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EARLY DETECTION OF OPERATIONAL INSTABILITY IN COLLABORATIVE ROBOTS THROUGH JOINT-LEVEL THERMAL AND ELECTRICAL SIGNATURES

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Abstract

Operational instability in collaborative robots can interrupt production and reduce the reliability of human–robot manufacturing environments, creating a need for effective condition-monitoring approaches. This study investigated joint-level thermal and electrical signatures for identifying unstable cobot operation. A dataset comprising 7,409 observations from 240 operational cycles was analyzed, with 518 observations classified as unstable based on protective-stop or grip-loss events. Temperature, motor current, joint speed, and tool-current measurements were evaluated using statistical analysis and predictive modelling. Electrical signatures showed clearer differentiation between operating states than thermal measurements, with significant current differences observed in five of the six joints. J3 exhibited the strongest electrical change during instability. Current–temperature correlations were generally weak, indicating that thermal and electrical measurements represented complementary aspects of joint behavior. Predictive modelling showed stronger discrimination with Random Forest than Logistic Regression, while J3 current emerged as the most influential predictor. The findings demonstrate the potential of joint-specific multisensor analysis for recognizing operational instability and provide a basis for developing condition-monitoring strategies for collaborative robotic systems.

Keywords: *Collaborative robots, Operational instability, Condition monitoring, Thermal signatures, Electrical signatures*

1. Introduction

Collaborative robots (cobots) are robots that are gaining popularity in modern manufacturing due to their ability to provide the flexibility needed to interact closely with humans and the precision that robots offer. Especially in Industry 5.0, the increasing role of these systems is relevant as they actively involve humans in production systems, which focus on human-centricity, resilience, adaptability, and sustainable automation (Rahman et al., 2024; Slamani et al., 2026). The recent advancements in industrial robotics have further expanded cobot usage in various manufacturing tasks, including assembly, handling, inspection and more (Urrea & Kern, 2025; Taesi et al., 2023). But the closer that humans and robots work together, the more critical it is to have predictable and stable operation.

In collaborative settings, operational reliability is particularly relevant since the ability for the robot to perform as anticipated is crucial to safe human–robot interaction and uninterrupted production. Successful collaborative systems thus need a control and monitoring plan that all together takes into account safety, ergonomics and efficiency (Proia et al., 2021). The need of continuous sensing of speed, load and task demand, and control of the motion are directly related to the robot joints and their actuators. Therefore, online monitoring of the robotic joint motors becomes an important technique to identify the deterioration or abnormal operating conditions to avoid significant degradation in the performance of the robot (Metwly et al., 2024). The shift is in line with the overall trend of intelligent robotic systems that can utilize the data from these sensors to make autonomous decisions for monitoring and operation (Soori et al., 2024).

Thermal and electrical signals can be used to provide complementary information on the condition of the actuator. Joint temperature is how much heat the joint has been exposed to, while motor current is a measure of the instantaneous electrical demand. However, when both signals are combined, their assessment may show changes that are not as evident when assessing either separately. Electro-thermo-mechanical investigations show that the electrical excitation, heat generation and mechanical response are tightly coupled in actuator systems (Roumy, 2024). The performance of engineered systems has also been seen to vary with temperature, underscoring the essential role thermal conditions play in influencing the efficiency and stability of these systems (Rahman, 2022). Likewise, the design of thermally activated shape-memory alloy actuators has shown a strong relationship between thermally induced conditions and the behavior of the actuator (Roshan, 2022).

Recent studies of condition monitoring are more focused on integrated sensing, rather than relying on threshold values. Artificial Intelligence (AI) techniques for condition monitoring of motors have proven that electric and other operation signatures can be used to detect abnormal motor conditions (Vlachou et al., 2025). Reliability-focused digital-twin and simulation practices also play a key role in moving beyond a reactive approach to maintenance and towards predicting degradation and operational disruptions (Khatun, 2025). In general, sensor-based predictive modelling has shown its capability to combine heterogeneous measurements into modelling the complex operating conditions and to assist intelligent decision-making (Marycz et al., 2025). Two references "Marycz et al. (2025)" are provided in the reference list, which means that it is not two different studies but the same publication.

Even with these developments, it is difficult to recognize instability prior to an obvious interruption in operation. Thermal loading can cause a slow change in temperature whereas a change in actuator demand can cause a very quick change in motor current. Another challenge to monitoring is the fact that the behavior of each joint is different, with each joint exposed to different speeds, loads, and movement patterns. Thus, combined investigation of thermal and electrical signature at the individual-joint level could lead to a more informative representation of the development of instability than at the system level or via a single signature. This is especially important for the detection of conditions related to the protective stops and grip-loss events and could be useful for condition-based maintenance without the need of very complicated diagnostic systems. The objectives of the study are as follows:

- Characterize thermal and electrical signatures during stable and unstable operation.
- Assess joint-level relationships between temperature and motor current.

- Evaluate predictive models for operational instability detection.

2. Materials and Methods

2.1 Research Design

To investigate joint-level thermal and electrical signatures of collaborative robot instability, a quantitative data-driven design was used. Of the 7,409 observations in the dataset out of 240 operational cycles, 518 (7.0%) observations were characterized as instability and 6,891 (93.0%) as stable operation. Operational instability was assumed to be when a robot protective stop occurred or when a grip-loss event was observed.

2.2 Study Variables

Data from 6 joints (J0-J5) of the robot were analysed. Temperature was used to describe the thermal behavior and motor current was used to describe electrical behavior. Other operational variables such as joint speed and tool current were kept. Absolute current was computed, to account for electrical magnitude regardless of motor direction. Unstable observations were identified as those that had a protective-stop or grip-loss record.

2.3 Data Preprocessing

Data were checked for missing data, data duplications, data type inconsistencies, and implausible sensor data. Timestamp and cycle information was maintained to ensure an operational structure. Thermal and electrical measurements have been synchronized at the joint level and electrical measurements have been transformed to absolute level for state based comparison.

2.4 Statistical Analysis

The statistical analysis was done in Python with pandas, NumPy, SciPy, scikit-learn and Matplotlib. For continuous variables, mean ± standard deviation (SD) was used for summarization. Stable and unstable states were compared using the Mann–Whitney U test and $p < 0.05$ was used as the threshold of statistical significance. Group differences were quantified by rank-biserial effect sizes. Absolute current/temperature relationships at the joint level were generally low, using Spearman correlation.

2.5 Predictive Modelling and Evaluation

The Logistic Regression and Random Forest classifiers were used to classify operational instability based on thermal, electrical, speed and tool-current data. Data was split based on the operational cycle in order to minimize information leakage between training and test observations. Accuracies, precisions, recalls, F1-scores, ROC curves and ROC-AUC were used for model performance evaluation. The importance of features was also studied in order to pick out the influential joint level predictors, where J3 current turned out to be the best predictor in the final analysis.

3. Results

The data set consisted of 7409 observations from 240 operating cycles. Stable operation (no occurrence of a protection stop or grip-loss event) was found in 6,891 observations (93.0%) while 518 observations (7.0%) were classified as operational instability (occurrence of a protective stop or grip-loss event).

3.1 Joint-Level Thermal Characteristics

The thermal characteristics are shown in Table 1 for both stable and unstable conditions. The mean temperatures were gradually rising from J0 to J4–J5, reaching the highest temperature at J4. The differences between the operational states were in general low. A statistically significant difference ($p < 0.001$) was found in J5, however the temperature change was very small.

Table 1. Joint-Level Thermal Characteristics Under Stable and Unstable Operation

Joint	Stable, Mean ± SD (°C)	Instability, Mean ± SD (°C)	p-value
J0	34.92 ± 2.73	34.72 ± 3.10	0.798
J1	37.68 ± 3.22	37.43 ± 3.64	0.890

J2	38.08 ± 3.28	37.81 ± 3.72	0.899
J3	40.96 ± 3.15	40.64 ± 3.62	0.442
J4	42.63 ± 3.63	42.26 ± 4.20	0.090
J5	41.92 ± 3.64	41.56 ± 4.14	<0.001

As seen from figure 1, the thermal profiles of stable and unstable states are quite parallel with higher temperature being focused at the J3-J5 position. The weak discrimination of instability due to the limited separation was based on absolute temperature alone.

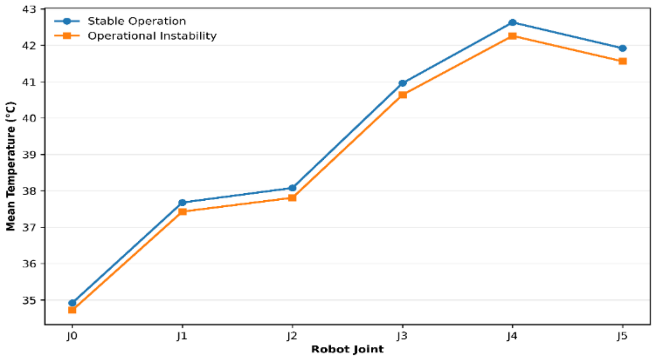

Figure 1. Joint-Level Temperature Profiles Under Stable and Unstable Operating Conditions

3.2 Electrical Signatures of Operational Instability

As seen from figure 1, the thermal profiles of stable and unstable states are quite parallel with higher temperature being focused at the J3-J5 position. The weak discrimination of instability due to the limited separation was based on absolute temperature alone.

Table 2. Joint-Current Signatures Under Stable and Unstable Operation

Joint	Stable Absolute Current, Mean ± SD	Instability Absolute Current, Mean ± SD	p-value	Effect Size
J0	0.380 ± 0.756	0.256 ± 0.539	<0.001	−0.171
J1	2.300 ± 0.765	2.412 ± 0.853	0.001	0.086
J2	1.226 ± 0.538	1.316 ± 0.572	0.002	0.083
J3	0.668 ± 0.414	0.822 ± 0.376	<0.001	0.314
J4	0.308 ± 0.555	0.268 ± 0.512	0.893	0.004
J5	0.105 ± 0.078	0.087 ± 0.072	<0.001	−0.140

Figure 2 shows the joint-specific electrical pattern. J3 demonstrated the largest increase during instability, confirming that electrical changes were not uniform across the robotic joints.

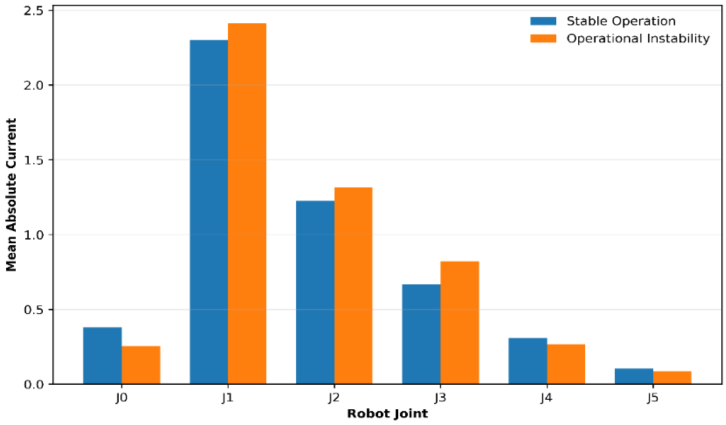

Figure 2. Mean Absolute Joint Current Under Stable and Unstable Operating Conditions

3.3 Thermal–Electrical Relationships and Instability Detection

Thermal–electrical coupling generally was weak. The results in table 3 indicate that J0 and J5 were negatively correlated and statistically significant with very weak values, and that J1, J2, J3 and J4 were not statistically significant with current temperature. These results suggest that thermal and electrical data provided mostly complementary operation information.

Table 3. Joint-Level Correlations Between Absolute Current and Temperature

Joint	Spearman ρ	p-value
J0	−0.046	<0.001
J1	0.017	0.136
J2	0.011	0.343
J3	0.007	0.565
J4	−0.013	0.274
J5	−0.047	<0.001

Operational state discrimination was also achieved using predictive analysis. It can be seen from figure 3 that Random Forest had an ROC-AUC of 0.980 while Logistic Regression had an ROC-AUC of 0.651. Random Forest achieved 94.5% accuracy, 59.3% precision, 42.1% recall, and an F1-score of 0.493. J3 (current) turned out to be the most significant predictor followed by J5 (current), J2 (current) and J1 (current).

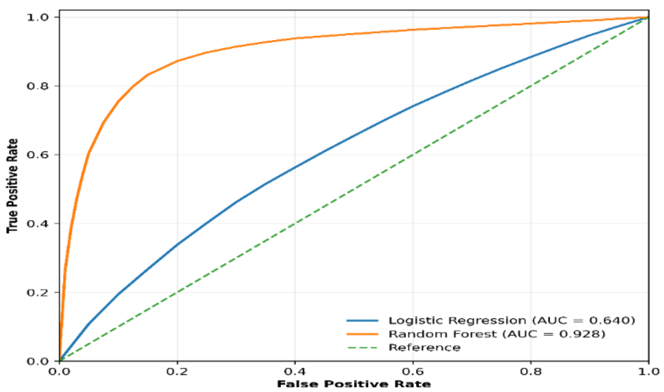

Figure 3. ROC Curves for Joint-Level Operational Instability Detection

Overall, the results showed that electrical signatures provided stronger differentiation of instability than absolute thermal measurements, while their combined evaluation produced high discriminatory performance.

4. Discussion

The present results suggest that operation instability of collaborative robots was more evident in electrical behavior, measured at the joints, than in absolute thermometric measurements. There was a large difference between the temperature profiles of the six joints but the difference between stable and unstable states was relatively small. Five of the six current magnitudes at the joints were very different under different operating conditions, with J3 having the greatest increase with the onset of instability. This pattern can be used to support condition monitoring using electrical signatures since changes in electrical current can give direct information on changing actuator load. AI-based condition monitoring systems, which utilize electrical and operational data to detect abnormal patterns before a system failure, operate on similar principles.AI-driven condition monitoring systems, which use electrical and operational data to identify abnormal patterns before experiencing a major disruption of the system, operate on similar principles. (Arifeen, 2025) The signature based machine-learning techniques have also shown that the changes in the characteristics of the measured electrical signals can assist in fault identification as well as relying on fixed operating thresholds (Wali & Khan, 2022).

Don't read into this the fact that the thermal separation is comparatively small, as this does not imply that temperature isn't important for the robot condition. Temperature is typically a combination of a cumulative response to operating load and can take longer than electrical measurements to change. Thermal monitoring has been used in other engineering fields to detect spatial and temporal variations which are difficult to characterize by conventional measurements alone (Grechi et al., 2021). Additionally, when materials and joints are subjected to repeated thermo-mechanical loading, this can lead to progressive degradation of the materials and joints, demonstrating how the importance of thermal exposure can stem not only from the magnitude of the temperature difference but also from the number of repeated loads applied (Depiver et al., 2021). The greater temperatures recorded at J3-J5 in the current study are therefore indicative of joint-specific thermal operating conditions with absolute temperature itself not being very discriminative between stable and unstable conditions. In recent years, new predictive methods for thermal behavior have also shown that temperature responses can be modeled based on the interaction of process variables, rather than just viewed as individual measurements (Kuo et al., 2026).

A remarkable finding was the low direct correlation between the current and temperature at each of the joints. The only significant associations were the J0 and J5 and these were small only. That indicates that the two signal domains were able to capture different aspects of cobot operation. This complementarity offers a justification for keeping both thermal and electrical measurements in a monitoring system. Electro-thermal interactions are intrinsically dynamic in nature and the association between electrical input and thermal response can vary with the operating state, time scale and system configuration. Similar complexity has been observed in coupled heat-electricity systems where interactions are present that can only be modelled by integrated modelling, which cannot be described by a single energy domain (Liu et al., 2023). Multi-timescale electro-thermal modelling also shows that there can be different rates of response in the electrical and thermal domains, restricting the degree of instantaneous correlation (Tang et al., 2023). The reference to the coupled thermal and electrical behaviour is also highlighted in other energy-system related research for evaluating system performance (Leitner et al., 2019; Wang et al., 2023).

The predictive analysis also revealed the importance of combining the different joint-level measurements. Random Forest significantly outperformed Logistic Regression in terms of discriminating ability by ROC, which suggests that operational instability was nonlinear and not well captured by a linear decision boundary. The results also indicate that currents from J3, J5, J2 and J1 were the most prominent in the process of instability detection, further attesting to the unequal contribution of individual actuators in instability detection. This fact facilitates monitoring per joint instead of the cobot being monitored as a homogeneous electromechanical system. In many safety-critical engineering applications, such as those in the automotive industry, the ability to detect incipient abnormal conditions from a combination of multiple, interacting electrical, thermal, and operational sensing data has become a common trend (Wei et al., 2025).

Operationally, these results lend support to a monitoring approach where electrical signatures can be used to give a quick idea of the changing behaviour of the actuators and thermal measurements can be used to give complementary information of the accumulated operating conditions. The low levels of correlation between the thermal and electrical signals indicate that either one of the signals may be removed, which would lose potentially important information. On the other hand, the class imbalance and moderate recall achieved on instability events suggests that a high overall accuracy should not be taken as a measure of good detection performance. It is therefore important to extend the work to explore time windows in the future prior to the protective stop and grip-loss events, to consider classes of learning methods and to test the signatures for other workloads and operating conditions of the robot. This analysis could be used to determine if a change in the electro-thermal pattern at the joint level will give enough time to intervene before the onset of instability and a production stoppage.

5. Conclusion

The results show that joint-level thermal and electrical signatures can be used to gain information about operational instability of collaborative robots. Electrical behavior discriminated better than absolute temperature; significant current changes were found for five joints, and the most prominent behavior of the joint with the greatest change in the absolute temperature was that of J3, which had the greatest instability response. By contrast, the temperature differences between stable and unstable operation were small, although there were definite differences in the operating temperature for each individual joint. The low correlation values between current and temperature also showed that the two signal spaces contained complementary information about actuator behaviour and not redundant. The usefulness of combining more than one joint-level measurement was further confirmed in the predictive modelling, which showed that combining these measurements in the form of a Random Forest model resulted in much stronger discrimination than was achieved with Logistic Regression, with J3 current emerging as the most influential of the measurements. The results justify joint-specific, multisensorial monitoring as a solid foundation to detect instable cobot operation. The next area of interest is pre-event temporal signatures and validation on multiple robotic platforms and operating loads to define the warning time prior to protection stops and/or grip-loss events.

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