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Development of a flexible predictive maintenance system in the context of Industry 4.0

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Abstract: Maintenance activities have changed over the recent years, through the digitalization of the field and the application of tools and concepts from Industry 4.0. By connecting and communicating with the production system, companies are now able to create knowledge about its current and future health state, allowing more and more efficient control over the equipment. This approach is called predictive maintenance, and its goal is to reduce unplanned downtimes and organize efficiently maintenance actions before failures and stoppages appear. However, to reach such performance, it is still quite challenging for the industrial actor to implement an Intelligent Maintenance System that will help with the data management. Therefore, this paper presents the approach that was used to develop and implement a predictive maintenance platform in the automotive industry context. This platform is built on open standards, and scalable regarding the different needs for data collect, storage, visualization, and analyses.

Keywords: Condition Monitoring, Health monitoring and diagnosis, Industry 4.0, Intelligent maintenance systems, Internet of Things, Predictive maintenance.

1. INTRODUCTION

The main driving factor for an industrial company is to remain competitive on its main field of activity, meaning to propose products of high quality, at reduced costs. To reach these goals, one of the key elements is to have the least possible breakdowns on the production system, or at the minimum to be able to detect them early on, to plan efficiently the corrective actions. This statement is especially true for the automotive industry, where consequences of non-quality and non-production can be disastrous for various aspects of the company: economics, legal, societal, environmental.

Industrial maintenance is one of the key activities that received a lot of attention in the past few years, with help from all the new concepts brought by Industry 4.0. The work presented in this paper is the continuation of (Ciancio et al., 2020), where a framework was presented for the implementation of a predictive maintenance system in an industrial context. The framework aims at showing all the aspects to be taken into consideration when deploying a predictive maintenance policy and is based on the PHM (Prognostics & Health Management) methodology. It is represented in Figure 1. A use case is presented using this framework, as well as open-source software to conduct a full study from data collect to alerting of maintenance teams on machine failure. A summary of the most important points is proposed below:

- Importance of expert knowledge on failure modes and data selection
- The data management system is of great importance, and must comply with a lot of aspects: security, flexibility, accessibility, pricing
- Most of the collected data is of type timeseries, which enables making close to real-time visualizations and analyses
- Extracting knowledge from the data is not always done through complex processing, but it often starts with an efficient way of sharing it through visual dashboards

From this first solution was developed a full predictive maintenance system, which will be described in this paper. Consequently, it is organized as follows. Section 2 proposes an overview of approaches related to the implementation of intelligent maintenance systems. Section 3 presents the methodology employed to deal with predictive maintenance practically, which is the base of the developed solution presented more in detail in Section 4. The architecture as well as the different blocks that compose the system are described. Finally, a conclusion and some perspectives are proposed in Section 5.

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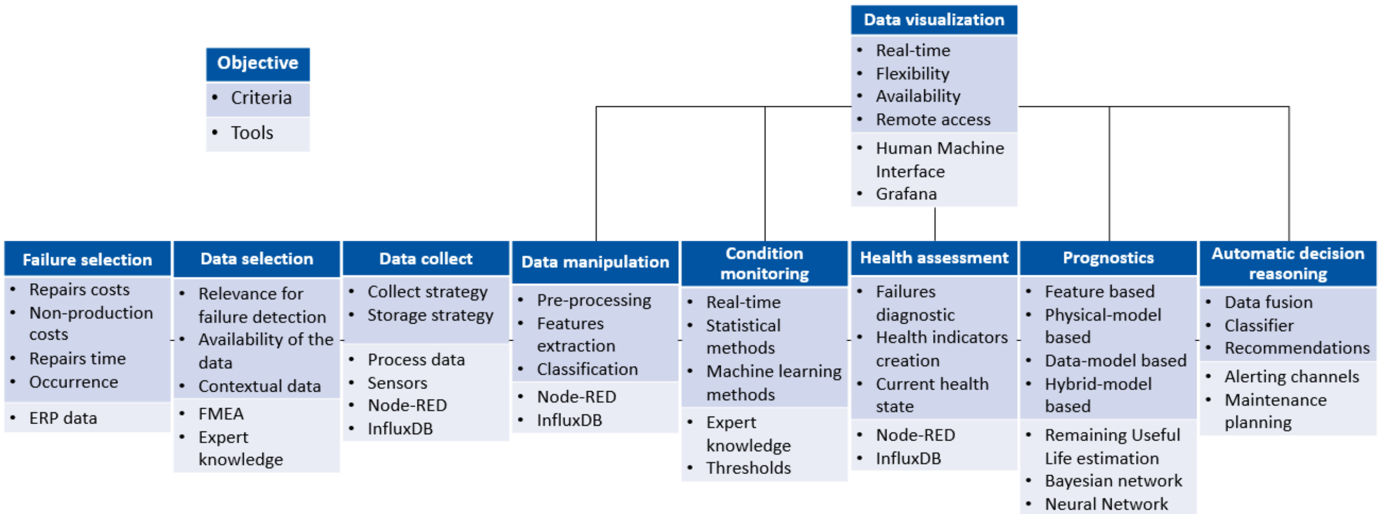

Fig. 1. Framework proposed in Ciancio et al. (2020)

2. RELATED WORK

2.1 Methodology

Many papers have been presenting approaches to develop intelligent maintenance systems across different industrial fields with success, but the main statement from these papers is the same: it is still quite challenging for the industrial actors to implement an efficient predictive maintenance system. These challenges are of different natures, but are coming from the complexity of such systems, because they deal with a lot of engineering fields. As an example, the deployment of a predictive maintenance solution on a specific machine will involve knowledge on the process, mechanical understanding of the system and related to the failure modes, knowledge on data collect, storage, analysis, and the place of the user must be taken into consideration: interactions, visualizations, alerting.

To illustrate this last statement, the existing standards and methodologies for PHM implementation make the understanding of the topic easier, the different functional blocks are clearly defined; however, the implementation in a real context is not as clear. As mentioned by (Sheppard and DeBruycker, 2018), the PHM topic is rather new, compared to other disciplines, and the various fields touched by PHM, such as data collect and analysis, are constantly evolving, making it difficult to come up with a general standard applicable in different industrial contexts. Moreover, even if the end solution must comply with different industrial context, specific needs and requirements of this context will impact the design of the final system deployed.

To tackle these challenges, (Garcia et al., 2019) proposes a methodology employed to design a predictive maintenance system, by describing the needs and requirements from the industrial actors. The goal is to have guidelines for implementation of predictive maintenance systems without being focused on a specific industry.
Similarly, a framework is proposed by (Schmidt et al., 2017), to manage the data through the different information systems available in the industrial context.
The methodology and solution presented in this paper use bricks coming from these requirements, as well as parts of the PHM methodology.

2.2 Implementation of such systems

Different approaches are proposed below, to implement practically predictive maintenance systems.

A full system is described in (Mourtzis and Vlachou, 2018), proposing a cost-efficient solution for the shop floor, using Raspberry devices and micro controllers, and also proposing state of the art communication between a cloud platform where the analyses are made, and the previous devices through OPC UA protocol.

(Ayvaz and Alpay, 2021) and (Bourezza and Mousrij, 2020) propose a system based on machine learning analysis on data coming from IoT systems.

A solution is proposed by (Cachada et al., 2018), based on the PHM principles, with various modules to manage the data such as the integration of augmented reality, to improve the decision system.

3 challenges of the current developments are shown and answered through a technical solution in (Christou et al., 2020), mainly the scattered data across different information systems, the difficulties to have multivariate analyses and the lack of possibilities to act directly on the production system according to predictions made.
From these works and observed challenges, we propose a solution that integrates several blocks to answer the common needs regarding predictive maintenance, while giving the opportunity to customize it according to specificities that can be encountered in the different industries.

2.3 Open-source and open standards

Finally, one of the key elements that appear in the previous papers and in (Isaksson et al., 2018) is the benefit to use open standards, and open-source software, because it allows a high flexibility for the development of all these applications.

This flexibility is required in the industrial context because there are specific needs and requirements. Therefore, and it is illustrated by the papers, specific developments are made to implement the most efficient systems.

This also constitutes challenges, as described in the methodology section, because it is quite difficult to have non-domain-centric applications. In this paper, the methodology used behind the application is described, similarly as by (Garcia et al., 2019), and later how it is deployed practically, using open-source tools, to enable flexibility and reconfiguration, and ease the deployment.

3. PROPOSED METHODOLOGY FOR THE PREDICTIVE MAINTENANCE SYSTEM

The methodology that was developed around the first framework can be found in Figure 2. It presents an overview of the different steps taken to implement predictive maintenance. The application that integrates a large part of the methodology was named Machine Health Management (MHM) and proposes a set of tools that tackle the different challenges discussed in Section 2. The various parts of the methodology will be described below.

The first part of the process starts with the studied machine or production system. Because machines can be quite complex with different parts dealing with different functions or steps in the production process, it is quite important to understand the failures modes. As proposed in the first study, the studied failures are first and foremost chosen regarding their impact on availability time and productivity of the machine. The interesting failures to study are most of the time the ones with high impact on costs and low occurrence, or the ones with high occurrences and low impact on costs. The failures that have low occurrence and low impact on costs will not benefit from the deployment of a predictive maintenance solution. The failures with high costs and occurrences should normally be dealt with very early when the production system is started, because mostly coming from design issues.

To study the relevance of failure modes to be studied, we propose three main solutions that are studied in parallel. These steps are the most important ones because they will define the final solution that will be implemented.

(1) The Computerized Maintenance Management System (CMMS) is a tool used to manage the maintenance within a company. Its main goal is to organize maintenance activities, follow-up on the different interventions and keep an historic of all this data. The interest here is to be able to analyze past data on the production system, to rank the different failures observed according to their costs and occurrences. The CMMS system is often linked to an Enterprise Resource Planning (ERP) system, which allows to understand the costs involved on spare parts. In the case of a new production system with no historical data, this system will help updating the list of chosen failure modes from the two other steps at a later time.
(2) Failure Modes and Effects Analysis (FMEA) is widely used in industry to understand the potential failures that can occur, and understand them better by analyzing their causes and effects on the impacted equipment. This tool can have different variations, by analyzing the process (PFMEA) for instance, or adding a criticality score to the failure modes (FMECA). However, its use in this methodology remains the same, and provides information on several steps.
First, it provides a list of failure modes that can be studied for predictive maintenance, probably not exhaustive, but enough to start the analysis. The main benefit is that it does not require the production system to be already in use, and therefore this study can be performed even in the early stages of conception.
Second, the a priori knowledge of causes and effects can help choosing a first set of data to be collected by the predictive maintenance system, and even help implementing extra sensors on the production system.
(3) Finally, experts knowledge also matters, similarly to FMEA, to choose the correct failure modes and the data to be collected. Some if this knowledge can be found within the FMEA, but experts here relate to several groups of people within the company that have knowledge about the way the production system operates. It includes for instance process engineers, automation engineers, machinery design department, maintenance technicians, operators and more. The importance of involving a wide range of "users" is to have theoretical and practical knowledge about failures that can, did or will appear on the equipment.

There is a practical reason behind the choice of only several impacting failure modes to be studied, compared to, for instance, a full assessment of the production system. The latter study can be successful but involving several failure modes and a large amount of data in the predictive maintenance system can prove to be very challenging to tackle. The risk is to propose a final solution that will be too fuzzy for the end user regarding prediction of health state, or not precise enough to take the correct actions. That is why, even if the solution is called data-driven, meaning that the model uses data analysis to propose solutions, there is still a necessary part of physics understanding involved, to correctly apprehend the failure mechanisms. When implementing a predictive maintenance system, it is often more meaningful to have a smaller dataset, but with data that has high correlation with the failure mechanisms that is being studied.

The previous steps give a first idea of the dataset that will be needed to study the selected failure modes. The next step is to understand if this data is available in the production system, meaning that the application will be able to connect to the source of the data to collect it. There are a lot of ways to connect and collect data through different protocols, and some will be presented in Section 4. To be successful in this step, knowledge about the automation system used, as well as Information Systems and Services (IS&S) is required. If extra sensors need to be implemented in the system, it is necessary to verify that the addition of such means of measurement will not create extra failure modes or weaknesses in the system. It means that the sensors should be as less intrusive as possible on its implementation system on the studied equipment.
There is also a requirement during this step to study and estimate the amount of data that will be collected and stored. The choice of data retention (meaning how long the data will be stored before being backed up or deleted)

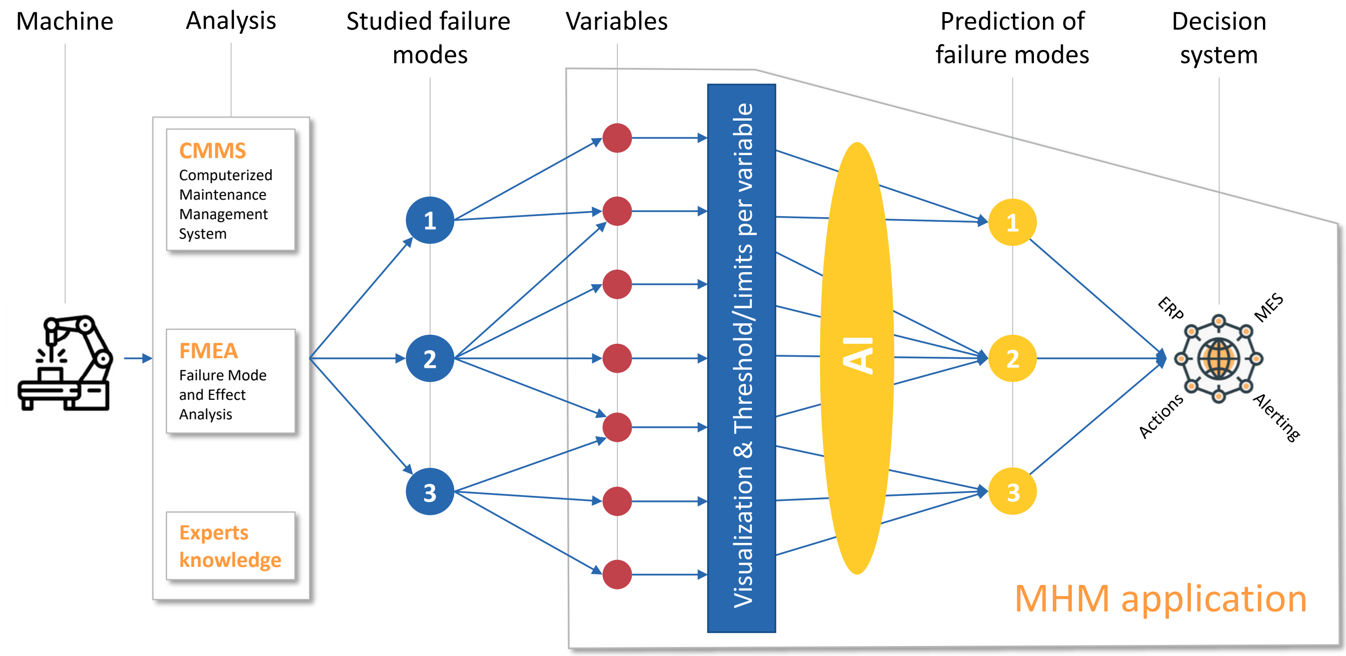

Fig. 2. Machine Health Management application model

is of importance, as the system will grow more and more with new studies being implemented.
As shown in the figure, this data (or variables) is the input of the system that composes the predictive maintenance application. Most of the data collected from the production system is time series data, meaning that it is collected every fixed interval of time, with its time (called timestamp) of collect. This type of data enables having visual representation of its evolution over time, and also making some advances analyses on it. Other types of data can be integrated, such as images (from 2D cameras or thermal cameras for instance). As per the figure, one variable can be used to analyze multiple failure modes, although it is only collected once.

It is described in the Introduction section that the first knowledge coming from data is most of the time with an efficient way of visualizing it. The main reason is that until implementing such system on the industrial equipment, it can often be seen as a "black box", meaning that the users cannot fully understand what is physically happening during the process. Time series data shows evolution of the system over time, and close to a real-time visualization (data can be collected every few milliseconds). It is a first strong step for the users to understand the machines and processes better and can also generate ideas about how the data should be monitored. An explanation is proposed in Section 4 regarding the users' interactions with the application.
Thresholds or limits are often the first type of monitoring that will be done on new studies of failure modes. These values can be known a priori from how the process works, or the acceptable limits of the mechanical parts that compose the production system. This first monitoring will also help implementing a first set of alerts for the users.

After these first interactions with the collected data, the next step is linked with Artificial Intelligence (AI), in its broad definition. The main goal at this stage of the methodology is to be able to create correlations between the data selected to predict appearance of the failure mode. It can be reached using various methods that will not be described here, but it can involve several manipulations and transformations on the data, which are available in the application. The data management system must integrate modules to perform these actions, such as implementation of machine learning models. Most of these analyses are multivariate because interactions and correlations between state of several data must be studied and taken into consideration.
The idea here is to create a specific monitoring for the failure mode, to be able to alert afterwards and point as precisely as possible where the issue is on the impacted production system. This notion of precision can relate to prescriptive maintenance (abbreviated as RxM). It is a maintenance activity more advanced than predictive maintenance in the way that the predictions are used to propose optimal alerting and actions to deal with the appearance of any failure mode (Nemeth et al., 2018). This precision allows the maintenance teams to be more prepared and plan specific actions related to the result proposed by the system.

Finally, the decision system is composed of numerous tools to share the correct information at the correct time and to the correct information system or user. There is a necessity to connect this predictive maintenance application to the most important information systems of the company, such as the ERP described at step 1, the Manufacturing Execution System (MES) to plan maintenance actions without disturbing the production. The system should also have the possibility to send action plans or work orders through the CMMS. It is also important that alerts can be sent from different channels to reach the users, the most commons are emails, SMS, internal communications applications such as Microsoft Teams. Alerting dashboards can also be created so that the production and maintenance teams can easily check the state of the equipment.

4. ARCHITECTURE OF THE PREDICTIVE MAINTENANCE SYSTEM

In this section, the actual architecture is described, as well as the different possible use of this application.

MHM includes functionalities related to the proposed steps of Section 3, more particularly:

- Propose a standard way of collecting data from numerous sources
- Apply different processing on the data, with the flexibility to add extra types of processing
- Monitor each data with a specific approach (threshold for instance), with the flexibility to add extra approaches
- Assess the state of each data, to propose indicators to follow the evolution of its behavior
- Alert the maintenance teams and create action plans regarding the prognostics that was done
- Propose efficient visualizations for all the different steps linked to data manipulation

To understand how the application works, a simplified overview is proposed in Figure 3.

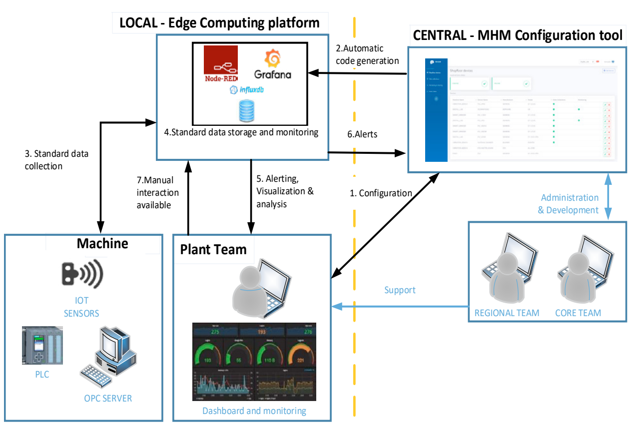

Fig. 3. Machine Health Management

The application can be seen as being on top of the Edge Computing solution that was selected and described in (Ciancio et al., 2020). It interacts directly with it through a web interface, which generates code without having to type it. The benefit is that it is open to users that may not have coding background, which will help them visualize and understand how the machine behaves.

The different modules are described below.

The first thing to understand is that MHM is a central tool developed in Java, which stores each model used to collect, store, and analyze the data. It is accessible through a web page and integrates all the previous models locally in the plant, where the user wants to create a monitoring. Once this code is pasted, it runs locally in the plant. One of the main benefits is that it opens this kind of monitoring to workers in the plants that don't necessarily have a coding background.

As a result, they can use the visual interface to configure what machine they want to address, what data they want to collect, how long they want to store it and what manipulations and monitoring they want to add (step 1). Once this configuration is done and validated, the application will automatically generate all the necessary code with the correct configuration inside the local plant server (step 2).

Because the local server is connected to the same network as the machines, it can connect to them using various communication protocols, for instance OPC UA, Modbus, MQTT, and also directly to the Programmable Logic Controller (PLC) of the machine through its proprietary protocol: Siemens S7 protocol for example (step 3).

Once this connection is done, data is stored locally, in a standard way, with possibility to add some extra information on the data, such as tags. This allows filtering the data for visualizations and analyses (step 4).

Some pre-configured dashboards exist, so that the user can visualize directly the newly collected data. Dedicated dashboards can also be created in Grafana, which can then be shared amongst plants. There is also the possibility to put in place some alerting regarding the monitoring rules, through the channels described before (step 5).

The different rules are part of the "AI" block in Figure 2. They are based in the current version on static thresholds, dynamic thresholds using SPC (Statistical Process Control), catching and counting events in the incoming data. Each rule can trigger a specific alarm to alert the maintenance teams, and the most advanced rules can also generate work orders to plan corrective actions directly with the ERP-CMMS system. There is also a possibility to combine several rules and generate targeted alerts if the root cause of the failure detected is known.

The alerts can also be visualized in the central application to keep historical data (step 6).

Finally, the importance of this step is that the user is still able to reach the "back-end" of the application (directly in Node-RED), to make some manual modifications, or even adding specific local monitoring. Plants tend to have more and more local skilled people on these topics, able to help with the coding. In this case, the code can be written in JavaScript in Node-RED and there is also the possibility to create analyses in R or Python (step 7).

This final step is important to underline, because as mentioned in the beginning, it is quite challenging to address all the existing machines within a company. In the case of Plastic Omnium, the Clean Energy Systems division is composed of more than 40 plants, all around the globe. As a result, the machines may differ, not in terms of process but of components used to build the machine. Therefore, the behavior of one machine to another may drastically change, as well as the environment in which they operate. That is why this notion of flexible tool matters, because it is not only a top-down application, but it can also be bottom-up.

The top-down aspect is linked to the developments made by the "core" team (as in Figure 3), which will propose specific monitoring on top failure modes directly to the end users, i.e. the plants. Using the application, they can replicate a model developed by experts, and operate it directly with the correct configuration.

The bottom-up aspect is linked to the local developments made on specific local issues, which can be also of interest for other plants. One of the main interests is that these developments can be done easily and quickly, on faulty equipment, which can increase the efficiency of the model created. As a result, these local developments can then be reinjected locally to other plants that may find themselves in the same situation as the original plant. Storing the models centrally, like in MHM, allows this way of working: the application can be seen as an "app center" similarly to what can be found in our smartphones.

5. CONCLUSION AND PERSPECTIVES

This paper tries to tackle the current challenges regarding implementation of intelligent maintenance systems to switch from corrective and preventive maintenance to predictive maintenance. The methodology that was developed behind the maintenance application is described, with all the different steps necessary to work efficiently on failure modes of the production systems. This methodology is not linked to the automotive industry, and can be adapted to other fields, and can also be implemented for new machines as well as already in-use machines. Finally, the architecture that was implemented in the industrial context is proposed, with a description of each module, and how the application can be used by various users having different knowledge and skills. The term flexible is employed for this system because it allows working both as a top-down and a bottom-up application.

The main benefit of the solution is that it is built on open-source software, and can be used by users with different profiles and knowledge. It allows data exploration and creating efficient monitoring that can be used for predictive maintenance, and proposes an easy way to implement solutions developed by the central team, or other users. There is a strong belief that most of the knowledge regarding machines' health state is coming from the daily users within the plants, and this tool gives them the opportunity to experiment and create broader solutions for the rest of the users.

Several improvements on the "AI" block proposed in Figure 2 will be conducted. One of them being the possibility to use statistical models such as ARIMA (AutoRegressive Integrated Moving Average) to predict timeseries, and train machine learning models directly on the data collected by the application. One of the key approaches is to train models on "healthy" data, to find anomalies when new data is checked by the model. The main reason being that in most cases, the machine or system will run in its correct state for long periods of time, and sometimes catching faulty data can be difficult. For instance, Novelty Detection models can help detecting anomalies on new data by comparing calculated scores, or Autoencoders, which learn a representation of the data and compares the expected outcome to the new data. The Edge Computing solution used, in combination with MHM, offers the possibility to do so and propose new features for the users. These new developments are made available because of the flexibility discussed throughout this paper, and they can be implemented easily to improve progressively the end solution.

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