Quantitative Analysis of Ambient Temperature Effects on Steptime Variations in Industrial Pneumatic Actuators

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Abstract: This paper presents a quantitative analysis of the influence of ambient temperature on the cycle time of pneumatic actuators in industrial production environments. Sub-cycle time periods, known as Steptimes, are used to characterize the duration of individual machine stages without requiring additional sensors. Building on the concept of Mini-terms and following the IEC 60848 GRAFCET standard, Steptimes are defined as the elapsed time between the activation and deactivation of PLC-controlled steps. Although the potential impact of ambient temperature on actuator performance is often acknowledged qualitatively, few studies have addressed this effect through precise, quantitatively measured data. In this work, a detailed experimental study is conducted using a PLC-controlled system composed of four automated modules. Steptimes and ambient temperature have been continuously monitored and their effects modeled statistically. The results show a consistent inverse correlation between temperature and Steptimes, as expected. The contribution of this research work is twofold: first, the feasibility and potential of using Steptime measurements to detect subtle environmental effects in industrial assembly lines is demonstrated. Second, the impact of ambient temperature in highly automated industrial assembly lines is quantitatively measured. By modeling subtle environmental effects, deviations in Steptime can be more accurately interpreted, reducing the risk of false alarms and improving system reliability.

1 INTRODUCTION

Monitoring sub-cycle time periods in industrial production machinery, such as the time taken for individual components to complete their tasks, provides valuable insights into their operational health. These measurements enable data-driven condition monitoring without requiring additional sensors, making them an efficient tool for industrial environments.

An early concept in this field is that of Mini-terms (Garcia and Montes, 2019a), (Garcia and Montes, 2019b), (García and Montés, 2019), defined as a subdivision of the cycle time. Mini-terms enable granular analysis of component behavior by isolating time intervals that reflect the performance of individual actuators or subsystems.

Building on this concept, (Zubieta et al., 2025) proposed a scalable and standardized methodology to define sub-cycle time periods of machines programmed in a PLC in compliance with the IEC 60848 standard, which defines the GRAFCET methodology. In this approach, sub-cycle time periods, referred to as Steptimes, are defined as the time elapsed between the activation and deactivation of a specific step within the machine's operating sequence.

Unlike Mini-terms, which typically focus on actuator movements alone, Steptimes can be applied to any functional step controlled by the PLC, including compound actions involving multiple elements. They are also task-based measurements rather than purely action-based, meaning they can distinguish between the same physical action performed in different contexts. For example, a pneumatic cylinder moving from point A to point B may exhibit different Steptimes depending on whether it is operating under load or unloaded. Variations in Steptimes can reveal early signs of degradation or anomalies in actuators, valves, or mechanical subsystems.

However, interpreting these time-based metrics

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without considering environmental factors such as ambient temperature can result in systematic deviations in timing being mistakenly classified as anomalies. This limitation motivates the present work, which aims to quantify the effect of ambient temperature on multiple pneumatic systems under real operating conditions.

Context-aware anomaly detection has become essential in industrial diagnostics, enabling differentiation between deviations induced by external factors, such as ambient temperature or workload, and genuine faults arising from internal component degradation. Contextual anomaly detection methods strive to capture anomalies between elements with some type of relationship, which is often unknown beforehand (Suárez-Varela and Lutu, 2025).

Among these extrinsic variables, ambient temperature is a critical but frequently overlooked factor. Temperature changes can alter air viscosity, pressure stability, and mechanical tolerances—especially in pneumatic components, which are highly sensitive to such physical conditions. While prior research and standards (International Organization for Standardization, 2010) acknowledge the general impact of temperature on compressed air systems, existing studies tend to be qualitative or based on simulations.

The main objective of this work is to quantitatively analyze the impact of ambient temperature on the cycle time of pneumatic actuators used in industrial production lines, focusing on Steptime variations observed in a PLC-controlled experimental setup. The ultimate aim is to enhance context-aware anomaly detection by distinguishing timing deviations induced by environmental conditions from those caused by actual component degradation. This distinction will contribute to more accurate and reliable predictive maintenance in industrial environments.

The results show that while some pneumatic cylinders exhibit a strong correlation between ambient temperature and Steptime duration, others remain largely unaffected. This actuator-specific variability highlights the need for localized context-aware monitoring rather than universal assumptions about temperature sensitivity.

This work makes two main contributions, by providing regression analyses, calculating R^2 values, and per-cylinder behavior across a large set of samples. On one hand, the results demonstrate that Steptime measurements can effectively capture subtle environmental influences in industrial assembly lines. On the other hand, the impact of ambient temperature in highly automated industrial assembly lines has been quantitatively measured, a factor often acknowledged but rarely quantified in existing literature.

The findings are especially relevant for researchers aiming to design robust, temperature-aware anomaly detection strategies in real industrial automation environments, as well as for those seeking to develop holistic and precise monitoring systems.

2 RELATED WORK

Understanding how component behavior evolves under different conditions is essential for developing robust condition monitoring and fault detection strategies in industrial systems. In recent years, there has been increasing interest in using time-based metrics, such as cycle durations or sub-cycle time intervals, to assess machine health without additional sensors. However, the interpretation of these metrics is often done in isolation, without considering external influences or contextual information.

This section reviews existing research in two relevant areas. First, the studies addressing the influence of ambient temperature on the performance of pneumatic actuators have been examined. This study focuses primarily on these components. Subsequently, an overview is presented of context-aware anomaly detection approaches that integrate environmental and operational context into fault-detection frameworks.

2.1 Environmental Influence on Pneumatic Actuator Dynamics

The influence of temperature on pneumatic systems has been recognized across various industrial studies, although it is often addressed only indirectly or qualitatively. In their review of artificial neural network applications for HVAC and thermal systems, (Mohanraj et al., 2012) mention that ambient temperature affects system dynamics and energy efficiency, yet no quantitative relationship is established between temperature and actuator behavior or timing.

(Sorli et al., 1999) present a dynamic model of pneumatic actuators based on thermodynamic principles, which includes temperature as part of the gas behavior within the actuator chambers. However, their study is simulation-based and does not provide experimental validation of how ambient temperature affects the cycle time of real actuators.

(Fang et al., 2018) experimentally analyze the effect of internal heating on the performance of a pneumatic engine. Although the study includes temperature variations and quantifies their influence on output power and torque, it focuses on energy engines rather than standard pneumatic actuators, and the heating is applied internally rather than through ambient changes.

(Park and Joung, 2022) examine how heat load influences the thermal control performance of pneumatic loop heat pipes. While this work includes precise temperature control analysis, it is focused on thermal management devices rather than actuator dynamics, and does not investigate timing or speed responses.

Finally, (Pham et al., 2020) explore the effect of humidity on friction in pneumatic cylinders. Although related, their focus is on surface interaction and tribology rather than dynamic response, and temperature is not examined.

Across these studies, the consensus is that environmental conditions (temperature, humidity) can affect pneumatic behavior, yet none of them offer a quantitative correlation between ambient temperature and pneumatic actuator cycle time. This gap is particularly relevant for condition monitoring and predictive maintenance, where timing deviations may be misinterpreted if temperature effects are not accounted for. The present work addresses this gap by providing a regression-based experimental analysis of ambient temperature influence on pneumatic actuator timing, validated through a PLC-controlled experimental setup representative of industrial systems, incorporating both pneumatic and electric actuators.

2.2 Contextual Anomaly Detection

Context-aware anomaly detection is increasingly relevant in industrial diagnostics, as it distinguishes deviations from extrinsic factors (e.g., temperature, workload) from true faults due to component degradation. In contrast, traditional methods often rely on fixed thresholds and neglect context, leading to false alarms.

(Chandola et al., 2009) classify anomalies into point, contextual, and collective types. A **point anomaly** occurs when a single instance deviates strongly from the dataset, such as an unusually high-value credit card transaction for a user.

A **contextual anomaly** is anomalous only in a given context. Detection requires distinguishing contextual attributes (e.g., time, location) from behavioral attributes (observed values). For instance, 5°C may be normal in winter but unusual in summer, or a high-value purchase typical at holidays but suspicious otherwise.

Collective anomalies arise when a group of related data points is anomalous as a whole, though each may appear normal individually. They often occur in time-series, sequences, or graphs—for example, a normal-looking sequence of computer operations that together indicate a cyberattack. Unlike point anomalies, they depend on inter-point relationships, and unlike contextual anomalies, they result from internal patterns rather than environmental attributes.

(Hayes and Capretz, 2014) proposed a two-stage framework for Big Sensor Data, combining univariate Gaussian detection with a context-aware post-processing layer built on MapReduce k-means clustering. By leveraging spatial, temporal, and operational metadata, the system remains scalable and reduces false positives. Tests on a commercial dataset showed that context filtering improves anomaly detection in large sensor networks.

Koio et al. (Juba and Koio, 2025) proposed a wearable IoT framework that monitors occupational hazards and falls by combining real-time analytics with context (ambient conditions, posture, motion). This approach reduces false positives and demonstrates the value of context-aware models for worker safety in high-risk environments.

3 EXPERIMENTAL SETUP

The experimental setup (Figure 1) includes four modules representing machines in a sequential line, programmed with GRAFCET methodology.

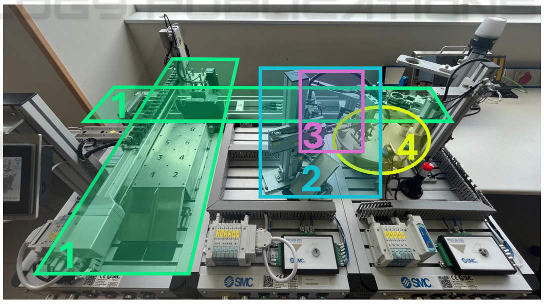

Figure 1: Experimental use-case.

Figure 2 illustrates the interaction between the four modules. Module 1 operates independently, while Modules 2, 3, and 4 are interdependent. Modules 2 and 3 function in parallel, although Module 2 exhibits a longer cycle time. Once both modules complete their respective tasks, Module 4 initiates its operation. Upon completion, the cycle restarts with Modules 2 and 3. As Module 2 consistently determines the overall cycle duration, it constitutes a bottleneck in the system, following widely accepted definitions in the literature (Azid et al., 2020), (Su et al., 2022), (Yang et al., 2022).

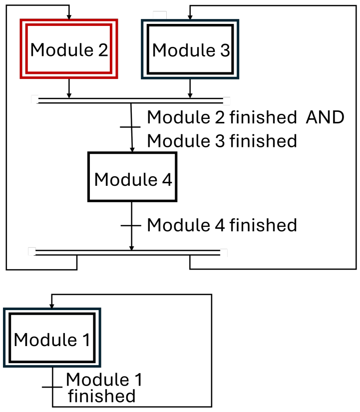

Figure 2: GRAFCET diagram from Modules 1, 2, 3 and 4.

The experiments were carried out using a Siemens 1516-F PLC, which acted as the central controller throughout the study. System data were collected using the OPC-UA client-server communication protocol. The four modules comprising the experimental setup are described below.

- Module 1: As can be seen in figure 3, it has two main components: (a) a crane with a vacuum gripper actuated vertically by a pneumatic cylinder to lift parts from a platform , and (b) a conveyor belt that transports the part and returns it to its initial position. The crane then replaces the part on the platform, repeating the cycle continuously.

(a) (b)

Figure 3: Module 1 setup.

- Module 2: This module has a horizontal pneumatic arm with a vacuum gripper mounted on a vertical pneumatic cylinder. The gripper picks a part from a rotary platform, transfers it to a second location, then returns it. The table advances one position and the cycle repeats (Figure 4).
- Module 3: This module has an arm that rotates around a vertical axis to reach two positions. At the first, it picks a part from a rotary platform with a pneumatic gripper on a cylinder; at the second, it delivers the part. The arm then returns it to the platform, and once Module 2 completes its task, the table advances and the cycle repeats (Figure 5).

Figure 4: Module 2 setup.

Figure 5: Module 3 setup.

- Module 4: This module is composed of a rotary table that receives two parts per cycle, one from Module 2 and one from Module 3. Once both parts are placed, the table rotates by one position. Modules 2 and 3 then pick up the parts from the new positions, perform their respective operations, and return the parts to the table. The platform rotates again, completing the cycle and initiating a new one (Figure 6).

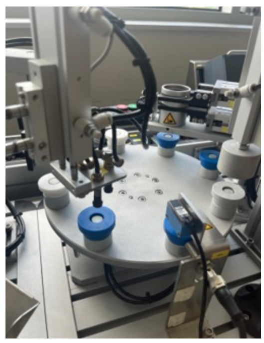

Figure 6: Module 4 setup.

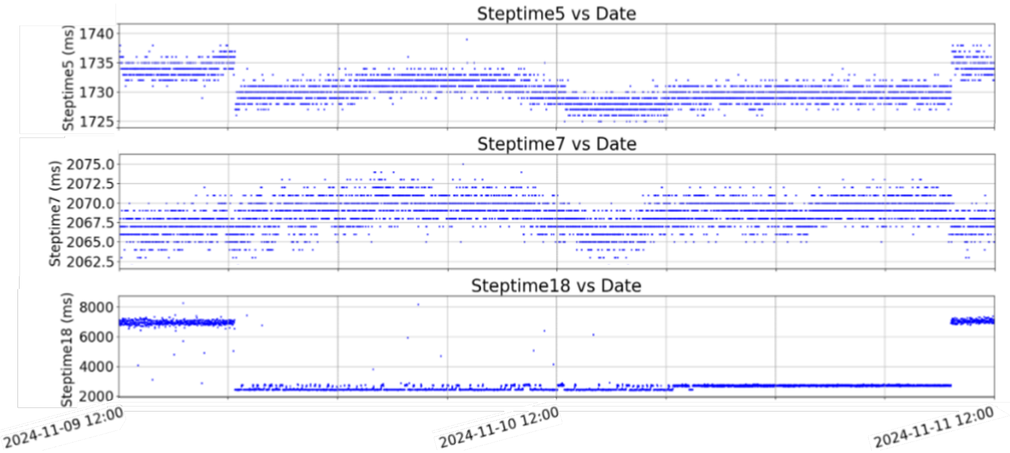

Figure 7: Time series data of Steptime5, Steptime7 and Steptime18 from the experimental use-case shown in section 3.

4 EXPERIMENTAL PROCEDURE

Environmental factors such as ambient temperature can affect the behavior of components like pneumatic cylinders and valves, thereby influencing the duration of operations within a production cycle. Previous work (Zubieta et al., 2025) has shown that anomalies in the production line are reflected in Steptime variations; accordingly, fluctuations in ambient temperature are also expected to impact Steptime values.

Experiments were carried out in a laboratory insulated from outdoor conditions and equipped with an air conditioning system that operated on working days but was inactive during weekends. During weekdays, additional heat sources included the automated setups, robots, and researchers, resulting in temperature oscillations between 22 and 25 °C. In contrast, weekends without air conditioning showed nearly constant temperatures close to 22 °C.

Steptimes represent the interval between the activation and deactivation of a specific step in the production line. Each time a step is deactivated, its Steptime is recorded. Figure 7 illustrates the high resolution and precision of Steptime measurements, showing the time series of Steptimes 5, 7, and 18 over two days of uninterrupted machine operation.

The literature indicates that the effect of ambient temperature in industrial assembly lines has been discussed only qualitatively, with few quantitative studies. To address this gap, Steptime measurements were collected across a range of temperatures and statistically modeled against ambient temperature, with the aim of assessing their thermal sensitivity and identifying the most affected stages.

5 RESULTS AND DISCUSSION

Table 1 summarizes the definitions of the Steptimes analyzed in this section.

Table 1: Definitions of Steptimes analyzed in Section 5.

	Step-time	**Definition**
Module 1	8, 3, 14, 17	Extension time of vertically mounted pneumatic cylinders (rod down).
	5, 9, 11	Retraction time of a vertically mounted pneumatic cylinder (rod down).
	15	Two parallel actions: retraction of a vertical cylinder (rod down) and a conveyor belt driven by an electric motor; duration set by the longer action.
Module 2	2	Extension time of a horizontally mounted pneumatic cylinder (unloaded).
	9	Extension time of a horizontally mounted pneumatic cylinder (under load).
	3	Extension time of a vertical pneumatic cylinder (rod down, unloaded).
	7	Extension time of a vertical pneumatic cylinder (rod down, under load).

Results in Figure 8 show a clear visual relationship between ambient temperature and Steptime 8. The time-series and ambient temperature (yellow) over six consecutive days of machine operation re-

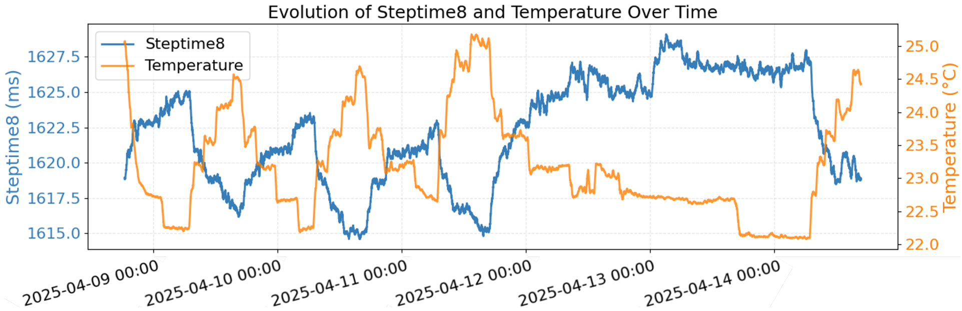

Figure 8: Temporal variation of Steptime 8 and ambient temperature.

veals a marked inverse correlation. During April 12–13, the temperature remained relatively stable, corresponding to the weekend when the laboratory air conditioning was turned off. Consistently, Steptime 8 also exhibited reduced variability in this period.

5.1 Statistical Analysis

To quantify the relationship between Steptimes and ambient temperature, a simple linear regression model was employed as shown in (1):

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (1)$$

where Y denotes the Steptime (ms), X the ambient temperature (°C), β_0 the intercept, β_1 the slope, and ε the random error term accounting for variability not explained by the model. β_1 shows how much Steptime (ms) is expected to change when the temperature increases by 1 °C.

On the other hand, model performance for each Steptime was assessed using the coefficient of determination (R^2), defined as in equation (2).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad (2)$$

where y_i are the observed values of a given Steptime, $\hat{y}_i$ the corresponding regression predictions obtained with the equation (1, and $\bar{y}$ the mean of the Steptime. R^2 therefore expresses, for each operation, the proportion of variability in its duration that is explained by ambient temperature. For example, $R^2 = 0.59$ for Steptime 8 indicates that 59% of its variation is attributable to temperature changes, whereas values close to zero imply that temperature has very little influence on those operations.

To determine whether the observed temperature–Steptime associations could be attributed to random variability, we tested the null hypothesis that the regression slope is zero ($H_0 : \beta_1 = 0$) for each Steptime. A two-sided t-test was used to obtain p-values, and statistical significance was interpreted at $\alpha = 0.05$. The p-value quantifies the probability of observing a slope at least as extreme as the estimated one if, in truth, temperature had no effect. We report exact p-values (values < 0.001 shown as "< 0.001") as indicators of statistical evidence; practical relevance is summarized by the slope (ms/°C) and R^2.

As in any linear regression, validity relies on the assumptions of linearity, independence, homoscedasticity, and approximate normality of residuals. These assumptions were not formally tested in this study, but the consistency of the results across different Steptimes and modules supports the adequacy of a linear model within the observed temperature range.

5.2 Statistical Analysis Results

Table 2 summarizes the regression results for the most relevant Steptimes from Modules 1 and 2.

Table 2: Selected Steptimes from Module 1 and Module 2.

	Step-time	Slope (ms/°C)	R^2	p-value	n (samples)
Module 1	3	-4.02	0.57	< 0.001	13851
	5	-5.64	0.53	< 0.001	13820
	8	-3.97	0.59	< 0.001	13809
	9	-5.56	0.45	< 0.001	13794
	11	-5.64	0.53	< 0.001	13797
	14	-3.98	0.57	< 0.001	13806
	15	-3.14	0.05	< 0.001	13693
	17	-3.49	0.50	< 0.001	13813
Module 2	2	-3.19	0.21	< 0.001	21697
	3	-1.17	0.02	< 0.001	21704
	7	-0.20	0.00	0.01	21681
	9	-3.40	0.03	< 0.001	21700

For Module 1, all Steptimes exhibit negative slopes, indicating that higher ambient temperature systematically reduces their duration. The effect sizes vary between –3.14 and –5.64 ms/°C, with Steptimes 5, 9, and 11 showing the strongest sensitivities. The corresponding R^2 values (0.45–0.59) suggest that between 45% and 59% of the variability in these Steptimes can be explained by temperature. All associated p-values are below 0.001, confirming that these trends are statistically significant.

By contrast, Module 2 Steptimes display weaker and more inconsistent relationships with temperature. Although the slopes remain negative, their magnitudes are generally smaller (–0.20 to –3.40 ms/°C) and the R^2 values are close to zero (0.00–0.21). This indicates that ambient temperature explains little of the timing variability in Module 2. Only Steptime 7 shows a marginally significant effect ($p = 0.01$) but with negligible explanatory power ($R^2 = 0.00$).

Figure 9 summarizes the most temperature-sensitive Steptimes across the entire use case, presenting the estimated slopes in ms/°C. Notably, all of these steps belong to Module 1.

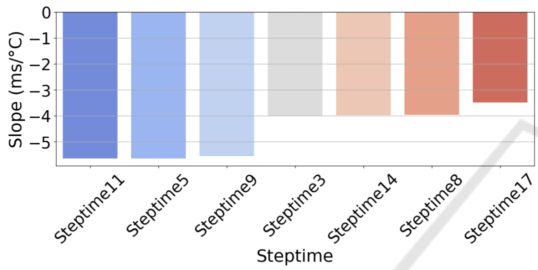

Figure 9: Estimated Temperature Sensitivity of the Most Affected Steptimes in the use case (all from module 1).

Extension-related Steptimes (3, 8, 14, and 17) exhibit more moderate slopes (between -3 and -4 ms/°C). This pattern suggests that the mechanical and pneumatic dynamics during retraction phases are more strongly influenced by temperature changes than during extension phases, possibly due to differences in internal chamber pressures and frictional forces.

Figure 10 presents the linear regression results for three representative Steptimes from Module 1. Steptimes 8 and 5 exhibit clear negative slopes, with estimated coefficients of –3.97 ms/°C and –5.64 ms/°C, respectively. Their corresponding R^2 values (0.59 and 0.53) indicate a moderate to strong linear correlation between ambient temperature and Steptime duration. These results confirm that both operations are significantly influenced by temperature variations, with Steptime 5 showing a particularly high thermal sensitivity. In contrast, a conveyor belt and a pneumatic cylinder operate in parallel within Steptime 15. Since both actions start simultaneously and the belt is the last to complete its task, the Steptime duration is determined by the belt. Due to the mechanical nature of the conveyor and its electric drive, it is barely influenced by temperature changes, which explains its low $R^2 = 0.05$.

Figure 11 shows regression results for four Step-

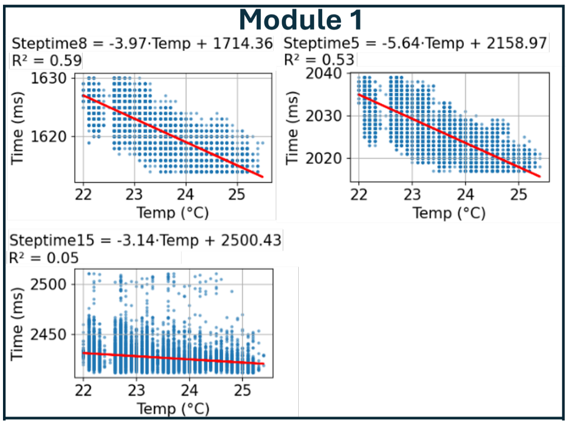

Figure 10: Linear Regression and R^2 between Steptimes(ms) from Module 1 and Temperature(Cº).

times from Module 2. Although slopes remain negative, the very low R^2 values (0.00–0.05) indicate that temperature explains little of their variability. Thus, Module 2 timing is largely unaffected by ambient temperature in the observed range. These differences highlight the need for actuator-specific analysis, as sensitivity may depend on movement type, load, or control strategy.

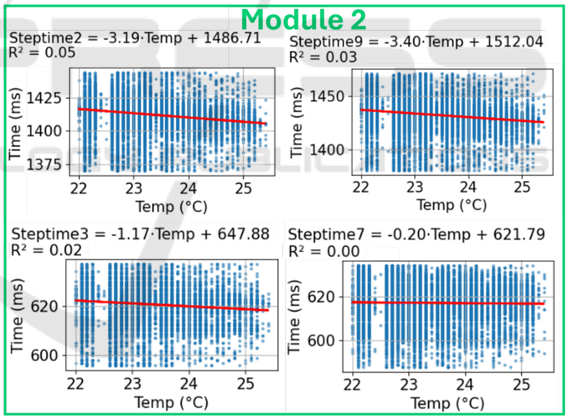

Figure 11: Linear Regression and R^2 between Steptimes(ms) from Module 2 and Temperature(Cº).

6 CONCLUSIONS AND FUTURE WORK

This study presented a quantitative analysis of how ambient temperature influences the cycle time of pneumatic actuators in industrial production lines. By monitoring Steptimes, the experiments demonstrated that temperature measurably affects operation durations. A simple linear regression model quantified this relationship through temperature coefficients (β_1) and coefficients of determination (R^2). The effect magnitude varied across steps, suggesting that mechanical configuration, load conditions, and movement dynamics shape each actuator's thermal sensitivity.

These findings demonstrate that Steptime measurements provide a sensitive, non-invasive indicator of environmental influences in assembly lines. Incorporating such context into monitoring can improve diagnostics, reduce false alarms, and enable earlier detection of genuine degradation.

On the other hand, no abnormal operation, faults, or failures of the pneumatic actuators were observed within the tested ambient range (22–25 °C). The influence of temperature was reflected exclusively in variations of Steptime values, without leading to performance degradation or malfunction.

Future work will develop a context-aware monitoring system to automatically distinguish whether Steptime deviations arise from external factors or genuine faults. The approach relies on correlations between Steptimes during normal operation: external influences will be reflected consistently in these correlations, whereas intrinsic faults will disrupt them.

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