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Regressive Event-Tracker: A Causal Prediction Modelling of Degradation in High Speed Manufacturing

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Abstract

The proposed work describes a dynamic regression based event-tracker for high speed production process. The methodology discussed is a causal system and provides trends and estimations of the sensors based on a flexible regression model of the historical sensor values. A safety threshold is defined that provides a boundary of the tolerant working for the regime condition of production. This threshold is used as a reference to calculate the remaining useful life of the critical component. The estimated remaining useful life is compared with the Weibull reliability analysis. The proposed methodology provides a remaining useful life of ∼ 10 weeks for the thermal regulator use-case when compared to ∼ 9 weeks for Weibull analysis. The overestimation of the methodology is discussed and along with the alternative methodology. The sensitivity analysis is conducted on the noise and training periods are studied for better prediction.

Keywords: predictive maintenance; machine learning; regression; failure-rate; event based prediction; Industrial IoT; Industry 4.0; degradation model; remaining useful life;

1. Introduction

Fast and causal prediction methodologies are becoming inevitable to achieve Industry 4.0 vision [11]. The current manufacturing approaches are leading to the generation of large asynchronous data (asynchronous Big Data) [34]. The most internet of things (IoT) application in these regards are still confined to rich automatic data collection industries such as telecommunication, image processing for medical application, as well as some internet and social media based service provisions. The proliferation of industrial IoT (IIoT) is inevitable but posing interesting challenges at present as mentioned in [25]. Industrial sensors are updated over time with various different partners involved, having holistic approach is difficult. The legacy systems in the workshop floors have hindered the application of machine learning and traditional big data analytical methods [18]. The authors in [26] have discussed the framework of industrial data management which provides a better understanding of having multi-middleware components to cater the end-users. The need for requirement gathering of the Industry 4.0 solutions has been elaborated by [4]. These have lead changes in the organisation, structural changes and the prediction modellings [22] to be 'Event-based' in Industry 4.0 [6, 9, 29].

The proposed methodology combines the state-of-the-art parameter bound regressive models and the event based prediction of the thermal regulator component in a compression moulding machine. Pure event-based models such as [5] and [12] provide state of the machine accurately; however fails to consider the historical data in majority of the cases to understand the trend or degradation [13] which has been addressed in the proposed method. There are efforts to model the data based on genetic algorithms and gene expressions as discussed by [33] and [12] respectively. The eigen space based modelling and principle component analysis for degradation and fault detection are applied in [15] and [30] respectively. The estimation of remaining useful life has been carried out using regression techniques. But the pure regression models lacks accuracy [21]. They are

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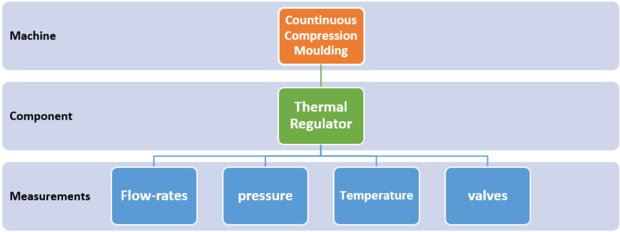

Fig. 1. System hierarchy of sensor acquisition in thermal regulator of continuous compression machine.

often used along with a complementary methodologies such as clustering algorithms [36], support vector machines [28, 32], statistical distributions [19] and multivariate analysis [20]. The estimation of remaining useful life by various methodologies has an advantage of understanding the prognosis, health and knowledge management of the system as discussed in [1, 8]. The research in physical based modelling (or digital twin) [1] has been computationally inefficient in the small and medium-sized enterprises (SMEs) scenario. Hence the scope is in deployment of linear, memory-less models which can adopt to the legacy systems seamlessly. The regression based event-tracker takes into account the historic trend in the training process. The industry 4.0 vision of predictive maintenance stems from the idea of cost effective and high productivity manufacturing [14]. However, the traditional preventive maintenance has proven to be inefficient or requiring higher training, costs and resources. The reliability analysis of the machines can indicate the survival time with a probability [3]. The proposed failure-rate Weibull analysis based on the regressive event-tracker reveals a mean time to failure for individual components which can promise an optimised maintenance schedules and has scope for providing an unified health indicator for prognosis and health management [23].

2. System description

A high speed closure manufacturing line, produces plastic caps for beverage and pharmaceutical containing bottles with a continuous compression machine. It has three super-components namely extruder, thermal regulator and hydraulic unit. The system hierarchy of sensor measurements in thermal regulator is described in Figure 1.

2.1. Thermal regulator

The modelling of thermal regulator is considered. The thermal regulators act as the cooling for the closure stamps. The sub-components and some key sensor acquisition of the thermal regulators are shown in Figure 2. The schematic of thermal regulator shows the flow of coolant (in this case water) at a pre-set temperature (T). The coolant is used to reduce the temperature of the formed plastic closures in the mould. The coolant gains temperature ($T_w \uparrow$) from the zones to be cooled down and goes through heat exchanger ($T_w \downarrow$) via filter for the components/parts of the machine to be cooled. The temperatures at

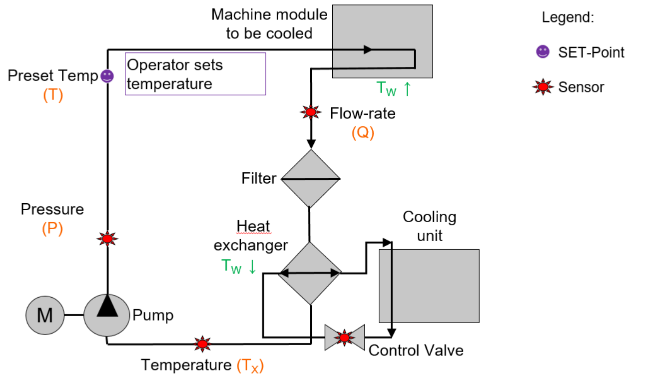

Fig. 2. Schematic of thermal regulator of continuous compression machine.

any given time (T_p) in the circuit after coolant passes through hot zones are $T + T_w$. The temperature, T_x, of the coolant after passing through heat exchanger should be same as the preset coolant temperature T as shown in Eq. 1.

$$T_x = \left(T_p - T_w\right) \approx T \tag{1}$$

The coolant circulates throughout the thermal regulator components to be cooled down by means a pumps that boosts the coolant flow. The system is monitored by flow-rate and pressure sensors, in order to detect any deterioration in the circuit components. Besides, an electrovalve is used for controlling the cooling power that is provided to the heat exchanger by an external cooling unit (chiller).

2.2. Failure mode analysis

The control system in the cooling circuit is described in Figure 3. The user set value of T is maintained in the thermal regulator using a feedback mechanism. The temperature error function, $\Delta T = (T_x - T)$ is determined as the difference between the post-heat exchanger temperature of T_x (output temperature as shown in Eq. 1) and user set value of T (input). If the ΔT is positive indicating increase in temperature of the coolant in the system, the motor pumps more water increasing the pressure from P to $P + \Delta P$. Hence, ΔT and ΔP are directly proportional to each other. The filter in the thermal regulator

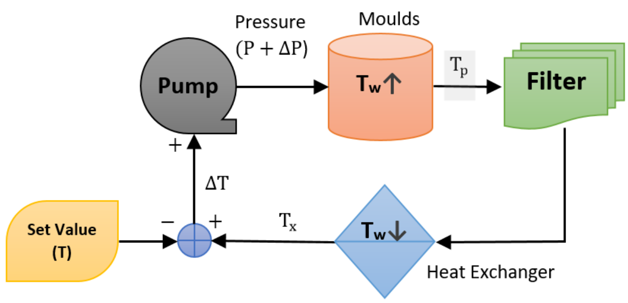

Fig. 3. The temperature control system of cooling circuit in the thermal regulator.

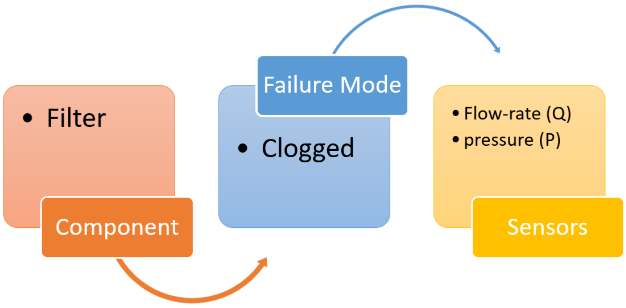

Fig. 4. The ontology of the filter clog failure mode in upper/lower moulds.

depreciates the system by progressively getting clogged by the coolant degradation, erosion of the components in contact with the coolant and penetration of particulate matter in the cooling circuits. Given the higher pressure drop in the filter due to its progressive clogging and the characteristic $P - Q$ curve of the centrifugal pumps, the flow-rate (Q) in the system decreases by ΔQ. The decreasing flow-rate causes increase in temperature in the coolant passing through the hot zones. The control system tries to compensate for decreased flow-rate by pumping more water causing increased pressure. Hence, the change in flow-rate ΔQ and change in pressure ΔP are inversely proportional. This phenomenon provides an opportunity to model the depreciation of the filter. The filter clog failure mode can be assessed by the failure mode, effects and critical analysis reports (FMECA) and from control system of the cooling circuit. The ontology of the failure mode is described in Figure 4. The failure mode ontology describes the relation between the sensor values, failure modes and components. This simulates the overall health and possibilities of failures of the entire system in retrospect. The other parameter measured such as temperature and pneumatic valve openings values are ineffective due to the control system described in Figure 3.

3. Regressive Event-Tracker

The preventive alarms are set in place to shut-down the system if the sensor values cross the thresholds. However, the operators prefers to set these preventive threshold to be way higher (or lower) because of the demand on non-stop production. This is despite the fact that there could be sudden breakdown and the sensor values have not reached the preventive thresholds. Hence, a safety threshold is proposed that can provide the intermittent health of the sensors and track the quality of the products and degradation of the machines. The sensor values can be modelled as a linear function with slope and intercept as shown in Eq. 2. The slope of the model, $\phi(t)$, is time dependant. The linear function is used as the model for sensor values. As the sensor values theoretically does not have any trend. Any trend reflected by the sensors as evident in the Figure 5 is purely due to degradation.

$$f(t) = \sigma + \phi(t) \cdot t + \varepsilon(t) \tag{2}$$

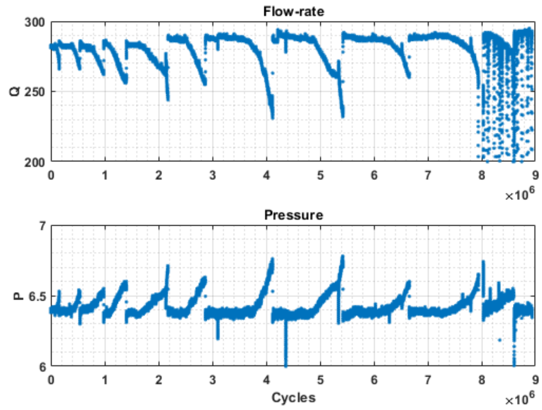

Fig. 5. Sensor values of coolant flow-rate (Q) and pressure (P). The sensor values are plotted against cycles.

The regressive event-tracker technique is a causal system in nature as it models historical and real-time values and tries to train the model, $f(t)$, to the sensor values and predict the future sensor values. The observations on slope of the model, $\phi(t)$, is: from Figure 5, the values of flow-rate, Q, is decaying and hence $\phi(t)$ will be negative. The $\phi(t)$ for pressure sensor, P, will be positive. The noise of the sensor values, $\varepsilon(t)$, makes the system very sensitive for small training set of data. Hence the for training the model the range is chosen for $\sim$ 10000 cycles (A cycle is defined as the process of one full turn of the carousel of the continuous compression machine). The model requires counting of production cycles, noise in the sensors could be transferred to $\phi(t)$ in the form of Poisson noise. By considering large sample size the addition of additive noise tends to 0. The presence of Poisson noise, if any, will be minimised by having large fit ranges, which minimises the noise by square-root function. This also means that the time it takes for the model to run is very high. The Table 1 demonstrates various training cycle ranges to noise reduction. There is a clear trade-off between time to train the model and noise factor. A useful user defined safety threshold (S) is defined for shutdown of components if the sensors crosses these values. The safety threshold could be a threshold for safety of the personnel working around the workshop floor or safety of the components or the degradation of the manufactured components. The remaining useful life, t_{RUL}, can be derived from Eq. 2 as the value of t when $f(t) = S$ as shown

Table 1. The trade-offs between noise reduction factor of $\phi(t)$ and wait time for the training of thermal regulator prediction

Training cycles	Noise $\varepsilon(t)$	% Noise	Wait time
1×10^1	3.16	31.62%	20 s 600 ms
1×10^2	10	10%	3 min 26 s
1×10^3	31.62	3.16%	34 min 19 s
1×10^4	100	1%	5 h 43 min 10 s

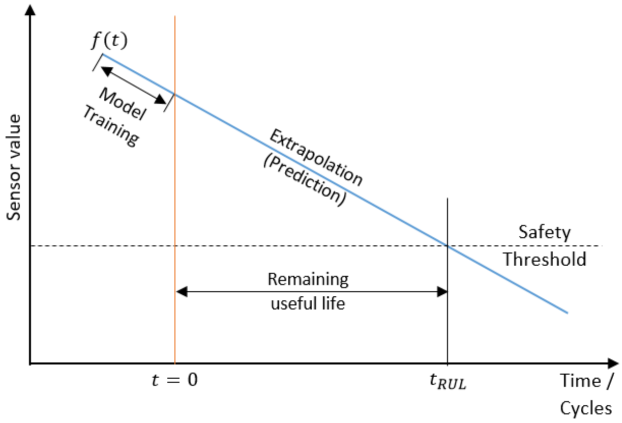

Fig. 6. The evaluation remaining useful life by regressive event tracking model.

in Eq. 3. The t_{RUL} is described in Figure 6 as a duration.

$$t_{RUL} = \frac{S - \sigma}{\phi(t)} - t \tag{3}$$

An example of modelling on coolant flow-rate depreciation is shown in Figure 7 for a training range of 1×10^5 cycles before current cycle at $t = 0$. The training of this range would be more than 2 days. However, the $\varepsilon(t)$ will be as negligible as $\sim 0.3\%$. A safety threshold $S = 250$ is assumed. From Eq. 3, the remaining useful life, t_{RUL}, is estimated at 3.0173×10^6 cycles or 10 week 1 day 21 h 41 min 59 s with a fitting confidence parameter of 95%.

4. Weibull Distribution

The Weibull distribution has been a standard form of failure, survival and reliability analysis [2, 7, 17, 27, 31, 35]. The normalised Weibull distribution can provide the relation between the remaining useful life or remaining useful cycles to the probability. In the use case, the relation between remaining useful life and remaining useful cycle is established by finding the cycle rate (cycles/second or Hz) or the time between the cycle, Δt

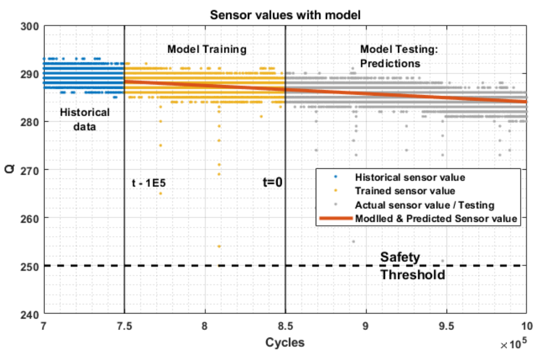

Fig. 7. $f(t)$ model between cycles 7.5×10^5 to 8.5×10^5 (current) with the estimated parameter of $\phi(t) = -1.689 \times 10^{-5}$ and $\sigma = 300.9$.

Table 2. Special cases of Weibull distribution with respect to shape and scaling factor values.

β	η	Notes
$\mathbb{R}_{\geq 0}$		Weibull distribution
$(3, 4)$	$\mathbb{R}_{\geq 0}$	Approaches Gaussian distribution
$(0, 1)$		Distribution of high failure-rate before regime condition
1	1	Exponential distribution
2	$\sqrt{2}\sigma$	Rayleigh distribution

(Eq. 4), with standard error of median, ε_M (Eq. 5).

$$\Delta t = \nabla t \tag{4}$$

The Eq. 5 is the standard relation between standard deviation, $\varepsilon_{\bar{t}}$, and standard error of median, ε_M.

$$\varepsilon_M = \sqrt{\frac{\pi}{2}}\varepsilon_{\bar{t}} \tag{5}$$

where $\varepsilon_{\bar{t}}$ is the standard deviation of time between cycles. This paves the way to estimating the remaining useful life in the form of distribution analysis and regressive trend tracking. The Weibull distribution definition is described as shown in Eq. 6.

$$f(t|k,\beta,\eta,t') = k \cdot \frac{\beta}{\eta}\left(\frac{t-t'}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t-t'}{\eta}\right)^{\beta}\right] \tag{6}$$

where t is time to failure, $f(t|k,\beta,\eta,t') = 0 \forall t < t'$, $\beta \in \{\mathbb{R}_{\geq 0} \mid \mathbb{R}_{\geq 0} \implies \mathbb{R} \geq 0\}$ is the shape parameter which determines the slope and $\eta \in \mathbb{R}_{\geq 0}$ is the scaling parameter of the distribution, $t' \in \mathbb{R}_{\geq 0}$ is the time offsetting parameter and $k \in \mathbb{R}_{\geq 0}$ is the scalar parameter. The advantage of Weibull distribution is that it takes the shape of other distribution when shape and scaling parameters take particular values as shown in Table 2.

The Weibull distribution has been a standard to understand the failure rate analysis. The shape β and scale η parameters of the distribution indicates the behaviour of the system, as well as prediction parameters.

4.1. Weibull Analysis of Data

To find the overall health of the thermal regulator based on the perspective of its critical sensors such as flow-rate (Q) and pressure (P) sensors, the statistical study has to be carried out for each estimation of t_{RUL}. The remaining useful life is estimated at every 1000 cycles interval for the training sample of 1×10^5 cycles. The estimates are filtered for out of boundary

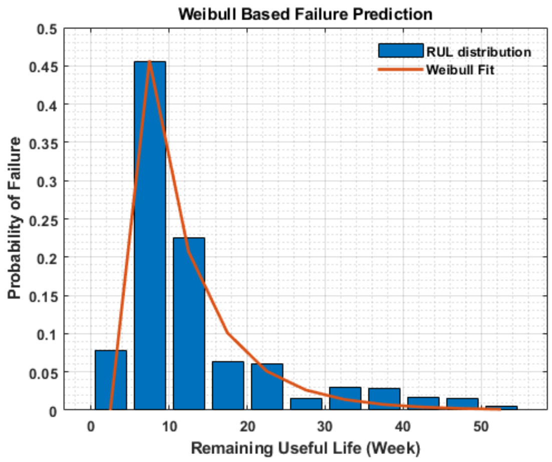

Fig. 8. The probability of failure estimation with respect to remaining useful life distribution for a safety threshold, S, is $\approx 15\%$ below set value in the transition/degradation period.

estimations as shown in Eq. 7.

$$t_{RUL} = t_{RUL} \; \forall \begin{cases} \phi(t) < 0 & \forall Q \\ \phi(t) > 0 & \forall P \end{cases} \tag{7}$$

The distribution of t_{RUL} for coolant flow-rate in weeks with a bin width of 5 days is shown in Figure 6. The distribution is modelled with the Weibull distribution of 4 parameters with the estimation parameters of $\beta = 0.8925$, $\eta = 6.113$, $t' = 2$ week 3 day 12 h 38 min 17 s and $k = 4852$. The distribution peaks at 9 week 3 day 12 h indicating the mean time for a filter to fail (or mean time for coolant flow-rate to cross safety threshold). The probability is of failure is relatively low because of the large interval (1000 cycles) between training. Based on the mode of the Weibull distribution model, the events can be classified by the time ranges from < 1 to > 10 week as shown in Figure 9. A decision support system will be alerted by the outcome of event-tracker prediction. The probability of breakdown [16] can also calculated from the range of event-tracker.

5. Conclusion

The proposed regression based event-tracker has an advantage of being causal system with fast prediction. For the thermal regulator the proposed prediction on health provides an estimation of $\sim$ 10 weeks. The reliability analysis show that the estimated reliability to be $\sim$ 9 weeks. The proposed method is assuming that the sensor values are linear and hence there is potentially an small error if the sensor value changes rapidly

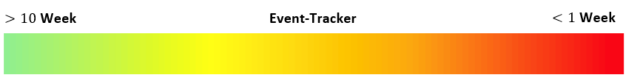

Fig. 9. The event-tracker based on regression and Weibull distribution.

compared to modelled historical values. This will also lead to a slight overestimate of remaining useful life, t_{RUL}. However, the t_{RUL} provides more accurate estimation as the sensor values approach towards the safety threshold. The other possibility is to model with a pair of exponential degradation functions [10]. The pair of exponential degradation functions might provide the flexibility in providing accurate predictions in case of rapid changes in the sensor values. The regression based event trackers are in agreement with Weibull theory of degradation. The computational complexity [24] is low compared to neural networks and deep learning making it attractive to SMEs. The complexity over time can be further reduced by increasing the interval between training length of data set and testing. The event of safety threshold, classified by the regression based distribution analysis are dynamic and can be translated to all sensors to build an ontology of machine breakdowns (a machine simulator) and provide a single health indicator of the entire workshop floor. The concept of having a mean time to failure for individual component provides an optimised scheduling for maintenance and will provide an holistic approach to prognosis and health monitoring.

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