multi-physics, multi-scale, probabilistic simulation of a complex product that uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin" (Grieves (2014)). The DT may also act as the digital counterpart to optimize the production system as a system of assets (machineries, production equipment).

In this case, it facilitates the decision-making at different asset lifecycle stages (Beginning of Life (BOL), Middle of Life (MOL) and End of Life (EOL)) and control levels (Strategic, Tactical and Operational levels) (Macchi et al. (2018)). In particular, it may support the production system condition monitoring and foster diagnostics and prognostics (Qi and Tao (2018)).

Based on the necessity to provide further insight into this smart maintenance vision of the DT, the work aims to investigate how the DT can underpin the development of Condition-Based Maintenance (CBM), with predictive capabilities, in case of low availability of Run-To-Failure (RTF) data of the asset under consideration.

The rest of the work is organized as follows: section 2 presents the background on some basics concepts from literature. Section 3 sets the research objectives and the research methodology. Section 4 develops the proof of concept DT solution within a laboratory environment. Finally, Section 5 summarizes the conclusions of the work and proposes possible forthcoming research lines.

2. BACKGROUND

The DT processes data obtained from sensors embedded in the asset and combines this information with historical, current environmental data and operating parameters, in order to determine, through simulation and data analytics, the asset health and performance under certain circumstances, limiting unreliability situations. Therefore, CBM may leverage on DT to control the production system in real-time and to improve decision-making process by pre-

dicting, through simulation and data analytics, its future performance (Macchi et al. (2018)).

2.1 Condition Based Maintenance

CBM is a program that recommends maintenance decisions based on the information collected through condition monitoring. The main idea is to utilize the asset degradation information, extracted and identified from on-line sensing techniques, to reduce and eliminate unscheduled downtimes and to optimize asset utilization (Jardine et al. (2006)). Diagnostics and prognostics are two important aspects activities in a CBM program. Diagnostics deals with fault isolation and identification, before or after the failure it has occurred. Prognostics is focused on the failure mode evolution and deals with fault prediction, before it occurs (Djurđjanovic et al. (2003), Lee et al. (2006), Guillén et al. (2016)). A CBM program can be used both to diagnose and to prognosticate the asset behavior and the process is typically composed by the following steps: i) Data Acquisition, ii) Data Manipulation, iii) State Detection, iv) Health Assessment, v) Prognostic Assessment, vi) Advisory Generation (ISO-13374-1:2003 (2003), Bengtsson (2003), ISO-13374-4:2015 (2015)).

2.2 RUL Prediction Models

Prognostics plays an important role in CBM. This part aims at forecasting a trend in the condition signals in order to derive the time in which the fault is likely to occur, i.e. the Remaining Useful Life (RUL) of the asset. In literature, there are various approaches that can be followed to derive the asset RUL (Lei et al. (2018)).

Physics model approaches model the degradation processes of machines by building mathematical models on the basis of the failure mechanisms or the first principle of damage (Cubillo et al. (2016)). Although they might be useful to model damage for simple mechanisms (e.g.: crack propagation in a steel sheet), they result to be too complicated for complex systems, since to achieve high accuracy in RUL prediction, it is necessary a complete understanding of the different failure mechanisms.

Statistical models fit available historical values into random coefficient models or stochastic process models in order to predict RUL. Uncertainties caused by the variability of these historical data (machine to machine variations, variations within measurements, etc.) are introduced into the model by means of random variances, as described by Lei et al. (2016). This makes statistical-based models result effective for describing the uncertainty linked to the RUL prediction.

Artificial Intelligence approaches (AI) aim at learning the degradation pattern of the machine relying just in the observations. They are a good choice for RUL prediction of complex mechanical systems that present a degradation pattern difficult to model. Thanks to the advances in Cloud Computing and Big Data, these models are gaining more popularity in the research world, (Lei et al. (2018)).

3. RESEARCH DESIGN

3.1 Research Objectives

The paper aims at developing a DT for maintenance purpose. Compared to conventional prognostic techniques, DT enables to integrate, into a unique virtual model of its physical counterpart (in this case the drilling machine), both real-time monitoring and prediction, relying on historical and real-time data. Real-time monitoring enables to collect and store data gathered from the physical system, and subsequently to make data analytics; simulation can be then adopted to speed up the prediction of the degradation process in order to investigate future behaviour. More specifically, the real-time data are collected to create a sufficient sample to make a first pattern recognition through data analytics; subsequently, simulation is adopted to achieve the prediction of the degradation process by means of a perturbation of the initial pattern. Afterwards, connection with sensors to achieve late synchronizations with the field allows to assess simulation results and to refine the prediction by adjusting it to the current pattern recognized in the degradation of the physical system. This goal is defined for many reasons. A major problem is typically due to the fact that most of the available literature on DT for maintenance takes for granted that historical RTF data of the asset under investigation are accessible. The truth is that these historical records are not always accessible in industrial environments. While it is true that Industry 4.0 is something that large companies are investing on, it is evident that many other small firms barely manage asset maintenance data (De Carolis et al. (2017)); therefore, they typically have no historical records of RTF data usable to develop a maintenance DT for their assets. Furthermore, the high reliability needed for some kind of assets (as also machine tools) leads to the fact that such failures are hardly observed. The proposed use of data analytics and simulation in the frame of the DT, based on a progressive adjustment of historical information with newly gathered data from field, aims to monitor and simulate the degradation process aligning to what is actually occurring in field, without strictly requiring a record of RTF data at the beginning.

Considering this challenge, the objective of this paper is the development of a Proof of Concept maintenance DT solution for a system/asset with low availability of RTF data, describing the entire process from data acquisition to RUL prediction, so that it can be easily extrapolated to systems/assets of different nature.

3.2 Research Methodology

To reach this objective, there is a need for an environment that eases the access to machinery. This machinery has to be retrofitted installing a proper set of sensors, to obtain the necessary data that allows conducting the required experiments and to finally construct the maintenance DT. The Industry 4.0 Lab (I4.0Lab) of the Manufacturing Group of the School of Management in Politecnico di Milano fulfils all these requirements (Fumagalli et al. (2016)).

Furthermore, the following requirements are made to guide the development of the maintenance DT:

- The DT has to rely on some previous available knowledge. According to the FMECA analysis carried out on the I4.0 Lab asset, it will monitor and control the drilling station, which has been resulted as the most critical machine in terms of risk (frequency and failure severity). Furthermore, since the drilling has several failure modes, the maintenance DT will focus on the most critical one: the possible imbalance in the drilling axis.
- The DT has to make use of the standardized process of MIMOSA OSA-CBM that follows the ISO-13374 standard, going through all its steps (ISO-13374-1:2003 (2003) and ISO-13374-4:2015 (2015)). In such manner, the description of how to build the maintenance DT will be as standard as possible and it can be applied to assets of different nature as well.
- The DT has to operate as a "watchdog agent" close to the process (the term "watchdog agent" is inspired by Djurdjanovic et al. (2003)). As such, the DT adds value to the process control by means of a CBM tool operated as edge computing, in order to react with a velocity of response suited for time-critical situations.
- The DT has to mirror the status of the machine, collecting and synchronizing data coming from different sources, such as the drilling PLC and sensors, including those ones installed as a retrofitting solution. Even not performing any kind of simulation based on physics model of the real system, the DT should be able to speed up the damage accumulation through the simulation of the degradation signal resulting from field.

For what concern the prognostic technique, the work relies on the development of an Exponential Degradation Model (EDM) (Gebrael et al. (2005)). The EDM is a parametrized model of the degradation signal related to the failure of interest. Thus, it can be applied to a population of machines: through its parametrization, it is indeed scalable to more machines. In particular, stochastic parameters, that follow some distributional form, are introduced to model the individual degradation characteristics, such as the rate of degradation. The stochastic estimation is obtained through a Bayesian updating capable to combine two sources of information: (i) the distribution of the parameters across the machines population; (ii) the real-time sensor information collected through condition monitoring, describing the degradation signal form of the individual machine. Thanks to these characteristics, the EDM results to be a good candidate to model machine degradation when low RTF data are available. On one side, it relies on looking at similar behaviour of similar machines (i.e. the population) to model the degradation; in this way, previous available results, also taken from literature, can be used to conjecture the individual degradation form. On the other side, it needs real-time sensor information to update the model, adjusting what known from historical data (and benchmarks in the population) to the current state of the degradation process of each individual machine.

4. DEVELOPMENT OF THE MAINTENANCE DT PROOF OF CONCEPT

This section describes the whole design process of building the maintenance DT using MATLAB/Simulink. Following

the main objectives set before, the explanation goes step by step through the different modules corresponding to the OSA-CBM standard: from data acquisition to advisory generation (Fig. 1).

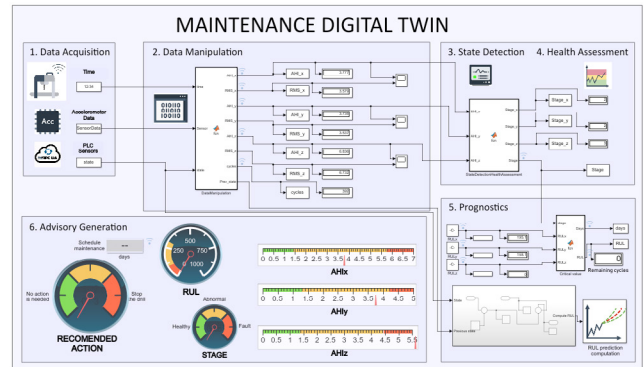


Fig. 1. The Maintenance DT. Overall flow of the system.

4.1 Data acquisition

The PLC of the drilling machine provides signals referred to the operational state of the machine. The DT obtains these signals using the OPC-UA protocol and the MATLAB-S function. These signals are then processed to derive the operational state of the station, that could be classified as *idle*, *working*, *error*, *emergency* and *energy-saving*.

The operational state of the machine is not enough to determine the real status of the asset. Since the drill is a rotary element, based on literature result, the monitoring of the vibration signal has been considered (Heng et al. (2009)). A low-cost and retrofit solution is provided, installing a Raspberry-Pi accelerometer to the drill axis as shown in the middle of Fig. 2. This device collects data with a frequency of sampling of 200 Hz. Considering that, on average, every cycle last 11 seconds, for every cycle 2200 values of acceleration are sent to a predefined server, which in turn stores the data in a Mongo Database. This database is accessible within the MATLAB environment by running a specific function that collects all the information of a certain sample: accelerometer's values in the three directions x , y and z , date and timestamp.

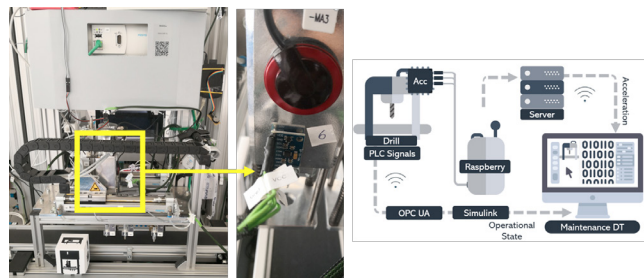


Fig. 2. Data acquisition system.

4.2 Data manipulation

The DT processes the gathered data to obtain meaningful information from it. When the PLC signals indicate that the drill is in working state, the DT starts to gather the

acceleration from the database and, once the operational state of the machine changes from *Working* to any other, the DT stops the collection. Once the acceleration data has been gathered, the Root Mean Square (*RMS*) of the acceleration signal is computed for each component, as defined by equation (1). The *RMS* gives an idea of the amount of energy dissipated during the working process by means of vibrations. In case damage occurs in the drill axis, due to an imbalance, the vibration level will increase. As this damage progresses, the energy dissipated by means of vibrations will increase too and this will directly impact the *RMS* value. Finally, the Asset Health Index (*AHI*) is computed as the maximum RMS_i , $i = x, y, z$ value. In Fig. 3, this value is illustrated by the blue line (envelope curve). It gives an idea of what is the maximum average level of energy dissipated by means of vibrations during each working cycle.

$$RMS_{acc_j} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}, \quad j = \{x, y, z\} \quad (1)$$

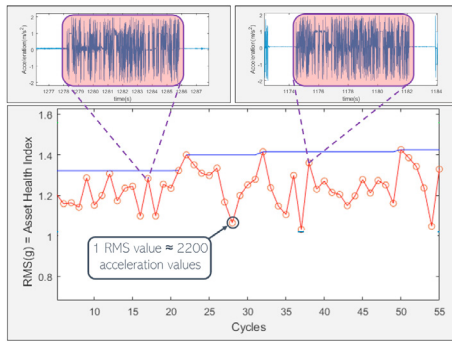


Fig. 3. Asset Health Index (*AHI*) computed as the maximum RMS_i value, $i = x, y, z$.

4.3 State Detection

Since there is no availability of historical data, it is necessary to determine what level of *RMS* indicates the healthy state of the machine. This task is achieved after launching a test production order of 100 workpieces in which the *RMS* of the three axes is measured. Then, these data are analyzed following a novelty detection approach, as described in Pimentel et al. (2014). To this end, a normality test on the sampled data is firstly needed. The results of the normality tests show that the *RMS* of the three axes follows a normal distribution:

$$RMS_i \sim N(\mu_i, \sigma_i) \quad \text{for } i = x, y, z$$

After completing these tests, the healthy state is properly modeled. This means that every new sample can be compared with the healthy class to see if it belongs to it. Assuming that all the samples obtained belonged to the healthy class, it is possible to model the confidence intervals that the *RMS* should not surpass when the machine is working in healthy state. Based on the literature regarding novelty detection, the confidence limit of the *RMS*, i.e. RMS^{Up} , is set to a distance of 3 times the standard deviation σ from the average value μ (Pimentel et al. (2014)). This procedure is the same for all the three axes.

$$RMS_i^{Up} = \mu_i + 3\sigma_i \quad \text{For } i = x, y, z$$

4.4 Health assessment

The fact that the *RMS* of a given cycle is above the previously established threshold does not directly imply that the machine is in a fault state. Indeed, the fault state could be related to a *RMS* value much higher than RMS^{Up} . What a $RMS > RMS^{Up}$ indicates for sure is that the system is behaving in an abnormal way, even if it is capable to perform the desired operation. For this reason, the degradation trend of the asset is divided into three states (see limits reported in Fig. 4):

- **Healthy state**, if $RMS < RMS^{Up}$. In this state, the system only monitors the acceleration signal without performing any kind of RUL estimation. In this way computational power is saved.
- **Abnormal state**, if $RMS > RMS^{Up}$ but the machine is still able to deliver its function ($RMS < RMS^{Fault}$). The DT starts predicting the RUL.
- **Fault state**, if $RMS \geq RMS^{Fault}$. In this state the machine cannot perform the operations it was designed for in the proper way.

The limit between healthy and abnormal states (RMS^{Up}) is established by checking normality in a well-sampled population. Conversely, the boundary of the fault state (RMS^{Fault}) cannot be directly obtained since there is no availability of RTF data. Anyhow, this threshold can be defined based on the knowledge of the process under analysis: even if the physics behind the failure mechanism is difficult to model, it is still possible to determine the limit of the fault state by comparing the machine with a reference one. In literature, this practice is widely extended (Chen et al. (2018)). In general, the level of this threshold may also reflect the company's risk aversion attitude. In this work the boundary of the fault state will be treated as a constant line and will rely on some similar results already present in literature (Lei et al. (2018)). After analysing the data set described in Nectoux et al. (2012), the beginning of the fault state is assumed to be equal to 4 times the value of RMS^{Up} .

4.5 Prognostic assessment

Regarding the prognostic side of the DT, following the main objective stated before, the availability of RTF data is taken as null. The vibration trend is considered similar to the one shown for the bearings analyzed in Nectoux et al. (2012), where the *RMS* follows an exponential trend. Due to these conditions, the choice of the RUL estimation method concluded in the selection of a random coefficient statistical method known as Exponential Degradation Model (EDM) (Gebrael et al. (2005)). The EDM (equation (2) and Table 1) enables the prediction of the future condition trend of systems in which no historical degradation records are available.

$$\widehat{HI}(t) = \widehat{RMS}(t) = \phi + \theta \cdot e^{(\beta t + \epsilon(t) - \frac{\sigma^2}{2})} \quad (2)$$

The maintenance DT has been programmed so that, after every working cycle, it automatically updates the coefficients of the EDM model. This enables to progressively adjust the model to the current degradation of the physical system. In this way, it is possible to obtain a real-time RUL prediction turning the DT into a "watchdog agent", that

Table 1. Margin settings

$\widehat{HI}(t)$	Health index estimation for time t , in this case $\widehat{RMS}(t)$.
ϕ	Intercept term considered as a constant.
θ	$\ln(\theta) \sim N(\mu_\theta, \sigma_\theta^2)$ - log-normal random variable.
β	Random variable, $\beta \sim N(\mu_\beta, \sigma_\beta^2)$.
$\epsilon(t)$	Noise term, $\epsilon(t) \sim N(\mu = 0, \sigma^2)$.

operates right next to the machine. Fig. 4 shows how, when the system enters the abnormal state, the trend \widehat{RMS} is plotted showing the message “Degradation Detect”. This graph is updated after the end of each cycle.

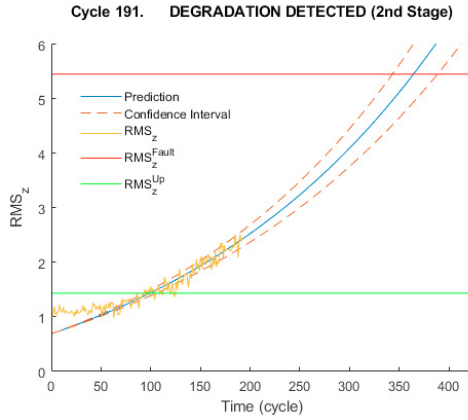


Fig. 4. RMS trend prediction.

As seen in Fig. 4, the DT also provides the confidence bounds of the prediction trend (orange dashed lines). When the DT spots the abnormality for the first time, this Confidence Interval (CI) is quite wide, however, as the EDM uses the data to update the coefficients, the CI get more narrow (Fig. 5).

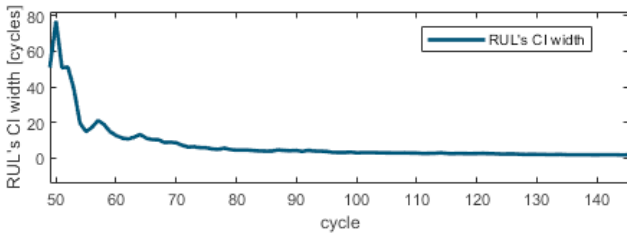


Fig. 5. Width evolution of the prediction trend CI.

Furthermore, the RUL estimation obtained is associated with a probability density function $f_{RUL}(t)$. By integrating the $f_{RUL}(t)$ it is possible to know the probability of failure at any time in the future.

$$\int_0^t f_{RUL}(t)dt = P_f(t)$$

4.6 Advisory generation

All the results previously described can be consulted thanks to the Advisory Generation module of the DT (bottom-left part of Fig. 1). Depending on the values of

the monitored parameters (RMS_i), three possibilities are given:

- **No maintenance is needed:** if all the monitored values are inside the healthy state bounds ($RMS_i < RMS_i^{Up}$)
- **Condition based maintenance action:** if any of the monitored parameters indicates that the drill is in abnormal behavior state ($RMS_i^{Up} < RMS_i < RMS_i^{Fault}$). Maintenance should be schedule in t^{days} , as it is indicated by the prognostics algorithm results.
- **Corrective Maintenance:** drill station should be stopped if any of the monitored parameters indicates that the drill is in fault state ($RMS_i^{Fault} < RMS_i$).

As mentioned before, the DT derives the probability of failure for every future cycle. Therefore, it is possible to check the moment of time in which the degradation will cause this P_f to go above a certain limit P_f^{max} . This moment of time gives an idea of when the maintenance action has to be carried out.

$$t^{cycles} = \left\{ t : \int_0^t f_{RUL}(t)dt = P_f^{max} = 1 - R^{min} \right\} \quad (3)$$

Where f_{RUL} is the probability density function of RUL, R^{min} is the minimum acceptable reliability of the system and t^{cycle} is the ideal moment to conduct the maintenance action. Since the time unit is cycles, which could be really big considering the long degradation pattern, it is converted to days (equation (4) and Table 2).

$$t^{days} = \frac{t^{cycles}}{\overline{UR} \cdot PC_{daily}} \quad (4)$$

Table 2. Margin settings

t^{days}	Number of days remaining until $R \leq R^{min}$ [days].
t^{cycles}	Number of cycles remaining until $R \leq R^{min}$ [cycles].
\overline{UR}	Average utilization rate of the drill [% utilization].
PC_{daily}	Daily production capacity of the drill [cycles/day].

For the case of the component under analysis, based on its criticality, R^{min} was set equal to 0.98.

5. DISCUSSION AND CONCLUSIONS

This paper develops a maintenance DT solution for a drilling machine that lacks of historical data, describing the entire process from data acquisition to RUL prediction, following the MIMOSA OSA-CBM standards. The machine is retrofitted through the installation of a low-cost accelerometer. The DT mirrors the status of the machine, collecting and synchronizing data coming from different sources, such as the drilling PLC and the accelerometer. It measures and analyzes the vibration signal to derive the health status of the machine and it is able to speed up the damage accumulation thanks to its simulation capabilities. It performs all these computations concurrently to machine, so this information gets updated progressively along time. As such, the DT adds value to the process control by means of a CBM tool operated as edge computing, in order to react with a velocity of response suited for time-critical situations. Furthermore, it uses this information to predict the future trend and to calculate the

RUL and, based on the maximum desired probability of failure, it also supports decision-making by providing the appropriate moment to perform the repair operation. For the RUL estimation, the maintenance DT implements a random coefficient statistical method through the so-called EDM. Thanks to this method, it is possible to apply the maintenance DT directly in assets in which no historical degradation records are available. The model is capable of providing a RUL prediction with some confidence bounds that get more precise as data arrives. The work paves the road for future researches in this field by bringing together the concepts of DT and CBM applied to machines. Some improvements could be first of all with respect to the data gathered. Indeed, it is possible to measure more signals and to derive an asset health indicator that reflects even better the drill status. Secondly, to implement the same concept in other machines of the laboratory line and build a maintenance DT for the whole assembly line. Last but not least, to integrate the CBM DT with scheduling optimization algorithm, to enhance in this way the decisional power of the tool.

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