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Combining First Principles and Machine Learning for optimal maintenance of electrical assets

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Résumé – Les acteurs industriels sont confrontés à un besoin accru de réduire le risque d’incidents imprévus et d’optimiser leur maintenance. Ces besoins appellent à une réponse double à la fois sur les détections court-terme et la surveillance de vieillissement long terme. Chez Schneider Electric nous répondons à ces deux problématiques en combinant l’apprentissage artificiel et les modèles physiques et statistiques, afin de fournir des services avancés pour les équipements de distribution électrique. L’apprentissage artificiel est utilisé pour modéliser les paramètres clés des équipements électriques en fonctionnement normal, afin de prédire le comportement normal attendu en toute circonstance. Un système de surveillance peut se servir de cette référence pour détecter des déviations statistiquement significatives, révélant un défaut potentiel. En ce qui concerne les modèles de vieillissement, ils sont basés sur des modèles physiques et statistiques, dans la continuité de l’état de l’art du Prognostic Health Management. Il s’agit ici de décomposer les équipements électriques en sous-systèmes, et d’identifier pour chacun d’eux l’ensemble des modes de dégradation concurrents et leurs facteurs d’influence (environnement et usage). En combinant cela avec les cinétiques appropriées nous pouvons estimer la fin de vie. Ces deux approches, court-terme et long-terme, sont combinées sur le terrain pour fournir des services de maintenance prédictive. Ils s’inscrivent dans une initiative plus large visant à partager des algorithmes avec l’écosystème de partenaires de Schneider Electric [SE, 2019-1].

Abstract – Industrial end users face an increasing need to reduce the risk of unexpected failures and optimize their maintenance. This calls for both short-term analysis and long-term ageing anticipation. At Schneider Electric we tackle those two issues using both Machine Learning and First Principles models, to provide advanced services for electrical distribution assets. Machine Learning algorithms are used to model key parameters of electrical assets in normal operation. They predict the expected normal behavior, which serves as a reference. The monitoring system can therefore detect statistically significant deviations from this reference, indicating potential failures. Concerning ageing models, they are based on First Principles, similar to Prognostic Health Management techniques. It consists in breaking down electrical assets into sub-assemblies, identifying for each of them all possible competing degradation modes and their influencing factors (environment and usage). Combining this with relevant kinetics laws we can estimate the expected end of life. These two approaches, short-term and long-term, are combined in operation to provide predictive maintenance services. They belong to a broader initiative aimed at sharing analytics beyond the Schneider Electric scope [SE, 2019a].

Mots clés – Pronostic, Apprentissage Artificiel, Modèles de dégradation, Vieillissement, Détection d’anomalies.

Keywords – Prognostic Health Management, Machine Learning, Degradation models, Ageing, Anomaly detection.

1 INTRODUCTION

Nowadays digitization and Industrial Internet of Things (IIoT) make it extremely easy to collect a vast amount of data concerning electrical assets, during their operational life in real time conditions on customer plants. It allows users to get information on all environmental and usage conditions for products in real situation, together with data on observed failures.

Collected data can be used to learn normal behavior models of assets. Such models are relevant to detect anomalies characterized by a statistically significant deviation from the normal situation. While this kind of anomaly detection method is suited for short term asset monitoring, it is not appropriate

for long term degradation trends. To capture such trends, we can use First Principles degradation models (i.e. physical degradation models such as Arrhenius law); they complete the monitoring system to get a global view on asset health.

In the following sections we will first detail the short-term strategies (section 2) then the long-term ones (section 3) and conclude (section 4).

2 SHORT-TERM ANOMALY DETECTION

2.1 Context and motivation

Electrical assets may experience issues under some conditions. One of the most dramatic consequence to avoid is fire, which may impact both humans and equipment, in addition to

stopping customer business / process. Electrical fires cause an estimated \$3 billion-plus of damage to non-residential structures in the United States and Europe every year according to the National Fire Protection Association (NFPA) and the European Fire Safety Alliance (EFSA).

Designing equipment and switchboards in accordance with IEC 61439 standards ensures a proper IP level and significantly reduces the risk of fire due to insulation failure or excessive temperature rise. Then, one of the leading causes of electrical fires in medium- and low-voltage installations is faulty power connections of cables, busbars, and circuit breakers, particularly when the connections are completed onsite [SE, 2019b].

Cable, busbar, and withdrawable circuit-breaker connections can start to deteriorate due to loose connections caused by improper tightening torque or constant vibrations over time. Deterioration can also occur because of damaged surfaces due to corrosion, excessive pressure, or excessive friction. [Hirschbold and Chabert, 2018] provide a review of these cases and their causes.

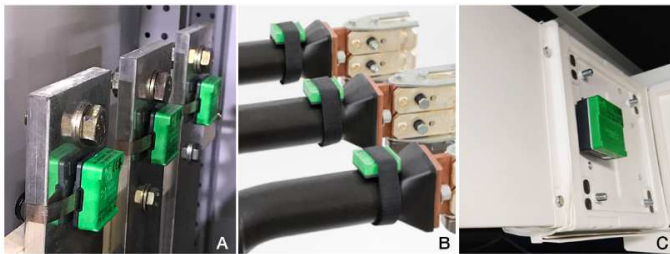


Figure 1. Wireless temperature sensors (Easergy TH110)

To prevent dramatic events to happen and detect such issues early, thermal surveys are typically performed using infrared (IR) thermography technology. However, these are done on a scheduled basis and may miss critical conditions occurring between scheduled scans. Continuous thermal monitoring overcomes these limitations by connecting wireless thermal sensors (Figure 1) to a data collection and monitoring infrastructure (Figure 2) [Hirschbold and Chabert, 2018]. [Hoffman et al., 2020] provide a review of alternate sensing technologies.

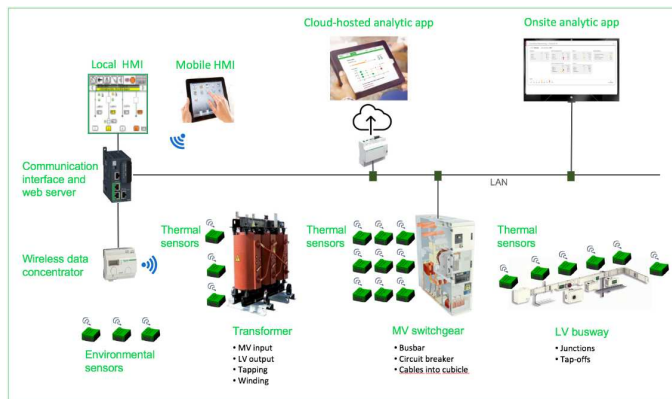


Figure 2. Continuous thermal monitoring architecture

Although such continuously collected temperature data provides a way to detect critically high temperature levels, typically using a “high temperature” threshold, resulting alerts might happen too late (reactive maintenance) as the threshold has to be set high enough to not trigger annoying false positives. This calls for a more adaptive temperature threshold,

based on context information: when the asset is not much loaded and external temperature is low, the threshold should ideally be lower than when the loads draw a large amount of current and external weather is already very warm. In the following section we show how such context-adaptive thresholds can be created with virtual sensors, so as to detect deviations early, before they transform into an actual fault (predictive maintenance).

2.2 Methodology

2.2.1 Soft / virtual sensors

Since 2012, Schneider Electric has developed a program to predict various industrial data based on usage and environmental conditions. Such idea of “Soft sensor”, also known as “Virtual sensor”, is not new and has been described in many ways in the literature and implemented in industrial products. For example, in the control theory domain, so-called “observer models” are fit to predict the discrete or continuous value of a variable. Popular models include white box detailed physical models, gray box simplified physical models, and black box data-driven models. The last two categories have their equivalent in, or reuse techniques from, the statistics and machine learning domains, learning models from appropriately pre-processed data. See [Curreri, 2020] for a review.

Gray-box models can be derived from the simplified physics of the asset or system at hand, for example with reduced order models and thermal-electrical equivalent models. Thermal radiation, conduction and convection are the main phenomenon at play when it comes to Temperature. Heat is mostly generated from drawn current through the Joule effect $P \sim I^2R$, as well as from magnetic induction.

For Machine Learning-based virtual sensors, popular pre-processing methods include *sliding window* to allow the model to pick up numerical delays and n-th order numerical derivative ; (*temporal*) *feature extraction* including rolling averages and other statistics, Fast Fourier Transform (FFT), Wavelets, etc. ; principal component analysis (PCA) and singular value decomposition (SVD) to compress and optimize input data so that models learn in a more robust way, etc. See [Curreri, 2020] and [Hoffman et al., 2020] for a review.

A virtual sensor can predict a category (classification) or a number (regression). Popular models include Linear and Logistic Regression, Kalman Filters (KF), Particle filters, Hidden Markov Models (HMM) and more generally Dynamic Bayesian networks (DBN), multi-layer Neural networks (NN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Relevance Vector Machines (RVM), Decision Trees and Regression Trees (DT, M5’), Random Forest and Xtreme Gradient Boosted Trees (XGBoost). See [Souza, 2016] for a review of the most popular techniques.

Generalization performance of the models can be estimated using split- or k-fold cross-validation, as per the Machine Learning state of the art. Usual performance metrics include the Root Mean Square Error (RMSE) and the R-squared (R^2).

2.2.2 Adaptive threshold: significant drift detection

Besides their use for better process control, virtual sensors are used to tackle many other problems, such as back-up of a real sensor, what-if analysis, sensor validation and fault diagnosis. The latter consists typically in monitoring a significant

deviation between the actual monitored data and the reference provided by the soft sensor.

A usual way to perform this step is to model the prediction error (so-called residuals) and use this model to detect a statistical outlier. Such models can be simple and straightforward (e.g. normal distribution, possibly leveraging generalization error statistics, see previous section); they can otherwise be integrated in the virtual sensor model itself (e.g. quantile regression forests [Meinshausen, 2006]). Fault detection *per se* can be as simple as bayesian inference or rely on the temporal nature of the data at hand to tackle both single-point deviations and consistent multi-sample deviations. Techniques from the field of Statistical Process Control (SPC) such as Control Charts, Cusum or EWMA can be relevant for this aim.

Figure 3 illustrates how such technology can be assembled to create an adaptive temperature monitoring solution and solve the problem described previously in *Section 2.1*.

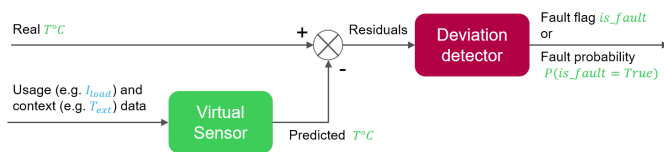


Figure 3. Virtual Sensor Fault Detection principle

2.2.3 Industrialization and deployment on the field

Our virtual sensor and virtual sensor fault detection analytics components have been industrialized at Schneider Electric in 2013 and 2016 respectively in the form of web service APIs on the cloud, so as to be reused in the various offers in the Schneider Electric catalog. Both are complementing the existing Avantis PRISM offer that was already present in the company's portfolio fault detection

The virtual sensor component was tested successfully onsite at a food and beverage industrial customer site as well as on several customer datasets, for example water pump networks. The virtual sensor fault detection approach was applied on a range of applications since 2016 including dry transformer overheating, solar panels soiling detection, LV or MV switchboards thermal monitoring, Air Handling Units (AHU) fault detection [Gao et al., 2019], refrigeration cabinet temperature sensor backup, and more. It was integrated within the Conext Advisor 2 and Asset Advisor software offers as part of the Schneider Ecostruxure suite.

Since 2019 this technology has been transferred into the Schneider Exchange platform [SE, 2019a] in the form of pay-per-use Analytics APIs, for all actors in the energy and automation ecosystem to leverage into their own business.

3 LONG-TERM AGEING MODELS

Since 2015, Schneider Electric has developed a program to develop algorithms to compute the ageing of assets with respect to time, environmental conditions, and usage conditions. The idea here is to offer new services to customers, based on advanced preventive maintenance and Reliability-Centered Maintenance features; these new algorithms may help developing time-based maintenance, spare part

management, condition-based maintenance, and predictive maintenance when used in simulation on what-if scenarios.

To do this, we must ensure that we can quantify usage and environmental conditions, and that we master the ageing laws with respect to these conditions. This is now possible thanks to digitization: we can rely on lots of data coming from assets in operation, providing information not only on their operational state, but also on their environment and usage, which can help define and tune ageing models, when compiled.

Rather than trying to define an approximative mission profile for our assets on customer plants, we can now have a clear view of the real environmental conditions (temperature, hygrometry, degree of salty atmosphere, concentration of corrosive gases, etc.) and of the real usage conditions (intensity, voltage, power, reactive power, harmonics, number of trips, etc.).

In addition, we have built a methodology that enables us to enrich the traditional physical ageing laws with a statistical approach that will be fed by data coming from digitization.

In the following sections, we will develop and explain this approach to determine a realistic value for the age of assets, leading to new services offers.

3.1 Ageing models history and limits

Since the early 1900's, many ageing models have been developed in the specialized literature [Pagès]:

- endurance models for mechanical devices;
- thermal ageing for electronic devices;
- resistance/constraint models for architecture;
- corrosion models for different metals;
- etc.

One common limitation of these models is that they rarely consider multiple environmental conditions, but more frequently they concentrate on a limited number of influencing factors (only the temperature for Arrhenius models, as an example).

Another limitation of these models is that they are rarely considered together, but are more often dedicated to a given situation, such as the corrosive atmosphere for metallic stick models for example.

What we are currently trying to do in Schneider Electric can be illustrated by what happens on our own car:

- it includes many different parts, with different ageing models (brakes do not age the same way as tires);
- it is sensitive to environmental conditions: the ageing of your car will not be the same, whether you live in Paris, Stockholm or Riyadh;
- it is sensitive to usage conditions: the ageing of your car will not evolve the same way if you drive very slowly and carefully and park your car in your garage each evening, or if you drive very nervously, with frequent harsh engine solicitations.

Anyway, when you drive your car, it may send you some visual warnings, suggesting you have a look on the motor, the oil level, or the air pressure in the tires. These warnings happen before the failure occurs, since they are based on the evolution of characteristics that reflect the health status of certain parts of the car. And all this information will be computed considering the environmental and usage conditions, then combined to provide valuable information to the driver.

For electrical devices such as a Low Voltage Circuit Breaker (LVCB), things are more complicated, because if one can rather easily measure a pression in the tires, the level of gasoline in a tank, or a rotation speed on a motor, it is much

more complicated to measure something on a device whose main mission is:

- a) to stay motionless 99.99% of the time;
- b) to react imperatively when solicited (since circuit breakers are safety devices).

Since we can't measure internal physical modifications in the breaker to infer a degradation, we must rely on models based on external environmental and usage conditions.

3.2 *New possibilities induced by digitization*

As explained in previous section, digitization allows now to know more about the way customers use their assets: with adequate sensors, we can monitor the *environmental conditions* (temperature, hygrometry, corrosive gases level, salt concentration in atmosphere, etc.) and the *usage conditions* (number of operations or trips, variation of intensity, harmonics and voltage impacting the asset, etc.). The sampling rate should be selected appropriately to provide a precise view of the asset's real life.

In parallel, thanks to internal failure event loggers we can also monitor the different failures the asset experiments, for each part of the asset: mechanics, electronics or electrotechnics.

Putting together this information will allow:

- to feed the ageing models with relevant information concerning the asset environment and the constraints it would be submitted to;
- to refine the ageing models when realizing that the predictions are either too optimistic or too pessimistic, considering precisely the given type of asset, rather than a wide family in an asset range. This improvement will be an evolutive process enabled by a methodology mixing physics-based and statistical approaches: we start from existing knowledge delivered by our experts and improve this knowledge by leveraging data coming from customers, from maintenance services, and from labs. In addition, Machine Learning capabilities may be used to process the data from multiple sources.

Relying on ageing and probability of failure information, we can then provide customers new services related to their connected assets, which will free them from performing tasks they are usually not that fond of managing: this may be connected services that deliver information related to risk of failure and need for maintenance, or this may be maintenance intervention initiatives on the assets, even before the customer has been warned that something went wrong.

Obviously, these services will be available only for the customers who will accept to share the connected data of their assets. In a broader way, one could think about extending the cooperation between end users in a dedicated segment, to ease the improvement of ageing models. This is already ongoing in the Oil & Gas domain: within the so-called OREDA initiative (Off-shore RELiability DAta), great petroleum companies [Sintef] share information about observed failures, increasing the accuracy of corresponding predictive models.

This approach could be extended to other domains. End users in a dedicated segment could arrange agreements to share data on failures which occurred in their respective plants, giving way for a high improvement in ageing models, with the help of manufacturers, specialists of their assets. Of course, this will take time, but the digitization trend is already there, enabling this perspective.

Schneider Electric has already started to build optimal ageing models, and to value them for providing new services to its customers. In the next section, we introduce the methodology used to describe the models, the high-level principles to improve them (relying on data), the way they are used, and finally, examples of new services for maintenance relying in ageing information.

3.3 *Methodology*

The methodology we have developed has been patented in 2018 [Patent]. It mixes a physical approach based on First Principles, providing information about the level of degradation for each asset part, then we transform this information into failure rate values, relying on statistical models.

As stated in [Chevalier-Boutin], we differentiate between:

- a) degradation modes, which we link with the physical evolution of the asset with respect to time, environment factors and usage conditions (but which do not lead immediately to a failure),
- b) failure modes, which characterizes an asset failure, and may result as the outcome of one or several degradation mode(s).

In practice, for each type of assets, we defined six steps, which read as follows.

1. Identify sub-assemblies. These sub-assemblies are elements that follow a dedicated and common life cycle (i.e. they can be replaced independently from the other parts) or are optional. They may or may not match the functional sub-assemblies. For a car, it may be the tires, consistent parts of the engine, or mechanics;
2. List degradation modes. With this list, we will also list the influencing factors for the evolution of each degradation mode. For the engine of a car, it may be the wear and the corrosion, and the influencing factors the driven distance, the temperature and hygrometry, and the average speed selected by usual driver;
3. Match degradation modes and failure modes. When a given sub-assembly is entirely degraded with respect to one of its degradation modes, identify which outcome it will have on the asset itself, as perceived by the customer. For a car tire, the outcome of wear may be an explosion, a puncture, or some adhesion loss;
4. Set failure prioritization. When we only have a global failure rate collected on field data, allocate the frequency of appearance for each degradation mode of each sub-assembly, according to asset technical experts. This step can also be fed by figures provided by the results of dedicated tests, or accurate feedbacks from customers. Obviously, with data coming from the field, these figures are likely to be revised on a regular basis;
5. Reallocate failure rates on degradation modes. Using the results of previous step on a reverse way, specifically when we only have one figure for the global failure rate of the asset, we can reversely allocate figures for each degradation mode of each sub-assembly, the sum of which matching the 100% figure representing the observed global asset failure rate. If we have more detailed figures on failure rates, the method applies even more easily. A figure for

global failure rate can be broken down for each failure mode, and then for each degradation mode. For a car motor, if we have only a global failure rate, we will allocate it on the different degradation modes according to the experiments or experts' opinion;

6. Attach a kinetic law for each degradation mode. Here, and using the influencing factors defined in the step N° 2, we define the way the subassembly ages, such as Arrhenius law for temperature, or Coffin-Manson model for temperature and humidity, or other specific models extracted from technical literature, experimental works, or standards. For specific parts, ageing factors are already listed in dedicated standards, which have been re-used here.

3.4 Model's improvement relying on data

Thanks to digitization and the data it provides, we will be able to use them to improve the forecasting of ageing assets in four directions:

- 1) Confirm the ageing factors corresponding to the different levels of degradation, both from environment and usage conditions;
- 2) Refine the breakdown of final degradation outcomes with respect to the different failure modes;
- 3) Improve accuracy of the values for final failure rates, as observed in the real conditions of the customers;
- 4) Precise the mission profile for each customer segment.

To do this, we can also rely on different sources of data:

- a) From the field returns (customer sites), which will provide both information on the failures, but also on the different factors used to predict them (related to environment and usage);
- b) From the minutes of maintenance operations performed by the company's maintenance services on customers' plants;
- c) From the failures collected on connected products, thanks to digitization;
- d) From the results of tests in manufacturer's laboratories.

Additionally, machine Learning techniques are also available, which could help extracting valuable information from huge masses of data.

Validating the models require simultaneously good knowledge of physics underlying the degradation processes, expert skills to criticize the forecasting induced by the models when applied on "what-if" scenarios, and statistical methods to compute an average failure rate from known returned field products. These three approaches are combined in that initiative, which relies on the good cooperation of people working in different parts of the company organization.

Obviously, the operating phase of this project will provide new field data, which will be used to tune up the ageing models, ensuring the best fit between predicted and field figures.

3.5 How the models are used

The models we have developed in our company are ready to be used by any internal application which needs to compute ageing indicators on our products, enabling maintenance optimization. This is done through a web-service, fed by the current ageing indicators (calculated in a previous step) and by the time series reflecting the values of all environmental and usage variables influencing the evolution of the ageing factors since previous computation (wherever available). The result of this computation is the updated value of the ageing indicators, including an estimation of the remaining useful life, and an

estimation for partial and global failure rates. This data will be used in the same way for the next iteration.

Products which are not permanently connected to the cloud can also benefit from this methodology, using several possible mechanisms: from embedded models and computation, to local data storage and computation thanks to mobile phones (which are able to get data directly from the product, using wireless techniques). In this last case, the results of computation will be made available both for the user on his mobile, but also pushed to the cloud whenever possible, to compile all information related to a given customer site and enable the use of these data to improve the models and build relevant trends.

Another major point concerning these models, is that they can consider the effects of a maintenance action, thus reducing the corresponding ageing indicator. Therefore, on each sub-assembly, and depending on the completeness of maintenance, we can either start again from the beginning (when changing a coil, for example), or reduce the ageing indicator by a given factor (for example when a renewal of grease is performed on a circuit breaker).

The computation is done iteratively, since this ageing engine is stateless: as inputs, it welcomes the current state of the considered asset and the current values of environment and usage factors, then provides the updated state of the asset. It can be called as often as the client wants it, this frequency depending for example on the criticality of the asset. "Stateless" means that if the customer wants to study the real evolution of his assets' health, he (or we) has (have) to store the data. This procedure is also used to forecast the health of the assets, playing what-if scenarios, hence enabling the pre-validation of models by comparing the predicted results with the opinion of experts in terms of failure frequency.

3.6 New services for design and maintenance

Multiple actors benefit from these models and the corresponding infrastructure. First, the end users get a better view of the impact of environment and usage conditions on the lifetime of their products. They can therefore put in place relevant actions to improve these conditions: for example, they would protect critical products with the adequate material, e.g. to reduce temperature (by adding fans whenever relevant), or to reduce the influence of corrosive gases (by adding dedicated hoods for corresponding products).

They also have the right information to optimize their maintenance (OPEX) and renewal (CAPEX) plans, and they can also compute what-if scenarios, such as: "What if the global temperature increases in my region? Which impact on my assets?" or "What if I buy dedicated equipment to provide air-condition to my assets? Will it be worthwhile in terms of life duration, given the expected Return on Investment?". The ageing estimation will also enable them to compare the performances of different customer sites (fostering benchmarking).

On another side, the manufacturer will also be able to improve the design of its products, since we now can get accurate information on the weakest parts of the assets (the ones more likely to be affected by frequent harsh environmental or usage conditions). This knowledge, well-centered on what the customers need from their assets, will help define more robust products within the next years.

In parallel, the knowledge of the customers' mission profiles will also be highly improved, which will help a better focus on real technical performance and endurance needed for the assets.

In addition, accurate information on ageing conditions enables field service teams to deliver more efficiently their maintenance offer.

And finally, segment end user communities could leverage this new information to make their internal operational standard evolve consequently. This could be done by sharing information among the communities, taking the example of the OREDA initiative [Sintef].

4 CONCLUSION

Digitization now brings a lot of data. This unlocks new possibilities for asset monitoring, both for short-term anomaly detection and long-term ageing estimation. For short-term, Machine Learning techniques have shown to be as efficient as gray-box physical models to tackle the problem of anomaly detection for a range of electrical assets, in particular for detecting thermal anomalies.

For long-term analysis, the quantity of collected data unlocks new models for ageing, new services, and new ways of considering the exploitation of products on site. Additionally, the improved knowledge on customer mission profiles will also enable designing products more adapted to the real usage of customers, and new data will also provide better estimations for failure rates and their evolution in time, under given conditions of environment and usage.

The systematic application of these types of models in the electrical field is rather new and will provide significant added-value in the field of assets and system maintenance. Finally, mutualizing these machine learning and ageing engines for various applications will ensure consistency, as viewed by the customers. And when it comes to sharing all these data among different actors, it will make their precision much higher than it used to be.

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