PREDICTIVE MAINTENANCE OF COOLING SYSTEM WITH SENSOR COMBINATION AND SCADA

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ABSTRACT

The cooling system has a fundamental role in the die casting process because the cooling system will directly affect the quality of the casting results. However, to ensure the cooling system works well from time to time is not easy. More frequent and regularly checking the cooling system is one possible way to ensure it. Nevertheless, this way is disrupting the casting process. In this paper, a predictive maintenance technique is proposed with autonomous analysis based on machine learning and sensor data. A SCADA system collects real-time data from several sensor combinations. This data is then passed to a machine learning algorithm for predicting cooling system conditions, i.e., predicting future system failure. The proposed predictive maintenance system is expected to be able to predict the damage better. Therefore, it will reduce the possibility of unplanned system failure. Also, it is increasing the maintenance process. The maintenance is carried out according to the cooling system conditions and without the need periodically check the cooling system.

Keywords: Predictive maintenance, SCADA, machine learning, cooling system, casting.

1. INTRODUCTION

The casting process's success depends on the cooling system's ability to maintain the cooling temperature. One of the most popular maintenance techniques is preventive maintenance. Preventive maintenance adheres to a time-based maintenance system (NASA, 2000). In other words, shortening the maintenance interval can reduce the probability of a system failure. Instead of increasing system reliability, significantly shortening the maintenance interval will disrupt the production process. Predictive maintenance techniques are then proposed to overcome this disadvantage, in which able to determine the maintenance schedule based on the latest machine/system conditions (Mobley, 2002).

Predictive maintenance techniques require good data support in order to determine the condition of the machine appropriately. Useful data for predictive maintenance is data that has a right level of accuracy, has a large amount, and has a time dimension that is close to real-time data. In the era of the industrial revolution 4.0, it is possible to get large amounts of data in real-time, which is supported by the development of information and communication technology (Lasi et al., 2014).

Enormous amounts of data are often referred to the Big Data. Big Data is then processed to produce the right maintenance decisions using machine learning algorithms. Machine learning will study large amounts of data autonomously to see data patterns. Based on real-time data from the sensor, it will be used to see the machine/system's condition in real-time. Real-time machine/system conditions will be used to determine the right time to perform maintenance.

In the last decade, there were only three papers that discussed predictive cooling system maintenance. Xayyasith et al. (2018) conducted research on predictive maintenance of hydroelectric cooling systems in Thailand. Suryadarma et al. (2020a) researched predictive maintenance techniques in the casting process cooling system using two temperature sensors. Then Suryadarma et al. (2020b) improved Suryadarma et al. (2020a) research by reducing the number of sensors used, from 2 temperature sensors to 1 turbidity sensor and reducing mathematical calculations. In this study, we will propose to improve the accuracy of the predictions by using two temperature sensors and one turbidity sensor. This study still uses SCADA (Supervisory Control and Data Acquisition) as a provider that supports Big Data and Machine learning, which will assist in data processing and decision making.

2. PREDICTIVE MAINTENANCE SYSTEM ARCHITECTURE

The predictive maintenance system architecture in this study is a refinement of the predictive maintenance system architecture (Suryadarma et al., 2020a) and (Suryadarma et al., 2020b). Figure 1 is a predictive maintenance system architecture using two temperature sensors (Suryadarma et al., 2020a). The cooling system uses water that flows from the water tank using a pump. Then the water flows into the mold casting. The water that passes through the mold casting becomes hot. There is an increase in temperature between the water at the mold inlet and at the mold outlet. The water that comes out of the mold outlet is then read by the temperature sensor and enters the heat exchanger. The water that comes out of the heat exchanger is measured again using a temperature sensor. Then the water that comes out of the heat exchanger goes back into the water tank. The difference in temperature of the inlet and outlet heat exchanger is then used to calculate the total heat transfer rate *(q)* on the heat exchanger in Watt. See Equation (1). Where $\dot{m}$ is the fluid mass flow rate (Kg/s), C_P is the specific heat of fluid at constant pressure (KJ/Kg.^{0}C), T_i is temperature inlet (^{0}C), T_o is temperature outlet (^{0}C), and the subscripts *h* refer to the hot fluids (Minkoff, 1992).

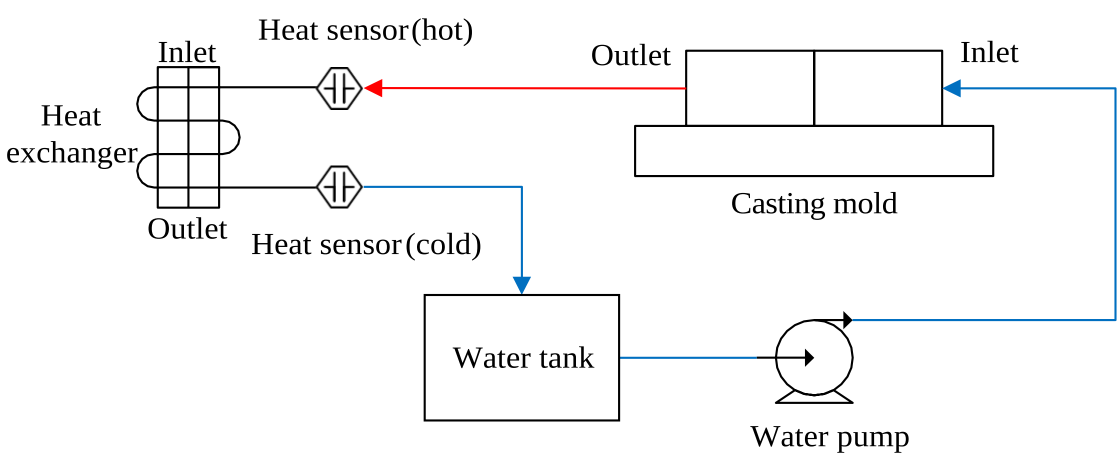

Figure 1. The predictive maintenance system architecture with temperature sensors (Suryadarma et al., 2020a)

$$q = \dot{m}_h c_{p,h}(T_{h,i} - T_{h,o}) \tag{1}$$

Figure 2 shows a predictive maintenance system architecture using a turbidity sensor (Suryadarma et al., 2020b). This predictive maintenance system architecture uses one turbidity sensor to monitor water turbidity, which will be used to determine predictive maintenance. The predictive maintenance system architecture using a turbidity sensor does not require further calculations. Turbidity data is directly used in machine learning algorithms to predict maintenance is carried out.

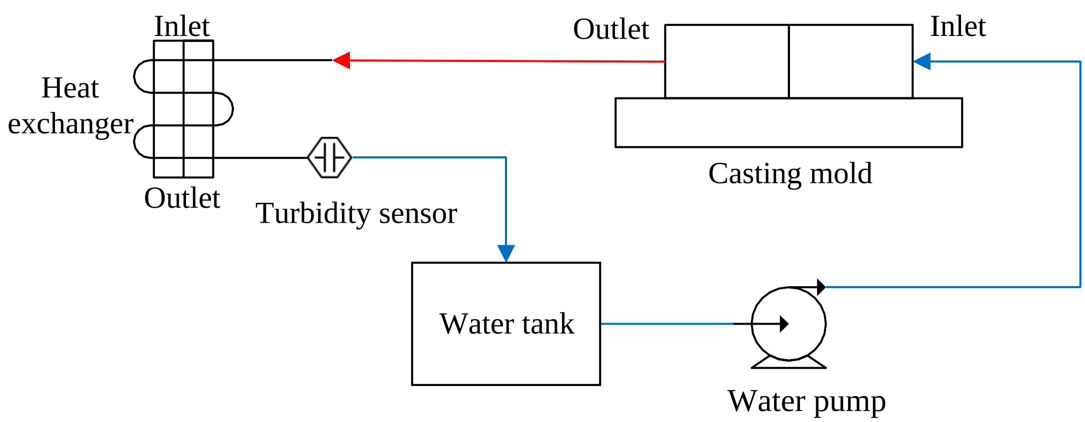

Figure 2. The predictive maintenance system architecture with turbidity sensors (Suryadarma et al., 2020b)

This paper combines the two predictive maintenance system architectures using temperature sensors and turbidity sensors. The proposed predictive maintenance system architecture is shown in Figure 3. In predictive maintenance system architecture with a combination of sensors, heat sensor 1 (hot sensing) is installed to the heat exchanger's inlet, heat sensor 2 (cold sensing) is installed to the heat exchanger outlet, and the turbidity sensor is installed on heat exchanger outlet.

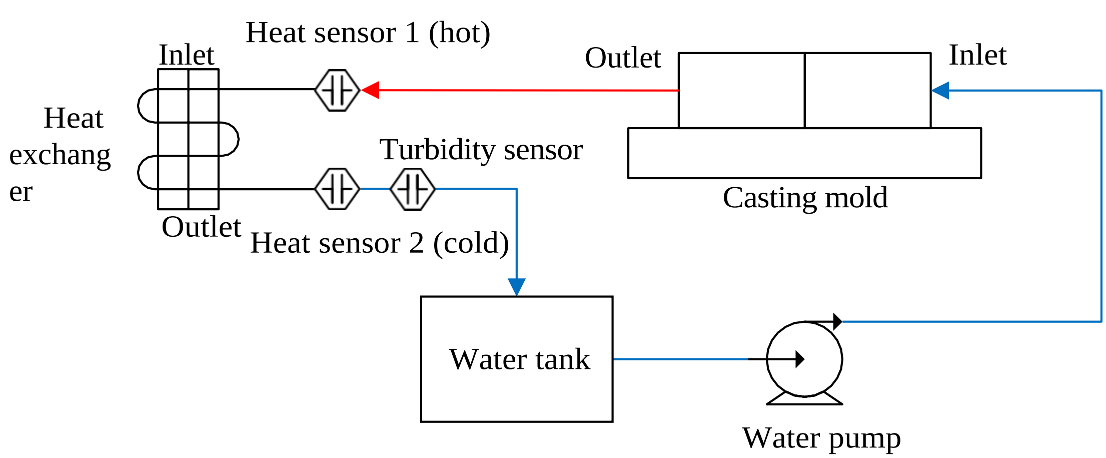

Figure 3. Proposed the predictive maintenance system architecture with sensor combination.

The Casting mold prototype on this paper using a continuous gravity die casting mold. The detail of the continuous gravity die casting mold used in this paper is shown in Figure 4.

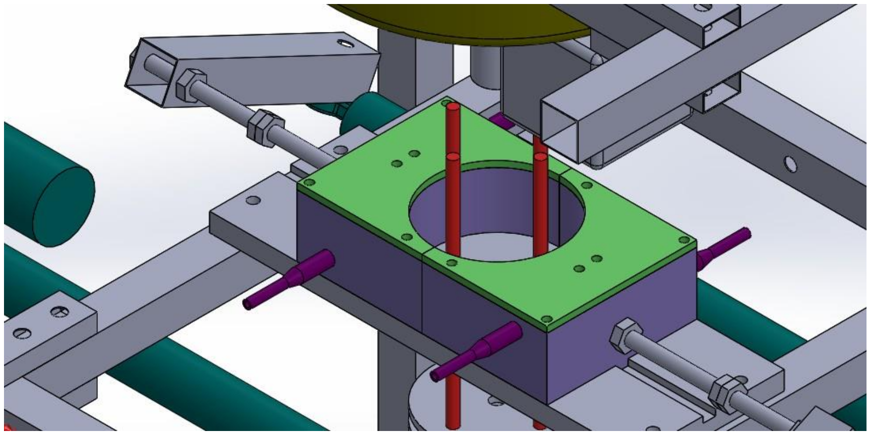

Figure 4. Prototype of continuous gravity die casting mold.

Continuous gravity die casting mold is part of the predictive maintenance prototype system that is built. The PLC will control the sensors installed in the cooling system. And then, PLC will send data from sensors in real-time to SCADA via an ethernet network. SCADA will store data in a database called Big Data. This large data will then be processed using machine learning algorithms to produce predictions for maintenance. Detail the prototype of the predictive maintenance system with sensor combination shown in Figure 5.

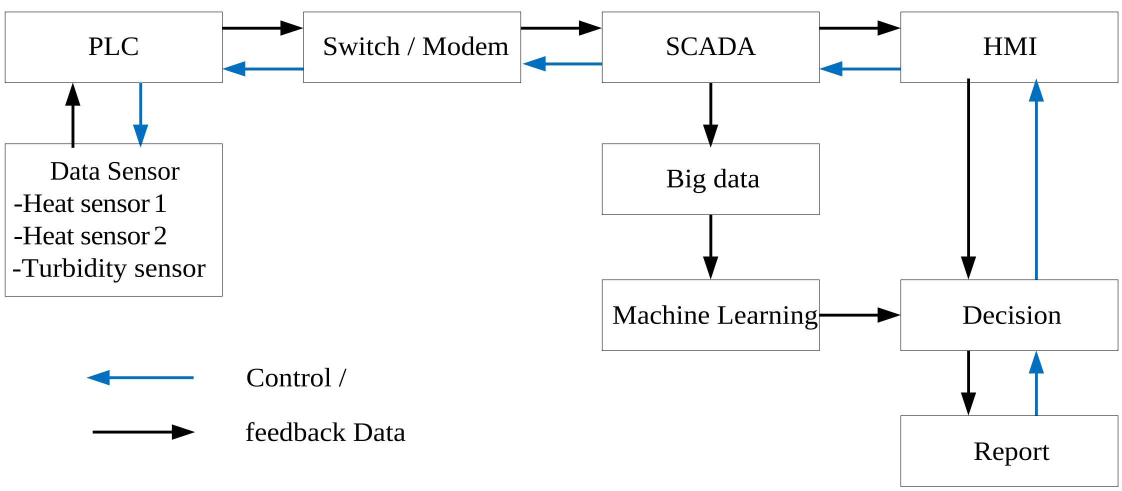

Figure 5. The prototype of the predictive maintenance system with sensor combination.

3. PROPOSED PREDICTIVE MAINTENANCE SYSTEM

This research uses stearic acid, which is melted into molten. The casting process starts with pouring molten into the mold. After the mold is full of molten, the cooling system starts working. Water begins to be pumped and flows through the mold. Temperature and turbidity data are taken 5 seconds after the cooling system starts working. The data is not taken immediately after pouring (shortly after cooling works) because the molten heat has not fully heated the mold. So that it can cause the difference in temperature of the inlet and outlet heat exchanger is not significant and causes the value of q to be very small.

The data for temperature and turbidity were taken as many as 30 data, with an interval of 2 seconds between them. After 30 data are fulfilled, SCADA will calculate the average of 30 data so that it becomes one single data for one cycle. The temperature data then calculated to be the total heat transfer rate (q) data. Then the total heat transfer rate (q) and turbidity (NTU-Nephelometric Turbidity Unit) data will be saved into the historical SCADA database.

SCADA historian will become Big Data, which is then used to predict using machine learning algorithms. In this paper, machine learning will use every 10 data to calculate linear regression. The results of this linear regression calculation will be taken the slope value as the rule-based classification algorithm input. Detail the experiment procedure shown in Figure 6.

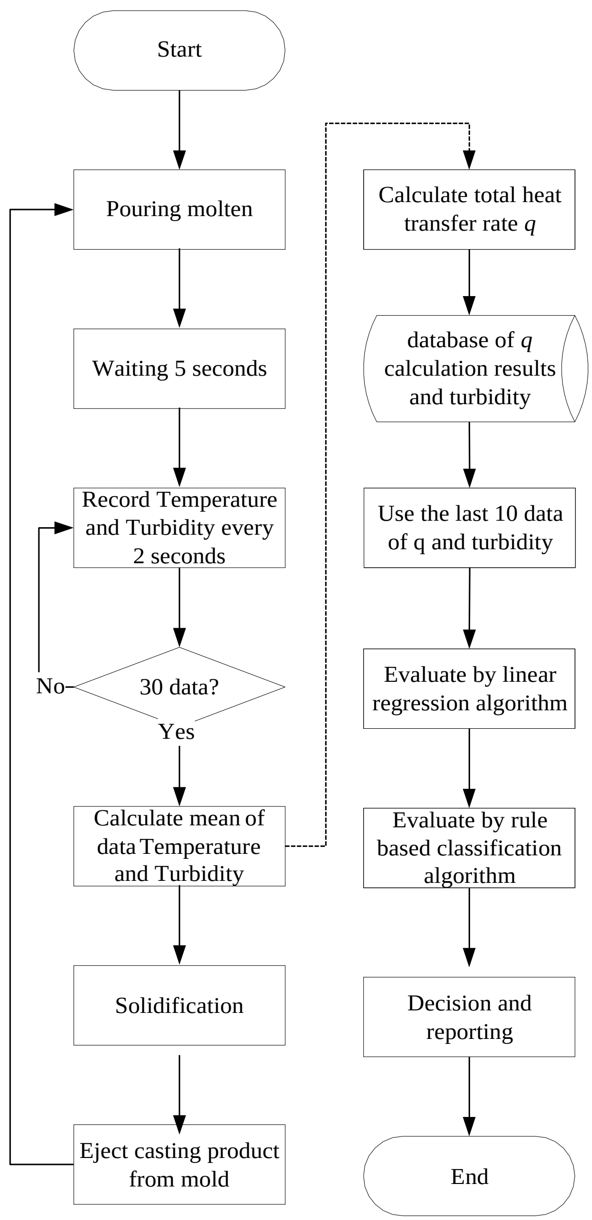

Figure 6. Experiment procedure.

4. EXPERIMENT AND DISCUSSION

The molten is made from melted stearic acid. Stearic acid is the raw material for making candles and has a melting point/freezing point of 66^0C-69^0C. In this experiment, stearic acid was melted, and the temperature was maintained at 100^0C. Then the molten is poured into the mold through an automatic faucet. As shown in Figure 6, each cycle will record 30 data and calculate the average value. And then, for the temperature data calculated the total heat transfer rate value *(q)* and the turbidity data used the average *NTU* value from 30 data collected. Detailed experimental data are shown in Table 1. The calculation of the total heat transfer rate (q) in the heat exchanger used the mass flow rate of fluid ($\dot{m}$) is 0.243 Kg/s. The specific heat of water at constant pressure (C_p) is 4.2 KJ/Kg.^{0}C (Bergman & Lavine, 2017).

$$y = ax + b \tag{2}$$

Linear regression analysis uses to explain the relationship between variables in 2-D sample space, following equation (2) (Hwang & Chen, 2017). Where y is the value of the total heat transfer rate (q), x is the cycle number series, a is the slope coefficient, and b is the constant coefficient. Follow as Figure 6, use the 10 data of the total heat transfer rate (q) or turbidity (NTU) to calculate the linear regression equation.

Table 1. Experimental data.

Number of Cycle	Temperature		Turbidity	
	q (W)	*a*	*(NTU)*	*a*
1	15.000	-	10.567	-
2	15.370	-	10.314	-
3	15.525	-	10.300	-
4	15.206	-	10.627	-
5	15.586	-	10.052	-
6	15.715	-	10.185	-
7	14.628	-	10.668	-
8	14.968	-	11.032	-
9	15.332	-	10.921	-
10	14.584	-0.051	11.238	0.086
11	15.097	-0.069	11.192	0.117
12	14.953	-0.071	10.344	0.078
13	15.588	-0.023	10.140	0.026
14	15.162	-0.021	10.810	0.034
15	15.362	0.018	10.038	-0.040
16	15.192	0.060	11.092	-0.048
17	15.813	0.069	9.908	-0.099
18	15.434	0.065	10.609	-0.078
19	14.747	0.043	11.114	-0.032
20	15.309	0.009	10.324	-0.010

Number of Cycle	Temperature		Turbidity	
	q (W)	*a*	*(NTU)*	*a*
21	15.351	0.002	10.937	0.053
22	15.561	-0.005	10.088	0.016
23	14.503	-0.036	10.729	0.004
24	15.551	-0.025	10.203	0.000
25	15.313	-0.018	10.101	-0.053
26	15.058	-0.035	10.568	-0.011
27	15.595	0.019	10.194	-0.062
28	16.011	0.074	10.285	-0.065
29	15.047	0.023	10.790	-0.003
30	15.091	0.009	10.861	0.015
…	…	…	…	…
141	15.842	0.062	9.715	-0.096
142	15.406	0.054	10.409	-0.081
143	15.650	0.066	10.424	-0.095
144	15.113	-0.014	10.733	-0.019
145	15.439	-0.039	10.735	0.036
146	15.669	-0.007	9.969	0.000
147	14.816	-0.030	11.062	0.018
148	15.517	0.004	10.810	0.037
149	15.032	-0.021	11.241	0.106
150	15.017	-0.069	10.914	0.114

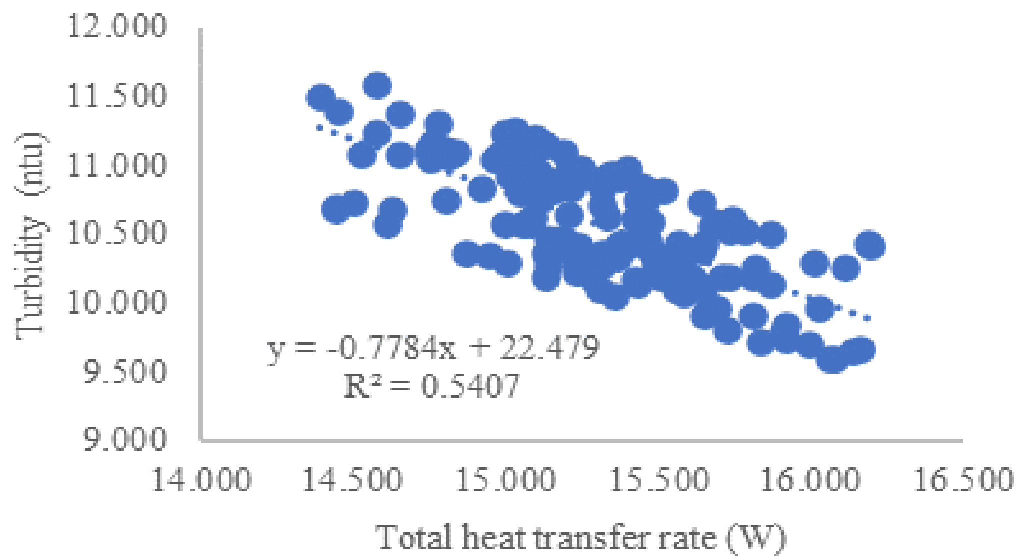

Figure 7. Relationship between turbidity and total heat transfer rate.

The turbidity and q data are plotted in a scatter diagram presented in Figure 7. In figure 7, there is also a linear regression line with the equation (3), and the value R^2 = 0.5407. Where *y* is the value of turbidity (NTU), and *x* is the value of *q* (W). It is implied that the relationship between turbidity and *q* is inversely proportional.

$$y = -0.778x + 22.479 \tag{3}$$

The definition of a cooling system can work properly if the value of *q* is greater than 0 (Suryadarma et al., 2020a). And then, if *x=0* substitute to equation (3), then y=22.479. In other words, the definition of a cooling system can work properly is if the value of turbidity is less than 22.479 NTU.

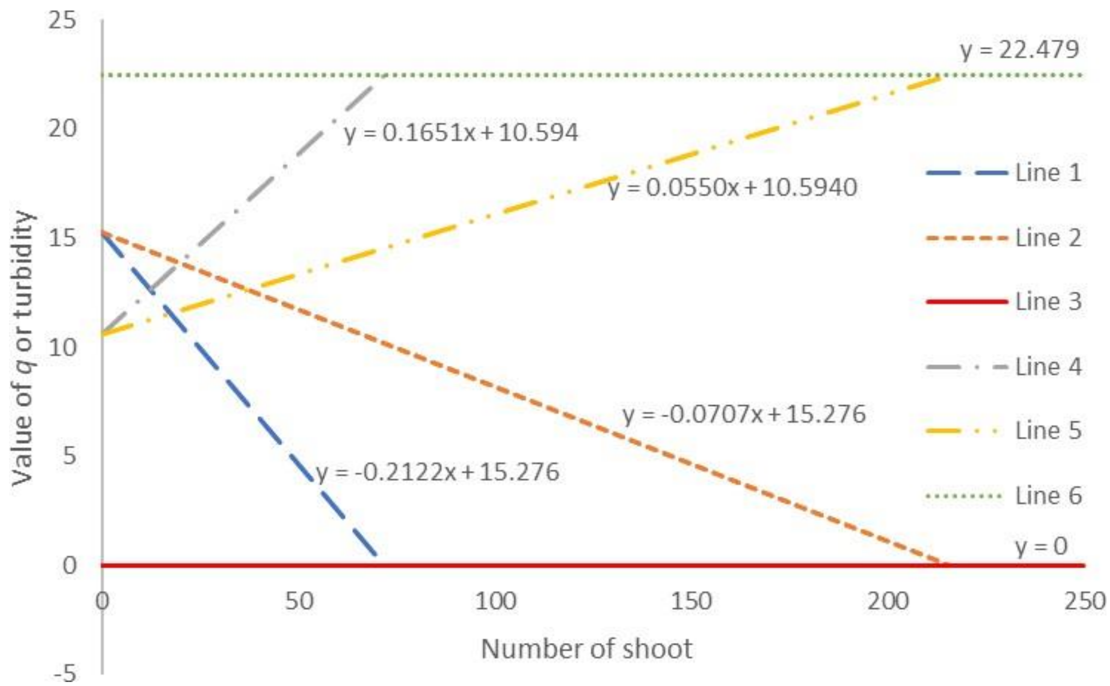

Figure 8. Rule-based classification base on linear regression slope.

Furthermore, using the rule-based classification algorithm to predict cooling system failure. The cooling system is categorized as run normally if it can operate more than or equal to 3 days, which is equivalent to 216 cycles (cycle time = 20 minutes). The cooling system is categorized as requiring minor maintenance if it can operate more than or equal to 1 day. It is equivalent to 72 cycles. The *q* value at the 0th shoot is assumed to be the average *q* value of 150 trials (15.276W). At the 0th shoot, the turbidity value is assumed to be the average turbidity value of 150 experiments (10.594NTU).

In Figure 8, Line 1-3 is a rule-based classification base on the total heat transfer rate. If the linear regression evaluation results of the *q* value are under the Line 1 area, it requires major maintenance. If the linear regression evaluation results of the *q* values between Line 1 and Line 2, it requires minor maintenance. If the linear regression evaluation results of the q values above Line 2, the cooling system runs normally. Line 3 is the minimum *q* value cooling system can still work. In Figure 8, Line 4-6 is a rule-based classification base on turbidity. If the linear regression evaluation results of the turbidity value are above the Line 4 area, it requires major maintenance. If the linear regression evaluation results of the turbidity values between Line 4 and Line 5, it requires minor maintenance. If the linear regression evaluation results of the turbidity value lower Line 5, the cooling system runs normally. Line 6 is the maximum turbidity value cooling system can still work (refer to equation 3).

In Figure 9, is a decision structure of rule-based classification by *q* slope. In Figure 10, it is a decision structure of rule-based classification by *NTU* slope. In Figure 11, it is a decision structure of rule-based classification by combinating slope. Deep cleaning is cleaning all cooling system components by draining the water in the hose, mold, heat exchanger, and water tank. Flushing water cooling is replacing the water in a water tank.

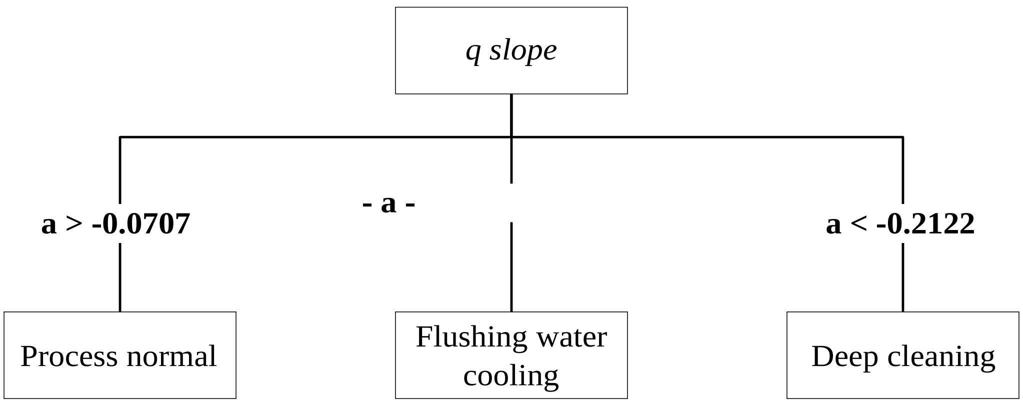

Figure 9. Decision structure of rule-based classification by *q* slope

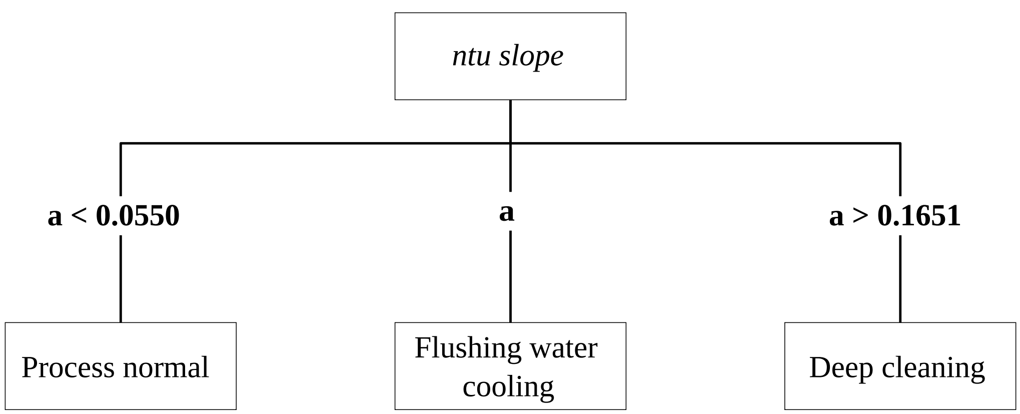

Figure 10. Decision structure of rule-based classification by *NTU* slope

Finally, a trial 150 data to compare the decision with temperature data, turbidity data and combinate data. Data comparison is shown in Table 2.

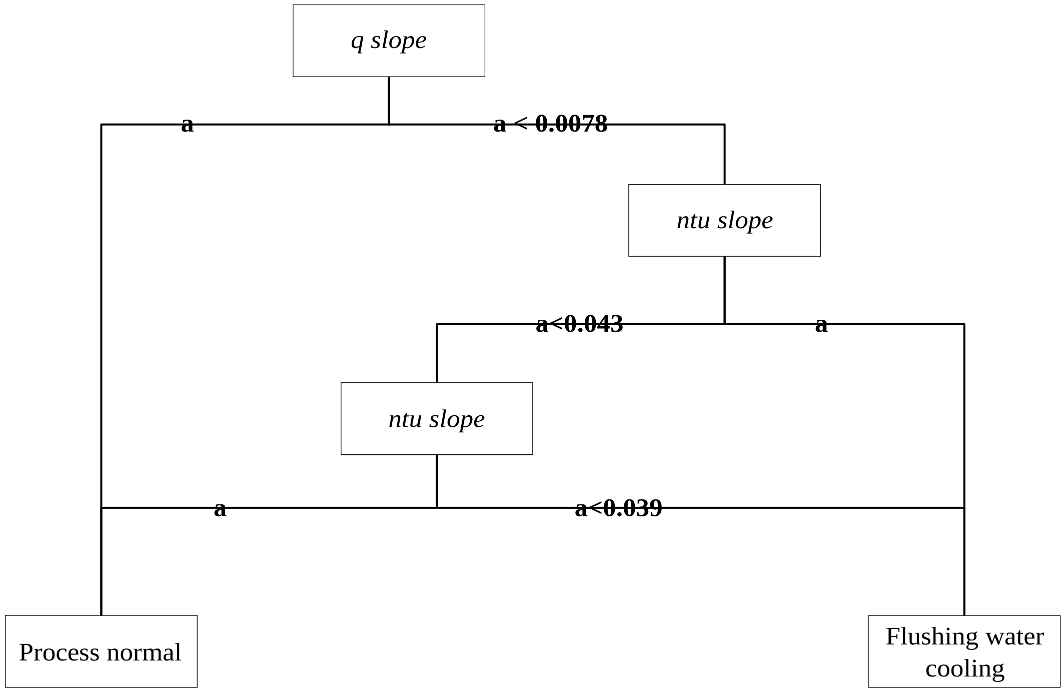

Figure 11. Decision structure of rule-based classification by combinating slope

Table 2. Comparative study of decision

Number of Cycle	Decision by			Y
	q	*NTU*	*combinate*	
10	flushing	flushing	flushing	flushing
11	flushing	flushing	flushing	flushing
12	flushing	flushing	flushing	flushing
13	flushing	normal	flushing	normal
14	flushing	normal	flushing	normal
15	normal	normal	normal	normal
16	normal	normal	normal	normal
17	normal	normal	normal	normal
18	normal	normal	normal	normal
19	normal	normal	normal	normal
…				
141	normal	normal	normal	normal
142	normal	normal	normal	normal
143	normal	normal	normal	normal
144	flushing	normal	normal	flushing
145	flushing	normal	normal	flushing
146	normal	normal	normal	normal
147	flushing	normal	flushing	flushing

Number of Cycle	Decision by			Y
	q	*NTU*	*combinate*	
148	normal	normal	flushing	normal
149	flushing	flushing	flushing	flushing
150	flushing	flushing	flushing	flushing

Refers to Table 3 Over judgment is when the predictive maintenance system decision states the system requires maintenance even though its actual state is in good condition. Miss judgment is when the predictive maintenance system decision says the system is in good condition even though the real condition requires maintenance. Match judgment is a condition when the predictive maintenance decisions match the actual conditions.

Table 3. Decision Tabulation Matrix

Judgement	Decision by		
	q	*NTU*	*combinate*
Over	16(11%)	2(1%)	13(9%)
Miss	0	28(20%)	0
Match	125(89%)	111(79%)	128(91%)

5. CONCLUSIONS

This paper discusses the combination of using sensors as a basis for predictive maintenance. Based on an experiment of 150 cycles, using a combination of sensors can better improve failure prediction so that it can reduce the potential for unplanned system failure. When used total heat transfer rate *(q)* to predict unplanned system failure, the prediction accuracy is 89%, then when used turbidity (NTU), the prediction accuracy is 79%. However, when used combination q and NTU data, the prediction accuracy increase to 91%. Furthermore, these research results are effortless in calculation and cost but powerful enough to predict unplanned system failure for manufacturing industry applications.

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