Causal Modelling for Predicting Machine Tools Degradation in High Speed Production Process ⋆

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Abstract: A dynamic health indicator based on regressive event-tracker algorithm is proposed to accurately interpret the condition of critical components of machine tools in a production system and to predict their potential sudden breakdown based on future trends. Through sensors/actuators data acquisition, the algorithm predicts the causal links between various monitored parameters of the system and offers a diagnosis of the health state of the system. A safety and operational robustness regime determines the acceptable thresholds of the operational boundaries of the electro-mechanical components of the machines. The proposed model takes into account the possibilities of sensor values being a piecewise-linear models or a pair of exponential functions with restricted model parameters, which can predict the runs-to-failure or remaining useful life until a safety threshold. The events caused by sensors passing through sub levels of safety threshold are used as a re-enforcement learning for the models. Each remaining useful life estimation diagnosis and prognosis analysis can be conducted on individual or an interconnected network of components within a machine. The overall health indicator based on individual useful life estimation is calculated by deriving the weights from event-clustering algorithm. The work can be extended to a network of machines representing a process. The outcome of the continuously learning real-time condition monitoring modus-operandi is to accurately measure the remaining useful life of the network of critical components of a machine.

Keywords: Prediction Methods, Industry automation, Regression analysis, Discrete event dynamic system, Maintenance engineering, Trends

1. INTRODUCTION

The manufacturing process is envisioning the Industry 4.0 objectives by moving towards predictive maintenance from preventive maintenance. The current state of predictive maintenance deployment has seen little progress due to the legacy equipment and latency by algorithms in high speed manufacturing. The prior hindrance has been taken care by the cloud services such as Orion context broker technologies in FIWARE project (da Cruz et al., 2019; Mehmood et al., 2019; Zyrianoff et al., 2020). The data are streamlined into the cloud service database from a traditional data acquisition systems. The hindrance from slow predictions by algorithms can be tackled by incorporating low complexity and low memory routines (Mohaar et al., 2016). The standard neural network and deep learning techniques require large training incidences of sensor value depreciation (Rivas et al., 2020). The time series predictions based on regressive models such as non-linear (Gaussian) (Belyaev et al., 2016), v support vector regression (vSVR) (Zheng et al., 2020), multivariate regression models (Yu et al., 2018) etc. still has immense application to fulfil (Lee et al., 2018; Burnaev, 2019; Moleda et al., 2020; Akhavan-Hejazi and Mohsenian-Rad, 2018). The regression models play vital role in realising the Industry 4.0 vision in SMEs due to the legacy technology that demands the predictive models to be plug-n-play or cost effective (McFarlane et al., 2020) with no overhead on memory and hardware. The hybrid methodologies have been explored in the predictive maintenance such as the regression models and event-based techniques (Vasilaki et al., 2017; Huang et al., 2019; Fadzil et al., 2019). The hybrid techniques are preferred in the industrial implementation of fast manufacturing process as it brigs out best of the methodology and adapt to the specific use cases (Zhou et al., 2019; Wang et al., 2020). These techniques are causal and provide the state of machine in real-time. However, these techniques lack historical data considerations to identify the trends

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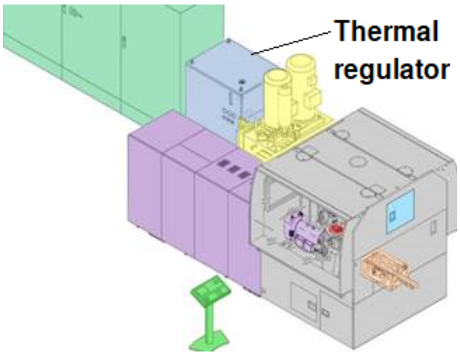

Fig. 1. CAD design layout of continuous compression machine indicating the location of thermal regulator.

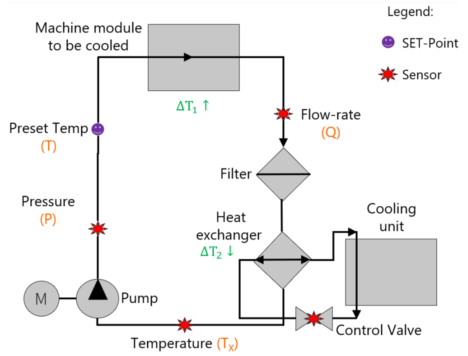

Fig. 3. Schematic of thermal regulator.

in the sensors. Hence machine learning based techniques such as regression analysis is more appropriate method.

2. CONTINUOUS COMPRESSION MACHINE

A continuous compression machine manufactures plastic closures (bottle caps) from molten plastic. It is a non-traditional method of moulding plastics when compared to injection moulding machines; as the latter method has been studied extensively about its energy performances (Madan et al., 2015), environmental impacts (Thiriez and Gutowski, 2006) etc. Where as the injection moulding machine injects molten plastic in the preform cast to create the desired shape (Liu et al., 2020). A continuous compression moulding is a technique of forming process by compression of molten plastic. This technology related studies have been conducted by Peltonen et al. (1992); Spelz and Schulze (1995); Christmann et al. (2017) and Mayer et al. (1998). The compression moulding machine has multiple components, however, the thermal regulator component (as indicated in Fig. 1) which cools the temperature of moving parts of the forming process is very significant in the quality of products as well as the health of the machine. The pneumatic valves, pumps, coolant, filter and heat exchanger are the important sub-components of the thermal regulator as shown in Fig. 2. As the objective is to monitor the health of the thermal regulator component by predicting the remaining useful life of each sub-component via measuring temperature, pressure, flow-rate and valve openings. The schematic of the thermal regulator is shown in Fig. 3. The temperature of the coolant (T) is set by the operator. The task of the heat exchanger control system of the thermal regulator is to regulate and stabilise the temperature (T) throughout the hydraulic circuit by modulating the valve openings of the coolant. Another control system in the coolant loop of the thermal regulator is maintaining the constant flow-rate (Q) of the coolant in the hydraulic circuit.

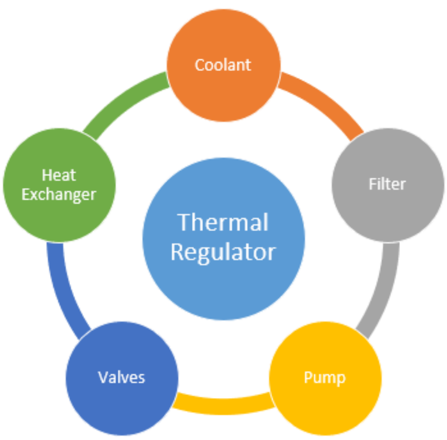

Fig. 2. Various Components of thermal regulator.

2.1 *System description*

The preset temperature (T) is maintained by the control system consisting of pneumatically controlled valves. The coolant gains the temperature of ΔT_1 from the forming process unit and the coolant passes through heat exchanger to cool down by ΔT_2. The final temperature, T_x, is expected to be equal to preset temperature (i.e. $\Delta T_1 = \Delta T_2$). However, due to the presence of filter a small variations are corrected by the pneumatically controlled valves of the heat exchanger to make $T_x \approx T$. The control system relation between valve and the temperature is shown in Fig. 4. The values of control valves are from 0% to -100%. The value 0% indicates that the valve is completely closed. Hence, no cooling operation is performed. If the temperature of the coolant is increased due to the presence of filter clogging, then the values of valves decrease to more negative values to introduce more cooling effect in the heat exchanger. From Fig. 4 it is evident that the heat exchanger always strives to maintain the temperature of the coolant constant.

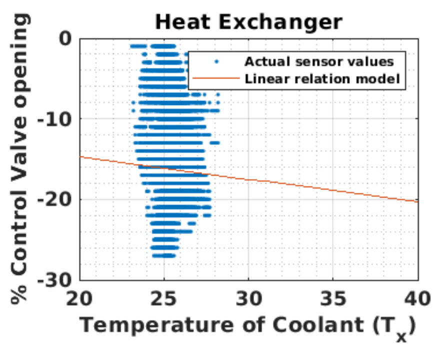

Fig. 4. The modulation of control valve openings by heat exchanger in maintaining the constant temperature in coolant loop.

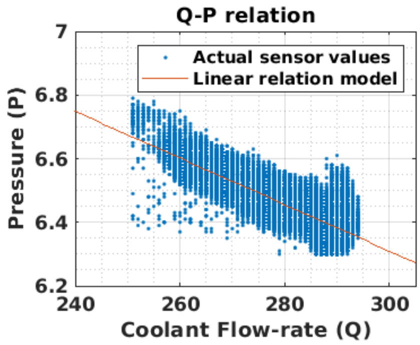

Fig. 5. The relation between flow-rate and pressure for the coolant.

2.2 Presence of Filter sub-component in coolant loop

The suspended particulates in the coolant are filtered by the filter sub-components progressively leading to clogs. This filter clogs reduces the flow-rate (Q) causing increase in pressure (P). Hence the control system behavioural model is shown in Fig. 5. The flow-rate of the coolant in the thermal regulator system is kept constant through feedback mechanisms from flow-rate sensors to pumps. The decrease in flow-rate (Q) of the coolant prompts the motor to pump coolant faster hence increasing the pressure (P). The decrease in coolant flow-rate is caused by clogging of the filter. The boundary values of the pressure (P) when the flow-rate, $Q = 0$, is 8.9. The boundary value of the flow-rate (Q) when the pressure, $P = 0$, is 1021.4. This helps manufacturing the tolerance values for the components of the thermal regulator.

3. FAILURE MODE: FILTER CLOG

The thermal regulator failure mode effects evaluation and critical analysis reports (FMECA) reveals the health of the thermal regulator and the production process is effected by the filter clogs. The progressive filter clog causes the flow-rate to decrease over time and hence increase in the pressure of the coolant. This critically puts progressive load on the pumps and causes burst in the pipes or related components. The depreciation of the filter can be directly translated into the sensors associated with the coolant loop i.e. pressure (P) and flow-rate (Q). As the objective is to predict the filter clogging process and hence calculate the remaining useful life, the other sensors in the thermal regulator can also be associated with the failure mode modelling. The combination of sensors and components build up the failure mode machine simulator as shown in Fig. 6.

4. REMAINING USEFUL LIFE ESTIMATION

The remaining useful life is estimated by the regression analysis on the flow-rate and pressure sensors. The model described in (1) is the model for predicting the future values. The $g(t)$ is the generic function which could be an exponential function or a linear function. σ is the offset or can be the preset value and $\varepsilon(t)$ is the noise in the sensor value which could be the combination of vibrations noise and noise from the instrumentation reading. $\phi(t)$ is the time varying degradation rate parameter which determines

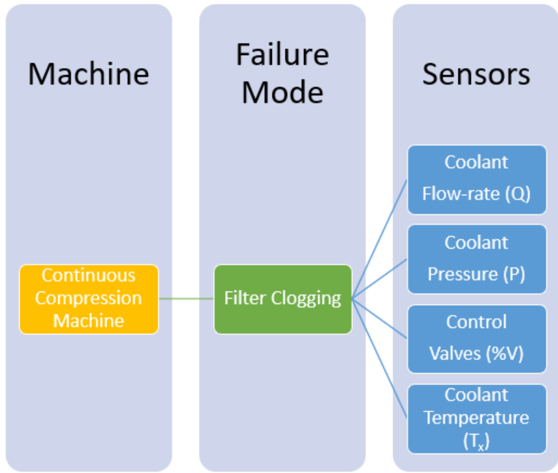

Fig. 6. Machine simulator of the failure modes

the direction of degradation, e.g. for flow-rate the $\phi(t)$ is a negative value and positive for pressure. The σ parameter is dominant when the magnitude of rate of degradation is low.

$$f(t) = \sigma + \phi(t)g(t) + \varepsilon(t) \tag{1}$$

For a linear model the $g(t)$ in (1) is deduced to $g(t) = t$; where t is time and for non-linear exponential models $g(t) = \Sigma^n a_n \exp(b_n t)$; where $\{a, b, n\} \in \mathbb{R}$. The linear model provides fast prediction of sensor values based on large historical values. The single exponential degradation models fail to estimate the future values of sensors when the degradation have large variances over multiple training samples as described in Fig. 7. Hence, the experimentation has provided a conclusive evidence of two exponential parameter degradation functions yield more accurate remaining useful life estimation as shown in Fig. 8. The first exponential term models the steep degradation and the second exponential term provides an extremely low curvature modelling the section with low degradation. The safety threshold S provides a minimum operational tolerance of the regime condition. If the sub-components' sensor value has crossed the safety threshold, then the component is not working in regime condition. This means the probability of breakdown is higher. The $R(t)$ is estimated at an interval of every 1×10^3 cycles and trained with 1×10^5. The remaining useful life, $R(t)$, is estimated to identify time remaining until the sensors cross this safety threshold. This is due the fact that the continuous

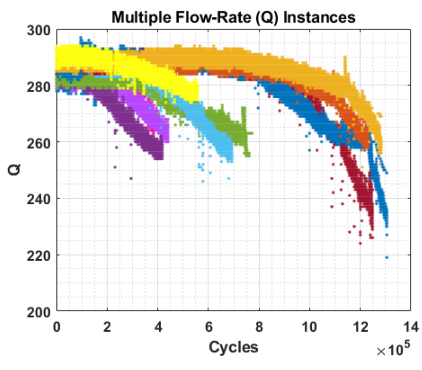

Fig. 7. The multiple instances of coolant flow-rate (Q) depreciation indicating the large variances in the mean life to failure.

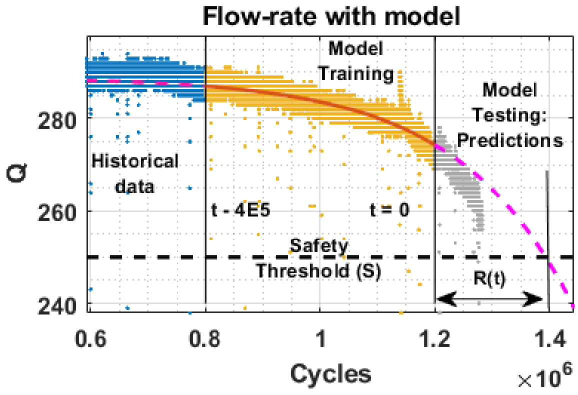

Fig. 8. The double exponential functions (with modelling parameters $a = [-0.03365, \; 288.9]$, $b = [5.062 \times 10^{-6}, \; 3.205 \times 10^{-13}]$) predictions for flow-rate from (1) and (2) with the learning sample of 4×10^5. The estimated $R(t) \approx 2 \times 10^5$ cycles. Similarly for pressure, Temperature and control flow, the $R(t)$ are estimated at 2.2×10^5, 7×10^5 and 2×10^4 cycles respectively.

compression machine is precision manufacturing process and it always needs to be in regime condition with low depreciation. From (1) and safety threshold, (S), the remaining useful life is estimated as shown in (2).

$$R(t) = \frac{S - \sigma}{\phi(t)} - t \qquad (2)$$

The noise in the sensors can affect the prediction. However by having a large historical value for training the model the effect of noise can be minimised.

5. FAILURE MODE MACHINE SIMULATOR

The modelling of all four sensors is carried out to understand the status of each components. The remaining useful life of $R(t)$ for each component is estimated and the weighting function described in (3) is used to estimate the effective remaining useful life of the machine,$R_{eff}(t)$. The effective remaining useful life is the linear combination of the $R(t)$. The weights are decided by the significance of the sub-component in the overall health of the thermal regulator.

$$R_{eff}(t) = w^{\intercal} R(t) \qquad (3)$$

The $w\{\cdot\}$ function can be a minima operator, where the lowest $R(t)$ is the $R_{eff}(t)$ as shown in Fig. 9. The event-

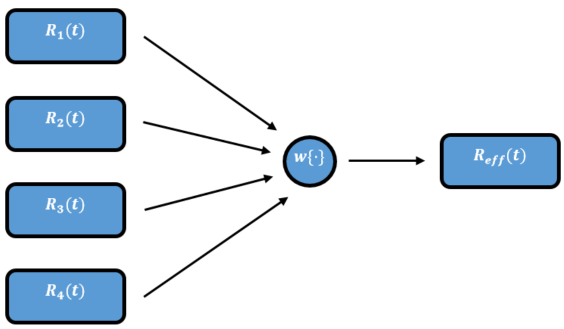

Fig. 9. The machine simulator with effective remaining useful life estimation from individual remaining useful life estimation of components.

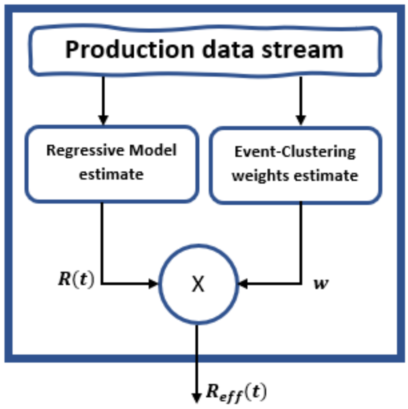

Fig. 10. The work flow for the effective remaining useful life estimation of the thermal regulator component.

clustering algorithms such as the ones described by Danishvar et al. (2013, 2014, 2018) are useful in identifying the significance or weights of sub-components in the system. The other way is by interviewing the maintenance engineers. From the event-clustering algorithm proposed in (Danishvar et al., 2014), the estimated the weights for flow-rate, pressure, control valves and temperature are 0.37, 0.27, 0.19 and 0.16 respectively. From (3), the effective remaining useful life, $R_{eff}(t)$, of the thermal regulator is $\approx 2.5 \times 10^5$ cycles. The work flow of the proposed algorithm is shown in Fig. 10.

6. CONCLUSION

The proposed methodology provides a causal system of regression based prediction of future sensor values. The training requires no prior knowledge of breakdown and degradation information. The algorithm automatically learns as the machine manufacturing in real-time. The training samples are the current and immediate historical samples making it faster with less training samples and more accurate than conventional neural network methodologies. The model $g(t)$ can be altered to the required industry with the diverse sensor values. The experimentation has proven that the two term exponential model found to be more accurately modelling the sensors. The depreciation model tracks trend of the sensors simultaneously and predict the current effective state of the machine. The proposed methodology can be extended to every single modules that drives a machine including the environmental parameters of humidity and surrounding temperature for condition monitoring in real-time. The prediction can be correlated to the FMECA and a cost based predictive maintenance plan can be deployed. The results of the experiment determines the single value health indicator and the non-linear behaviour of the degradation that is close to an exponential behaviour. In future, the potential of the work is to monitor and control the parameters of the exponential model to create customised maintenance schedules.

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