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ORIGINAL ARTICLE

A predictive maintenance approach based on real-time internal parameter monitoring

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Abstract Since continuous real-time components or equipment condition monitoring is not available for injection molding machines, we propose a predictive maintenance approach that uses injection molding process parameters instead of machine components to evaluate the condition of equipment. In the proposed approach, maintenance decisions are made based on the statistical process control technique with real-time data monitoring of injection molding process parameters. First, machine components or equipment of injection molding machines, which require maintenance, is identified and then injection molding process parameters, which may be affected by malfunctioning of the previously identified components, are identified. Second, regression analysis is performed to select the process parameters that significantly affect the quality of the lens and require a high degree of attention. By analyzing the patterns of real-time monitored data series of process parameters, we can diagnose the status of the components or equipment because the process parameters are affected by machine components or equipment. Third, statistical predictive models for the selected process parameters are developed to apply statistical analysis techniques to the monitored data series of parameters, in order to identify abnormal trends. Fourth, when abnormal trends or patterns are found based on statistical process control techniques, maintenance information for related components or equipment is notified to maintenance workers. Finally, a prototype system is developed to show feasibility in a LabVIEW® environment and an experiment is performed to validate the proposed approach.

Keywords Predictive maintenance · Statistical process control · Real-time monitoring · Internal parameter-based diagnosis

1 Background

As manufacturers want to be competitive in the dynamically changing market, they are putting a lot of effort into increasing the efficiency of production systems, which is partially achieved by decreasing unplanned operation stops. The competitiveness of production systems is affected by their maintenance procedures as well as maintenance design and operation [1]. More than 30 % of the maintenance costs are caused by misplaced maintenance schedules, which lead to unnecessary production costs [2]. In particular, in the injection molding production line of phone camera lenses, unexpected stops may cause a waste of expensive raw material which remains in nozzle or screw zones. Therefore, manufacturers are more interested in exact maintenance scheduling to maintain smooth operation and prevent unexpected stops.

Maintenance is defined as restoring systems or products to their desired operational status or taking all available measures to keep them at the desired operational status [1]. Generally,

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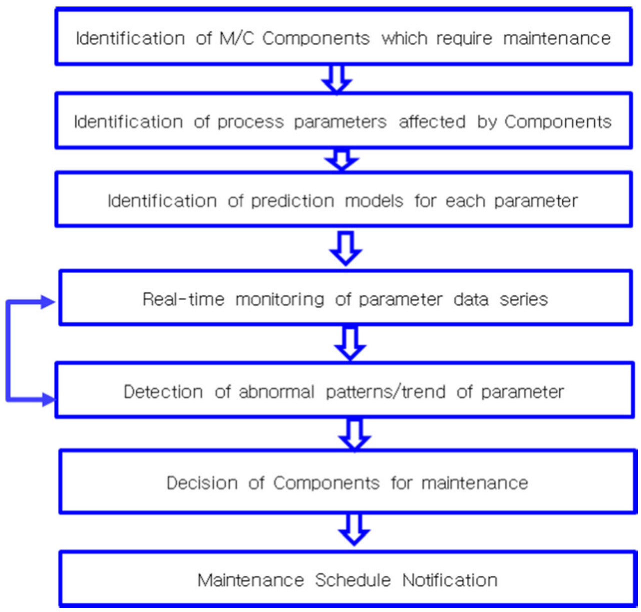

Fig. 1 Predictive maintenance approach procedure

maintenance can be classified into three categories: corrective, preventive, and predictive maintenance (also known as condition-based maintenance (CBM)) according to ISO standards [1, 3, 4]. Corrective maintenance is defined as restoring equipment or parts of equipment to operational status when systems are out of order or parts are malfunctioning. Corrective maintenance may cause high risk in maintenance scheduling and performing because it does not consider adequate maintenance moment unlike preventive or predictive maintenance [5, 6]. Preventive maintenance is defined as scheduling all planned maintenance activities to prevent malfunction or failure and keeping equipment in the desired operational condition. A lot of research has been spent on the preventive maintenance approach. Lee and Ni proposed a decision-making architecture to determine maintenance and product dispatching policies based on both condition monitoring and the dynamic relationship between machine degradation and associated product quality [7]. Their approach premises that real-time product quality can be obtained. Therefore, their approach may not be applied to manufacturing processes without real-time product quality monitoring. Predictive maintenance, also known as condition-based maintenance, attempts to evaluate the condition of equipment by performing periodic or continuous real-time equipment condition monitoring. The ultimate goal of predictive maintenance is to

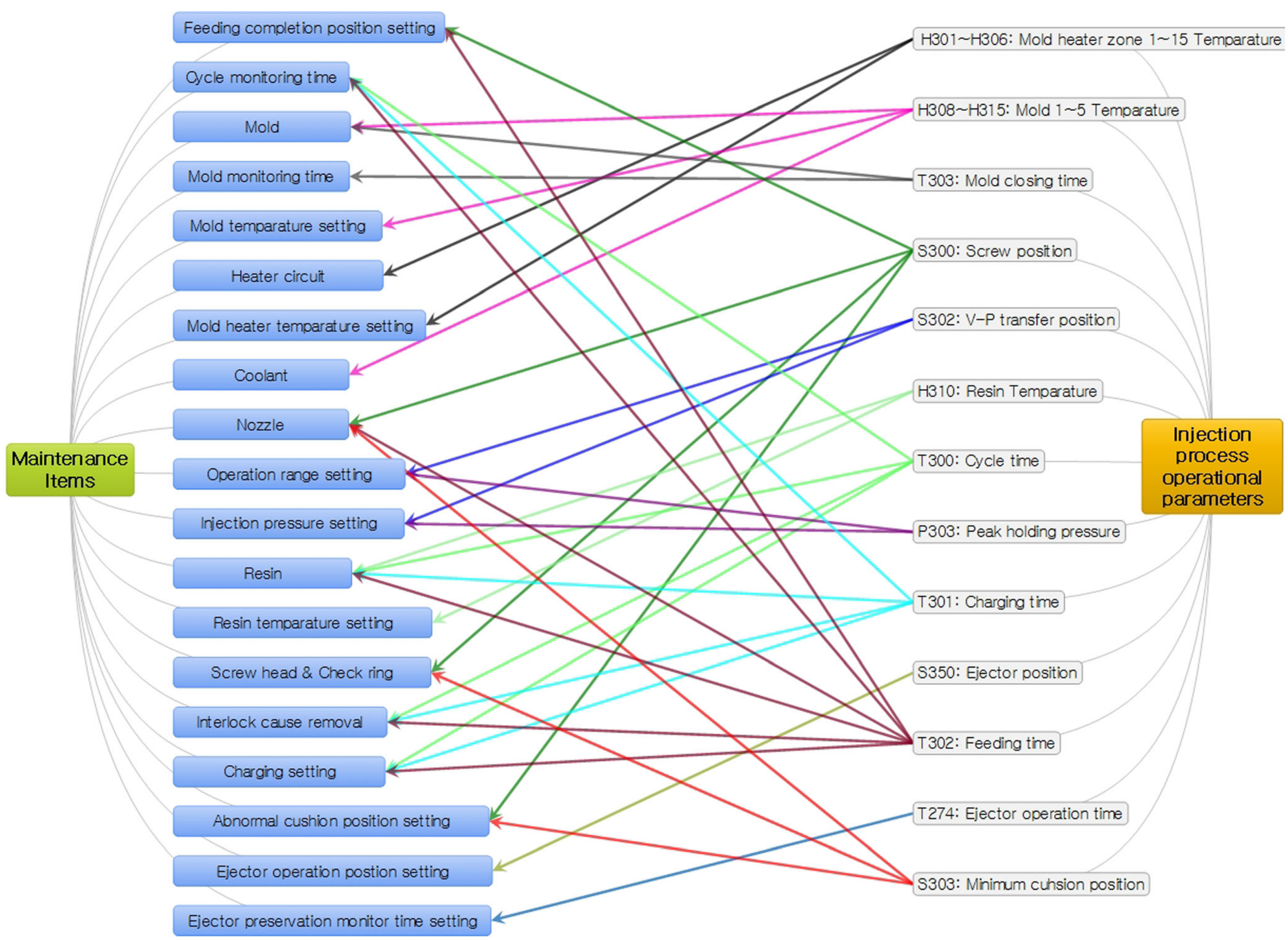

Fig. 2 Relationship between maintenance components and process parameters

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Regression Analysis: C4(Bottom) versus T302, S302, ...

The regression equation is
C4(Bottom) = 2843 - 4.78 T302 - 32.6 S302 + 12.0 S303 + 0.0621 P303 - 1.45 S300
             - 12.2 H301 + 11.5 T300

Predictor      Coef   SE Coef       T      P
Constant     2842.5     193.3   14.71  0.005
T302        -4.7783    0.3080  -15.52  0.004
S302        -32.631     1.948  -16.75  0.004
S303         12.012     1.625    7.39  0.018
P303       0.062090  0.009270    6.70  0.022
S300        -1.4471    0.1720   -8.41  0.014
H301       -12.2391    0.7994  -15.31  0.004
T300         11.529     1.137   10.14  0.010

S = 0.0634356   R-Sq = 99.8%   R-Sq(adj) = 99.1%

Analysis of Variance

Source          DF       SS       MS       F      P
Regression       7  4.23345  0.60478  150.29  0.007
Residual Error   2  0.00805  0.00402
Total            9  4.24150

Source  DF   Seq SS
T302     1  0.92094
S302     1  0.03940
S303     1  1.32352
P303     1  0.85988
S300     1  0.14630
H301     1  0.52976
T300     1  0.41363

Unusual Observations

Obs  T302  C4(Bottom)     Fit  SE Fit  Residual  St Resid
  1  6.28      0.3000  0.2980  0.0633    0.0020     0.52 X

X denotes an observation whose X value gives it large leverage.
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Fig. 3 Result of regression analysis with 13 parameters

perform maintenance at a scheduled point in time when the maintenance activity is most cost-effective and before the equipment loses performance within a threshold. Condition-based maintenance differs from preventive maintenance by basing the need for maintenance on the actual condition monitoring of the machine rather than on some pre-set schedule [8–12].

Operation stops and maintenance costs are significantly decreased by adopting a proper maintenance strategy [13]. As the corrective maintenance approach is generally adopted in the real-world field, it is accompanied by sudden operation stops and additional costs due to other parts being affected by sudden stops. Practically, it is impossible to prevent the malfunctioning of machines. Furthermore, this approach requires long-term or continuous monitoring and it cannot cover all of the machines or components that require maintenance. The status monitoring method, through visual inspection, is considered as standard and adopted by most companies. However, in practice, there are lots of cases where sensors or X-ray cannot be used to detect a machine's degree of degeneracy.

Predictive maintenance is attracting more interest than routine maintenance, which is performed when a machine fault occurs. The predictive maintenance techniques help determining the condition of in-service equipment or systems in order to predict when maintenance should be performed. Predictive maintenance allows convenient scheduling of corrective actions and prevents unexpected equipment stops. The key is the right information at the right time. By knowing which equipment or components need maintenance, maintenance work can be better planned, and what would have been unplanned stops are transformed to shorter and fewer planned stops, thus increasing equipment availability. This approach usually uses principles of statistical process control techniques to determine at what point in the future maintenance activities will be appropriate. To evaluate equipment condition, predictive maintenance utilizes nondestructive testing using sensors, vibration, sound level analysis, and other real-time tests. Generally, predictive maintenance includes procedures that monitor information about the machine status and plans the maintenance schedule accordingly [14–16]. Liao et al. [15] and Pan et al. [16] proposed a data-driven machinery prognostic approach for machine performance assessment and prediction. However, the real-time monitoring based on sensors is not always possible for every type of machine. For example, continuous real-time component or equipment condition monitoring is not available for injection molding machines.

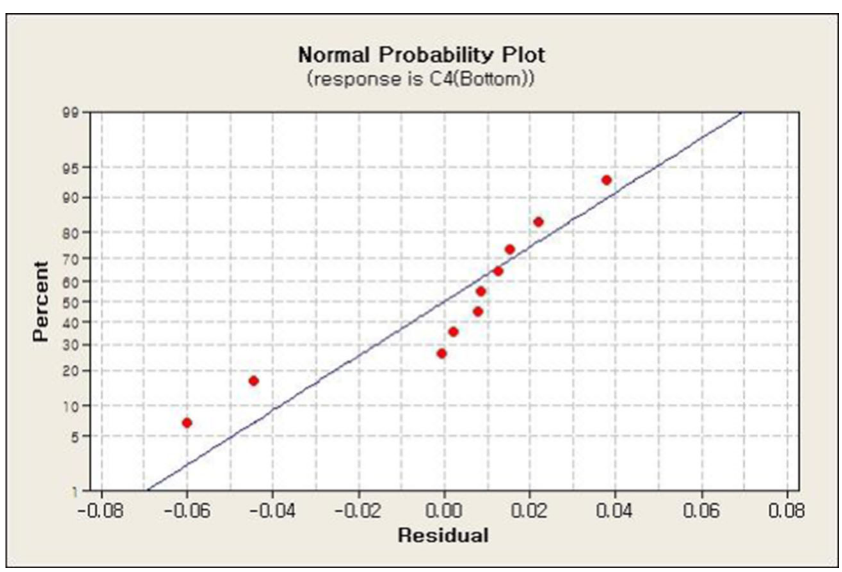


Fig. 4 Result of goodness-of-fit test of regression model with 13 parameters

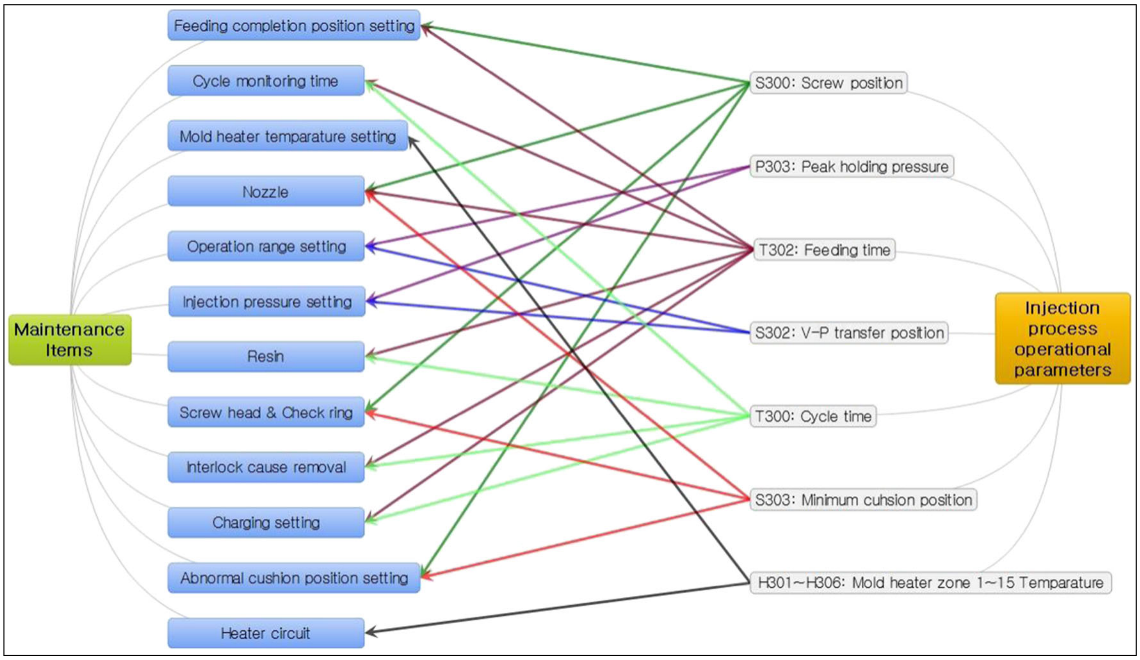


Fig. 5 Relationship between maintenance items and significant process parameters

Therefore, in this paper, we proposed a process parameter-based predictive maintenance approach which is performed on injection molding machines of phone camera lens production lines. First, we identified injection molding machine components or equipment and their related process parameters and then derived the influence relationship between the process parameters and machine components or equipment (many-to-many relationships). Second, we analyzed the process parameters data series using statistical analysis. In this analysis, we used the aspheric form accuracy of the lens as the response variable and process parameters as independent variables. From the analysis results, we identified the process parameters that do not significantly affect the response value and excluded them from the process parameter list for the predictive maintenance approach. Furthermore, we might assure that we can predict the status of the components or equipment by monitoring statistically significant process parameters and evaluating their trends or patterns. Third, we derived prediction models for significant process parameters. We used real-time monitored data series of process parameters for the prediction model. Fourth, we monitored the real-time data series of process parameters and evaluated them. We adopted Nelson rules which are used in statistical process control techniques to detect abnormal patterns or trends. Fifth, when abnormal patterns or trends of parameters are detected, the related components or equipment of the parameter are found by referring to the fault tree database and maintenance workers are notified. Finally, a prototype system was developed to show feasibility

Fig. 6 Part of *p* values for each rule and their combinations. **a** Set of *p* values for each rule with example *K*. **b** Set of overall *p* values for rule combination

Rule	K	P-value
Rule 1	4	0.0016129
	5	0.0002330
	6	0.0000034
Rule 2	9	0.0039063
	10	0.0019531
	11	0.0009766
Rule 3	5	0.0625000
	6	0.0312500
	7	0.0156250
	8	0.0078125
Rule 8	6	0.0048855
	7	0.0017722
	8	0.0006328
	9	0.0002232
	10	0.0000779

(a) Set of p-values for each rule with example K

K				Overall P-value
Rule 1	Rule 2	Rule 3	Rule 8	
4	7	5	6	0.0831382
4	7	5	7	0.0802697
4	7	5	8	0.0792199
4	7	5	9	0.0788425
4	7	5	10	0.0787087
4	7	6	6	0.0525761
4	7	6	7	0.0496120
4	7	6	8	0.0485273
4	7	6	9	0.0481373
4	7	6	10	0.0479990
4	7	7	6	0.0372951
4	7	7	7	0.0342832
4	7	7	8	0.0331809
4	7	7	9	0.0327847

(b) Set of overall p-values for rule combination

Fig. 7 Predictive maintenance notice

in a LabView® environment and an experiment was performed to validate our approach.

The remainder of the paper is organized as follows. In Section 2, a predictive maintenance approach is described. After an introduction to our approach, Section 3 describes the implemented prototype system and discusses research results. Finally, Section 4 concludes the paper by discussing limitations and suggestions for the proposed approach.

2 Predictive maintenance approach

In this paper, we propose a predictive maintenance approach for injection molding machines of a phone camera lens production line. The predictive maintenance procedure decides the maintenance point of time for components or equipment using real-time data series analysis of process parameter. Figure 1 shows the schematic procedure of our approach. At first, through a literature survey, we identified the components or equipment of injection molding machine that need a high degree of attention for maintenance, and their related injection molding process parameters, which are affected by machine components or equipment. Second, we used regression analysis to identify the parameters which significantly affect the quality of injection molding products. We used the aspheric form accuracy of the lens as a quality indicator and process parameters as independent variables. Through regression analysis, we selected the parameter set that significantly affects the response variable, that is, the aspheric form accuracy of the lens. This means that we can indirectly predict whether some components or equipment are malfunctioning or not by real-time monitoring of significant process parameters. Third,

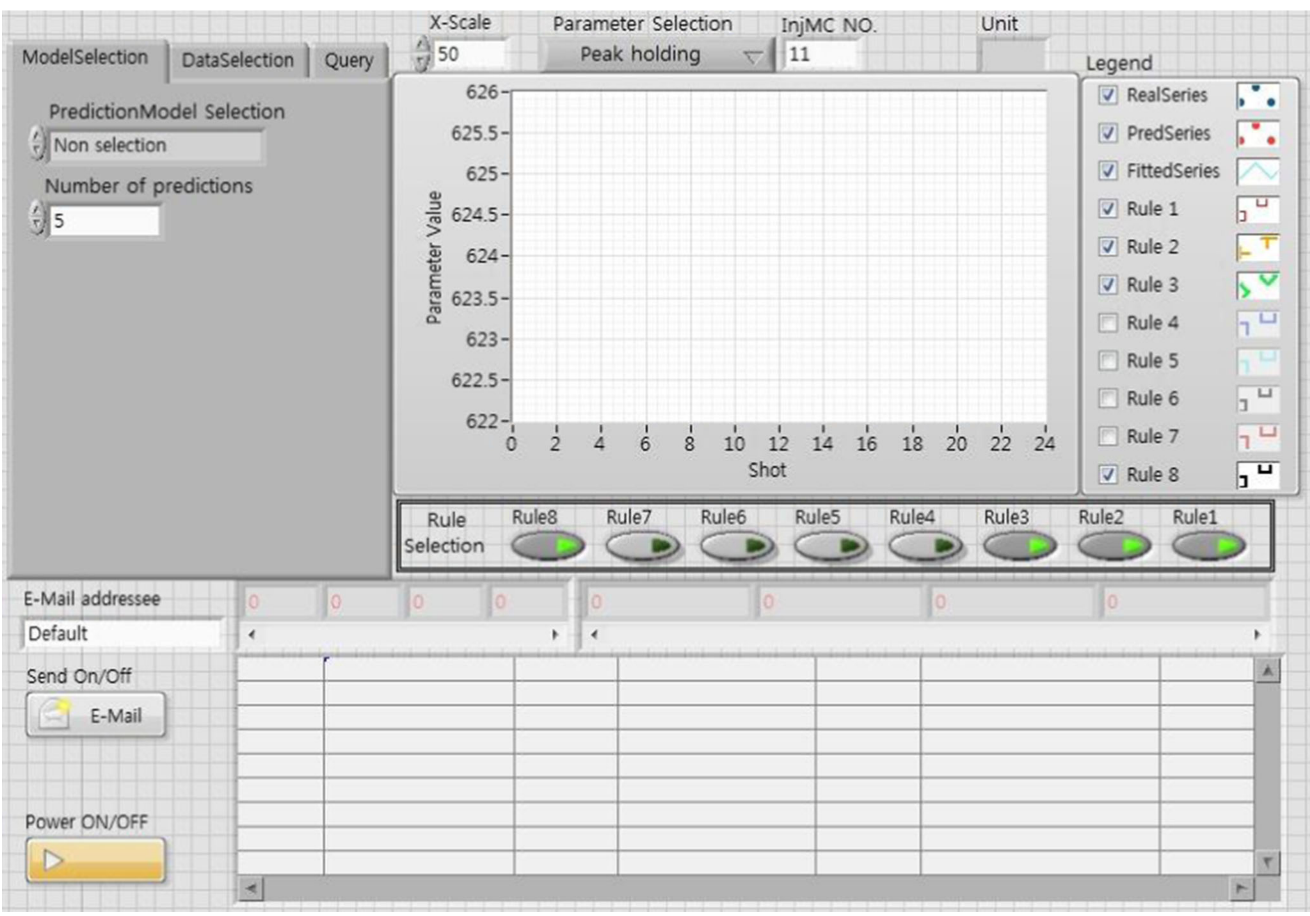


Fig. 8 Snapshot of implemented prototype system

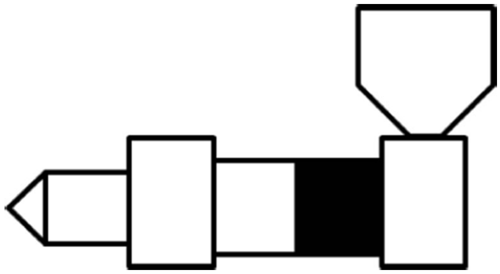


Fig. 9 Schematic representation of mold heater zone 1 of barrel component

we developed statistical time series models to predict the patterns of each parameter and to decide its maintenance point of time when abnormal patterns or trends are detected [17]. Finally, using the real-time monitored parameter data series and predicted values, we evaluate the trends or patterns against the Nelson rules [18]. When statistically abnormal patterns are detected, maintenance information is notified to maintenance workers by referring to the fault tree database for machine components or equipment. By referring to the fault tree database which can relate the parameters to equipment or components, we can identify the most probable target equipment or component on which to perform maintenance actions before severe fault occurs.

Table 1 Data series of mold heater zone 1

Shot	Parameter	Value date
0	250	2015-02-14, 16:01:141
1	250.1	2015-02-14, 16:01:442
2	250	2015-02-14, 16:02:146
3	250	2015-02-14, 16:02:451
4	250	2015-02-14, 16:03:153
5	250	2015-02-14, 16:03:454
6	250	2015-02-14, 16:04:157
7	250	2015-02-14, 16:04:461
8	250	2015-02-14, 16:05:163
9	249.6	2015-02-14, 16:05:469
10	247.7	2015-02-14, 16:06:172
11	245.3	2015-02-14, 16:06:474
12	243.3	2015-02-14, 16:07:180
13	242	2015-02-14, 16:07:482
14	240.7	2015-02-14, 16:08:186
15	240	2015-02-14, 16:09:490
16	239.75	2015-02-14, 16:10:194
17	239.5	2015-02-14, 16:10:492
18	238.6	2015-02-14, 16:11:198
19	238.2	2015-02-14, 16:11:501
20	237.65	2015-02-14, 16:12:202
21	236	2015-02-14, 16:12:508
22	234.05	2015-02-14, 16:13:207
23	232.1	2015-02-14, 16:13:512
24	230.9	2015-02-14, 16:14:211

2.1 Selection of significant parameters

Through a literature survey, we identified 13 parameters as candidate injection molding process parameters that may affect product quality. We also identified the related machine components or equipment that affect the parameter status and then derived the influence relationship between components and parameters from the maintenance manuals and literature survey. Figure 2 shows the relationship between 13 process parameters and their related maintenance items. Then, we performed regression analysis to determine the parameters that affect product quality. We used form error as the response variable and 13 parameters as independent variables. Figure 3 shows the result of regression analysis to select significant parameters, and Fig. 4 shows the result of the goodness-of-fit test for our regression model. The figures show that our regression model, which identified 7 significant parameters, was adequate. That is, 7 parameters—screw position ("S300" in the figure), peak holding pressure ("P303" in the figure), feeding time ("T302" in the figure), V-P transfer position ("S302" in the figure), cycle time ("T300" in the figure), minimum cushion quantity ("S303" in the figure), and mold heater zone ("H301"~"H306" in the figure)—were significant to our response variable, that is, form error, and we may predict the quality of the product by monitoring these process parameters. Figure 5 shows the reduced relationship between the 7 parameters and their related components or equipment. Therefore, we chose these 7 parameters as our monitoring parameters for the predictive maintenance model.

2.2 Predictive maintenance procedure

In the predictive maintenance model, to decide whether the patterns of the monitored data series are abnormal or not, we adopted Nelson rules, which are usually used in statistical process control techniques. Nelson rules are a method in statistical process control of determining if some measured process variables are out of control. The rules are applied to a control chart, one of the most famous statistical process control techniques, on which the magnitude of some process variable is plotted against the time axis. The rules are based around the mean value and standard deviation of the samples. Applying these rules indicates when a potential out-of-control situation has arisen. However, there will always be some false alerts and the more rules applied the more false alerts will occur. For some processes, it may be beneficial to omit one or more rules. Equally, there may be some missing alerts where some specific out-of-control situation is not detected. Empirically, the detection accuracy is known to be good [18–20].

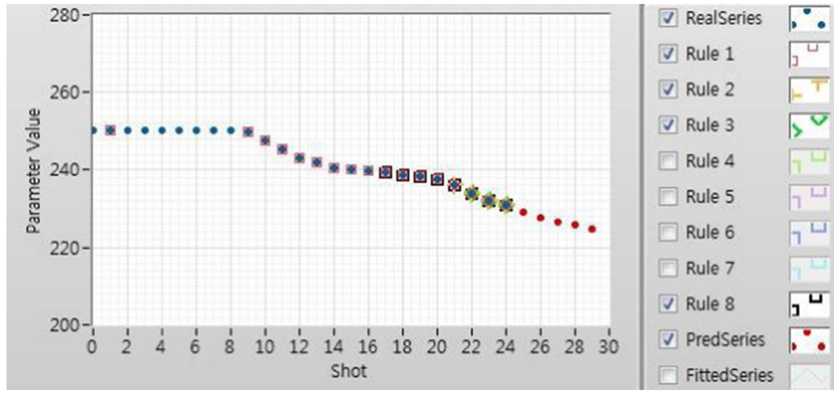


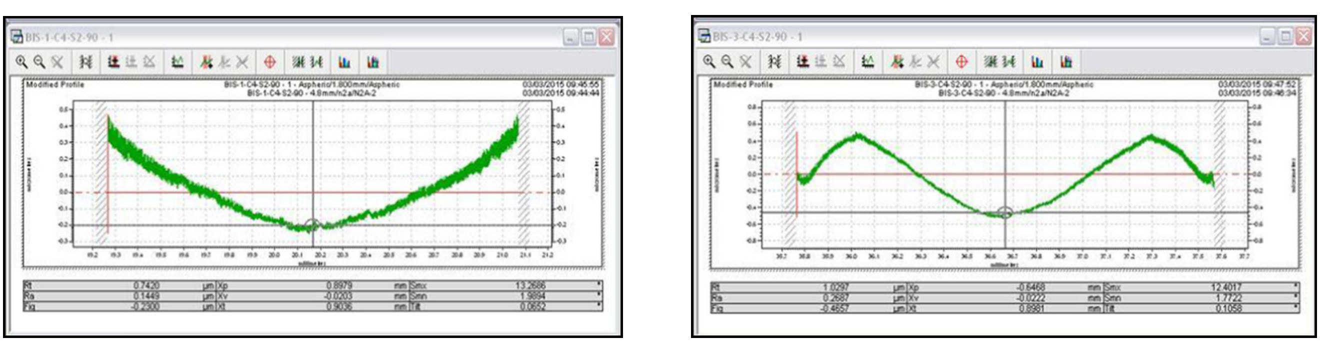
Fig. 10 Mold heater zone 1 in injection molding experiment

To use in our decision procedure for pattern abnormality, we selected four rules—rules 1, 2, 3, and 8—out of the eight Nelson rules set because these four rules were highly recommended for use in the detection of wear or breakdown of equipment or machine components [19]. To apply these four rules in our prediction model, we must choose the parameter K values (used as K sigma limits or K run length), which is used as the threshold in the rule criteria.

To choose parameter K values for each rule of the rule set, we must select a type I error value. In the statistical process control application, every organization provides a policy or direction that can define an allowable false alarm rate or type I error value in statistical terms. Figure 6 shows the set of p values for K values in each rule and their combinations of four rules. Therefore, for a given type I error value from the company's policy, we can select a rule combination to use in the detection of abnormal patterns of monitored or predicted data series in our predictive models. In fact, since the predicted data series are inherently smoothed, rules other than rule 1 are meaningless for predicted data series and, therefore, we only apply rule 1 to detect those falling outside K sigma limits for the predicted data series and four rules for the detection of abnormal patterns in the monitored real data series. When an abnormal pattern is detected in data series of any process parameter, we can identify the maintenance items by referring to the relationship shown in Fig. 5. From the relationship information and fault tree database, the target maintenance items are prioritized and maintenance notices are automatically sent to maintenance workers, as shown in Fig. 7.

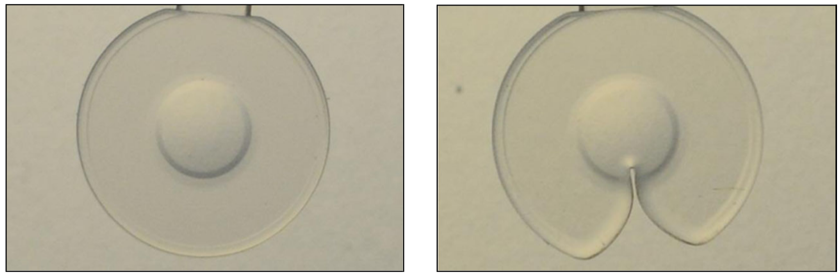
3 Prototype system of predictive maintenance model

In this paper, a prototype system is developed to demonstrate the feasibility of the proposed approach and validate it. The prototype system is implemented using a LabView® and SQL Server environment. Figure 8 shows the snapshot of the prototype system. On the top left side is the predictive model selection menu with which users can select the statistical prediction model. Users can compare the prediction models with mean-squared error (MSE) criteria and select an adequate model to use in the system. Currently, a few models, such as various regression and exponential smoothing models, have been implemented. At the top middle, users can select the injection machine and process parameter to which the prediction model is to be applied and maintenance is performed. On the right side, there is a legend option menu where users can select items that will be shown in the display panel in the middle area. In the middle of the window, there are rule set buttons with which users can select the rule set to apply in the predictive model. At the bottom list box area, abnormality status information such as injection shot number, time, parameter, maintenance information, etc., is described when they are detected.



(a) well-formed lens (b) deformed lens

Fig. 11 Result of FTS measurement of the aspheric area of lenses. **a** Well-formed lens. **b** Deformed lens



(a) well-formed lens (b) deformed lens

Fig. 12 Photos of an acceptable lens and deformed lens. **a** Well-formed lens. **b** Deformed lens

To demonstrate our approach's feasibility and validate it, we performed an experiment using a phone camera lens injection molding machine. The injection molding cycle begins when the mold closes, followed by injection of the resin into the mold cavity through a nozzle. For the resin to flow through the nozzle, the raw material must be heated and melted. Once the mold cavity is filled with the melted resin, a holding pressure is maintained to compensate for material shrinkage. In the next step, the screw turns, feeding the next shot to the front screw. This causes the screw to retract as the next shot is prepared. Once the product is sufficiently cool, the mold opens and the product is ejected. Without proper operation of the mold heater zone areas, the raw material cannot smoothly flow into the mold cavity and form as the target product [21]. In the test experiment, we selected mold heater zone temperature (H301 in Fig. 5) as the target injection molding process parameter. Figure 9 shows the schematic representation of the heater zones of an injection machine nozzle. The shaded area is mold heater zone 1. Maintenance items such as "mold heater temperature setting" and "heater circuit" affect the heater zone temperature parameter, as shown in Fig. 5. We selected exponential smoothing as the prediction model for heater zone temperature.

The injection molding machine for this experiment is the 30-ton Sumitomo model (SE30DUZ) which is used to produce phone camera lenses. For the lenses, the machine used EP-5000 resin for the injection molding. We performed test injection molding with an intentionally broken heater circuit during injection molding. We collected the mold heater zone temperature data using our developed injection molding machine controller interface application. The data series of the mold heater zone 1 parameter is monitored with our controller application. The data series for mold heater zone 1 collected in the experiment is shown in Table 1. The first column shows the injection shot number, the second column shows the zone 1 temperature, and the third column shows the point of time of the experiment injection molding.

The monitored data series represented in Table 1 is collected and inserted into the implemented database and simultaneously plotted on the middle display panel, as shown in

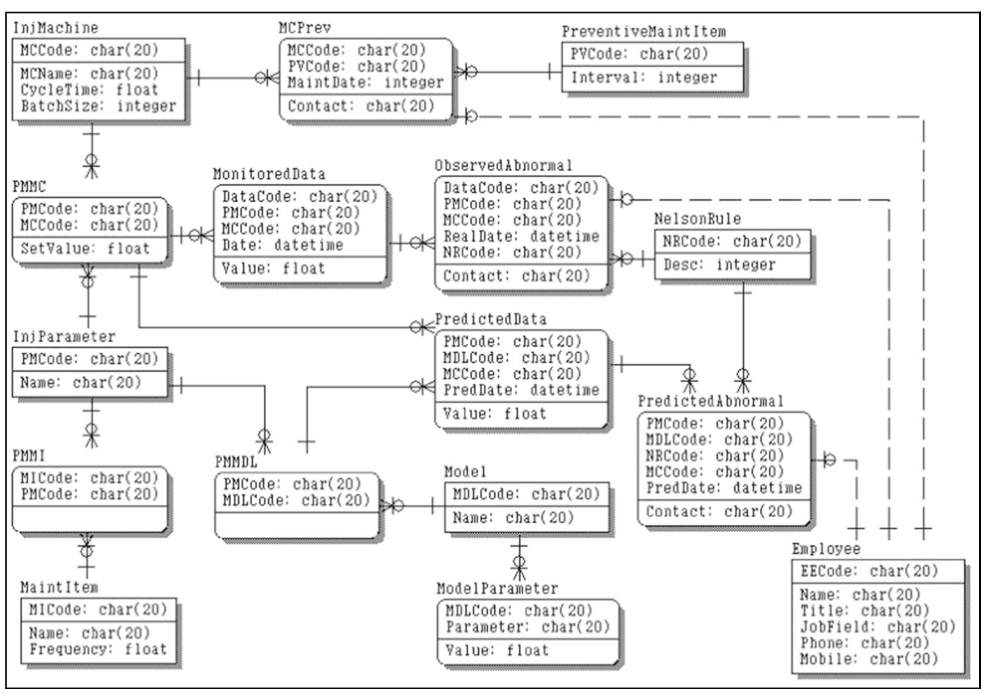


Fig. 13 Snapshot of the database design for proactive maintenance

Fig. 10. Whenever new shot information is inserted, the patterns, which are formed from recent data series (based on the number of K values), are evaluated against the selected rule set and the abnormality results are displayed in the middle display panel if there is any rule violation by the data series.

In our example, as the user selected “rule 1,” “rule 2,” “rule 3,” “rule 8,” “RealSeries,” and “PredSeries” using the legend option menu, the rule evaluation results and predicted data series are shown in the middle display panel. The blue circles without any other shape (shots 0 and 2 through 8) indicate that they were normal injection molding shots, and the red circles represented in shots 25 through 29 show the fitted data series. The points in the red squares (shots 1 and 9 through 24), yellow diamonds (shots 21 through 24), green diamonds (shots 22 through 24), and black squares (shots 17 through 24) indicate that they are violating rules 1, 2, 3, and 8, respectively. This means that the previous designated points are violating presumed randomness. Therefore, the related maintenance items or components, the mold heater circuit or mold heater temperature setting of zone 1, must be notified to examine whether it works properly or not, as shown in Fig. 7. In Fig. 7, the frequency of the heater circuit is 2 while the frequency of the mold heater temperature setting is zero. This means that the maintenance worker must check the heater circuit first and then the mold heater temperature setting status.

Figure 11 shows the sample results for the Form Talysurf (FTS) measurement system, which is used to check the surface roughness and straightness of form of the aspheric area of a lens. The figure shows that the center area of a well-shaped lens is in aspheric form, but the center area of a badly shaped lens is not in aspheric form. Figure 12 shows the sample photos of an acceptable well-shaped lens, which was molded under good heater zone temperature conditions, and a deformed lens, which was molded under abnormally low heater zone temperature conditions caused by a broken heater circuit.

To manage maintenance information such as maintenance history, relationships between process parameters and their related components or equipment, fault tree information, etc., we developed a maintenance support database. Figure 13 shows the part of the database schema designed for our maintenance support system. It includes the required entities for a predictive maintenance system.

4 Conclusion

This paper proposed a predictive maintenance approach for an injection molding process. In the paper, because continuous real-time equipment condition monitoring is not available for injection molding machines, we propose a predictive maintenance approach that uses injection molding process parameters to evaluate equipment condition. First, to provide comprehensive support, the paper identified all possible maintenance components or equipment based on a literature survey. Second, the injection molding process parameters that are affected by malfunctioning of components or equipment were identified. To identify process parameters that significantly affect the quality of the lens, we performed regression analysis. Third, we identified influence relationships between process parameters and machine components or equipment through a literature survey. Fourth, we developed statistical predictive models for the process parameters that will be used to detect abnormalities in data series patterns. Finally, we developed a prototype system for a predictive maintenance approach using an experimental example to demonstrate how predictive maintenance can be effectively managed and to validate our approach. The proposed approach can also be applied to similar manufacturing machines.

Further research issues include applying more prediction models such as neural network or SVM. Furthermore, for maintenance items that are not covered by predictive maintenance, a preventive maintenance approach can be additionally applied based on the checking period of maintenance components or equipment.

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