Product quality driven auto-prognostics: low-cost digital solution for SMEs

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Product Quality Driven Auto-Prognostics: Low-Cost Digital Solution for SMEs

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Abstract: Setting out existing prognostics solutions in small and medium enterprises (SMEs) is accompanied by challenges. These include employing expensive sensors, acquisition systems; and attending geometric limitations. Additionally, these solutions call for a specialist to take on feature engineering, machine learning algorithm selection, etc. Presented in this paper is a low-cost digital solution (intelligently integrate cost-cutting off-the-shelf technologies) for SMEs via product quality driven auto-prognostics. First, we develop upon existing solutions by addressing their drawbacks viz. cost, geometric limitations via a new product quality-centered condition monitoring strategy. Every SME must investigate the quality of their products, and therefore the authors believe this to be a low-cost solution. Next, the proposed solution integrates automated machine learning via Auto-WEKA, an off-the-shelf open-source technology. Lastly, the practical advantages of the proposed solution over the existing sensor-based solution were investigated via a case study. Results depict that this low-cost prognostics solution is vital for maintenance planning in SMEs.

Keywords: Prognostics, quality, digital manufacturing, low-cost solutions, automated machine learning.

1. INTRODUCTION

Prognostics offers comprehensive solutions for achieving competitive advantages in the global market by improving reliability, maintainability, and safety of the industrial assets. Thus, close attention is paid towards the advancement in prognostics for manufacturing. For instance, Jain and Lad (2016) developed an efficient prognostics model coupled with feedforward backpropagation neural network, multi-sensor fusion viz. dynamometers, accelerometers, etc., and complex feature screening. Nevertheless, it requires expensive sensors to be installed on the machine, which makes it inconvenient. Marinescu and Axinte (2008) showed that the dynamometer is costly and the use of any monitoring technique adds extra cost to the manufacturer. A methodology for condition monitoring (CM) data collection without the use of sensor will be more convenient for SMEs; which is not reported in the literature.

Chen et al., (2018) applied a deep belief network to the prediction of life with multiple signals and compared support vector regression and artificial neural networks for prediction. An analytical investigation suggested that the deep belief network achieved excellent performance in terms of accuracy, stability, and speed. Palau et al., (2019) presented a novel prognostics methodology. Herein, the information obtained through sensors is synthesized into a complex index of current condition of the asset. Bukkapatnam et al., (2019) introduced mathematically complex nonparametric learning approach for prognostics. From these; it is observed that feature engineering, selection of the best machine learning algorithm and its optimal hyperparameters is crucial and requires core predictive

analytics skills. Vogl et al., (2019) presented a review of prognostic capabilities and best practices for manufacturing. It is witnessed that there is a substantial body of knowledge in this area, and it is mostly focused on relatively expensive solutions that are often unaffordable to small and medium enterprises (SMEs). Herein, the two key challenges identified are:

a) The available prognostics solutions utilize high-end sensors viz. dynamometer, accelerometer, etc. and data acquisition systems for condition monitoring data collection. These equipment are not just expensive but often come with geometric restrictions and therefore require changes in the existing system. For prognostics solutions to be applicable in SMEs; the need is to have a new CM strategy that successfully attempts to develop upon existing solutions by addressing their drawbacks like, cost, system rigidity, geometric limitations, etc.

b) Mostly, the available prognostics solutions involve complex data preprocessing, feature engineering, best machine learning model selection, hyper-parameter optimization, and implementation on a deployable platform. These tasks require highly skilled and expensive personnel as well as licensed software solutions to do these activities. Herein, SMEs need an open-source off-the-shelf technology where non-expert users can do all these activities efficiently.

In essence, the broader challenge is to introduce end-to-end, low-cost, and off-the-shelf open-source prognostics solutions in a sector characterized by limited capital investment and research potential. Accordingly, this paper concerns the

development of a low-cost digital solution to address this via new product quality driven auto-prognostics.

First, we develop on standing solutions by addressing their shortcomings viz. cost, system inflexibility, geometric limits, etc. via a new product quality-centered condition monitoring strategy. The rationale being that every SME records this for quality control and that it can be measured with a relatively inexpensive portable measurement system. Next, the proposed solution integrates automated machine learning via Auto-WEKA, an off-the-shelf open-source technology. More specifically, given a prognostics dataset, the proposed solution explores the best feature subset, hyper-parameter settings for many algorithms, and recommends to a non-expert user which method will likely have excellent generalization performance, using model-based optimization techniques, and hence to achieve improved prognostics. This product quality driven auto-prognostics is key for planning and decision making in an operational setting for SMEs.

The novelty is in the conceptualization and development of an end-to-end, low-cost, and off-the-shelf open-source digital solution for SMEs. This solution allows a reliable life prediction of the asset with just a simple product quality measurement and can be easily deployed and operated by a non-expert user. An added contribution lies in the outcomes; the practicability of the proposed solution over the existing sensor-based solution was investigated via a case study. Promising results depict that this low-cost digital solution is vital for maintenance planning in SMEs.

2. LOW-COST DIGITAL SOLUTION

The developed solution seeks to exploit low-cost equipment and open-source technologies for sensing and machine learning. The details of the proposed end-to-end, low-cost, and off-the-shelf open-source prognostics solution for SMEs are given in the following sub-sections.

2.1 New product quality-centered condition monitoring

Condition monitoring is a systematic process of health condition data collection for the evaluation of the asset's performance. In practice, sensors, namely, dynamometer (Jain and Lad 2015, Jain et al., 2019); accelerometers (Azeem et al., 2019); acoustic emission (Nasir et al., 2019), multi-senor fusion (Jain and Lad 2016), etc. are installed to gauge the health of the system. These sensors provide vital information for making important decisions affecting manufacturing operations. However, these sensors are not just expensive but come with several issues like cost, system inflexibility, geometric limits etc. Thus, the intention is to come up with a CM approach that eliminate these shortcomings.

On the other hand, in literature, few analytical investigations (Jain and Lad 2017, Sezer et al., 2018, Jain and Lad 2019) concludes that correlation subsists in the middle of quality and asset degradation. Thus, in our strategy, we aim to utilize the product quality information to represent the condition of the system. The primary rationale being that every SMEs collect this for quality control and that it can be measured

with a relatively inexpensive portable measurement system. Accordingly, the new product quality-centered condition monitoring strategy without the use of expensive sensors is suitable for SMEs. In product quality-centered condition monitoring, the product quality can take any form viz. surface roughness, dimensions, etc. depending upon the application or product. Furthermore, it can be measured by any inexpensive portable quality measurement equipment. Accordingly, during the CM data collection phase, product quality is measured from the beginning of the operation, and till the failure of the system. This enables run-to-failure data generation centered on product quality. This product quality-centered CM data is then used to map the relationship between product quality and failure via training the prognostics model. In the real environment, the trained prognostics model will be used for the remaining useful life (RUL) prediction.

2.2 Auto-prognostics

Prognostics is the prediction of the remaining useful life of the asset based on its current condition. Much work is done in literature towards the development of novel solutions for prognostics (Vogl et al., 2019). In these solutions, users need to make several kinds of choices viz. feature screening, choosing a modelling algorithm, and tailoring its hyperparameters; it is thought-provoking to make the right choice. Thus, proper execution of prognostics model call for a specialist to take on data preprocessing, feature engineering, machine learning algorithm selection, hyper-parameter optimization, and execution on a deployable platform. Herein, SMEs need an open-source off-the-shelf solution where non-expert users can do all these activities efficiently. Accordingly, the proposed solution integrates automated machine learning via Auto-WEKA, an off-the-shelf open-source technology.

In auto-prognostics, data preprocessing, feature engineering, machine learning algorithm selection, hyper-parameter optimization is done automatically by leveraging Bayesian optimization. Herein, the solution uses the sequential model-based algorithm configuration optimizer to solve the combined algorithm selection and hyperparameter optimization via Auto-WEKA (Thornton et al., 2013, Kotthoff et al., 2017, Kotthoff et al., 2019). Source code: https://github.com/automl/autoweka. More specifically, given a prognostics dataset, the proposed solution explores the best feature subset, hyper-parameter settings for many algorithms, and recommends to a non-expert user which method will likely have excellent generalization performance to achieve improved prognostics.

3. RESULTS AND DISCUSSION

The practicability of the proposed solution is investigated via a case study from the manufacturing environment.

3.1 Case study

A scenario from the manufacturing environment on the subject of prognostics of the CNC milling cutters is considered. In general, prognostics of CNC milling cutters is carried out by installing a dynamometer with fixtures, acquisition systems, and doing complex cutting force analysis (Marinescu and Axinte 2008, Vogl et al., 2019). In this case study, we show how the proposed low-cost digital solution can be applied for prognostics. Figure 1 illustrates the new product quality-centered condition monitoring strategy for the scenario, as mentioned above. Herein, a 6mm diameter CNC milling cutter performing face milling operation to generate a flat surface (mild steel workpiece; 165 × 100mm) with set operating condition; feed = 300mm/min, speed =1000RPM, depth of cut = 0.25mm, is used for the investigation. Six run-to-failure experiments were executed. Quality of finished product in terms of surface roughness was measured using an inexpensive portable surface finish measuring instrument (HANDYSURF E-25A/B). This unit is portable and gives quick results. The pick-up and driver unit can be used for measurement in any position viz. horizontal surfaces, vertical, sloping and ceiling surfaces. To make an in-depth analysis of product quality eighteen surface roughness parameters (in micrometer) are calculated according to ISO '97 / JIS '01 / DIN, table 1 gives the list of measured parameters. These parameters provide a more informative signature to characterize the health condition. The workpiece surface roughness was measured whenever a new layer was cut; after every 1320mm of machining distance. The measurements are carried out with a measuring length of 4mm and cut off length of 0.8mm. Parameters values were read from five equally divided regions of the finished surface. Each of the values of the parameters was repeated five times and the average of these readings was recorded as the final value.

In this new product quality-centered condition monitoring strategy, no sensor or fixture is installed on the machining system. Similarly, the surface finish measuring instrument is not need to be mounted on the machining system and is set aside separately avoiding geometric limitations.
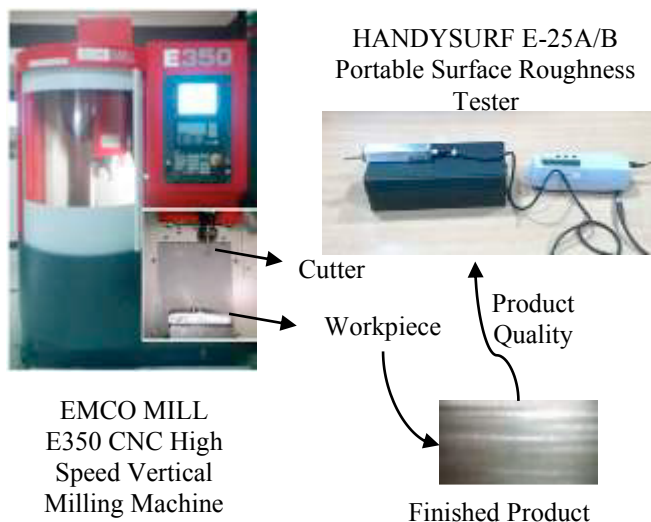

Fig. 1. New product quality-centered condition monitoring.

3.2 Auto-prognostics: performance assessment

In general, given a prognostics dataset, the user needs to select the optimal subset of features intelligently. Then, select the best machine learning algorithm and its optimal hyperparameter setting which maps the relationship between health condition and failure. This is a complicated and predictive analytics skill-driven task. Auto-Prognostics aid SMEs non-expert users in these analytics tasks. Herein, given a prognostics dataset, the proposed solution explores the best feature subset, hyper-parameter settings for many algorithms, and recommends to a non-expert user which method will likely have excellent generalization performance to achieve improved prognostics.

The new product quality-centered condition monitoring strategy helps SMEs generate the required prognostics dataset. Herein, the run-to-failure data of six milling cutters (333 samples) with eighteen roughness parameters and time as additional feature is used to generate the required prognostics dataset. Then, Auto-Prognostics automatically determine the best prognostics model and its parameters. As a final point, the chosen prognostics model can be used as follows:

```
AttributeSelection as = new
AttributeSelection();

ASSearch asSearch =
ASSearch.forName("weka.attributeSelection
.GreedyStepwise", new String[]{"-B", "-
N", "886"});
as.setSearch(asSearch);
ASEvaluation asEval =
ASEvaluation.forName("weka.attributeSelec
tion.CfsSubsetEval", new String[]{"-M"});
as.setEvaluator(asEval);
as.SelectAttributes(instances);
instances =
as.reduceDimensionality(instances);
Classifier classifier =
AbstractClassifier.forName("weka.classifi
ers.meta.AttributeSelectedClassifier",
new String[]{"-S",
"weka.attributeSelection.BestFirst", "-
E",
"weka.attributeSelection.CfsSubsetEval",
"-W", "weka.classifiers.lazy.IBk", "--",
"-K", "2", "-X", "-I"});
classifier.buildClassifier(instances);
```

The performance of this prognostics model derived via Auto-Prognostics was investigated to distinguish its suitability, stability, quality, reliability, applicability, robustness, and comprehensibility in a manufacturing scenario. Table 2 gives details of the implementation results achieved from Auto-Prognostics. Herein, the suitability of the results of the prognostic is gauged in terms of mean absolute error, mean absolute logarithmic error, and root mean square logarithmic error. These metrics measure how the model makes close RUL predictions to the actual RUL. Metrics values as low as 0.3 displays prediction is near to the actual RUL,

summarizing the suitability of the model. Next, the stability of the results of the prognostic is gauged in terms of relative absolute error and root-relative absolute error. These metrics measure the variance in the predictions. Metrics values as low as 3% shows the lower variance in prediction.

Likewise, the quality of predicted RUL in the relation of actual RUL is recognized in terms of the correlation coefficient, Kendall's tau, and Spearman's rho. Metrics values of almost 1, shows that predicted RULs are having a strong positive relationship with the actual RULs. As well, the reliability of predictions is high depicted by the lower root mean squared error. The training time (for the model that is tested) of just 0.005 seconds depicts the applicability of the model in a real environment. Lastly, robustness is measured by evaluating the model via 10-fold cross-validation. Figure 2 illustrates the predictions. Herein, predicted RULs almost overlap with actual RULs. These implementation results show that the proposed Auto-Prognostics is capable of effectively exploring the best feature subset, hyper-parameter settings for many algorithms, and recommends to a non-expert user a prognostics model with excellent generalization performance.

3.3 Comparative analysis with industrial-grade sensor-based solution

We compare the results obtained from the proposed low-cost solution with the available industrial-grade sensor-based solution. In CNC milling cutter prognostics cutting force sensor-based solutions are the most popular in industry. Herein, the condition monitoring strategy consists of industrial-grade hardware and software configurations. A Kistler dynamometer (type 9257B) is installed to measure the orthogonal components of cutting force in feed direction, and transformed to voltages by the Kistler multi-channel charge amplifier (type 5070). The force signal is acquired by the Kistler Data Acquisition (DAQ) module (type 5697A) with 1,000 Hz sampling frequency. Total seventeen arithmetic features viz. average force, maximum force level, total amplitude of force level, etc. are extracted with time as an additional feature. For appropriate comparison the sensor-based prognostics model is also derived via proposed Auto-Prognostics. Table 3 gives the details of the comparative performance assessment. Herein, as expected the results obtained from industrial-grade sensor-based solution are better compared to the proposed solution. However, the results from low-cost solution is very much comparable. The suitability of the results obtained from the proposed low-cost solution is more than 80% equivalent to the results obtained

from the sensor-based solution. Moreover, the quality of RUL predictions from the low-cost solution is almost equivalent to the RUL predictions obtained from sensor-based solution. Whereas, the reliability of results is 68% equivalent to the results from sensor-based solution. In addition, the applicability of the low-cost solution is almost equivalent to the sensor-based solution. Lastly, if we compare the cost of equipment's required for the proposed low-cost solution; it is considerably lesser than the cost of industrial-grade sensor-based solution. From the trade-off perspective and based on this comparative performance and cost assessment the proposed low-cost digital solution appears vital for maintenance planning in SMEs.,

Table 1. List surface roughness parameters

S.No.	Parameters
1	Arithmetic mean deviation of profile
2	Ten point height of irregularities
3	Maximum roughness
4	Mean width of profile elements
5	Root mean square deviation of profile
6	Maximum profile peak height
7	Peak-to-valley roughness
8	Base roughness depth
9	Peak count
10	Profile depth
11	Material Ratio of the profile
12	Core roughness depth
13	Reduced peak height
14	Reduced valley depth
15	Material portion 1
16	Material portion 2
17	Oil retention volume
18	Reduced valley depth ratio

Table 2. Performance assessment of auto-prognostics

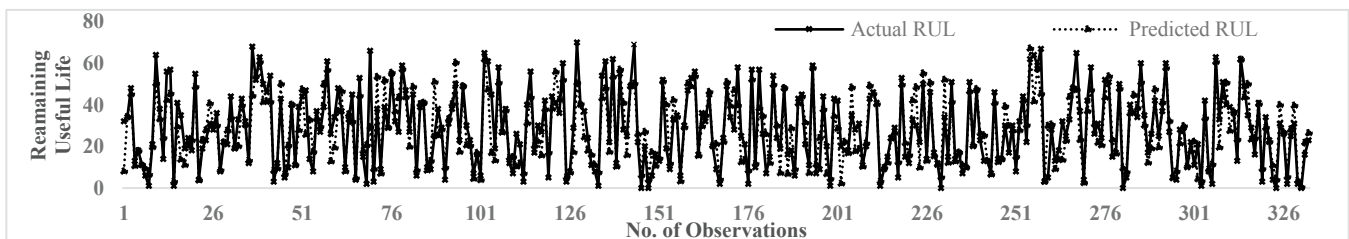|	Performance Metrics	Value
Suitability	Mean Absolute Error	0.25
	Mean Absolute Logarithmic Error	0.01
	Root Mean Square Logarithmic Error	0.03
Stability	Relative Absolute Error (%)	1.64
	Root Relative Absolute Error (%)	2.18
Quality	Correlation Coefficient	0.99
	Kendall's Tau	0.99
	Spearman's Rho	0.99
Reliability	Root Mean Squared Error	0.40
Applicability	Training Time (s) (Test Model)	0.005

Fig. 2. 10-fold cross-validation performance.

Table 3. Comparative performance and cost assessment: proposed solution vs industrial-grade solution

	Performance Metrics	Proposed Low-Cost Solution	Sensor-Based Solution (Industrial-Grade)	Performance Equivalent (%)
Suitability	Mean Absolute Error	0.25	0.07	82
	Mean Absolute Logarithmic Error	0.01	0.01	100
	Root Mean Square Logarithmic Error	0.03	0.01	98
Quality	Correlation Coefficient	0.99	1	99
	Kendall's Tau	0.99	0.99	100
	Spearman's Rho	0.99	0.99	100
Reliability	Root Mean Squared Error	0.40	0.08	68
Applicability	Training Time (s) (Test Model)	0.005	0.001	99

	Equipment's Requirement	Overall Cost (GBP)
Proposed Low-Cost Solution	Portable Surface Roughness Tester (Mitutoyo 2020)	1836
Industrial-Grade Sensor Based Solution	Dynamometer; DAQ Module; Amplifier; (Kistler 2020)	10000-30000

4. CONCLUSIONS

Proposed is this paper is a low-cost digital solution for SMEs via new product quality driven auto-prognostics. The purpose was to provide SMEs with an end-to-end, low-cost, and off-the-shelf open-source prognostics solution. The key contributions are as follows:

- A new product quality-centered condition monitoring strategy is proposed avoiding expensive sensors. Herein, condition monitoring can be easily carried out with any inexpensive portable surface roughness tester.

- Auto-Prognostics integrates automated machine learning via Auto-WEKA, an off-the-shelf open-source technology. Herein, given a prognostics dataset, the proposed solution explores the best feature subset, hyper-parameter settings for many algorithms, and recommends to a non-expert user which method will likely have excellent generalization performance, using model-based optimization techniques, and hence to achieve improved prognostics.

- The performance of proposed solution is investigated via case study to make a distinction about its suitability, stability, quality, reliability, applicability, robustness, and comprehensibility in a manufacturing scenario. As well, comparative performance and cost assessment in contrast to the industrial-grade sensor-based solution verified the viability of the proposed solution for SMEs.

In essence, the proposed low-cost digital solution is key for maintenance planning and decision making in an operational setting for SMEs. In future, the proposed solution can be comprehensively evaluated from a socio-technical perspective viz. assessing workforce qualifications, etc.

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