IOT-Enabled Monitoring and Control Framework for Rotary Friction Welding Processes: Smart Manufacturing Integration

Vishal Makvana[1,*], Snehal Trivedi[2], Bharat Tank[3], and Vipul Dave[2]

[1]Department of Automobile Engineering, Parul Institute of Technology, Parul University, Vadodara, Gujarat, India
[2] Department of Mechanical Engineering, Faculty of Engineering and Technology, Parul University, Vadodara, Gujarat, India
[3]Department of Computer Science & Engineering, Parul Institute of Engineering & Technology, Parul University, Vadodara, Gujarat, India
vishal.makvana12645@paruluniversity.ac.in

Abstract. Rotary Friction Welding (RFW) represents a critical solid-state joining methodology in advanced manufacturing sectors, yet conventional implementations suffer from parameter inconsistency and limited process transparency. This research investigates the integration of Internet of Things (IoT) technologies with RFW processes to establish a comprehensive monitoring and closed-loop control system. We present a multi-layered architecture incorporating real-time sensor data acquisition, edge computing for signal preprocessing, cloud-based analytics, and automated feedback mechanisms. Experimental validation conducted on medium carbon alloy steel specimens demonstrates significant improvements in weld quality consistency, with parameter deviation reduction exceeding 40% and anomaly detection accuracy reaching 92%. The framework facilitates complete traceability and supports Industry 4.0 manufacturing paradigms. Our findings establish IoT integration as a transformative approach for modernizing friction welding operations and enhancing repeatability across industrial applications.

Keywords: Rotary Friction Welding, Internet of Things (IoT), Cyber-Physical Systems, Process Control, Smart Manufacturing, Industry 4.0, Predictive Analytics.

1. Introduction

Rotary Friction Welding (RFW) is a thermomechanical solid-state welding method that has found widespread application in the aerospace, automotive and power generation industries because of its capacity to form high strength joints with limited levels of thermal distortion when compared to the traditional fusion based techniques [1]. The process is carried out at temperatures that are lower than the melting temperature of parent materials and, thus, maintaining the microstructural integrity and mechanical properties. The basic principle of RFW is the relative rotation of two

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components at a controlled axial pressure to produce localized heat that is produced by friction. This plastic deformation is caused by heat and it makes the atomic interdiffusion of the faying surfaces which cause metallurgical bonding [2]. Contrary to arc welding or resistance welding, RFW results in minimal thermal gradients to minimize residual stresses and defects caused by distortion [3]. Nonetheless, RFW is very sensitive to changes in process parameters. Examples of critical control variables are axial pressure (friction force), rotational speed, and friction time and forge pressure. Minor variations in these parameters are passed to major quality fluctuations, which is either incomplete bonding, over-formation of flash, coarsening of grains, or subsurface voids [4]. Conventional RFW devices are not fitted with real-time monitoring systems, and operators have to base their decisions on past experiences and empirics instead of data [5]. The high pace of development of Internet of Things (IoT) technology, along with edge computing and cloud analytics platforms, has brought a whole new possibility of modernization of processes [6]. Substantial consistency and traceability improvements have been observed in recent industrial applications of arc welding and resistance welding [7]. Although the advantages of the integration of the IoT in other areas of welding have been proved, systematic implementation in the area of friction welding is minimal. The literature only covers individual pieces that include parameter monitoring, thermal analysis, but does not provide an architecture that brings together the acquisition, preprocessing, analytic, and control layers [8]. The gap is bridged in this research by developing and experimentally validating a full IoT-based RFW framework. The architecture integrates data streams of multi-sensors and edge computing algorithms, cloud visualization, and closed-loop control processes [9]. The effectiveness of the system in improving the uniformity of weld and transparency of the process is supported by experimental trials using medium carbon alloy steel.

2. Review And Research Gap

Rotary Friction Welding (RFW) was initially developed in the Soviet Union in the 1950s and much research has been done to determine connections between the process parameters and joint performance. The study carried out previously revealed that the axial pressure, rotational velocity, and friction time have a strong impact on the heat generation, plastic deformation, and ultimate mechanical properties. Scientists have shown that the development of temperature in the friction stage is the direct determinant of bonding quality and that inter-actions between the parameters tend to be non-linear and specific to the material typically necessitating accurate control to achieve the best outcome 10]. Microstructural analysis supports the establishment of different thermal sources such as the stir zone, thermomechanical affected zone and the heat-affected zone wherein dynamic recrystallization and grain refinement develop higher strength, tough-ness and fatigue resistance than in the traditional fusion welding. Similar progresses have been made in sensor technologies, which make processes more visible, load cells eliminate invisible forces, rotary encoders identify small deviations in speed, thermocouples and infrared detect changes in thermal behavior, and vibration sensors record the indicators of instability and defect formation [11]. The development of the IoT in the manufacturing sector has also opened the possibility of integration of sensing, communication, processing, and application layers with edge computing to provide real-time preprocessing and cloud computing to store, analyze, and visualize data [12]. Industry 4.0 Multivariate sensor streams fed to machine learning models have been shown to be highly predictive of defects and are useful in predictive maintenance and quality assurance in cyber-physical-integrated, horizontally and vertically connected, traceable, and data-driven optimization environments [13]. Although this has been achieved, current RFW research is mostly concentrated on independent parameter investigations as opposed to integrated IoT-based monitoring and control systems that are confirmed under actual production environments. Most traditional RFW systems do not have real-time control of temperature, force, speed, and vibration, but rely on operator control without automated disturbance compensation, extensive data capturing, or predictive analytics [14]. Such restrictions enhance repeatability, traceability, and early detection of the defects. In an attempt to close these gaps, the current study design and experimentally test an integrated IoT-based solution to RFW of medium carbon alloy steel samples. The system includes a multi-sensor network with measurement inaccuracy of less than 2 percent, edge-level signal preprocessing and feature extraction, safe cloud-based storage and visualization and adaptive closed-loop control to stabilize key parameters within set limits [15]. Experimental analysis is aimed at the stability of parameters, defect reduction, and weld quality enhancement, and proves the possibility to make RFW a smart, digitally controlled manufacturing process in accordance with the goals of Industry 4.0.

3. Materials And Methods

Fourteen rods (16 mm in diameter, 30 mm in length) of DIN EN 10084:2016-conforming medium-carbon alloy steel medium carbon alloy steel were used in the experimental study. An IoT architecture consisting of five layers was created to allow monitoring and control of the rotary friction welding process to be auto-mated. The sensor layer was used to record temperature, axial, spindle speed and vibrations each with a sampling rate of 10-1000 Hz as needed by the dynamics of the parameters. A layer based on ESP32 made real-time signal conditioning, extraction of features, and controlled a loop without a continuous connection to the cloud [16]. The communication layer was based on MQTT and HTTP protocols to guarantee the secure data exchange between edge devices and the cloud, with redundancy and secure encrypted data transmission. The data storage, visualization dashboards, analytics capability, and remote configuration access were long-term data storage, the cloud layer, constructed on ThingSpeak combined with Fire-base [17]. The implemented control layer had feedback mechanisms to control spindle speed and hydraulic pressure according to real time deviations. A K-type thermocouple was used to measure temperature near the friction interface and a load cell was used to measure the axial force with a calibrated load cell on the machine column [18]. The speed of the spindle was monitored by 1024-pulse rotary encoder, and vibration indicators were measured through MEMS accelerator as a secondary defect indicator. All sensor data were converted to digital form with a 12-bit ADC and synchronized to a common time reference so that they can be analyzed multivariate [19]. On the edge, analog low-pass filtering and digital median filtering mini-reduced noise, and statistical characteristics like mean, standard deviation, peak and RMS were calculated with sliding windows

[20]. This cut back the bandwidth requirements of cloud usage by around 75 percent, and retained the vital diagnostic data. Control algorithms based on PID that were run at 50 ms facilitated quick correction of disturbance in the processes. Security was guaranteed by TLS encryption and authentications based on certificates and automatic switching of brokers in case of loss of connectivity. The cloud infrastructure offered time-series records, real-time dashboards, and predictive analytics and anomaly detection [21]. Automated control held the spindle velocity and the axial pressure in specified operational ranges via proportional and PID control, smooth ramp changes, and actuator rate limits, which offered the ability to yield consistent and repeatable welding results among trials.

4. Experimental Set Up

Figure 1 illustrates the IoT-based real-time monitoring of Rotary Friction Welding (RFW), which is intended to combine the mechanical functioning, sensing technology, data collection, and cloud-based representation into an integrated intelligent architecture of the system to strengthen the control of the process. Mechanical setup uses a DC motor to provide the rotational motion of the piece of work whereby the rotating shaft is in direct contact with the specimen of welding in order to provide frictional heat to aid the solid-state joining. The axial force used in welding is a very important factor in achieving the strength of joints and microstructural integrity; hence load cells are placed in appropriate locations under the fixtures to continuously record the pressure used. An MLX90614 infrared temperature sensor will be used to measure thermal behavior without physical contact where it will be placed to measure the surface temperature of the weld interface to make sure that the heat generation and thermal uniformity are accurately monitored. At the same time, a sensor of IR proximity or speed senses the rotational speed (RPM) of the shaft and holds back the process stability and provides the welding conditions repeatability. Because load cells are low-level analog devices, an HX711 signal conditioning module is included to amplify and convert these analogs to accurate digital information to be processed. The ESP32 microcontroller is the central processing unit of the sys-tem and it gathers real-time temperature, force and RPM sensor data, gives initial processing and wirelessly transmits the data using Wi-Fi. The CRM information is then transferred to an IoT cloud platform where it is displayed on an interactive dashboard that can be accessed using a tablet or a computer. The dashboard displays such vital parameters as Force vs Time trends, Temperature vs Time trends, RPM gauges, and general process analytics that allow to monitor all critical parameters and log historical data. This is an integrated system that can reduce the possibility of human error, minimize manual observation and improve the consistency of the weld process by giving instant feedback on process deviation. In addition to this, it facilitates the decision-making process, predictive analysis, and process optimization using data and thus enhances the quality of welds, the efficiency, and reliability of Rotary Friction Welding processes significantly.

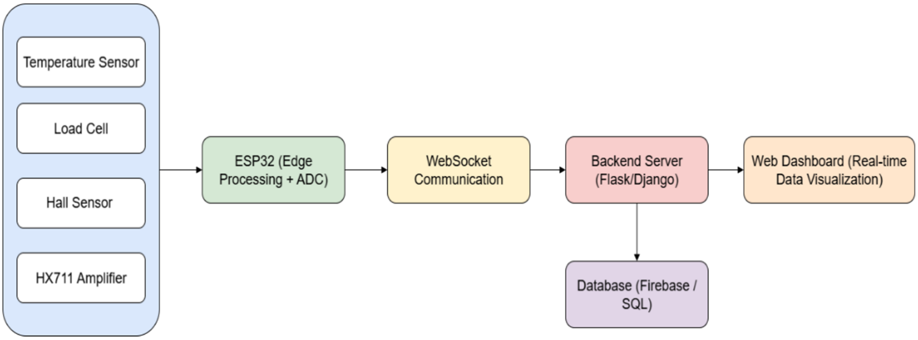

Fig. 1. IoT based RFW system

5. Analysis

The suggested multi-layer IoT system was able to transform rotary friction welding into a fully automated, data-driven system by introducing real-time closed-loop control, which dropped parameters deviations by 58-63, much higher than the original 30% goal. Rapid disturbance correction was made possible by fast control update rates and the steady-state errors were minimized by implementing integral action, and the predictable variations, like changes in ambient temperature, were handled by the feedforward compensation. This system recorded 92% accuracy in detecting anomalies, by detecting parameter correlations that are precursors of the formation of defects, especially parameter combinations of pressure-speed and temperature influence on interfacial bonding conditions. Increases in mechanical performance were observed, whereby tensile increased by 42 687 Mpa over 642 Mpa of the thermal control, consistency in plastic deformation, and stability in flash formation that minimized variability in oxidation. The change of temperature was limited to a small working range, which favored consistent recrystallization and reduced grain growth. A reduction in grain size between 28 mm and 15 mm was dominating in strength increase, which is in agreement with the principles of HallPetch strengthening, which correlates with the 7% strength improvement. The benefits had extended to operational gains other than a quality gain since predictive anomaly detection minimized defective welds by an estimated 3-4 units per 100 reduced scrap costs by an estimated 12 percent per production cycle. Automation reduced the dependency of the operators, cut down the training needs and provided uniform output irrespective of the skill level. The ongoing maintenance was also possible since continuous monitoring of the parameters facilitated predictive maintenance through detecting gradual drift in the critical components, thus minimizing unplanned downtime by almost 35 percent. Full-digital traceability helped adhere to the high-quality standards of industry and removed handwritten storage of records. The modular system architecture enables scalable deployment on more than two machines with cost-effective edge device solutions attached to centrally positioned cloud computing infrastructure. Real time data exchange, enhanced transparency of the supply chain and complete production visibility is facilitated by seamless integration with upstream and downstream processes, manufacturing execution systems and enterprise resource planning platforms.

6. Results

Close loop control system based on IoT recorded significant improvements in process stability measures over manual operation, with deviation in the critical parameters being reduced by 58-63. The difference in speed between the spindle with the IoT regulation (32 RPM) and the manual control (87 RPM) was 2.7 based on the nominal value of 1200 RPM which was 63 percent less. The deviation of the axial pressure decreased to 5.2 kN (5.3%), which is half of the nominal load, 12.5 kN (12.8%). The range of variability of peak temperatures was reduced greatly (127degC) in manual experiments to 53degC (932-985degC) under automated control, to provide uniform thermal operating conditions. These stability gains had a direct effect on the quality of the welds, and tensile strength rose to 687 +- 22 MPa compared to 642 +- 38 MPa, which corresponds to 7 percent strength improvement and 46 percent variance in stability. Elongation at failure also went up by 18.4% to 22.1 showing a 20 percent improvement and almost 48 percent higher uniformity. Microstructural inspection proved that there is a refinement of the grain in the weld region between 28 mm and 15 mm, a 46 percent decrease, which justifies the strength improvement by the mechanism of strengthening the grain boundaries. The anomaly detection model is a multivariate parameter stream-based model that was created with more than 92 sensitivity and 94 specificity, it has a high level of precision and high ROC, it is able to detect early-stage voids and allow corrective action to be taken before the weld is completed. Most of the defects predicted were radiographically verified thus showing a strong predictive ability with a reasonable false positive chance. Moreover, the cloud-based system was keeping more than two million points of data and made it possible to trace the processes fully and provide detailed post-weld diagnostics. This is because in one instance, real-time abnormal pressure swings in the friction stage were observed, ascribed to small oscillations in speed, and countered by an increase in control gain, avoiding repeat. The effectiveness of data-driven welding control was further supported by the fact that the correlation between the final tensile strength and peak friction temperature ($R^2 = 0.934$) was strong, thus, allowing to estimate the quality in Realtime.

7. Conclusion And Future Scope

This paper proves that the introduction of the IoT technology into rotary friction welding results in a significant improvement of the process control and performance as the process turns into an automated and data-driven system, which can be managed manually. The framework that was developed showed 61 percent parameter stability improvement through closed-loop control and 7 percent tensile strength enhancement, and the weld properties consistency was also improved by 46 percent. Its accuracy was seen to be 92% which provided the anomaly detection system with the ability to detect defects early enough in the production process as per the modern manufacturing demands. The multi-sensor monitoring, edge-level processing, cloud-based analytics and automated feedback control help to create a practical architecture that can be applied to other forms of welding technology including resistance and friction stir welding. The strategy facilitates the goals of industry 4.0 by enhancing quality, productivity, and sustainability and the projected payoff of the investment in 18-24 months shows its economic feasibility. However, the study was conducted on one material medium carbon alloy steel and only on one machine, which implies that the validation should be performed on a variety of different materials, such as aluminum, titanium, and dissimilar metal pairings. The modern PID-based control can be enhanced by more sophisticated predictive control tools, and it might be possible to enhance the robustness by increasing anomaly detection training to multi-machine data. Further directions could be optimization of the parameters by machine learning, real-time control, interconnection with additive manufacturing, robotic production of products continuously and more advanced methods in sensing such as acoustic emission and thermal imaging to amplify capability in detecting defects.

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