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Dynamic Predictive Maintenance in industry 4.0 based on real time information: Case study in automotive industries

B. Einabadi*, A. Baboli, M. Ebrahimi*****

* Université de Lyon, INSA-Lyon, LIRIS Laboratory, UMR 5205 CNRS, France
(e-mail: behnam.einabadi@gmail.com).
** Université de Lyon, INSA-Lyon, LIRIS Laboratory, UMR 5205 CNRS, France
(e-mail: armand.baboli@insa-lyon.fr).
*** FPT POWERTRAIN TECHNOLOGIES FRANCE S.A., Bourbon Lancy, France
(e-mail: mojtaba.ebrahimiu@external.cnhind.com).

Abstract: In order to respond to today's dynamic needs of customers, customized mass production systems have been more and more developed that, are facing with different challenges. Maintenance planning and scheduling is one of the most important manufacturing components in such systems, due to importance of availability and high investment for this kind of system. In order to consider real machine operation state, recently, predictive maintenance method is proposed. However, in traditional methods, historical failure data is the main source for this planning. In this paper, we propose a methodology for dynamic predictive maintenance for a real case in automotive industries with considering multi-component structural and positive economic dependencies between them. In our methodology, we propose to gather data science with mathematical optimization method. Prediction of Remaining Useful Life (RUL) of machine parts has been made by Artificial Neural Network method with considering sensors data. With this RUL values and other cost values and optimization model parameters, and by solving proposed mathematical model, an optimal schedule is achieved with minimization of maintenance costs. Through a dynamic proposed procedure, when a new data is received, RUL values and model parameters are readjusted and new optimal solution for maintenance planning and scheduling can be achieved. Further, some scenarios are defined for analyzing the dynamicity of the proposed procedure and relating results, conclusion and perspectives of these researched are discussed.

Keywords: Dynamic Predictive Maintenance, Artificial Neural Networks, Real-Time Data, Remaining Useful Life, Optimization, Mixed Integer Programming, Multi-Component Maintenance, Industry 4.0

1. INTRODUCTION

In the highly competitive world market, traditional mass production system needs to move toward customized mass production to be able to propose a family of product for the same functional. Industry 4.0 or Intelligent Manufacturing Systems (IMS) is the most relevant and successful answer to today's challenges, by making vertical, horizontal and End to End integrations between different components of manufacturing system and member of supply chain and by using real-time data. Due to important investment for this kind of system, flexibility and agility in the one hand and efficiency and high level of availability of system, on the other hand, become more and more important.

Maintenance activities are one of the main components of intelligent manufacturing system, so that optimization of maintenance and more integration between maintenance and production makes the factory smart. In this way, predictive maintenance (PdM) is an important subject in industry 4.0 (Chiu, Cheng, & Huang, 2017).

Traditionally, most of the methods use only historical failures data of the equipment and use preventive maintenance strategy which was followed by considering a mean time and regular maintenance. This kind of strategy arise the problem that when the maintenance activity has been done, there is fifty percent probability that the part or system could have continued without failure, so, on the one hand, we have faced extra costs, and on the other hand, it may occur failure between the two successive maintenance time and this will result in shutdown and lost production and hence, corrective maintenance costs. Further, by considering and updating related data of the equipment, as it is received from the shop floor, the mean time of regular maintenance can be updated, and a new strategy, called 'Dynamic Preventive Maintenance' can be applied. Recently, it has been noted that there is necessary to consider actual operation condition of the equipment by collecting information and data from condition monitoring process (Ahmad & Kamaruddin, 2012). The monitoring information is normally obtained by installing sensors in the equipment. The effort is to find prognostic to predict next failure of the machine and perform the maintenance before the predicted time. This is the main concept of 'Predictive Maintenance'. By using the equipment, there is possible to receive and to take into account the new data and information, allowing to update the maintenance schedule. We call this concept as 'Dynamic Predictive Maintenance'.

In comparation with preventive maintenance in fixed periods, PdM advantageous can be pointed as following: 1) Reduce

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unnecessary maintenance interventions, 2) Increase spare part usage life by exploiting as much as possible form spare part, 3) Reduce or prevent system shutdown by tracking and analyzing failure of machine and 4) Increase available production time.

Predictive maintenance has been investigated both in single component and multi-component environment. In single component, the maintenance policy has been considered for single part or the whole machine as a unit. Analyzing multi-component that are related to each other, has been followed by three main dependencies between components in the literature (Keizer, Flapper, & Teunter, 2017): i) Stochastic or Functional dependencies (effects of failure or degradation between components), ii) Structural dependencies (physical position of the components and their access limitation), iii) Economic dependencies (combining components to run the maintenance in one time, that could be cost saving or expensive).

We observed that in the most recent research papers in this context, the applied method come from data science methods or optimization and simulation methods separately. As we want to take steps toward solving real world problem, there is a need to change the simple assumption of common mathematical models. For this objective, we propose to utilize data science methods and connect it with optimization model in order to readjust the model parameters according to real world problem. We have also considered structural and economic dependencies of the components.

The rest of this paper is organized as follows. Section 2 describes the last research works; Section 3 develop proposed methodology, mathematical modeling and solving approach; Section 4 present the case study and obtained results; Section 5 presents states some conclusions and perspective of future works.

2. Literature review

We categorized this papers in predictive/dynamic predictive and CBM as a structure that is depicted in the (Fig. 1).

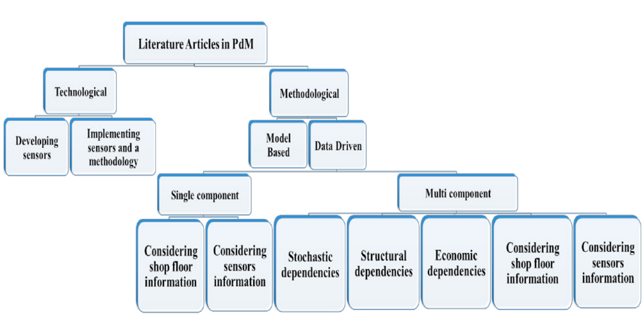

Fig. 1. Structure of the studied articles

There are several articles dealing mostly with technological aspects and monitoring systems. Another important category that is attracting more attention concern the methodological proposed PdM and can be divided in two categories of model based and data driven based. In model-based methods, physical dynamics of the equipment/system is studied to model the degradation process while, in the data driven methods, the attention is to use the available data and use of statistical models. Data driven models are single component or multi-component as it is in real world machines.

2.1 Technological based predictive maintenance

Different monitoring technologies in different application have been studied as, monitoring sensors of vibration, temperature, air pressure and noise level in the mine ventilator equipment by (Dong, Mingyue, & Guoying, 2017), voltage transducers, current transducers to analyze the condition of hydro generators by (Ribeiro et al., 2014), and infrared thermography technology for electrical equipment by (Huda & Taib, 2013).

2.2 Model based PdM

(Yiwei, Christian, Binaud, Christian, & Haftka, 2017) proposed a model based prognostic that measures the fatigueless crack failure growth in the fuselage panel of the fleet of short range commercial aircrafts, to quantify future damage size distribution. (Macek, Endel, Cauchi, & Abate, 2017) Studied the dynamics system of biomass-fired boilers efficiency for the application of heat generation to analyze the main failure which is soot accumulation during its operation.

2.3 Data driven PdM (Single component)

Most of the PdM researches have utilized a degradation function probability in order to model the degradation process of a component or finding a degradation threshold like as (Kaiser & Gebraeel, 2009). In this way, different data, such as historical data, sensors information (Curcurù, Galante, & Lombardo, 2010), operational data (He, Han, Gu, & Chen, 2018) and process parameters information (Liu, Dong, & Peng, 2013) as well as output quality data (Lindström, Larsson, Jonsson, & Lejon, 2017) as shop floor information, has been employed. Some of the researchers has considered one or two of such data, but they did not consider all at the same time.

In some of the research works, real time data has been considered and based on this, they have developed dynamic models, while the others have taken into account historical data of failures and usage/removal data, and some researches that have considered both.

In view of methodology, applying data science techniques have got more attention recently, by using historical data (Baptista et al., 2018) or sensors data (Dong et al., 2017).

2.4 Data driven PdM (Multi-component)

There are different dependencies between components. Earlier studies on multi-component maintenance has been followed in economic dependencies, by finding a grouping policy for triggering maintenance by cost analysis. (Wildeman, Dekker, & Smit, 1997). Further, in this context for PdM and dynamic PdM, number of research has been done (Pargar, Kauppila, & Kujala, 2017) and (Nguyen, Do, & Grall, 2017).

(Lee & Pan, 2017) considered structural dependencies in a multi-level hierarchical structure of system and (Srivastava & Mondal, 2016) analyzed multi-components in N-series structure, both in dynamic PdM or PdM context.

3. Methodology

In this paper, we propose to use Artificial Neural Networks (ANN) method for prediction of Remaining Useful Life (RUL) of the components by using sensor data of machines. Then, by receiving this value and other model parameters and using them in proposed mathematical cost model, the output will give us maintenance scheduling of the components that can be a decision-making support system for the decision makers. Further, in a dynamic procedure and by receiving new sensor data and by updating model parameters, the process of decision-making output will be re-executed and the decision can be readjusted.

For implementation of prediction, we have used most known type of ANNs which is Multi Perceptron Layer (MLP). It is important to recall that the most prediction problems are solved by this type of ANN, like as (Yan, Meng, Lu, & Li, 2017), by considering vibration, power, sound and laser image sensor data, and other types of neural networks, like as Radial Basis Function (RBF) neural networks are mostly used for classification problems.

3.2 Mathematical model

The proposed mathematical model minimizes the maintenance costs for non-repairable and repairable parts, according to the following:

For the non-repairable and repairable parts, there is a trade-off between set-up cost for the group of parts and remaining useful life (RUL) of the part. So, by changing the part before reaching to the end of its useful life, the system will be charged for not using the part for some periods. On the other hand, when we analyze the possibility of running maintenance of the other components in the same group, the system will make cost saving in the long time as the number of maintenances for the same group and consequently, the following number of set-ups will be reduced.

For the repairable parts, the trade-off deals with the purchasing cost of a new part and the repairing cost of part in its useful time which we have considered to be increasing due to time. Normally, when the number of repair increases, the next expected time to maintenance will be shortened. So, if we want to reproduce the same time of working for this part, we have to pay more cost. Therefore, a dynamic table must define for the repairing cost of each part in each period.

For both parts, there is a penalty of downtime cost if the maintenance period is scheduled more than their remaining useful life, since in manufacturing systems especially in automotive industries, downtime cost for the production line is very important. This may happen when in shop floor environment and after prediction alert of the parts for the need to the maintenance, production manager dose not decide to stop the machine because of the force of ordering due dates. By considering the risk of failure, if part is used more than its predicted remaining useful life and by assigning down time cost, proposed model tries to assign the schedule period into RUL of each part.

The mathematical model and its indices, parameters and decision variables are presented in the following:

Indices

i	number of each part $i \in 1,2,\ldots N$ (N= total number of parts)
j	index of the group number $j \in 1,2,\ldots A$ (A= total number of groups)
t	number of period $t \in 1,\ldots,T$ (A= total number of periods)

Parameters

C_i	Cost of purchasing part i (Euros)
CC_i	Cost of changing (renewing) part i (Euros)
CR_i	Cost of Repairing part i for the repairable parts (Euros)
ACR_{it}	Actual Cost of Repairing part i in period t for the repairable parts (Euros)
$CGSU_i$	Cost of Group Set-Up (Operation of opening machine cost + down time cost) of part i in its group (Euros)
CDT	Cost of Down Time of machine per period (Euros)
LMP_i	Last Maintenance Period of part i (Number of period: that could be day, week or month)
N_i	Number of last repairment of part i after renewal (Quantity)
ETM_i	Expected Time to Maintenance part i (According to failures or change plan) (unit in periods)
RUL_i	Remaining Useful Life of part i coming from machine learning prediction (unit in periods)
G_{ij}	A binary parameter for indicating if part i belongs to group j take the value of 1
Now	Current date (Decision Period) (unit in periods)
M	Big number M (for the modeling)

Decision Variables

MP_i	Maintenance Period of part i
XP_{it}	(0, 1) Maintenance scheduling of part i in period t
R_i	(0, 1) If the part i has to be repaired or not
RN_i	(0, 1) If the part i has to be renewed or not
H_i	(0, 1) If part i is scheduled to be maintained after its expected time to failure→0, otherwise→1
D_{jt}	(0, 1) If even one part from each group is scheduled to be maintained in period t→1, otherwise→0
K_{jt}	(0, 1) Number of parts from each group that is scheduled to be maintained in period t

Mathematical Model

$$Min \sum_{i=1}^{n} ((C_i + CC_i) * RN_i) + ((CR_i) * R_i) + \left(\left(\frac{C_i}{ETM_i}\right) * (RUL_i - (MP_i - Now)) * (H_i)\right) + ((MP_i - Now - RUL_i) * CDT * (1 - H_i)) + CGSU_j * \sum_{j=1}^{A} \sum_{t=1}^{T} D_{jt} - CGSU_j * \sum_{j=1}^{A} \sum_{t=1}^{T} (D_{jt} * (K_{jt} - 1)) \quad (1)$$

S.t

$$R_i + RN_i - 1 \quad \forall i \quad (2)$$

$$Now \leq MP_i \quad \forall i \quad (3)$$

$$MP_i \leq (LMP_i + 2 * ETM_i) \quad \forall i \quad (4)$$

$$LMP_i + (ETM_i * 0.5) \leq MP_i \quad \forall i \quad (5)$$

$$MP_i \geq t - M * (1 - XP_{it}) \quad \forall i, t \quad (6)$$

$$MP_i \leq t + M * (1 - XP_{it}) \quad \forall i, t \quad (7)$$

$$\sum_{t=1}^{T} XP_{it} = R_i + RN_i \quad \forall i \quad (8)$$

$$MP_i - Now - RUL_i - 1 \geq (-M) * H_i \quad \forall i \tag{9}$$

$$MP_i - Now - RUL_i \leq M * (1 - H_i) \quad \forall i \tag{10}$$

$$\sum_{i=1}^{N} XP_{it} * G_{ij} \geq D_{jt} \quad \forall t, j \tag{11}$$

$$\sum_{i=1}^{N} XP_{it} * G_{ij} \leq M * D_{jt} \quad \forall t, j \tag{12}$$

$$\sum_{i=1}^{N} XP_{it} * G_{ij} = K_{jt} \quad \forall t, j \tag{13}$$

$$XP_{it}, R_i, RN_i, H_i, D_{jt} \in \{0,1\} \quad MP_i \geq 0 \quad \forall i, t \tag{14}$$

The objective function is the minimization of: 1) renewing or repairing cost, 2) lost cost of part when we run maintenance sooner than its expected time to maintenance, 3) downtime cost when the machine is stopped, 4) group set-up cost and 5) group set-up cost saving for future maintenances. The unit is in Euros.

Constraint number (2) identifies whether the part has to be repaired or renewed. Maintenance period of each part must be greater than current period. Also, due to real technical knowledge, in the one hand, maintenance period of each part could be maximum two cycle of its expected time to maintenance and in the other hand, each part must be used at least more than 50% of its Expected Time to Maintenance (ETM), which are the object of constraints number (3) to (5). A binary variable has been defined in constraints number (6) to (8) in order to identify maintenance period of each part according to its maintenance period. A binary variable which is defined in constraints number (9) and (10) so that, if the maintenance period is greater than its corresponding remaining useful life, this binary variable tacks the value of 0, otherwise 1. Another binary variable is defined in constraints number (11) and (12) in order to investigate whether there is even one part from each group that is scheduled in period t. It takes the value of 1, otherwise 0. Constraint (13) calculates the number of parts in each group that is scheduled in each period. Constraint (14) represents the conditions on the decision variables.

3.2.1 Solving Mathematical Model

We transformed the nonlinear model to linear model. In order to solve the proposed mathematical model with its input data, firstly we have tried to solve the model by exact optimization software. GAMS© software and its CPLEX algorithm to solve the Mixed Integer Programming (MIP) is used. 3 different sizes and solution time is a reasonable time which is satisfactory for these ranges of size or more.

3.3 Dynamic Procedure

We take real world assumptions and parameters in our problem. For this, RUL of the parts is calculated based on real condition of machine through sensor data. Then, by solving optimization model, we have an output for the maintenance scheduling of the parts, and it can be used in a decision support system for decision maker in their maintenance planning.

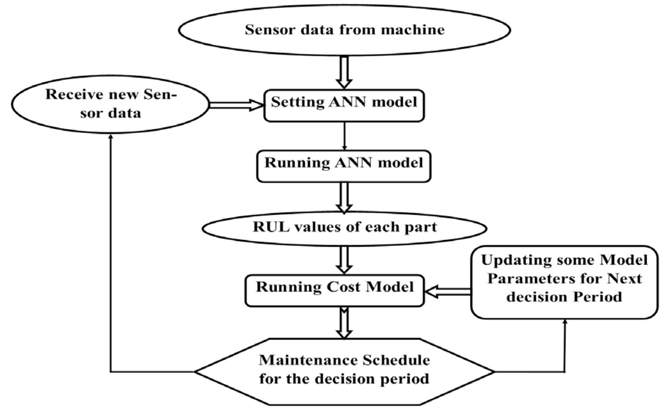

Fig. 2. Dynamic Decision-Making Procedure

After receiving each new sensor data, by setting ANN and getting new RUL values as well as re-adjusting some optimization model parameters, the model can be run again and new maintenance schedule will be appeared. The whole process has been depicted in (Fig. 2). Through some scenarios, we have shown some examples of dynamic implementation and results. They are discussed in the next section.

Scenario A) suppose that we have passed 28 periods and the remaining useful life degradation trend is decreased exactly same value period by period.

Scenario B) supposing that we have passed 28 periods and random 50% of parts degrade constantly period by period, 20% of parts degrade less than constant degradation and 30% degrade more than constant degradation period by period.

Scenario C) supposing that we have passed 50 periods and some repairing or renewing has been executed for some parts, and the last maintenance periods and number of repairs after renewal has been updated. RUL of parts also degrade constantly period by period.

Scenario D) supposing that we have passed 50 periods and some repairing or renewing has been executed for some parts, and the last maintenance periods and number of repairs after renewal has been updated. Also, randomly 70% of parts degrade constantly period by period, 15% of parts degrade less than constant degradation and 15% degrade more than constant degradation period by period.

4. Case study and Results

We have considered 24 parts in 5 different groups from one of CNC machine of Fiat Power Train Technologies FPT as case study. Sensor data of Temperature (T), Vibration (mm/s) and Energy consumption (Kw) of machine are considered as input features. The result of the case study is depicted in (Fig. 3). For example, the part number 14 has to be renewed in period 44, and part number 10 has to be repaired in the period 52. As it is shown, the schedule is allocated to 6 different periods.

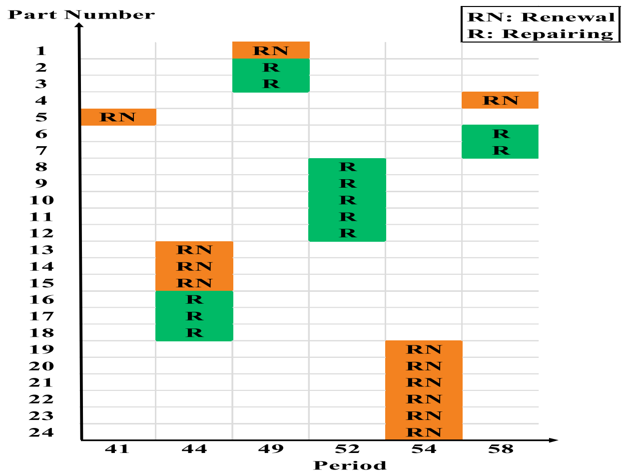

Fig. 3. Optimum Maintenance schedule with identification of renewal or repair

All the parts are scheduled within their Remaining useful life period; so that all the H_i variables have got the value of 1, meaning that downtime costs are avoided with this consideration. Other types of costs for this model are shown in Table 1. In fact, these values are extracted from different equations in the objective function which is the equation (1) to (3). As it is observed, the schedule is in a way to use as much as possible from the useful life of the parts as the value of cost of lost RUL is quite less. Also, due to opportunistic group maintenance, there is a high value of set-up cost saving as the model has minimized the number of set-ups with respect to the other costs.

This problem and 4 scenarios schedules in several periods for maintenance is illustrated in (Fig. 4). Also, different costs for each problem are illustrated in (Fig. 5).

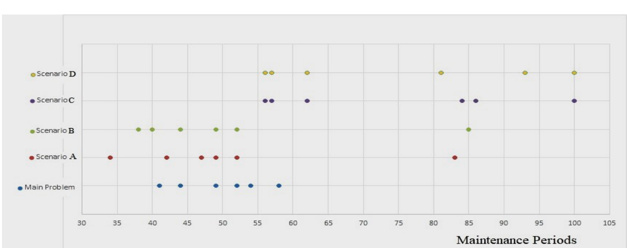

Fig. 4. Maintenance scheduled periods for the 5 problems

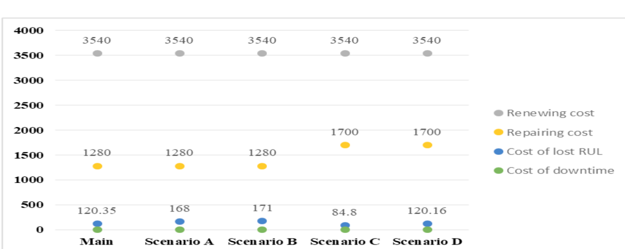

Fig. 5. Cost of renewing, repairing, lost RUL and downtime in 5 different problems

Comparison of Scenario A with B:

As it is seen, the initial maintenance period for main problems starts in period 41, while by the passing of time and changing the RUL and parameters, it is seen that for some parts the schedule has come backward to start sooner and for other parts it has come forward to be maintained later. The importance is that according to change of parameters, dynamic scheduling with minimum cost is achieved and the maintenance planning cost adjust itself dynamically.

In the view of optimal costs changes, all of the costs are the same as main problem except the cost of lost RUL which has increased in scenarios A and B. As result, this shows the robustness of the optimization model, since through minimum expected cost it will give the schedule, so, by changing the maintenance periods Optimal maintenance schedule is achieved.

Comparison of Scenarios C with D:

After passing 55 periods, some parts are maintained, and number of repairs for non-repairable parts after renewal and last maintenance periods are updated, the costs result shows that the repair cost has been increased since in new maintenance intervals. There is a big difference in set-up cost and set-up cost saving, as it is seen in figure 15. In scenario C, these two costs have been worsen due to the increase in number of set-ups. The robustness of the optimization model is also confirmed in these two scenarios, since the change in costs are just in set-up costs which is evident and natural.

Table 1. All costs of optimal solution

Renewing cost	Repairing cost	Cost of lost RUL
3540	1280	120.35
Cost of downtime	Set-up cost	Set-up cost saving
0	11200	+35700

5. CONCLUSIONS

We found prediction of parts RUL via data science and more specifically from Multi-Layer Perceptron Artificial Neural Networks by using the sensors data. The other cost parameters for proposed optimization cost model has been obtained with discussion to company experts and their available data. By solving the proposed mathematical model in exact resolution approach, we can find that the optimum maintenance scheduling. The solution gives the maintenance periods within the RUL of parts in order to avoid a big downtime cost. The model is also trying to use as much as possible from RUL of parts and finally to minimize the setup cost by grouping the parts in same period, so that setup cost saving is increased.

In order to analyze the dynamic nature of production and machine state, through dynamic scenarios we found that the optimization model gives the optimum scheduling by changing some maintenance periods of parts, and their corresponding costs changes are not considerable and we can expect the maintenance costs into an acceptable range.

It is necessary to recall that the maintenance planning is strongly linked with replenishment policy in the one hand and with the production planning in the other hand. We may have not considered some parameters or some facts, so, we propose our methodology as decision support system that can help the decision maker in finding best decision. An example could be the availability of machine for maintenance all the time, which is not considered in our optimization model, but it is possible by adding a new constraint satisfy this limitation.

For the future works, in the prediction models, it can be considered more input features like as the information of production as well as the quantity and the type of the manufactured parts, since due to flexibility context of today's manufacturing, producing different kinds may result different pressure on the machine. Another interesting point can be the integration of data and information from environment shop floor and analyze the effect of environmental features like temperature degree of shop in the prediction of RUL.

Developing new machine learning tools and applying them in the prediction of RUL through operating information of machine and big data of sensors, and finding models with more precision can definitely help in having better results. Furthermore, trying to find failure or degradation relationship and correlations between machine parts are also an important aspect that data science can help to achieve this.

Another important aspect for future researches is the Study about dynamic frequency of receiving data, updating of data and sizing problem of sensors.

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