Essential Sensors and Fault Detection Algorithms for Manufacturing Processes

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Abstract – **Comprehensive fault detection in manufacturing processes often relies on added sensors to detect individual faults, creating added cost to the equipment. Modern machine learning data methods can be applied to detect multiple faults within patterns of data from several sensors, thereby reducing the number of added sensors needed. The problem then becomes to find a cost-effective set of sensors that can detect the maximum number of faults with the minimum number of sensors. We develop here an optimization trade-off strategy to compare the fault detection capability against the number of sensors needed given alternative fault detection algorithms. For a plastic extrusion process with four faults, we find all faults can be detected with five sensors, 90% of the faults can be detected with four sensors, and one can be detected with a single sensor of (barrel temperature). The approach can be applied to decide upon the number of sensors desired for the fault coverage needed.**

Keywords – **Fault Detection, Sensor Selection, Machine Learning, Manufacturing Systems, Predictive Maintenance, Optimization**

I. INTRODUCTION

Fault detection in manufacturing processes is often a necessary element of industrial maintenance, to reduce the durations of unplanned downtime. Empirical studies show that deploying preventive maintenance sensors can yield payback periods of less than one year by reducing downtime and maintenance labor [1]. However, each additional sensor, costing roughly AU $300 for hardware plus installation and recurring network fees, adds to both upfront and lifecycle expenses, create a trade-off between detection performance and economic feasibility [2]. Optimizing sensor counts is therefore necessary for cost-constrained settings such as Small, and Medium Enterprises (SME) manufacturers, where a reduction in maintenance costs via predictive maintenance must be balanced against capital outlay [3].

Industry leaders often solve this problem through heuristics to address the most critical assets in hopes of using a minimal sensor set of a few well-chosen sensors, rather than blanket coverage strategies. Data-driven and model-based approaches being particularly successful in industrial processes due to their straightforwardness and efficiency [4]. This leaves room for more optimal sensor selection strategies.

Recent works have further developed means for more fault coverage through development of improved data-driven analyses. Comparison between signal, statistical and machine-learning methods on feature generation and data processing has been discussed [5], as well as intelligent feature selection algorithms made with Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to minimize the number of features used while maximizing the classification performance of the fault detection system [6]; Case studies using accelerometers to detect severity of nozzle cloggage in 3D printer and faulty bearings suggests that high frequency temporal data could be used to detect multiple faults indirectly [7,8]. Other researchers review current use of different sensor types for multi-fault detection in material extrusion additive manufacturing processes [9] and compare performance of different machine-learning fault detection algorithms [10,11].

Despite these developments, optimal sensor selection remains understudied. While a framework and strategy of optimum sensor location and network design has been discussed [12], the methods rely on the correctness of cause-effect modeling. Furthermore, a data-driven FMEA frameworks reveal that fault detection accuracy plateaus when sensor counts exceed an optimal subset, making a rigorous sensor selection methodology essential [13]. This draws interest to compare performance of fault detection algorithms with different sensor configurations.

This paper develops a method to trade-off the minimal number of required sensors for different numbers of faults that are detectable for a manufacturing system. This allows the targeting of the fault-detection capability, thereby enabling economic monitoring systems that do not compromise on desired detection robustness.

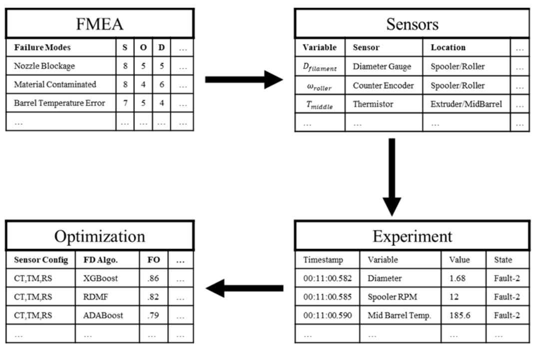

Fig. 1. Workflow of the proposed methodology

II. METHODOLOGY

We define a fault detection system as the combination of selected sensors installed within a manufacturing system, their associated time series data captured, and fault detection algorithms that make use of this data to detect a list of faults, where each of them needs to be identified. Inspired by fault development process in Aerospace, we adopt similar steps to start the analysis that leads to optimization.

Our approach comprises four stages (Fig. 1):

A. Develop the list of possible faults through a typical manufacturing process failure modes and effects analysis (FMEA).
B. Generate a comprehensive list of alternative sensors that might be used.
C. Conduct experiments to gather time series data on faulty and fault-free conditions, which then can apply different fault detection algorithms and assess accuracy.
D. Iteratively apply the performance assessment of different algorithms using various sensor subsets, then select the optimum set based on the trade-off sensor count and number of faults detected.

A: FMEA

The process begins by identifying and prioritizing potential fault modes via their severity and occurrence likelihood. The manufacturing process is studied for how components, equipment and process can be in error. The ideal outcome would address a comprehensively sorted list of faults.

B: SENSORS AND FAULT DETECTION ALGORITHMS

Next is to generate ideas for sensing each fault, which could be based on physical property, expert knowledge and industry practices. Usually, one sensor can measure one physical property, and may contribute to one or more detected faults. Sensors that allow higher sampling rate, higher precision, less variability and could detect multiple faults often carry higher costs, and less pricey alternatives exist with trade-offs in performance. Sensor type, location and property measured of each sensor are considered in this stage. Processes with existing sensor infrastructure could cross-check with the populated sensor list and evaluate the current sensor deployment. Alternatively, processes with no sensor infrastructure could utilize the list with on-site knowledge and lightweight process modelling to kick start the deployment process.

A list of fault detection algorithms will be populated based on the potential data. Many of the sensory data would be temporal, along with off-line product measurements for non-continuous processes. Candidate architectures include tree-based ensembles (XGBoost, AdaBoost, Random Forest), deep networks (fully-connected ANN, 1D-CNN, Transformer, RNN/LSTM), and anomaly-detection models (Autoencoder, Isolation Forest). Feasibility of detailed deployment would take computation power, data density, and data format into account. Various feature extraction techniques will need to be considered based on type of data (image, float, etc.) alongside with selected algorithms. Performance could be measured by F1-score, AUC, or similar on held-out data serves as a baseline for each sensor configuration.

C. EXPERIMENT

With the selected sensor being implemented in the process, data could be collected either from historical operations (with existing sensor infrastructure) or running the process in a more controlled manner to generate high quality labelled dataset. It is preferred to run the process in normal and all desired faulty states that are non-destructive, lab-replicable to ensure data coverage for the next step.

D. COMPARISONS AND TRADE-OFF SELECTION

Data collected from the experiments will then be used as the testbed for searching the optimum configuration. Starting from a single sensor (or in the other direction, with all sensors), different tactics could be used to expand the sensor subset and locate the better performing ones. Although brute-forcing all combinations will provide full coverage, the computational power required for such search grows exponentially with sensor count. Therefore, heuristics such as greedy, meta-heuristic or SHAP indices strategies could be implemented to speed up searching time for larger number of sensors and faults. Metrics of the searched configurations will be visualized in two ways: average fault detection performance over sensors deployed of different algorithms, and number of faults detected over sensors deployed.

Here we compare performance per configuration by Pareto analysis, with objectives maximize F1-score and minimize number of sensors. A configuration is Pareto-dominated if another is at least as good on all objectives and strictly better on one; the remaining non-dominated configurations form the Pareto front, such as F1-score over sensor count. From this front we report at most two preferred choices:

A. Knee-point: after min–max normalizing axes, we draw the chord between the two extreme non-dominated points and select the configuration with the largest perpendicular distance to this chord—the point of maximum marginal gain before diminishing returns.
B. Minimum-sensors under a performance floor: we impose $min_k F1_k \geq 0.90$ across all fault classes k, and among feasible configurations, we choose the one with fewest sensors; tie-break by higher F1-score, then lower sensor count. If no configuration meets the 0.90 floor, we instead select the one with maximum performance floor and report the achieved minimum.

A plastic filament extruding process is used as a case study to apply and validate the proposed methodology.

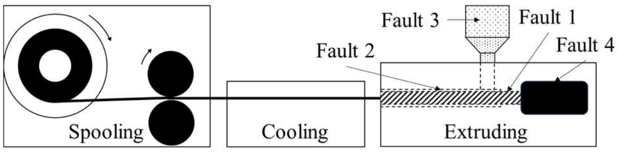

Fig. 2. Illustration of the filament extrusion process indicating location of selected faults

III. RESULTS

A common manufacturing process is the extrusion of plastic (Fig. 2), where pellets in a hopper are fed into a barrel which rotates, squeezes and liquifies the pellets into molten plastic which then exits the nozzle in continuous form, to be cooled and pulled at a controlled speed, and finally wound onto spools. To develop a fault detection capability, the process of Section II was followed. The faults that can arise were identified (Step A) including screw damage, temperature error, contamination and motor speed error. We consider four faults in the extrusion process that are non-destructive and easy to replicate in lab.

Next, sensors for each fault were considered (Step B). This includes but is not limited to thermistors, diameter gauge, and rpm counter encoder. In total, twenty different sensors were considered. Of these, eight were implemented on the extruder in an experimental mode to understand their effectiveness with the consideration of cost and ease of implementation. Time-series data was then collected using a designed experiment approach, with normal and selected faulty operation states running at least 60 minutes. After being resampled into 15-second windows, features were extracted and used on training selected machine learning methods to classify different fault categories under different sensor configurations. Statistical and temporal features are extracted on all sensor data, with frequency domain features only viable on the total current drawn sensor, which has a sampling rate of 750Hz.

This study selected four commonly used classification algorithms for fault detection: XGBoost, ADABoost, Random Forest and Support Vector Machine (SVM) to illustrate the concept. Models were trained by iteratively stepping through all possible combinations of sensors for each fault detection algorithm, and their performance are compared by the F1-Score of five classes (one normal and four faulty states) using two criteria, average and threshold. Extending from this, we have also tested 5 different sensor selection heuristics to make comparison with the brute-force results: random forest, mutual information, SHAP, F-value and PCA, and in both forward (from single sensor to all) and backward (from all sensors to single).

The results are as follows: Fig. 3 shows how the F1-Score average behaves with the use of extra sensors, with Table I being the sorted results of different configuration used in this figure. Fig. 4 shows how number of detected faults changes with extra sensors and with different criteria of defining "fault detected". In this case, faults are considered detected if the F1-Score is above the designed threshold (0.75, 0.8, 0.9). Fig. 5 shows how average F1-Score changes when adding or removing sensors with different heuristics for such action, compared with the brute-force results (black solid line) which are the same values as Fig. 3.

TABLE I
SORTED RESULTS OF DIFFERENT SENSOR CONFIGURATIONS

Sensor Configuration	Algo rithm	F1-O	F1-1	F1-2	F1-3	F1-4
CT	XGB	.519	.593	.785	.818	.989
CT,TM	XGB	.745	.667	1.00	.769	.989
CT,TM,RS	XGB	.860	.769	1.00	.889	.989
CT,TM,RS,VM	RD MF	.893	.897	1.00	.921	.989
CT,TM,RS,VM, DF	XGB	.911	.903	1.00	.936	.989
CT,TM,RS,VM, DF,TF	RD MF	.913	.867	1.00	.952	.989
CT,TM,RS,VM, DF,TF,TB	RD MF	.904	.897	1.00	.938	.989
CT,TM,RS,VM, DF,TF,TB,TH	RD MF	.904	.839	1.00	.952	.989

CT: Total Current Drawn TM: Middle Temperature RS: Spooler RPM
VM: Motor Voltage DF: Filament Diameter TF: Front Temperature
TB: Back Temperature TH: Hopper Feed Temperature
XGB: XGBoost RDMF: Random Forest
-O: Normal -1: Screw Damage -2: Barrel Temperature Error
-3: Material Contamination -4: Motor Speed Error

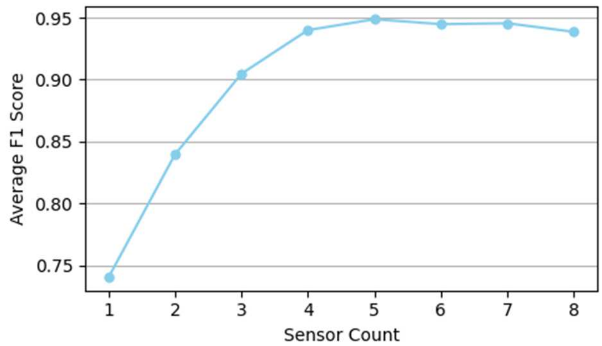

Fig. 3. Best of F1-Score over number of sensors, averaged over the different fault detection algorithms. More than 5 sensors add no improvement.

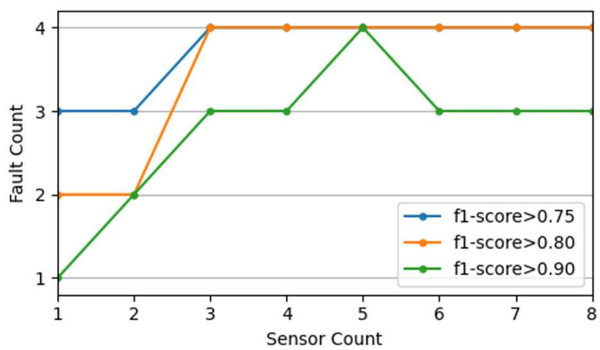

Fig. 4. Number of faults detected versus number of sensors, using best fault detection algorithm for each. If a F1 score of 0.75 is acceptable, only 3 sensors are needed; for an F1 of 0.90, 5 sensors are needed.

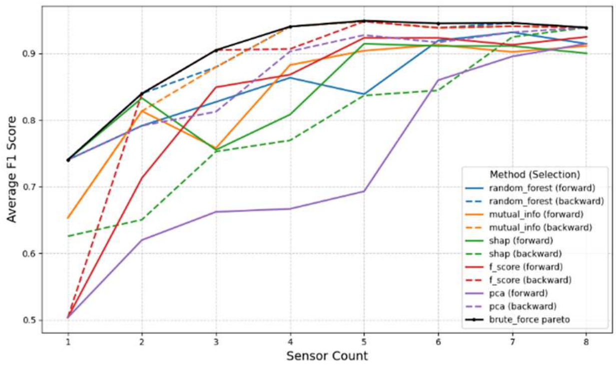

Fig. 5. Best of F1-Score over number of sensors with different sensor selection heuristic, averaged over the different fault detection algorithms. Brute-force enumerations approximate the Pareto front; heuristic curves approach but do not exceed it.

IV. DISCUSSION

Our results reveal three key findings. Fig. 3 clearly demonstrates that the average F1-Score for fault detection generally increases with the inclusion of more sensors. The plateau observed in the F1-Score after four sensors indicates a point of diminishing returns, where extra sensors offer minor improvements. This highlights the importance of optimizing sensor deployment to achieve a balance between performance and cost-effectiveness, as detailed in Table I which presents a more granular view of these configurations and their associated F1-Scores. This also quantifies how blanket coverage strategies could be less beneficial in terms of fault detection performance.

Fig. 4 further elaborates on the impact of sensor count by illustrating how the number of detected faults changes under three different F1-score thresholds: a lower F1-score threshold allows for the detection of more faults, albeit with potentially higher false positives, while a stricter threshold identifies fewer faults but with greater confidence. The observed fluctuations in the number of detected faults with increasing sensor count for higher thresholds, suggest that certain sensor combinations are more effective at identifying specific fault types and achieving higher classification confidence. In this study, using four sensors with Random Forest is the preferred configuration which balances sensor count and fault detection performance at the "knee point", while using five sensors with XGBoost is the only solution if a minimum of 0.9 F1-Score is required for all faults.

The sensor selection heuristic comparison in Fig. 5 suggests that removing sensors (backward) seems to be a better strategy than adding sensors (forward) in many scenarios. In this study, the use of random forest, mutual information and f-value to remove sensors exhibit closest performance to the brute force results, while drastically reducing the number of iterations. Using PCA as the sensor adding strategy seems to be least effective in this case, where it adds sensor in a very different order starting from barrel temperature instead of total current draw.

We use F1-score primarily due to class imbalance and equal per-fault importance in this plastic filament extrusion case study, however, PR-AUC (precision-recall area), MCC (for overall quality under imbalance), and per-fault confusion matrices could also be considered to evaluate fault detection.

V. CONCLUSION

This study proposed a pipeline for SMEs that has existing data collection infrastructure to strategically determine the sensors needed for fault detection. By applying this methodology to a plastic filament extrusion scenario, we illustrated how machine-learning algorithms with different sensor configurations could optimize fault detection performance. Findings highlight that while increasing sensor count generally improves fault detection performance, a point of diminishing returns is observed, emphasizing the importance of balancing performance with cost-effectiveness. Furthermore, the analysis shows the possibility that additional sensors may negatively impact the detection performance on some of the faults.

On the other hand, the current methodology primarily focuses on known faults. Ensuring observability of the process would require expert knowledge integration and specialized sensors deployment. Furthermore, additional time-series data specific feature extraction techniques could be utilized, and data collecting in different sampling rates will have an impact on the overall cost of the sensor deployment but may affect the fault detection performance as well. Brute forcing the combinations of will consume too much time and computation power with a larger number of sensors, where better heuristics and optimization techniques should be considered. This study also assumes faults to be equally weighted, as well as sensors and algorithms, which is not true when more advanced and higher cost sensors are included in the scope.

This study could be further improved by incorporating fault, sensor and algorithm cost into the optimization process and conducting a cost-benefit analysis, which helps businesses to intuitively interpret the results. [14] shows a possible cost-benefit analysis in deploying sensors in buildings by converting energy, comfort and maintenance improvements into dollar sign, which is a good reference of the future work. Additionally, better fault performance metrics could be introduced based on their priority and severity (in FMEA), and including additional prediction indices, would provide a more holistic evaluation of efficacy and robustness of each configuration of the fault detection system. Insights and findings of this study may also help building up more efficient heuristics used in the configuration comparison step.

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REFERENCES

[1] E. Johnson, “The True Cost of an Hour’s Downtime: An Industry Analysis | Siemens Blog | Siemens,” Siemens.com, 2024. https://blog.siemens.com/2024/07/the-true-cost-of-an-hours-downtime-an-industry-analysis/

[2] Amazon, “Industrial Equipment Monitoring– Amazon Monitron Pricing – Amazon Web Services,” Amazon Web Services, 2024. https://aws.amazon.com/monitron/pricing/

[3] H. Brink, A. Krych, O. R. Cardenas, and S. Tiwari, “New potential from analytics-driven maintenance technologies | McKinsey,” www.mckinsey.com, Jul. 19, 2021. https://www.mckinsey.com/capabilities/operations/our-insights/establishing-the-right-analytics-based-maintenance-strategy

[4] Y. Seid Ahmed, A. A. Abubakar, A. F. M. Arif, and F. A. Al-Badour, “Advances in fault detection techniques for automated manufacturing systems in industry 4.0,” Frontiers in Mechanical Engineering, vol. 11, Apr. 2025, doi: https://doi.org/10.3389/fmech.2025.1564846.

[5] I. ul Hassan, K. Panduru, and J. Walsh, “Predictive Maintenance in Industry 4.0: A Review of Data Processing Methods,” Procedia Computer Science, vol. 257, pp. 896–903, Jan. 2025, doi: 10.1016/j.procs.2025.03.115.

[6] M. Ghahramani, Y. Qiao, M. C. Zhou, A. O'Hagan and J. Sweeney, "AI-based modeling and data-driven evaluation for smart manufacturing processes," in IEEE/CAA Journal of Automatica Sinica, vol. 7, no. 4, pp. 1026-1037, July 2020, doi: 10.1109/JAS.2020.1003114.

[7] A. Isiani, L. Weiss, H. Bardaweel, H. Nguyen, and K. Crittenden, “Fault Detection in 3D Printing: A Study on Sensor Positioning and Vibrational Patterns,” Sensors, vol. 23, no. 17, 2023, doi: 10.3390/s23177524.

[8] Z. Wang, J. Yang, and Y. Guo, “Unknown fault feature extraction of rolling bearings under variable speed conditions based on statistical complexity measures,” Mechanical Systems and Signal Processing, vol. 172, p. 108964, Jun. 2022, doi: 10.1016/j.ymssp.2022.108964.

[9] A. Oleff, B. Küster, M. Stonis, and L. Overmeyer, “Process monitoring for material extrusion additive manufacturing: a state-of-the-art review,” Progress in Additive Manufacturing, vol. 6, no. 4, pp. 705–730, Dec. 2021, doi: 10.1007/s40964-021-00192-4.

[10] D. Neupane, M. R. Bouadjenek, R. Dazeley, and S. Aryal, “Data-driven machinery fault diagnosis: A comprehensive review,” Neurocomputing, vol. 627, p. 129588, Apr. 2025, doi: 10.1016/j.neucom.2025.129588.

[11] Y.-J. Park, S.-K. S. Fan, and C.-Y. Hsu, “A Review on Fault Detection and Process Diagnostics in Industrial Processes,” Processes, vol. 8, no. 9, 2020, doi: 10.3390/pr8091123.

[12] K. He, M. Jia and C. Liu, "A Review of Optimal Sensor Deployment to Diagnose Manufacturing Systems," in IEEE Access, vol. 6, pp. 27418-27432, 2018, doi: 10.1109/ACCESS.2018.2834556.

[13] B. Ervural and H. I. Ayaz, “A fully data-driven FMEA framework for risk assessment on manufacturing processes using a hybrid approach,” Engineering Failure Analysis, vol. 152, p. 107525, Oct. 2023, doi: 10.1016/j.engfailanal.2023.107525.

[14] L. Zhang, M. Leach, J. Chen, and Y. Hu, “Sensor cost-effectiveness analysis for data-driven fault detection and diagnostics in commercial buildings,” Energy, vol. 263, p. 125577, Jan. 2023, doi: https://doi.org/10.1016/j.energy.2022.125577.