



Review

Smart Drilling: Integrating AI for Process Optimisation and Quality Enhancement in Manufacturing

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Abstract

Drilling is fundamental to the assembly of aerospace structures, where millions of fastening holes must meet stringent structural and geometric requirements. Despite significant technological advances, hole quality remains sensitive to nonlinear and stochastic interactions between mechanics, thermal effects, tribology, and structural configuration. This review consolidates recent advances in intelligent drilling, focusing on how sensors and artificial intelligence (AI) are integrated to enable process understanding, prediction, and control. In-process monitoring modalities (e.g., cutting forces/torque, vibration, acoustic emission, motor current/active power, infrared thermography, and vision) are examined with respect to signal characteristics, feature design, and modelling choices for real-time anomaly detection, tool condition monitoring, and phase/interface recognition. Predictive quality modelling of burr, delamination, roughness, and roundness is discussed across statistical learning, kernel methods, and neural and hybrid models. Offline parameter optimisation via surrogate-assisted and evolutionary algorithms is considered alongside adaptive control strategies. Practical aspects of robotic drilling and multifunctional end-effectors are highlighted as enablers of embedded sensing and feedback. Finally, cross-cutting challenges (e.g., limited, heterogeneous datasets and model generalisability across materials, tools, and geometries) are outlined, together with research directions including curated multi-sensor benchmarks, multi-source transfer learning, physics-informed machine learning, and explainable AI to support trustworthy deployment in aerospace manufacturing.

Keywords: aerospace manufacturing; smart drilling; tool condition monitoring (TCM); machine learning; predictive modelling



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1. Introduction

Every modern aircraft, automobile, or wind turbine begins with a hole. Indeed, it is not surprising that drilling is one of the most pervasive and strategically important manufacturing processes, enabling the assembly of critical components across the aerospace, automotive, energy, biomedical, construction sectors, and so on. Among these, the aerospace industry is certainly the most heavily involved, since alternative joining techniques to riveting rarely find practical application in primary structures. By way of example, a single commercial airliner requires on the order of 1.5 to 3 million drilled holes for its assembly, while a fighter aircraft may still demand between 200,000 and 300,000 fasteners [1]. Each of these holes must comply with stringent dimensional and quality requirements to guarantee structural integrity and flight safety. Despite its apparent simplicity, drilling embodies a

complex interplay of mechanics, thermal phenomena, tribological interactions, and material responses that strongly influence the productivity, dimensional accuracy, and structural integrity of the final component [2,3]. In high-value industries such as the aerospace sector, where thousands of holes must be produced with high-level precision [4], drilling is not only the most common but also one of the most challenging processes, since defects such as delamination, burrs, and dimensional inaccuracy directly compromise structural performance and safety [5]. In recent decades, technological advancements have significantly enhanced drilling performance. The introduction of advanced tool materials and coatings, new tool geometries, high speed spindles, and advanced drilling strategies (e.g., orbital, vibration-assisted, and cryogenic drilling) has mitigated some of these challenges, reducing the intrinsic difficulties in processing special alloys, composites, and stack materials [6,7]. However, these advances remain insufficient to fully meet the throughput and reliability demands of modern manufacturing [8,9]. In addition, the increasing adoption of hybrid materials (e.g., CFRP/Ti, CFRP/Al stacks), thin and lightweight structures in next-generation aircraft, automobiles, and energy systems has posed new challenges [10,11]. These include non-uniform tool workpiece interactions, workpiece deflection, variability in chip evacuation, destabilisation of cutting forces, no easy choice of the drilling tool, accelerated tool wear, and susceptibility to thermal damage, which often render traditional process approaches inadequate for predicting and controlling hole quality [12,13].

Alongside these technological challenges, the transition to Industry 4.0 and smart manufacturing has radically redefined how drilling is understood and controlled, accelerating the integration of advanced sensors, data analytics, and AI into drilling operations. Modern CNC and robotic drilling systems are now capable of capturing multi-sensory signals (forces, torque, vibrations, acoustic emissions, thermal, energy, and visual data) in real time, transforming drilling into a data-rich process environment. This sensor-rich environment creates unprecedented opportunities for in-process monitoring, anomaly detection, and adaptive control [14]. Using these signals, AI techniques enable predictive monitoring, adaptive control, and optimisation strategies that were previously unattainable with classical methods [15,16].

Data-driven and AI models, ranging from adaptive neuro fuzzy inference systems (ANFISs) to deep learning frameworks, have demonstrated predictive capabilities far beyond classical physics-based models [17]. These approaches can accurately predict tool wear, cutting forces, torque, delamination, and surface roughness, while also enabling adaptive parameter control in real time. For example, as reviewed by Mohamed et al. [18] tool condition monitoring (TCM) frameworks based on sensor fusion allow the continuous estimation of tool health, moving from periodic inspection to proactive, autonomous decision-making in high value manufacturing. Optimisation frameworks that integrate AI with metaheuristic algorithms have further advanced the field: for instance, as pointed out by Boukredera et al. [19], torque-driven control strategies combining machine learning (ML) with differential evolution as metaheuristic optimisation algorithm have been shown to maximise the penetration rate while mitigating vibrations and premature tool failures. Similarly, Sarhan [20] demonstrated that ANFIS-based smart drilling models can predict thrust force and torque under varying wear conditions, thereby maximising tool utilisation and ensuring dimensional accuracy when drilling mild steel.

Beyond monitoring and control, vision-based inspection systems are rapidly closing the loop. Telecentric machine vision platforms enable the in process measurement of countersink depth and normal deviation during automated drilling and riveting, drastically reducing the downtime associated with offline inspection [4]. By way of example, as demonstrated by Lee et al. [21] in the robotic drilling of composites, a hybrid classification model, consisting of a pretrained convolutional neural network (CNN) and a support vector

machine (SVM) image classifier, can achieve over 90% accuracy in hole quality assessment, offering scalable solutions for the inline quality assurance of large aerospace components. These methods not only ensure quality but also provide continuous ground truth data to refine AI models and enable self-correcting process control [14].

In the specific domain of CFRP drilling, a recent review proposed by Ge et al. [9] emphasised the superiority of data-driven methods over purely physics-based approaches, which often rely on oversimplified assumptions or require prohibitive computational resources. AI-based methods can deliver rapid, accurate predictions of defects such as delamination and burrs, tool wear progression, and material transition points in hybrid stacks, making them indispensable for next-generation composite manufacturing. Taken together, these developments mark a shift from drilling as a parameter-based process to drilling as a data-enabled, AI-driven system. Sensors, vision systems, and intelligent algorithms are transforming drilling into a pillar of smart manufacturing.

Despite clear benefits, AI for drilling faces intrinsic limitations. Generalisation hinges on data quality and coverage, which are often scarce or heterogeneous across materials, tools, and setups. Each method also presents specific drawbacks. For instance, statistical and kernel-based models such as SVM and LS-SVM perform well with small datasets but require careful hyperparameter tuning, scale poorly, and offer limited physical interpretability. Neuro-fuzzy systems such as ANFIS are transparent but become computationally burdensome and unstable as input dimensionality increases. Neural networks and deep architectures such as CNN and RNN/LSTM/GRU deliver strong predictive power but demand large, well-labelled datasets and are often perceived as black boxes, complicating validation and industrial acceptance. Metaheuristic optimisation methods—including evolutionary approaches (GA, DE, ES) and swarm-based paradigms (PSO, ACO)—enable flexible multi-objective trade-offs but entail high computational cost, stochastic convergence behaviour, and sensitivity to initialisation and constraint handling. Hybrid AI-optimisation frameworks can further enhance performance but increase model complexity, reduce interpretability, and challenge real-time deployment. These factors call for a balanced integration of physics-based knowledge, data curation, and computational efficiency to ensure robust, transferable, and industrially deployable smart drilling systems.

To provide greater clarity on the role and maturity of AI in intelligent drilling, this review article situates itself at this intersection between fundamental drilling science and AI-enabled decision-making. Specifically, Section 2 revisits the fundamentals of drilling mechanics and process variables; Section 3 analyses recent AI applications in process monitoring, tool wear prediction, and quality modelling; Section 4 discusses challenges and research gaps; and Section 5 presents the conclusions and future perspectives for scaling smart drilling systems.

2. Fundamentals of Drilling in Manufacturing

2.1. From Conventional to Advanced Drilling Processes

Drilling has traditionally been carried out using the conventional twist drill, which, despite its simplicity and cost-effectiveness, often proves inadequate when facing the increasingly stringent requirements of modern manufacturing. In particular, when drilling advanced materials such as titanium alloys, nickel-based superalloys, carbon-fibre-reinforced polymers (CFRPs), or metal/composite stacks, conventional drilling is prone to challenges including high cutting forces, accelerated tool wear, delamination, burr formation, dimensional inaccuracies, and heat-induced damage [5,22].

In recent decades, numerous innovative drilling techniques have been proposed to overcome these limitations. Orbital drilling, also known as helical drilling, where the tool follows a controlled helical trajectory instead of a pure axial plunge, has gained widespread

industrial adoption, especially in aerospace assembly, due to its ability to reduce thrust force, facilitate chip evacuation, and minimise delamination in composite and stacked materials [23]. A variant of this approach, the so-called circular drilling strategy, has been proposed by Durante et al. [2] for CFRPs. In this method, a pilot hole is first produced and then enlarged by exploiting the lateral cutting edges of specially designed tools that follow a circular trajectory until the final diameter is reached, thereby reducing the risk of delamination.

Ultrasonic and rotary-assisted drilling (UAD and RAD) superimpose high-frequency vibrations on the drilling motion, reducing friction, improving surface finish, and extending tool life across a wide range of materials including CFRPs [24], CFRP/Ti stacks [25], CFRP/Al stacks [26], as well as metals such as aluminium [27] and titanium alone [28]. These techniques derive from well-established approaches such as vibration-assisted drilling and peck drilling, traditionally used to break long chips and reduce heat accumulation [29].

Other advanced strategies include cryogenic drilling, which uses liquid nitrogen as a cooling medium, significantly lowering the cutting temperature and tool wear while preventing the thermal degradation of CFRPs and thermal softening in metallic alloys [30]. Minimum quantity lubrication (MQL) and hybrid approaches combining MQL with cryogenics [31] have also been explored to reduce environmental impact while enhancing tool performance.

Considering the increasing industrial focus on hybrid composite/metal structures, a further trend for maximising hole quality is drilling each constituent material with its own optimal process parameters. In this regard, Panico et al. [13] proposed a self-adaptive one up drilling strategy for CFRP/AA7075-T6 stacks. The methodology involved first identifying the optimal cutting parameters for each material separately and then applying an automatic parameter switching during stack drilling. The switching point was dynamically recognised through real time monitoring of spindle active power, enabling the tool to operate with CFRP-specific parameters in the composite layer and then automatically adapt to aluminium-specific parameters when entering the metal. This approach significantly reduced delamination in CFRPs and burr formation in aluminium, while ensuring better hole roundness and lower overall defect occurrence at the interface. Such process auto adaptation strategies demonstrate the potential of integrating real-time monitoring with adaptive control to enhance drilling performance in hybrid aerospace structures.

In recent years, robotic drilling has emerged as a flexible solution for large-scale aerospace structures, enabling automated positioning and integration with advanced sensing and quality control systems [21]. Continuous advancements in robotic arms for machining applications have shown significant performance improvements compared to earlier generations [32]. Moreover, the process data collected during robotic drilling can be leveraged to develop smart manufacturing applications, such as digital twin technology, further improving efficiency by enabling real-time monitoring and decision-making [33]. Modern end-effectors in robotic drilling often integrate actuated normal-adjustment mechanisms, tool changing, and embedded sensors (force/torque, displacement, AE/vibration) to support online condition monitoring and adaptive control. For instance, Shi et al. [34] developed a compact normal adjustment cell to maintain perpendicularity on curved aerospace skins, embedding sensors for closed-loop adjustment. Similarly, Frommknecht et al. [35] introduced a multi-sensor measurement system for robotic drilling where the end-effector itself contributes pose estimation, reference alignment, and process feedback. These integrated end-effector systems thus act not only as a digitalisation interface but also as compact multifunctional platforms [36]. Within a single unit, they incorporate subsystems for alignment, force/torque monitoring, vibration/acoustic sensing, and adaptive

actuation, thereby overcoming the need for external monitoring devices and enabling a more streamlined, self-contained approach to process control.

Equally crucial has been the evolution of drilling tools. For monolithic materials such as aluminium alloys, HSS (high-speed steel) and carbide drills remain the standard, often with optimised point angles to balance cutting forces and tool life. For special alloys like Ti and Inconel, solid carbide drills with advanced coatings such as TiAlN, AlCrN, and diamond-like carbon (DLC) have been widely employed to resist adhesion, reduce friction, and withstand high thermal loads [37]. In contrast, when drilling composites, their intrinsic anisotropy requires specially designed geometries such as step drills or candlestick drills to mitigate delamination and fibre pull-out [38].

The complexity increases further with stacked materials, such as CFRP/aluminium or CFRP/Ti, commonly used in aircraft fuselages and wing structures. Here, tool design must simultaneously address the conflicting requirements of soft ductile metals (chip evacuation, adhesion control) and abrasive, brittle composites (fibre breakage, delamination). Hybrid geometries, diamond-coated carbides, and multi-layer coatings have been developed to balance these effects [39].

Consequently, the design of drilling tools has become a central research focus. Advances encompass not only substrate materials (from HSS to ultra-fine grain carbides and polycrystalline diamond), but also innovative coatings (TiAlN, AlTiN, diamond, and nanocomposite coatings) that improve wear resistance and reduce heat generation. Tool geometry optimisation, covering point angle, helix angle, chisel edge thinning, and step geometries has proven essential for minimising damage in composites and extending tool life in alloys [40].

In summary, drilling has evolved from a conventional, standardised operation into a highly specialised and diversified process family. Modern approaches integrate advanced kinematics (orbital, ultrasonic, vibration-assisted), innovative cooling/lubrication strategies (cryogenics, MQL), and tailored tool designs (optimised substrates, coatings, and geometries) to meet the stringent requirements of single-material and multi-material structures. This evolution represents the technological foundation upon which AI-driven and smart manufacturing strategies can be effectively deployed.

A summary of this technological evolution is provided in Table 1.

Table 1. Evolution of drilling technologies from conventional to intelligent systems.

Phase	Key Technological Innovation	Main Benefits/Motivations
Conventional drilling	Standard twist drill (HSS, uncoated carbide)	Simple, cost-effective, mature technology, but limited for advanced materials
Enhanced mechanical kinematics	Orbital/helical drilling, circular drilling	Reduced thrust forces, improved chip evacuation, lower delamination
Assisted drilling techniques	Ultrasonic-assisted drilling (UAD), rotary-assisted drilling (RAD), peck drilling	Lower friction and heat, longer tool life, improved surface finish
Advanced cooling and lubrication	Cryogenic drilling (LN ₂), MQL, hybrid cryo-MQL	Lower cutting temperatures, tool wear reduction, eco-efficiency
Self-adaptive parameter control	One-up/auto-adaptive drilling with real-time spindle power monitoring	On-the-fly feed/speed adjustment, defect reduction, interface damage control
Robotic and sensor-integrated drilling	Robotic drilling systems, multi-sensor end-effectors, real-time alignment and pose correction	Autonomous positioning, process flexibility, digital twin connectivity
Intelligent and AI-driven drilling	Data fusion, AI-based monitoring, predictive quality control	Closed-loop control, zero-defect production, energy-aware optimisation

2.2. Key Quality Indicators (Thrust Force, Torque, Burr, Delamination, Tool Wear)

A reliable assessment of hole quality in drilling operations requires the monitoring of a set of key process indicators, which directly reflect the interaction between the cutting tool, the workpiece, and the drilling process parameters. Among the most relevant, active drilling power, thrust force, torque, burr formation (for metals), delamination (for composites), roundness, and tool wear have been widely recognised as critical variables for both process optimisation and quality assurance.

- Thrust force is one of the primary indicators of drilling performance. An increase in thrust force during the production of multiple holes is typically indicative of a growing tool wear state, with the predictable consequences on hole dimensional inaccuracies [5]. Several studies have shown that lowering thrust force through optimised tool geometry or advanced strategies effectively reduces the risk of delamination damage in composites and burr height in metals, thereby improving hole quality [23,38].
- Torque provides complementary information by quantifying the resistance encountered by the cutting edges during the drilling process. High torque values are often associated with increased friction, adhesion phenomena in ductile alloys (e.g., Al and Ti), or the excessive wear of the cutting lips [40]. In composite/metal stacks, torque fluctuations have been identified as a key feature for detecting the transition between layers and for developing adaptive control strategies [13]. However, torque is generally more difficult to interpret and less straightforward compared to thrust force.
- The use of data such as thrust force and torque typically requires load cells, which are costly, require maintenance, and may complicate process monitoring in assemblies with complex geometry or when drilling is performed in semi-automatic conditions. A valid alternative is to use devices for monitoring active power during drilling. Although several studies and applications have already demonstrated the use of thrust force and torque for predicting hole quality and tool wear [41], active power has recently emerged as an effective indicator for both process monitoring and hole quality assessment. Since spindle power is directly related to the product of torque and rotational speed, it provides a global measure that incorporates the combined effects of thrust and torque in a single parameter. An important advantage is that spindle active power can be directly acquired from modern CNC machine tools and robots without the need for external sensors, thus offering a cost-effective and non-invasive monitoring solution [15].
- Acoustic emission (AE) has become a widely used signal for tool condition monitoring in drilling, particularly for composite/metal stacks. These hybrid structures are extensively applied in aerospace components, like fuselage panels, where mechanical fastening requires high-quality holes. However, due to the very different machining properties of metals and composites, drilling is associated with rapid tool wear, delamination in composites, and burr formation in metals. Since tool life is short and quality risks are high, online process monitoring is essential [42]. AE sensors detect high-frequency elastic waves generated by chip formation, fibre breakage, matrix cracking, and interactions between the tool and the workpiece, and are therefore sensitive to tool wear progression. In the drilling of CFRP/Ti stacks, AE has been successfully applied to distinguish different drilling phases (entry, interlaminar transition, exit) and to correlate changes in frequency bands with flank wear and tool fracture. This makes AE a powerful in-process monitoring technique for predicting tool wear, reducing premature tool replacement, and improving hole quality in aerospace drilling operations [43]. Furthermore, integrating AE with other signals such as thrust force or spindle power has been shown to enhance the robustness of monitoring systems, reducing false detections and improving predictive accuracy [44].

Regarding the typical quality indicators of the drilled hole, it is necessary to mention burr formation, delamination, roundness, cylindricity, and tool wear.

- Burr formation is a persistent issue in the drilling of metallic alloys such as aluminium, stainless steel, and titanium. Burrs not only require costly post processing operations (deburring, reaming) but can also compromise fatigue life and assembly tolerances [22], considering that burr height and morphology depend on tool wear state, feed rate, and exit support conditions. In this regard, both innovative tool designs and drilling strategies have been developed over the years to minimise burr formation [30]. An example of burr formation is shown in Figure 1.

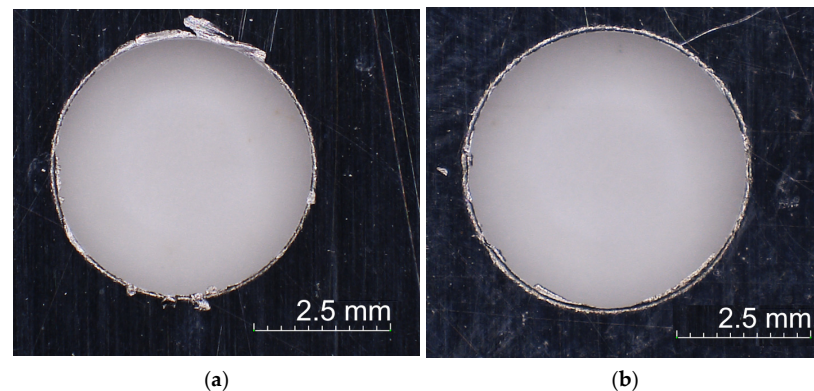


Figure 1. Examples of burr formation on the exit edge of holes in AA7075-T6: (a) uniform burr; (b) crown burr.

- Delamination is the most common and severe defect in composite drilling, arising from interlaminar stresses that exceed the resin–fibre bonding strength [6]. Entry delamination occurs when the cutting edge pushes fibres downward at hole initiation, while exit delamination is primarily caused by excessive thrust during tool break-through. Both phenomena lead to reduced load bearing capacity and the early onset of fatigue failure in aerospace structures. Strategies to mitigate delamination include optimised drill geometries [45], circular and orbital drilling strategies [2] (see Figure 2), and parameter adaptation when transitioning across hybrid stacks.

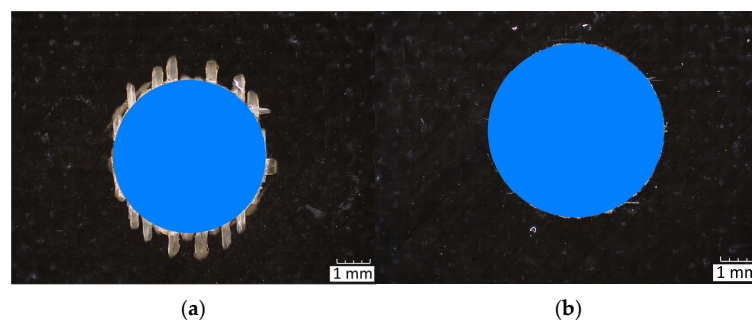


Figure 2. Exit surface of a CFRP hole obtained with (a) conventional drilling and (b) circular cutting strategy proposed by Durante et al. [2].

- Roundness, cylindricity and coaxiality are important geometric accuracy indicators [46], as they directly influence the ability of a hole to accommodate fasteners or load bearing inserts, which is essential in aerospace and automotive assemblies. Deviations from ideal geometry often result from tool deflection, uneven wear, or vibrations during drilling. For example, the loss of roundness and cylindricity compromises interference fit and load transfer efficiency in riveted joints, while poor

coaxiality between successive stacked layers can induce misalignment and stress concentrations [4,47]. Advanced drilling methods such as orbital drilling and robotic drilling, combined with real-time sensor feedback, have been shown to significantly improve hole geometry, achieving tighter tolerances and reduced variability across large batch productions.

- Tool wear represents both a quality indicator and a limiting factor for productivity. In drilling, wear typically manifests as flank wear, chisel edge rounding, and edge chipping, which progressively increase thrust force and torque, thereby accelerating delamination and burr formation [43]. CFRPs, due to their abrasive fibres, cause rapid edge degradation, while Ti alloys promote adhesion and diffusion wear at elevated temperatures. Tool coatings such as TiAlN, AlCrN, and diamond-like carbon have been widely investigated to extend tool life, while in-process monitoring using acoustic emission, thrust force, or spindle power signals is increasingly adopted to detect wear progression in real time [39,40].

It is therefore important to note that the combined monitoring of all these indicators not only ensures compliance with stringent aerospace and automotive standards but also provides the foundation for developing AI-driven predictive models and adaptive control strategies.

3. Applications of AI in Drilling

3.1. Process Monitoring

Real-time process monitoring is the pillar of smart drilling: it turns raw sensor data (forces, torques, vibrations, acoustic and thermal emissions, spindle power, images) into actionable information about process health and hole quality, fast enough to adapt feeds/speeds, prevent defects (delamination, burrs), and plan maintenance. In aerospace drilling, especially CFRP, and aluminium and titanium alloys, multi-sensor monitoring plus AI has proven effective for predicting quality, detecting layer transitions and monitoring tool health, even on robotic cells.

The effectiveness of an intelligent machining system depends on the quality and reliability of the sensory data that describe the physical phenomena occurring at the tool–workpiece interface. Effective monitoring requires (i) the correct choice of sensor modality, (ii) proper mounting and synchronisation, and (iii) suitable sampling and data acquisition strategies to preserve the dynamic content of the signals. While modern CNC machine tools are equipped with encoder and load sensors for axis control, these native systems provide only indirect information on cutting performance and are insufficient for capturing the dynamic complexity of drilling. For this reason, the integration of additional sensors, either on the tool, the spindle, the fixture, or externally mounted, has become necessary for enabling in-process monitoring and data-driven decision-making. Figure 3 schematically illustrates the main areas of a CNC machining centre that can host additional sensors for process monitoring. At the tool–holder interface, sensorised holders or embedded dynamometers enable the acquisition of cutting forces and torque, which are critical indicators of hole quality and strongly correlated with key measures of delamination in CFRP and burr formation in aluminium alloys. The fixture, or work-holding system, can be instrumented with force platforms or strain gauges to capture reaction forces transmitted through the workpiece, thereby providing complementary information on tool–workpiece interaction. In addition, the machine base and structural frame can be equipped with accelerometers to measure global vibration levels and structural deflections, serving as indirect yet robust indicators of process stability. Moreover, the spindle unit itself is directly connected to the electro spindle drivers, making this position strategic for monitoring the active power consumption of the spindle motor. Since active power reflects the instantaneous cutting loads, its continuous

monitoring provides a non-intrusive and industrially scalable solution for tracking tool wear, identifying abnormal process conditions, and estimating energy efficiency. Finally, modern CNCs already incorporate integrated machine monitoring systems, such as spindle current sensors, encoders, and drive feedback loops. Although originally designed for control purposes, these embedded systems can be exploited as low-cost data sources for process monitoring and tool condition assessment.

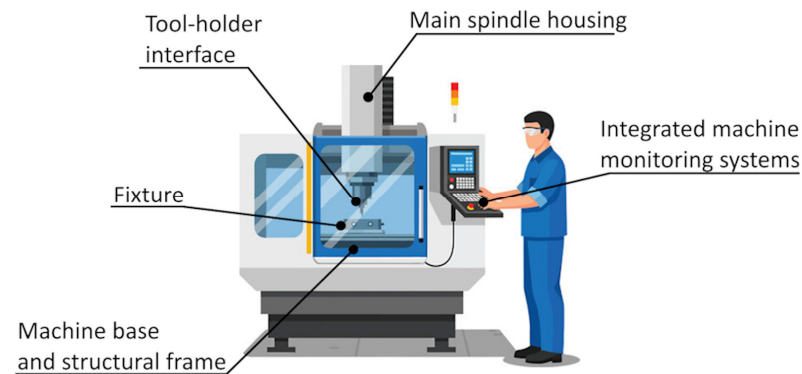


Figure 3. Possible locations for sensor integration in a CNC machining centre.

3.1.1. Force and Torque Measurements

Measurement of cutting forces and torque is the most direct approach for assessing the state of the drilling process. Piezoelectric dynamometers have long been considered the gold standard in laboratory environments because of their high sensitivity, stability, and frequency response. In this framework, it is important to distinguish between two levels of exploitation of force and torque data. When acquired and processed in real time, these signals enable the continuous tracking of thrust and torque trends, thus supporting anomaly detection, the identification of material transitions, and the prevention of sudden process instability. Conversely, when the same datasets are analysed offline, they provide the basis for establishing quantitative and qualitative correlations between the dynamic load system and the final hole quality. Such correlations have been reported for a variety of defects and metrics, including the relationship between abnormal thrust force levels and delamination in CFRP (and burr height in metallic alloys), or the overall force signature and surface integrity descriptors such as roughness, roundness, and circularity. An illustrative example of thrust force and torque signals acquired during drilling tests is reported in Figure 4. In this case, the measurements were carried out using a KISTLER 9257A dynamometer for thrust force (Figure 4a) and a KISTLER 9277A25 load cell for torque (Figure 4b). The plots clearly highlight the typical evolution of the load system in different material configurations: aluminium alloy AA7075-T6, CFRP laminate, and the hybrid CFRP/AA7075-T6 stack. In each case, distinctive quantitative characteristics (maximum thrust force and torque peak) and qualitative characteristics (load increase curve slope, load fluctuations due to material nature, transition mode from one material to another in the case of stack drilling) can be observed.

Nevertheless, the industrial deployment of dynamometers is limited by their cost, large size, and workspace restrictions. To overcome these disadvantages, several integrated and hybrid sensing solutions have been developed. Byrne and O'Donnell [5] developed one of the earliest fully integrated force-sensing spindles, embedding two custom piezoelectric rings directly into a direct-drive motor spindle. A bearing sensor ring, positioned behind the thrust bearing and equipped with 22 piezoelectric elements, enabled high-sensitivity measurement of axial forces, while a flange sensor ring, equipped with combined compressive and shear sensors arranged in diagonal pairs to mitigate thermal drift, provided three-component force measurement. Their configuration ensured that the sensor were

positioned in the main force flux of the spindle, thus maximising sensitivity. Drilling tests demonstrated that the integrated sensors reproduced the feed force signature with accuracy comparable to a rotating dynamometer, while additionally capturing non-cutting phenomena such as axis accelerations, spindle preload changes, and minor collisions. Complementing this approach, Totis et al. [48] proposed an innovative plate dynamometer specifically designed for high-speed drilling and milling with small cutter diameters. The device integrates three triaxial piezoelectric sensors arranged in a triangular configuration below a monolithic plate. Its geometry was optimized via finite element analysis to maximise stiffness, minimize dynamic cross-talk, and achieve frequency bandwidths exceeding 3 kHz under real operating conditions. Static calibration revealed errors below 1% FSO and cross-talk below 2%, while milling and drilling tests confirmed superior dynamic performance, making the system suitable for high-speed and micro-scale machining applications. Hybrid approaches have also been proposed to address the inherent limitations of piezoelectric sensors in static force measurement. Rezvani et al. [49] developed a sensing vise combining in-house-fabricated PZT elements and strain gauges. The PZT sensors, embedded within layered jaws and poled in axial and shear modes, provided high-bandwidth measurement of dynamic machining forces, whereas strain gauges mounted inside a cross-shaped groove captured quasi-static clamping forces. The fused signals enabled simultaneous monitoring of clamping stability and cutting loads, allowing the authors to quantify how dynamic milling forces affect workholding integrity. Reported errors ranged between 6–17% for dynamic force components and ~19% for static clamping forces, demonstrating the feasibility of real-time dual-modality force sensing. More recently, Zhang et al. [50] developed an integrated smart tool holder (BT40) in which a dedicated force-sensing unit based on an improved Maltese cross-beam structure is mounted between the taper shank and the tool clamping section. The elastic body is instrumented with 24 high-sensitivity silicon strain gauges arranged on four measuring arms and grouped into six full-bridge circuits, enabling fully decoupled measurement of three force components (F_x , F_y , F_z) and three moments (M_x , M_y , M_z). A multi-objective optimization of the cross-beam geometry was carried out to maximise strain (and thus voltage sensitivity) while maintaining sufficient stiffness, resulting in a first natural frequency of 1740 Hz, higher than commercial SPIKE[®] holders and suitable for spindle speeds up to about 13,000 rpm in two-flute tools. The sensing unit is combined with an embedded acquisition and wireless transmission module (amplifier, anti-aliasing filter, 16-bit ADC, STM32 processor and WiFi link), allowing fully autonomous real-time monitoring during milling and drilling. Static calibration showed voltage sensitivities up to 0.059 mV/N and 2.11 mV/Nm, with maximum measurement error of 0.57% and cross-interference below 6.41%, confirming the suitability of the system for accurate six-axis cutting force monitoring in industrial environments.

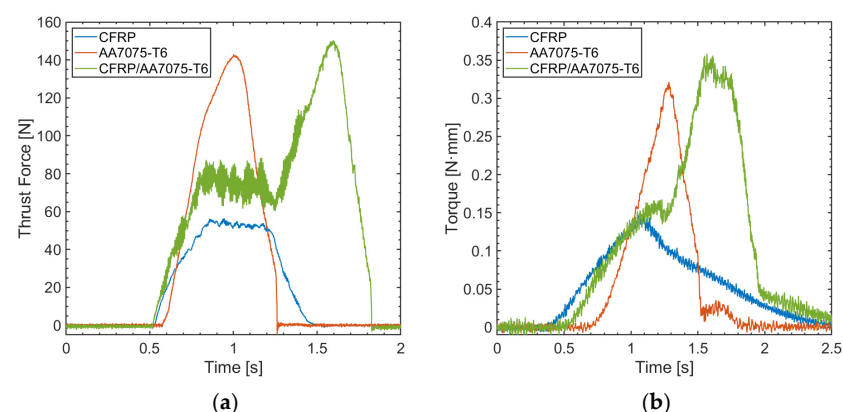


Figure 4. Examples of thrust and torque signals acquired during drilling with (a) KISTLER 9257A and (b) KISTLER 9277A25, respectively.

3.1.2. Vibration Monitoring

Vibration monitoring is an effective and non-invasive method of process analysis, especially for functional units where thin-walled structures are used and hybrid stacks are highly sensitive to vibration and instability. Spindle-mounted piezoelectric accelerometers are frequently used thanks to their broad frequency response, enabling the detection of chatter onset and tool–workpiece interaction even at acquisition rates ≥ 10 kHz. For example, Vogla et al. [51] highlighted the potential of spindles with integrated accelerometers to estimate cutting forces and track tool wear in real time within intelligent manufacturing paradigms. In deep-hole drilling, Uekita & Takaya [52] proposed a time–frequency-based tool condition monitoring strategy, demonstrating that wavelet-derived features enable the accurate identification of chatter onset and tool degradation. The detection of chatter through statistical techniques has also been addressed; Messaoud et al. [53] employed multivariate control charts on vibration data for live drilling monitoring, showing the early detection of chatter events. The utility of these vibration-based methods extends to real workpiece quality assessment. Further evidence is provided by Gerken and Biermann [54], who developed a mechatronic system for directional and angular control in BTA deep-hole drilling. Their study demonstrated that the accurate detection and compensation of vibration-induced angular deviations are crucial to ensuring both process stability and borehole precision. Complementing these mechatronic approaches, Remme et al. [44] investigated the use of control internal data (CID) from CNC systems as a proxy for vibration monitoring in drilling processes. Although the sampling rate of such signals is significantly lower compared to accelerometers, their study showed that CID can provide meaningful information on process dynamics, enabling cost-effective and easily integrable monitoring strategies for industrial applications. Finally, Bombinski et al. [55] highlighted the role of vibration analysis within advanced TCM architectures. Their work emphasised that simple RMS (root mean square) indicators, common in commercial systems, are insufficient for aerospace requirements, and that advanced time–frequency analysis combined with machine learning enables reliable detection of natural wear, accelerated wear, and catastrophic tool wear.

3.1.3. Acoustic Emission (AE) Monitoring

Recent research has demonstrated the effectiveness of acoustic emission (AE) in capturing the transient phenomena associated with tool wear, damage initiation, and defect formation during drilling of aerospace materials. Mathiyazhagan and Meena [56] systematically investigated the use of AE sensors to predict tool wear in CFRP drilling under both dry and cryogenic conditions. Their results showed that AE features such as amplitude, RMS, and frequency-domain signatures provided early and reliable indicators of tool degradation, which could be further enhanced through machine learning models such as extra trees (ETs) and random forest (RF). The study demonstrated that AE-based monitoring not only enables accurate real-time wear prediction but also supports the evaluation of cooling strategies, revealing that cryogenic drilling significantly reduced overall wear but introduced distinct AE patterns linked to the brittle fracture of the matrix. In hybrid stacks, the application of AE has been validated as an effective tool for correlating tool condition with process dynamics. Leng et al. [43] analysed AE signals during the drilling of CFRP/Ti-6Al-4V stacks, showing that RMS and wavelet packet energy of AE signals correlate strongly with flank wear progression. They reported that certain frequency bands exhibited consistent increases in energy as tool wear advanced, providing reliable features for tool condition monitoring. Importantly, the study highlighted that chip–tool interaction and sudden tool fractures manifest as transient AE bursts, which must be distinguished from steady wear signals to avoid misclassification in automated monitoring systems. AE

monitoring has also been linked to defect formation at the workpiece level. Kimmelman et al. [22] focused on burr formation mechanisms in CFRP/Al stacks. By analysing high-resolution AE spectra at the drill exit, they demonstrated that burr initiation could be detected in specific frequency bands, confirming that AE can act as a predictive indicator of exit damage in metallic layers. More recently, Yan et al. [7] applied AE monitoring to analyse damage evolution during CFRP drilling. As shown in Figure 5, the AE waveform and the corresponding RMS curve clearly distinguish the entrance, steady drilling, and exit stages. The authors demonstrated that AE activity increases sharply at tool entry, stabilises during material removal, and exhibits marked fluctuations at breakthrough due to fibre pull-out and matrix cracking. Time-frequency processing (FFT and STFT) also enabled the identification of frequency bands associated with specific damage mechanisms (matrix cracking—60, 120 kHz; delamination—120–200 kHz; fibre fracture—210, 340 kHz) which remained consistent across different cutting parameters. Importantly, variations in RMS behaviour were found to correlate with exit-side defects, confirming that AE descriptors can serve as reliable indicators of drilling-induced surface damage.

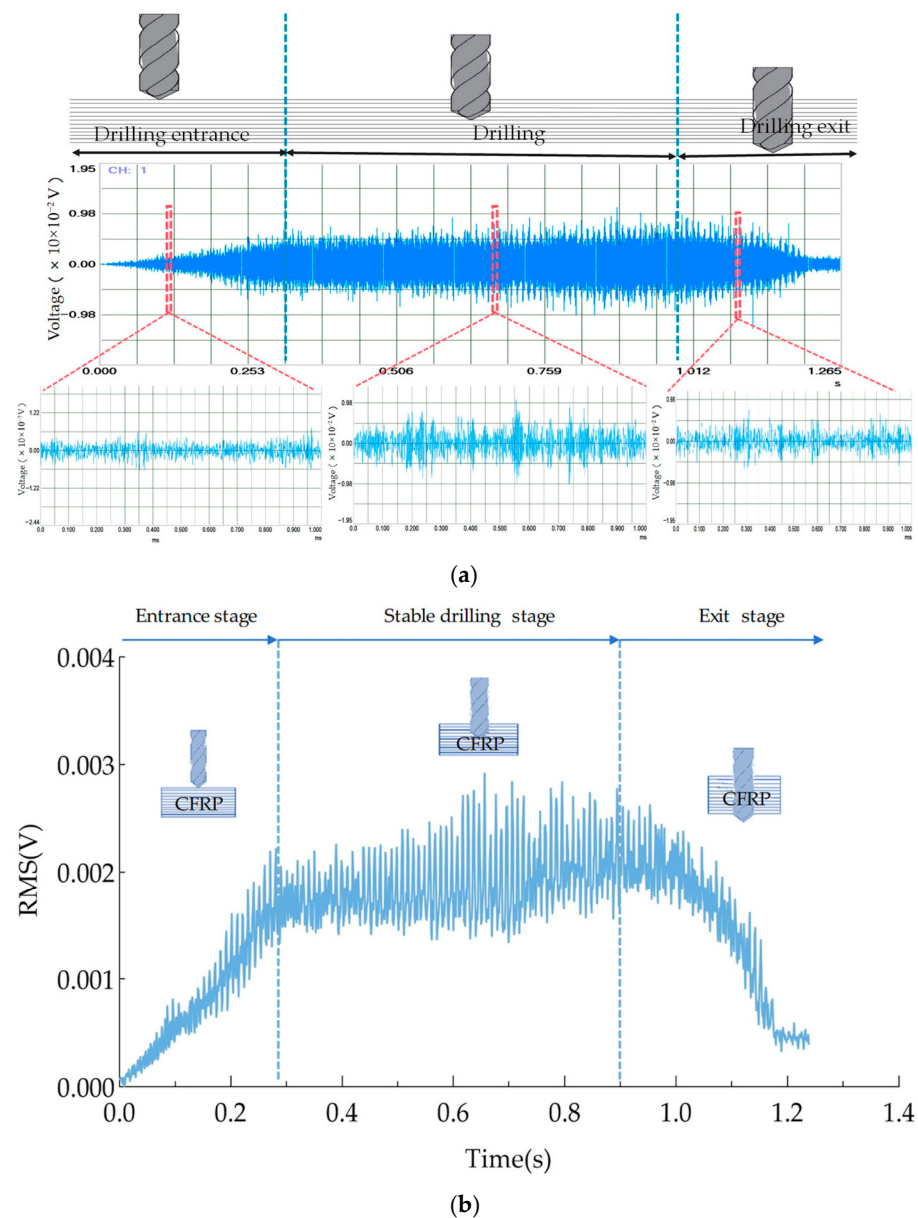


Figure 5. (a) Acoustic emission waveform acquired during CFRP drilling; (b) RMS evolution of the AE signal during CFRP drilling [7].

3.1.4. Spindle Current and Power Monitoring

Among indirect, machine-native signals, spindle motor current and the corresponding active power are particularly attractive for drilling because they can be accessed through the CNC drive without additional hardware at the tool–workpiece interface, enabling the rugged, non-intrusive monitoring on production machines. In three-phase motorised spindles, active power is obtained by combining the line voltages and phase currents (e.g., Hall-effect probes on phases U–V–W) and removing idle losses; the signal reflects the torque required to cut the material and therefore tracks load changes due to material transitions, chip evacuation, and tool wear. Reviews like those of Shokrani et al. [14] and Mohamed et al. [18] already recognised current/power as effective surrogates of cutting forces for process supervision and tool condition monitoring, although with lower bandwidth than force/AE sensing. This limitation stems from the spindle/drive dynamics, which filter out fast transients, hence current/power excel for slow-varying phenomena (e.g., wear growth, average load) and event detection at process time scales, but not for tooth-passing or very high-frequency content. Early drilling studies exploited this relationship quantitatively. Kim et al. [57] estimated drill wear in real time from spindle motor power by linking a mechanistic torque model to measured power and demonstrated the reliable tracking of flank wear during twist-drilling, establishing a template for physics-informed, power-based TCM in hole-making. Similarly, Corne et al. [15] investigated Inconel 625 drilling and demonstrated that spindle power signals acquired from machine load metres could be effectively correlated with both feed rate and thrust force (see Figure 6a). By processing these signals through neural network models, they achieved wear prediction error as low as 0.8–18% and successfully detected premature tool breakage from power surges exceeding 20% of baseline value. More recently for aerospace composites, Domínguez-Monferrer et al. [16] analysed large-scale CFRP production data and showed that carefully processed spindle power features (after segmentation, filtering, anomaly removal, and entry-point detection) correlate with tool degradation with low dependence on nominal cutting parameters, confirming industrial viability of power as a control indicator for drilling campaigns. The approach has now matured into real-time supervisory control. For instance, Panico et al. [13] instrumented a CNC with a Nordmann WLM-3s/SEM-Modul-e system (three Hall-effect current probes between inverter and spindle, on-board computation of active power see Figure 6b) and used the dynamic component of the active-power trace to detect the CFRP/aluminium interface in one-up drilling of CFRP/AA7075-T6 stacks. The tool monitor issued a digital trigger to the CNC when a characteristic power increase marked material transition, enabling on-the-fly switching from CFRP-optimal to aluminium-optimal speed/feed without any external force sensor. A simple first-order high-pass filter (cut-off = 0.5 Hz) emphasised transient changes; the method proved repeatable across holes and led to improved control of burr delamination while maintaining cycle-time efficiency. In addition to conventional CNC machine tools, semi-automatic and automatic drilling units widely used in aerospace assembly represent another important source of machine-native signals. These units, often deployed for the high-volume production of rivet and fastener holes, are typically equipped with independent electric driver for spindle rotation and feed actuation. Haoua et al. [58] offered a representative example by analysing an electric drilling unit (eADU) for AA7175/CFRP stacks. They showed that spindle and feed currents, when processed together with vibration and force signals, can discriminate the material being cut with high accuracy. Using random forest models, they achieved up to 99–100% correct classification relying solely on motor current features, thus enabling robust material recognition and laying the basis for adaptive drilling strategies.

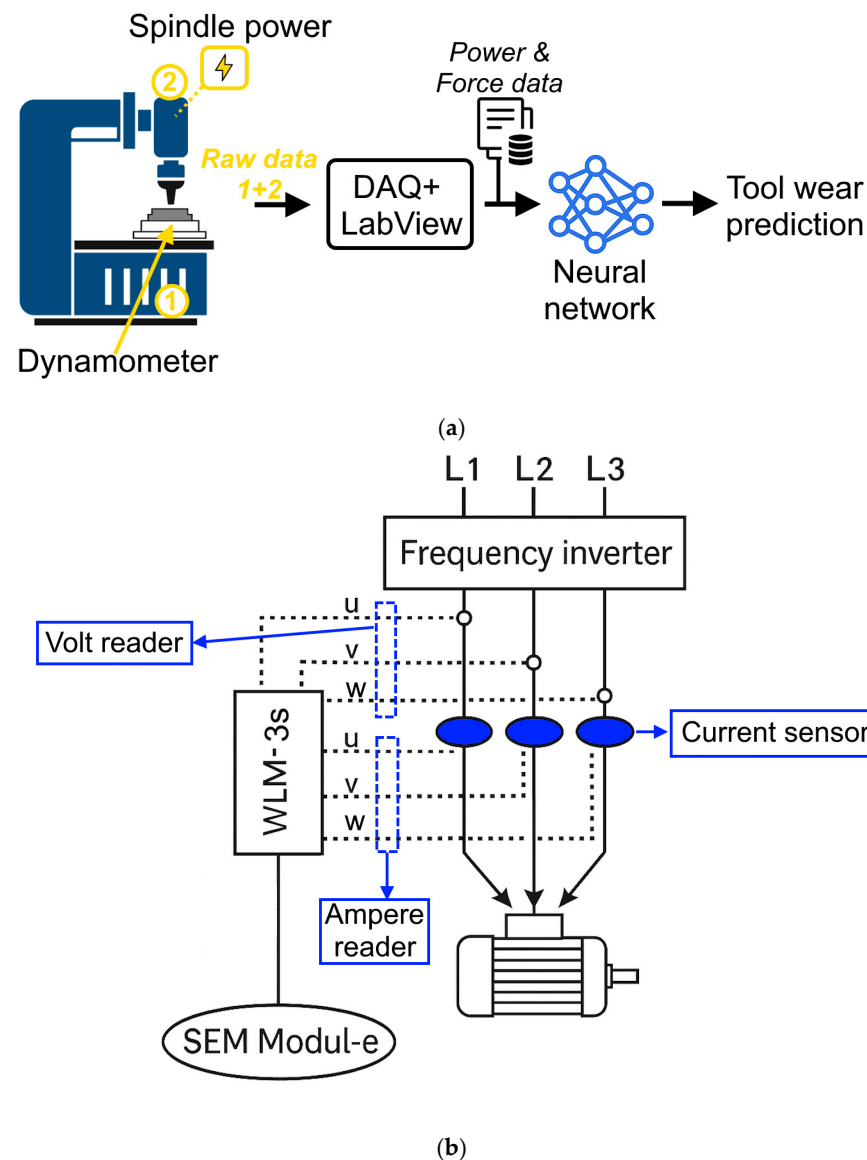


Figure 6. Representative examples of spindle/current monitoring approaches in drilling. (a) Experimental setup from Corne et al. [15]; (b) System configuration used by Panico et al. [13].

3.1.5. Thermal and Vision-Based Monitoring

Temperature evolution during drilling critically affects both process mechanics and hole quality. Localised heating can drive matrix softening [12], burr development [59], and accelerated tool wear [6]. Monitoring cutting temperature, therefore, offers valuable insight into process condition and defect formation [60]. Cutting temperature measurement techniques can generally be divided into two categories: contact methods, such as thermocouples embedded in the tool or workpiece, and non-contact methods, primarily based on infrared pyrometry or thermography. Concerning contact methods, thermocouples are widely used solution in laboratory environments. Moghaddas et al. [61] compared multiple approaches, including surface-mounted thermocouples, sensors embedded in the workpiece, and thermocouples integrated within drill cooling channels, when drilling aluminium 6061 and steels under ultrasonic assistance. Their results demonstrated that thermocouples located inside the drill channels ensured the most reliable and repeatable measurement compared to the other two systems adopted, enabling direct estimation of tool-tip temperature. Nonetheless, tool-integrated thermocouples are invasive, affect drill fabrication, and remain difficult to apply in industrial contexts where tool replacement

is frequent. Non-contact infrared thermography has therefore emerged as a powerful alternative for in-process diagnostics. Xu et al. [62] monitored CFRP drilling with a FLIR A615 infrared camera, capturing the complete temporal evolution of thermal fields during drilling with diamond-coated tools. They showed that maximum temperatures are reached during the full engagement of the cutting edges and decline rapidly as the drill exits the laminate. Importantly, the thermal profiles were linked with hole quality metrics, indicating that controlling process parameters to limit peak temperatures helps prevent matrix softening and dimensional inaccuracies. Complementary evidence was provided by Fu et al. [63] who investigated drill-exit temperature behaviour in unidirectional and multidirectional CFRPs. Using high-resolution microscopy infrared imaging, they demonstrated that drill-exit zones are particularly susceptible to thermal accumulation, with peak values often exceeding the glass transition temperature of epoxy matrices (160–200 °C). These elevated exit temperatures were directly correlated with increased delamination and splintering, confirming the critical role of thermal monitoring in predicting exit damage in composite materials.

Beyond thermal effects, optical sensing has also been increasingly exploited to monitor drilling performance and evaluate hole quality. In this context, the term vision-based monitoring refers to both the in-process observation of the cutting zone using high-speed or microscopy cameras, and to the post-process inspection of the machined holes through machine vision and image analysis techniques. In the context of drilling thin-walled aerospace assemblies, vision-based monitoring has recently gained importance as a non-intrusive tool to capture the transient structural deformations that occur under cutting loads. In particular, the interlayer gap that develops between stacked sheets represents a critical defect precursor, strongly affecting hole roundness, burr formation, and delamination. Conventional force measurements alone cannot fully characterise its evolution, whereas high-speed optical systems provide direct evidence of the dynamic separation of the layers during drilling. Panico et al. [64] employed a high-speed camera (Olympus i-SPEED 3) in combination with thrust force acquisition to monitor the formation of the interlayer gap in aluminium stringer-skin assemblies. Complementary work (Panico et al. [65]) integrated high-speed imaging with digital image correlation (DIC) techniques, providing quantitative displacement fields across the skin and stringer during drilling. Together, these contributions highlight that high-speed optical monitoring represents a valuable tool for smart drilling applications, as it enables the real-time detection of structural instabilities such as interlayer gap formation, while simultaneously providing robust experimental evidence for the validation of analytical and numerical models aimed at predicting and mitigating such defects.

Recent advances in vision-based monitoring have highlighted the potential of integrating optical inspection directly into drilling systems to achieve real-time assurance. Yu et al. [4] developed an in-process countersink inspection approach for the automated drilling and riveting of aircraft panels. The system combined a high-resolution CCD camera with a telecentric lens, mechanically coupled to the drill unit, thereby ensuring the coaxial imaging of the countersink. Through an edge-following algorithm refined with RANSAC (random sample consensus) fitting, the method enabled the concurrent measurement of countersink depth and normal deviation with high robustness against industrial noise, scratches, or chatter marks. Complementary efforts have targeted the detection and classification of hole features under complex surface textures typical of CFRP laminates. Li et al. [66] introduced a semi-supervised deep learning approach for circular hole detection in composite parts. By leveraging local exponential patterns (LEPs) for texture segmentation and training a compact U-Net model with round loss, the system achieved measurement accuracies of up to 0.03 mm without requiring large annotated datasets.

This demonstrates the potential of combining traditional image-processing features with machine learning to address challenges such as noisy textures, uneven illumination, and variability in composite layups encountered in robotic drilling. Building on these developments, Lee et al. [21] proposed a hybrid classification model for in situ hole quality assessment in the robotic drilling of CFRPs. Their system employed an industrial camera integrated into the robotic end-effector to capture hole images immediately after drilling, which were then processed through a CNN-SVM framework. The classifier achieved 90% prediction accuracy in distinguishing acceptable from defective holes based on delamination factor thresholds. The study demonstrated that vision-based monitoring can be effectively implemented at production scale, reducing the reliance on offline inspection stations and enabling smart manufacturing practices in aerospace assembly. An overview of the vision system is presented in Figure 7, which illustrates the integration of the imaging module into the robotic end-effector, the acquisition sequence, and an example of image processing for hole geometry measurement.

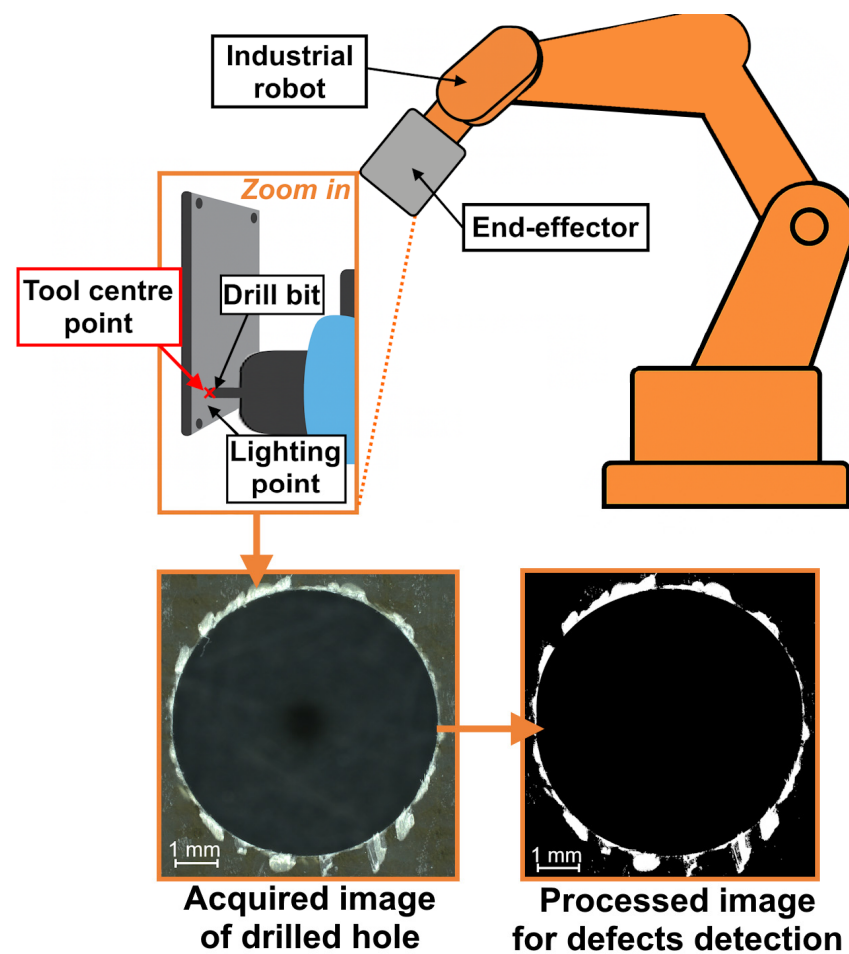


Figure 7. Vision-based monitoring system for in-process hole quality evaluation in robotic drilling. Multifunctional end-effector (MFEE) mounted on an industrial robot and representative hole images before and after processing. Adapted from [21].

Table 2 provides a comparative summary of the main monitoring approaches discussed in Section 3.1, highlighting their sensing principles, extracted features, correlated quality indicators, and representative applications from literature.

Table 2. Summary of the main process monitoring approaches in drilling, with indication of typical sensors, extracted signal features, correlated process indicators, and representative references.

Monitoring Method	Typical Sensors	Main Features Extracted	Correlated Process Indicators	Representative References
Force and torque monitoring	Piezoelectric dynamometers, spindle-integrated sensors, instrumented toolholders, hybrid vise sensors	Thrust force, torque, slope of load curve, breakthrough signature	Delamination (CFRP), burr height, surface roughness, roundness, tool wear	[5,48–50]
Vibration monitoring	Accelerometers (spindle-mounted, tri-axial), mechatronics systems, CNC internal data (CID)	RMS values, frequency spectra, time–frequency wavelet features	Chatter detection, tool wear progression, process stability	[44,51–55]
Acoustic emission (AE)	Piezoelectric AE transducers, broadband sensors (kHz–MHz)	RMS, amplitude, burst vs. continuous signals, frequency bands, wavelet packet energy	Tool wear, matrix fracture, delamination onset, burr initiation in metallic layers, surface roughness	[7,22,43,56]
Spindle current and power	Hall-effect current probes, machine load metres, SEM-Modul-e, eADU drivers (spindle + feed currents)	Active power, dynamic component, power surges, segmented signal features	Tool wear, breakage detection, material transition recognition, energy efficiency	[13,15,16,57,58]
Thermal monitoring	Tool/work thermocouples, embedded drill-channel thermocouples, IR pyrometers, IR cameras	Peak temperature, spatial distribution, drill-exit hot spots	Matrix softening, delamination growth, burr formation, tool wear acceleration	[61–63]
Vision-based monitoring	High-speed cameras, digital image correlation (DIC) coaxial CCD with telecentric lens, industrial cameras integrated in robotic MFEEs	Interlayer gap evolution, displacement fields, hole geometry, delamination factor, countersink depth	Structural instabilities, burr/delamination onset, dimensional accuracy, defect classification	[4,21,64,65,67]

3.1.6. Multi-Sensor Integration and Monitoring Architecture

Although individual detection methods provide fundamental information on the specific aspects of the drilling process, their integration is essential to achieve robust and comprehensive process supervision. Multi-sensory fusion allows complementary information to be extracted from heterogeneous signals enabling a more complete characterisation of the process and the related quality results. Whenever possible, these sensors should be embedded directly within the spindle, tool holder, or robotic end-effector, ensuring close coupling with the cutting zone. Such configuration minimises latency, cross-talk, and electromagnetic noise, while improving signal fidelity and responsiveness. In cases where direct integration is not feasible, the use of external instrumentation, such as load cells placed beneath the fixture or force platforms under the workholding system, must be carefully engineered to reduce transmission paths that can attenuate or distort mechanical signals. Proper structural design and calibration are therefore essential to preserve signal integrity and prevent energy absorption by intermediate components.

The data fusion layer must ensure temporal alignment and consistent scaling among signals of different bandwidths. Standardised communication protocols (EtherCAT, OPC UA) and synchronised acquisition through a shared data bus facilitate coherent datasets. Hybrid feature engineering, combining physical indicators (e.g., thrust-to-power ratio) and statistical descriptors, should be implemented to improve interpretability and enable cross-domain learning. At the decision-making and control level, the goal is to transform raw monitoring data into actions on the drilling process. Once processed and merged, signals from different sensors can be interpreted by integrated AI models that operate directly on the drilling equipment. These lightweight models, typically CNNs or hybrid CNN-LSTM architectures, are designed to perform real-time inferences at the edge, i.e., on the hardware located within the machine controller or end-effector, without relying on

external computers. The role of these embedded models is two-fold: first, they classify the process state; second, they enable adaptive control by sending feedback commands to the machine (e.g., the controller may automatically reduce the feed rate when signs of delamination appear, lower the spindle speed when the power consumption exceeds a threshold, or modify the drilling cycle if chatter or chip congestion is detected). This continuous loop—measurement, interpretation, correction—forms a closed-loop feedback system, allowing the drilling process to self-adjust in response to real-time variations.

However, to preserve the dynamic responsiveness of the system, the integration of such architectures must remain computationally lean and structurally compact. Excessive data handling, complex fusion pipelines, or redundant communication layers can increase latency and reduce the control bandwidth, ultimately compromising the adaptive capabilities of the system. Therefore, real-time architectures should prioritise efficient data flow, lightweight algorithms, and hardware–software co-design to guarantee fast, stable responses.

Beyond experimental validation, several commercially implemented solutions already exemplify how multi-sensor architectures can be deployed in manufacturing environments. A representative example is provided by Desoutter Tools [68], whose semi-automatic drilling systems for aerospace assembly integrate current and power monitoring directly into the drive motors of the feed and rotation axes. Similarly, the Nordmann WLM-3s/SEM-Modul-e system [69] represents a scalable industrial solution for active power monitoring in CNC machines. Another industrially mature example is the Pro-Micron SPIKE[®] sensory tool holder [70], which embeds strain gauges in a wireless, telemetry-based architecture capable of measuring torque, axial force and bending moments in real time. This system, successfully adopted in both automotive and aerospace machining, allows direct measurement at the tool–holder interface, ensuring high signal fidelity and straightforward integration with CNC or robotic controller. These examples illustrate that industrial deployment becomes practical when sensing is directly embedded within the functional components rather than relying on bulky external setups.

In terms of implementation cost, commercial sensorised holders or current-monitoring units typically range from a few thousand up to several tens of thousands of euros, depending on features such as sampling rate, telemetry, and integration capabilities. However, the major cost driver is not the hardware itself, which remains relatively affordable, but the system-level integration, including calibration, data synchronisation, software connectivity, and certification for aerospace use. Integration cycles may span several months per production cell and require coordination across mechanical, electrical, and IT domains.

Finally, at this level of system integration, the energy balance of smart drilling should be assessed from a broader perspective. In addition to the energy consumed directly for material removal, the overall calculation must also include the operating energy of auxiliary subsystems (i.e., such as sensors, signal amplifiers, cooling units, and integrated processors). This holistic view is essential for assessing the true sustainability of smart drilling systems, ensuring that the benefits in terms of process intelligence do not lead to increased energy requirements.

3.2. Tool Condition Monitoring and Wear Prediction

In recent years, tool condition monitoring (TCM) for drilling has taken a decisive leap forward, moving from predominantly empirical, post-process approaches to predictive and prescriptive strategies capable of acting in real time. Two converging forces are at the root of this shift: on the one hand, the spread of indirect signals already available from numerical controls (power, current, internal drive data) supplemented by high frequency channels (acoustic emission and vibration) that are easy to integrate at the machine; on the other, the

maturity of artificial intelligence algorithms, now able to learn complex regularities from heterogeneous sensor streams under latency and robustness constraints compatible with the shop floor.

The framing literature confirms this trajectory. Mohamed et al. [18] outline the TCM pipeline in five stages (acquisition, pre-processing, feature engineering and selection, modelling and deployment), highlighting the shift from dedicated and costly sensors to industrially accessible signals (cutting forces, spindle power/current) that can be enriched with AE/vibration. They also point out that these measurements are affected by noise and therefore require sophisticated signal processing and dimensionality-reduction techniques.

3.2.1. Signal Acquisition in Drilling

In drilling operations, accurate signal acquisition is essential to capture the dynamic behaviour of the process. In this context, several sensor-based approaches have been developed to acquire these signals and enable the reliable assessment of tool wear and process conditions. On the sensor side, the following has emerged:

- Cutting forces: highly sensitive to wear, but difficult to implement industrially with bench dynamometers.
- Vibrations: acquired with piezoelectric accelerometers or micro-electromechanical systems (MEMSs), correlated with roughness and instabilities but difficult to filter.
- Acoustic Emission (AE): wide frequency range (100 kHz–1 MHz), excellent for detecting wear, chipping and fractures; also provides early warning in case of unstable cracks.
- Motor current/spindle power: easily accessible in modern CNCs, already used in commercial TCMs, though less sensitive to high-frequency fluctuations.
- Thermal signals: useful in difficult-to-cut materials (e.g., Ti and Inconel) but limited by thermal inertia and integration hurdles.

Recent developments have introduced more compact and wireless sensor systems to facilitate real-time monitoring in production environments. These include embedded micro-sensors and multi-sensor platforms, including strain gauges, MEMS, AE and gyroscopes, often integrated into the tool holder or spindle. Advances in communication protocols such as Wi-Fi, Bluetooth, and ZigBee have further enabled flexible data acquisition architectures, allowing decentralised monitoring and seamless data transmission to cloud-based AI platforms.

3.2.2. AI Models and Representative Studies

The review proposed by Munaro et al. [67] shows that SVM and Artificial Neural Networks (ANNs) remain solid references for wear prediction and remaining useful life, while random forest, gradient boosting machines (GBMs), and deep networks (CNN and recurrent neural networks, RNN) are increasingly adopted as data breadth and frequency grow, or when time–frequency representations are used. Against this backdrop, drilling is a particularly demanding case: constrained chip evacuation, heat concentration in the hole, critical phases (entry/exit) and, above all, material transitions in stacks (e.g., CFRP/Al and CFRP/Ti) that abruptly change the signal signature. Right here, the combination of the right signal, the right model, and physical awareness proves decisive.

To understand how to make a truly data-driven TCM work in drilling, it is useful to observe cross-cutting patterns emerging from representative experimental studies. A first lesson comes from high-frequency AE. Proponents start from the observation that traditional force monitoring systems, while accurate, are often complex to integrate on production lines, whereas AE sensors offer a compact and more easily deployable solution. Representative works have shown that the AE spectral content is not undifferentiated noise

but encodes distinct mechanical events: flank friction, chip impact, edge chipping, and chisel-edge engagement produce signatures in stable bands. In particular, Klocke et al. [71], with an experimental drilling campaign on the DA718 superalloy and C45 steel, transformed the raw AE signal (1–2 MHz acquired with a Kistler 8152A sensor and Kistler 5025A1 amplifier) into the frequency domain via FFT and then analysed it with unsupervised k-means clustering, which groups data by minimising the mean squared distance. This allowed them to separate the different AE sources and correlate specific frequency bands with the wear state.

The authors highlighted a repeatable correlation between 150 and 250 kHz and flank friction, and a 250 kHz peak linked to the chisel edge, turning this structure into discriminative features capable of separating even severe wear states ($VB > 70 \mu\text{m}$) with very high accuracy [71]. The study showed that AE source separation, combined with clustering algorithms, is an effective route to estimate the wear state in-process during drilling operations. The practical consequence is two-fold: (i) AE becomes the primary sensor to intercept the most dangerous damage mechanisms early; (ii) blind feature extraction (global statistics) gives way to physically anchored time–frequency maps that AI can leverage with greater stability and less overfitting.

Where AE is not available or hardware must be minimised, a single force channel can be enough if treated as a sequence. In the drilling of Inconel 718, Mahmood et al. [72] built a very clear signal-to-model chain. From axial force measurements acquired via a Kistler 9123C load cell, they applied singular spectrum analysis (SSA) to obtain a denoised signal and computed 15 statistical features (RMS, variance, standard deviation, skewness, kurtosis, peak-to-peak, waveform/margin/peak index, etc.). Subsequently, to avoid overfitting and accelerate training, they applied principal component analysis (PCA) to compress from 15 to 3 the dimensions of features, and then a bidirectional long-short term memory network (BLSTM) that reads drilling as a sequence of phases (drill-in, steady, and drill-out) and uses past/future context to distinguish wear types (flank, chisel, crater, and outer corner). The result (97.94% accuracy) indicates that the model's temporal intelligence compensates for sensor sparsity, provided that the signal is correctly segmented and normalised.

The authors also performed a comparison on common data, re-training several literature baselines: random forest and other machine learning methods, as well as a CNN applied to spectrograms derived from the force signal (with image augmentation). In this setup, the CNN performed worst (image conversion and negative effects of negative transfer), the RF was unstable on multi-class problems with many trees, and the proposed SSA-BLSTM maintained the best accuracy and robustness. This is a template that can be replicated on the shop floor: one sensor, a light pre-processing chain, and a moderate recurrent model.

An even more economical channel is vibration. In AISI 316 drilled with HSS bits, an accelerometer on the clamping system provides sufficient signals for early wear detection, as reported by Simon et al. [73]. Vibrations were acquired with an accelerometer mounted on the workholding system and sampled with an NI-DAQ at 20 kHz, while wear (VB_{max}) was measured offline under the microscope. By selecting a core of five statistical features (standard deviation, sample variance, standard error, kurtosis, and sum) and using a K-Star classifier, an accuracy of 79.56% was achieved. The data were processed with Weka, and feature selection was performed with several methods, including greedy stepwise and J48 decision tree, to optimise dimensionality reduction. Although far from deep learning performance, this shows that, with solid feature selection, even low-cost sensors can close the loop on legacy equipment or manual stations, where the primary goal is not the last percentage point but preventing serious drifts before they compromise quality. The

overall workflow adopted by Simon et al. [73] for vibration-based tool wear monitoring is summarised in Figure 8.

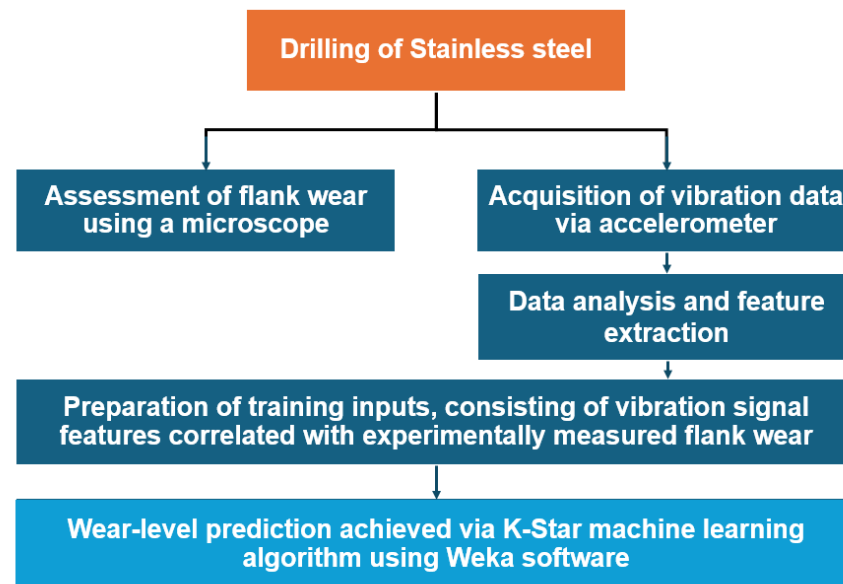


Figure 8. Workflow for tool wear monitoring: flank wear measurement, vibration data acquisition, feature extraction, dataset preparation, and classification using the K-Star algorithm in Weka [73].

Composite drilling is where AE shows its full strength. In the drilling of CFRP both under dry and under cryogenic conditions, Mathiyazhagan and Meena [56] decomposed AE with wavelet packet transform (WPT), associating bands to specific mechanisms: friction/wear (62.5–125 kHz), matrix cracking (125–187.5 kHz), and fibre fracture (187.5–75 kHz), with >500 kHz for tool chipping/fracture. AE signals were acquired with PAC WD-20 sensors (100–1000 kHz) coupled to the workpiece and automated machine learning (AutoML) implemented with the PyCaret library was used, whose flowchart is shown in Figure 9. Direct wear measurement was performed under the microscope, recording the flank wear width (VB). For predictive modelling, AE and process data (number of holes, speed, feed, cutting environment, tool coating, delamination, roughness) were used to train several ML algorithms through PyCaret AutoML and, among the 18 models tested, the best were ET with $R^2 = 0.966$ and MAE = 4.177 and gradient boosting regressor (GBR) with $R^2 = 0.951$. Feature-importance analysis highlighted that number of holes, cutting environment (dry vs. cryogenic), tool type, and AE characteristics (frequency, RMS) are the most relevant factors for wear prediction. The study is a good demonstration that integrating AE + WPT + AutoML is an effective, non-invasive solution for online tool-wear monitoring in CFRP drilling, enabling not only accurate real-time wear estimation, but also process-optimisation strategies oriented to sustainability.

On Ti-6Al-4V, force–vibration integration benefits from meta-heuristic hyperparameter optimisation: Chen et al. [74] developed a predictive model for tool-wear monitoring in drilling based on the combination of adaptive particle swarm optimisation (APSO) and least squares support vector machine (LS-SVM). From a sensor standpoint, a Kistler 9625B dynamometer was used for cutting forces and a B&W14100 sensor mounted on the workpiece for accelerations, while flank wear was monitored under the microscope, stopping tests once 0.8 mm wear was exceeded.

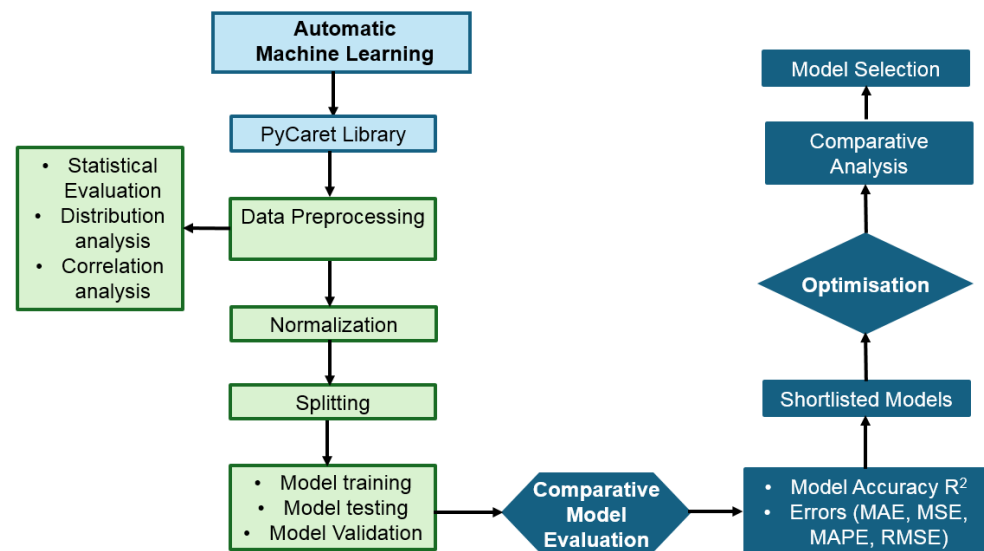


Figure 9. Workflow of the automated machine learning framework, illustrating the pre-processing, model training, validation, and optimisation stages used for predictive analysis [56].

The central idea was to optimise LS-SVM parameters automatically via APSO, improving its ability to correctly recognise the wear state compared to standard LS-SVM. The authors showed that an APSO-tuned LS-SVM reduces (compared with LS-SVM alone) the average error from 4.6% to 0.91%, especially in wear-transition regions where algorithms tend to get confused.

The message is pragmatic: when working with heterogeneous features and medium-size datasets, tuning makes the difference, and a well-tuned kernel is better than a poorly trained deep model.

The deployment aspect should not be overlooked. In low-automation contexts, Dayam and Desai [75] developed an intelligent system for monitoring tool-wear state and identifying the onset of chatter in legacy manual drilling machines. The work stems from the need to digitalise legacy machinery, lacking advanced control systems and relying on operator experience. The Smart Monitoring System framework to identify drill wear states and machining stability is shown in Figure 10.

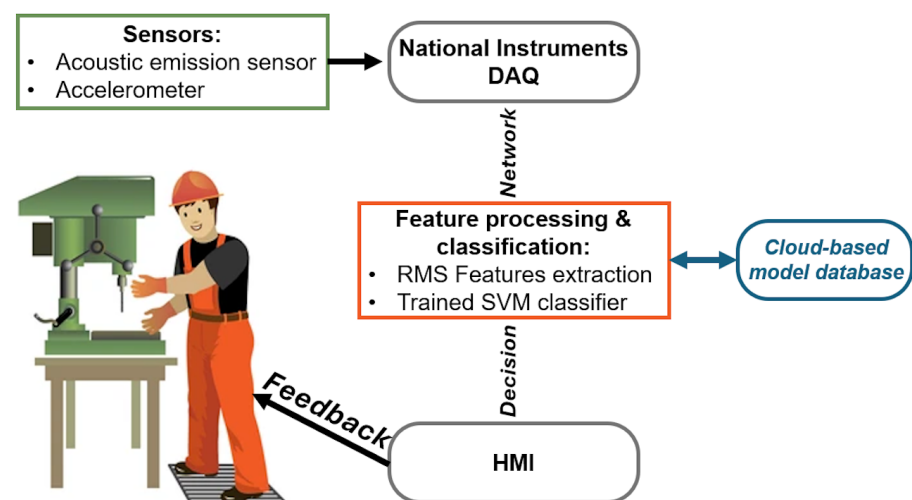


Figure 10. Schematic of an intelligent drilling monitoring framework integrating sensors (AE and vibration), data acquisition, feature extraction, and SVM-based decision-making with operator feedback through HMI and cloud connectivity [75].

The authors designed a system based on AE sensors and accelerometers, mounted near the workpiece and on the spindle, respectively, to acquire in-process information. Signals are pre-processed (spectral subtraction for AE, median filters for vibration) and the main extracted features are RMS amplitudes, strongly correlated with wear state and process stability. For decision-making, the system uses a quadratic-kernel SVM, trained on labelled datasets that combine sensor data with direct measurements of flank wear (according to ISO 8688 [76]) and chatter conditions. Results show that the classifier achieves higher than 98% accuracy across all tested combinations, with evaluation metrics (accuracy, precision, recall, F1, MCC) close to 1. The system was integrated with a human-machine interface (HMI) capable of providing real-time visual feedback on wear and chatter, also suggesting corrective parameters like the spindle speed. The authors emphasise that the proposed solution is easily implementable on legacy manual machines with minimal hardware modifications and can be extended to other machining operations. It is also a concrete example of integrating operator expertise into machine-learning models to support less experienced personnel.

With a view to industrial scalability, many implementations start from CNC native signals. In drilling of Inconel 625, Corne et al. [15] showed that the active spindle power read from the load metre correlates well with forces, increases with wear and, when fed to multi-layer perception (MLP) trained with Levenberg–Marquardt (LM), conjugate gradient (CG), and Bayesian interference (BI), enables VB prediction with errors comparable to force-based models, yet without dynamometers or additional cabling. The LM algorithm achieved the best performance (minimum mean square error, MSE, and maximum correlation), with an optimal number of five neurons. Wear prediction accuracy with power data showed an error between 0.8 and 18.4%, very close to that obtained with force data (0.4–17.9%). In testing, the R^2 coefficient reached 95.6% with power (vs 84.7% with force), indicating the high competitiveness of power data for industrial applications.

The trade-off is clear: while spindle power lacks the sensitivity of AE to capture micro-events, it offers superior cost-effectiveness and integration. The next step is to implement such monitoring directly at the machine edge, enabling real-time control with minimal latency. In shop floor-oriented work, Chehrehzad et al. [77] created a digital shadow on an industrial edge device: fusion between dynamometer signals (F_x , F_y , F_z , torque) and CNC-native streams (current, torque and encoder) feeds bidirectional long short-term memory (Bi-LSTM) and bidirectional gated recurrent unit (Bi-GRU) models trained with Bayesian hyperparameter optimisation. Experiments were conducted on AISI 1045 steel with TiAlN-coated carbide drills (diameter 8.5 mm, 140° point) on a Spinner U1530 CNC machining centre. A total of 2676 holes were drilled under dry conditions; flank wear measurements were taken every 48 holes using a Leica S9 I stereomicroscope, recording wear on both flanks. VB regression achieved an error lower than 10 μm , with GRU more accurate in early/late phases and LSTM showing better performance in the intermediate wear region. This is, in every respect, a blueprint for bringing AI on edge, with reduced latencies, robustness to real streams, and easy scalability toward digital twins.

The above discussed studies demonstrated the increasing maturity and diversity of AI strategies for real-time TCM across materials and industrial scenarios.

3.2.3. Guidelines and Design Principles

From the comparative analysis of the reviewed studies, several cross-cutting principles can be extracted to guide the development of reliable and scalable TCM systems for drilling operations.

A first consideration concerns data quality and representativeness. The predictive power of any AI model strongly depends on the amount, variability, and reliability of the

training data. Sensor calibration, synchronisation, and the selection of relevant process parameters must be carefully addressed to ensure consistent feature distributions and to prevent bias during model training. Balanced datasets covering different wear stages and cutting conditions are essential to improve generalisation and reduce overfitting.

Equally important is the selection and pre-processing of input features. Raw sensor signals often require filtering, segmentation, and normalisation to reduce noise and highlight wear-sensitive patterns. Feature extraction techniques such as time–frequency analysis, wavelet transforms, or statistical descriptors should be tailored to the specific signal type. Dimensionality reduction methods, such as PCA or t-SNE, can also enhance model efficiency and interpretability.

Practical implementation guidelines derived from recent studies include the following:

- Segmentation: split signals by drilling phases (entry, full engagement, exit) and, for stacks, by layers to reduce non-stationarity. Models such as BLSTM explicitly benefit from this organisation [72], and AE changes spectrum at phase transitions [71].
- Normalisation: power or forces scaled by diameter avoid bias among different drills; for AE/vibration, band–energy ratios on WPT make tests with similar setups comparable [15,56].
- Feature extraction: prefer physically interpretable features (e.g., AE band 150–250 kHz linked to flank friction) over blind statistics to improve transferability [71].
- Model selection: choose according to data and constraints: (a) SVM/LS-SVM (preferably APSO-optimised), RF/ET/GBM excel with curated features and medium datasets; (b) MLP are excellent for slow CNC signals (power/current) [15]; (c) LSTM/GRU are needed when the sequence is informative (AE/vibration) [72,77].
- From prediction to action: use thresholds on power/torque to trigger strategies (pecking, exit ramp-down, parameter switching). Edge models or HMI feedback can support operators or close the loop on CNC/robots [15,77].

Another key aspect is the integration of TCM into industrial environments. Real-time deployment requires lightweight models capable of running on embedded or edge devices, efficient data-streaming architectures, and robust communication protocols. Scalability and cybersecurity should be considered from the design phase to ensure reliable operation within smart-factory ecosystems.

Finally, evaluation and benchmarking are crucial to validate TCM solutions. The use of standardised datasets, unified performance metrics, and cross-validation procedures allow reproducible and comparable results across studies. The continuous monitoring of model drift and retraining with updated data are also necessary to maintain long-term stability.

Overall, the message is that smart drilling is not about picking the best algorithm but about composing the blocks well with strong physical awareness of the process: which signals are cost-effective and reliable in that context; which features truly reflect damage mechanisms; which model withstands data and execution constraints; which action should be tied to the diagnosis to avoid defects (delamination, burrs, poor roundness) while maintaining productivity. A review of the available literature shows that this data, decision, and then action engineering already constitute a reality: from band-aware AE to predict wear in CFRP [56], to a single force channel read as a sequence to distinguish the type of damage [72], to power as a scalable surrogate to bring TCM onto existing lines [15], up to the edge digital shadow that anticipates full integration with digital twins [77]. It is along this concrete, industrial trajectory that the rest of the article builds: from monitoring as a reliable diagnosis to adaptive control that makes drilling a self-optimising process.

3.3. Process Optimisation

The optimisation of drilling processes in aerospace manufacturing represents complex, multi-objective problem where hole quality, tool life, and productivity must be balanced. Classical statistical approaches such as Taguchi designs [78–80] and response surface methodology (RSM) [81,82] have provided valuable insights into parameter windows, but their applicability remains limited when the process is governed by nonlinear and stochastic interactions. This is particularly the case in the drilling of thin multi-material and homogeneous stacks, where multiple coupled mechanisms occur simultaneously: elastic deformation and local bending of thin sheets, intermittent tool engagement across interfaces, tool–material friction under variable contact conditions, and stochastic chip evacuation dynamics. These phenomena generate responses that are highly sensitive to small variations in boundary conditions and tool geometry, resulting in scattered force and torque signals and large variability in defect formation. Consequently, drilling thin stacked structures cannot be adequately represented by simple linear models, but instead required data-driven or metaheuristic optimisation frameworks capable of capturing nonlinear couplings and probabilistic behaviours.

To address these challenges, two complementary AI-based approaches have been developed. The first concerns offline parameter optimisation, where process variables are tuned using data-driven models and metaheuristic algorithms to identify optimal cutting condition before production. The second focuses on adaptive control strategies, in which drilling parameters are adjusted online in real time, guided by sensor feedback from the process. Together, these approaches provide the foundations for smart drilling, enabling both predictive optimisation and closed-loop adaptation, which will be discussed in detail in the following subsections.

3.3.1. Offline Parameters Optimisation (AI-Based Algorithms)

Offline optimisation exploits AI to pre-compute drilling setups that trade off quality and productivity before the production run, thereby reducing trial-and-error and capturing the inherently nonlinear behaviour of hole-making. One study conducted on CFRP is the hybrid framework by Wang and Jia [83], where a full-factorial campaign (spindle speed, feed rate, point angle) was used to train a feed-forward ANN that maps process parameters to thrust force and exit-delamination factor. Then, the trained surrogate served as the objective function for Non-dominated Sorting Genetic Algorithm (NSGA-II), with a three-objective formulation (minimise thrust and delamination, maximise material removal rate) and an explicit delamination constraint. Because NSGA-II returns a dense Pareto set, fuzzy C-means clustering was introduced to select a handful of representative operating points for confirmation tests. The ANN delivered high fidelity (average relative error $\approx 3.0\%$ for thrust, 1.4% for delamination; $R^2 \approx 0.984$ and 0.909 , respectively), and the clustered Pareto solutions reproduced the expected trade-offs in validation drills. Figure 11 provides the workflow adopted. For aluminium alloys, Tzotzis et al. [84] modelled AA6082-T6 drilling with both RSM and ANN surrogates (inputs: tool diameter, cutting speed, feed; outputs: thrust force F_z , torque M_z , average arithmetic roughness R_a). After identifying significant terms via ANOVA, the authors compared generalisation performance using Mean Absolute Percentage Error (MAPE) and then applied a desirability-function optimisation to select balanced parameter sets. RSM achieved MAPE values of 2.14% (F_z), 3.49% (M_z), 6.16% (R_a), while ANN achieved 2.19% , 1.82% , 2.85% , respectively. Extending to metal-matrix composites (MMCs), Ghadai et al. [85] proposed an ANN + NSGA-II hybrid approach for drilling a hybrid aluminium MMC fabricated using stir casting process. A feed-forward ANN was trained to predict material removal rate (MRR) and surface roughness, and then embedded as the fitness function within NSGA-II to generate a Pareto front from

which 35 nondominated parameter sets were extracted. The outcome is directly actionable for offline planning: operators select a point on the Pareto front according to production priorities (e.g., higher MRR vs. lower roughness), exemplifying transferable methodology. Finally, Turan et al. [86] investigated the dry drilling of AA6082-T6 alloys using a Taguchi L27 design of experiments that combined tool coating, feed rate, and cutting speed. The measured responses included surface roughness, cutting temperature, and dimensional accuracy metrics such as hole diameter error, circularity, and cylindricity. Three predictive frameworks, Taguchi, ANN, and adaptive neuro-fuzzy inference system (ANFIS), were comparatively trained both on raw experimental data and on single-to-noise (S/N) ratios. Model performance was assessed using mean absolute deviation (MAD), MSE, root mean square error (RMSE), and R2 indices. The results highlighted two important aspects for offline optimisation: (i) the ANN consistently exhibited the highest reliability and predictive capability across all outputs, outperforming both Taguchi and ANFIS models; and (ii) training with S/N ratios systematically improved prediction robustness compared to training with raw values.

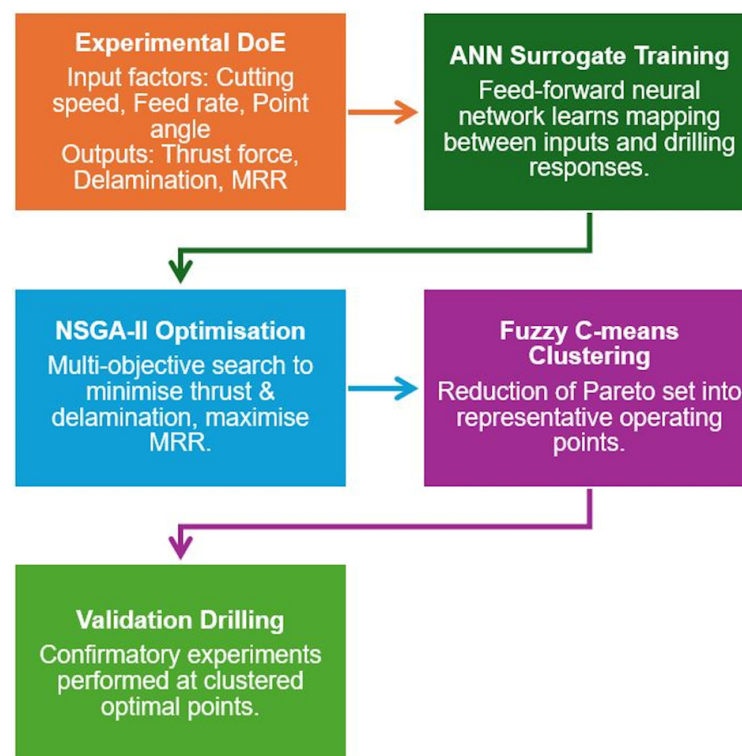


Figure 11. Hybrid optimisation workflow combining ANN surrogate modelling, NSGA-II multi-objective search, and fuzzy C-means clustering, validated by drilling experiments.

Offline optimisation in drilling has also been extensively addressed through evolutionary algorithms, the most representative of which are genetic algorithms (GAs) and particle swarm optimisation (PSO). These techniques are particularly well suited to multi-objective problems where the design space is highly nonlinear and multimodal, as they allow large parameter domains to be explored efficiently and converge towards global optimisation. Aich et al. [87] applied a hybrid framework combining support vector machines (SVMs) with particle swarm optimisation (PSO) to minimise delamination in drilling of GFRP laminates. In their study, spindle speed, feed rate, drill diameter, and laminate thickness were used as input parameters, while the delamination factor was the response variable. The optimised SVM-PSO surrogate was subsequently exploited to identify parameter settings that minimised delamination. Kalita et al. [88] extended the direct use of GA and PSO

for parameter optimisation in GFRP drilling. Based on a Box–Behnken response surface design with four process factors (laminate thickness, drill diameter, spindle speed, and feed rate), they constructed an empirical model for delamination factor and then applied both GA and PSO to identify global minima. Both algorithms reached similar optimal solutions, but PSO exhibited faster convergence and required less computational time. As an additional exemplar of evolutionary search applied to drilling, Mercy et al. [89] investigated the self-healing CFRP laminates manufactured by embedding dicyclopentadiene microcapsules in an epoxy/glass system and performed a drilling campaign in which the microcapsule size and loading were varied alongside the cutting conditions. The study jointly tracked thrust force and in-process temperature at the drill point, showing that the microcapsule content markedly affected both responses. Crucially, the authors formulated a multi-response genetic optimisation (i.e., multi-objective GA) to compute Pareto-optimal trade-offs that simultaneously minimise thrust and temperature, thereby providing pre-production operating windows when thermal-mechanical interactions are couples and difficult to capture with simple regressions.

Beyond these case-specific applications, a broader spectrum of evolutionary algorithms has been explored for drilling optimisation. Table 3 provides a comparative overview, outlining their potential applications, strength, and limitations. Genetic algorithms (GAs) and particle swarm optimisation (PSO) remain the most widely adopted, particularly for multi-objective trade-offs. Differential evolution (DE) has recently gained attention for its robustness in continuous optimisation tasks, such as energy-efficient drilling and torque supervision. Ant colony optimisation (ACO), although less conventional in machining, has been successfully applied to tool path planning in multi-hole drilling, where minimising cycle time is critical. Hybrid frameworks, which combine surrogate modelling (e.g., ANN; SVM; ANFIS) with evolutionary search, further expand the design space exploration and enable accurate multi-response optimisation. Collectively, these methods illustrate how evolutionary computation provides versatile strategies to capture the nonlinear, stochastic behaviour of drilling and guide parameter selection before production.

Table 3. Evolutionary algorithms applied to offline drilling parameter optimisation: main applications, advantages, limitations, and representative studies.

Algorithm	Main Application in Drilling	Advantages	Limitations	Representative Studies
Genetic Algorithm (GA)	Optimisation of cutting parameters (speed, feed, geometry) to minimise thrust force, torque, burrs, delamination, or maximise productivity	Robust global search; effective for both discrete and continuous variables; well-established in manufacturing	Risk of premature convergence; relatively high computational cost	[88,89]
Particle Swarm Optimisation (PSO)	Optimisation of process parameters for defect reduction (delamination, roughness) and surrogate model tuning	Fast convergence; simple implementation with few parameters; efficient in continuous domains	Can stagnate in local minima; performance sensitive to swarm size and coefficient	[87,88]
Differential Evolution (DE)	Optimisation of drilling energy efficiency, torque/thrust management, vibration reduction	Strong exploration capability; robust for continuous optimisation; fewer control parameters than GA	Sensitive to scaling (F, CR) and population size; fewer drilling applications compared to GA/PSO	[19,90]
Ant Colony Optimisation (ACO)	Optimisation of drilling sequences and tool paths to reduce total path length and machining time in multi-hole components	Highly effective for combinatorial optimisation; scalable to complex geometries; significant machining time reduction	Computational effort grows with number of holes; not suitable for continuous process responses	[91,92]
Hybrid frameworks (e.g., ANN + NSGA-II; SVM + PSO; ANFIS + GA)	Multi-response optimisation combining parametric tuning with surrogate-based prediction (forces, roughness, delamination, MRR)	Combine predictive accuracy of surrogates with global search of evolutionary algorithms; yield Pareto-efficient solutions	Require large training datasets; computationally more sensitive; interpretability can be limited	[83,85]

3.3.2. Online Parameters Optimisation

Although offline optimisation provides pre-calculated operating windows, its static nature is insufficient in drilling environments characterised by variability mainly related to material properties, boundary conditions, and tool wear progression. Online parameter optimisation would solve this limitation by dynamically adjusting process variables in real time, based on sensor data and predictive models. Despite the encouraging outlook, some challenges remain for large-scale industrial adoption. Online optimisation requires the integration of low-latency sensors, robust feature extraction under noisy conditions in the manufacturing environment, and computationally efficient algorithms that can be implemented at the machine or edge level. However, the growing availability of embedded sensors and industrial edge computing platforms offers a promising path toward scalable implementation.

Sadek et al. [93] introduced a cyber-physical adaptive control system (CPACS) for the drilling of hybrid stacks. The framework combines real-time tool wear detection, derived from feature extraction of spindle power signals, with a predictive drilling force model capable of estimating axial force distribution across stack layers and interfaces. The control logic dynamically adjusts the feed rate to remain below a critical force threshold, thus preserving hole quality while extending the tool life. The CPACS performs in-process learning: extracted power features are continuously updated to refine the GPR model used for wear prediction. Experimental validation on CFRP/aluminium/CFRP stacks demonstrated that the system doubles tool life and reduced the total cycle time and cost by up to 50% compared with conventional strategies, while ensuring damage-free hole exits. Wegert et al. [94] developed a sensor-integrated single-lip deep hole drilling tool capable of monitoring thermomechanical variables directly at the cutting zone. The tool was equipped with embedded acceleration and temperature sensors, with real-time data transmission through wireless and wired telemetry systems. These signals were processed through a soft sensor model, correlating cutting parameters, forces, torque, and thermal loads with subsurface properties such as residual stress, microhardness, and grain refinement. By integrating this model into a closed-loop controller, drilling parameters (feed and rotational speed) could be dynamically adjusted to maintain the desired subsurface integrity. The study demonstrated that such an adaptive control framework can effectively steer residual stress into the compressive regime and optimise hardness and roughness without the need for secondary finishing processes. Yan et al. [95] proposed two strategies, one based on time-domain analysis and the other on frequency domain analysis, for low-frequency vibration-assisted drilling (LFVAD) of CFRP/Ti stacks. Both methodologies are based on real-time processing of the thrust force signal to dynamically adjust the cutting parameters when crossing the interface between materials, with the aim of limiting delamination and dimensional variations. A different approach was studied by Haoua et al. [58]. As illustrated in Figure 12, they developed a two-phase smart drilling framework where machine learning models trained on multi-sensor data enable real-time recognition of material transitions and adaptive adjustment of drilling parameters, thus enhancing process stability and hole quality, who introduced a method for recognising materials in multi-material stack drilling operations using an automated electric drilling unit (eADU). Their strategy combines a random forest model with the fusion of data from multiple sensors (cutting forces, vibrations, electrical signals from motors, and lubrication/cooling conditions). Signal processing in the time and frequency domains made it possible to reliably distinguish the characteristic signatures of CFRP and aluminium alloys, allowing for the adaptation of cutting parameters in line and improving the overall quality of the hole.

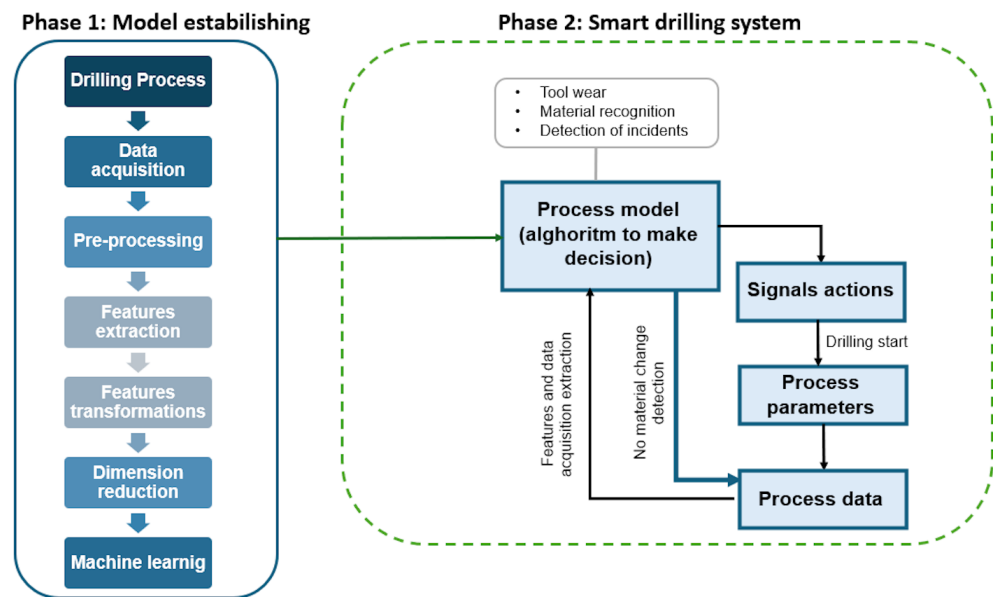


Figure 12. Framework of the smart drilling system proposed by Haoua et al. [58], consisting of two phases: (1) model establishment through multi-sensor data acquisition, signal processing, feature extraction and machine learning, and (2) real-time adaptive drilling with process monitoring, material recognition, and parameter adjustment.

Finally, Hu et al. [96] presented a sensor less self-adaptive method for drilling CFRP / Al stacks, based on the analysis of the equivalent impedance of a drilling device assisted by longitudinal-torsional vibrations. The electrical impedance of the piezoelectric transducer varies characteristically during the different stages of penetration and, in particular, shows discontinuities at the interface between materials. These variations were exploited to develop an online recognition algorithm capable of accurately identifying the position of the interface and activating the automatic change in cutting parameters. Tests have shown significant improvements in both hole diameter deviation and surface quality compared to conventional drilling. Finally, as anticipated in Section 3.1.4, Panico et al. [13] demonstrated an industrially viable self-adaptive strategy based on spindle power monitoring (see Figure 5b). By extracting the dynamic component of active power, their method reliably detected the CFRP / AA7075-T6 interface during one-up drilling, automatically triggering parameter switching without additional sensors. This approach proved to be repeatable and effective in mitigating delamination and burr formation at the interface between the two materials, compared to the traditional approaches of drilling the hybrid stacks with compromise parameters.

Although the examples discussed demonstrate the feasibility of real-time auto-adaptation in drilling, their number remains limited compared to the broad literature on offline parameter optimisation. Most reported strategies are still case-specific, validated under controlled laboratory conditions, and often constrained to particular material/tool combinations. This highlights that online adaptive frameworks for drilling are still at an early stage and require further development and industrial validation to achieve an adequate level of maturity.

3.4. Predictive Quality Modelling

Predictive modelling of drilling quality aims to predict hole defects before or during machining, using models trained on experimental data or data from sensors.

3.4.1. Predictive Models for Delamination in CFRP and Hybrid Stacks

Delamination is one of the most critical defects in drilling carbon-fibre reinforced plastics, as it compromises structural integrity and fatigue life. Its onset is governed by a nonlinear interaction between tool geometry, fibre orientation, thermal-mechanical loading, and local bending of thin plies, making its prediction a central challenge in smart drilling.

Early attempts on regression-based models to capture global correlation between drilling parameters and delamination. Ghasemian Farad et al. [97] employed partial least squares (PLSs) regression to predict delamination in CFRPs as a function of spindle speed, feed rate, and drilling geometry. Their model achieved nearly 99% accuracy, showing that even relatively simple statistical learning techniques can be effective when supported by well-designed experimental campaigns. However, these approaches struggle with generalisation across tools, materials, or boundary conditions. ANNs have subsequently been introduced to overcome such limitations by capturing nonlinear mappings. With the increasing availability of high-frequency and multimodal sensor data, more advanced deep learning models have been investigated. Choi et al. [98] introduced a multimodal one-dimensional convolutional neural network (1D CNN) to predict delamination in CFRP drilling performed with industrial robots. Their framework fused heterogeneous data streams, including thrust force, torque, vibration, spindle current, voltage, acoustic emission, and post-process imaging, into a single predictive model (see Figure 13). The multimodal CNN not only enhanced prediction accuracy but also enabled real-time inference, highlighting its industrial applicability for online monitoring.

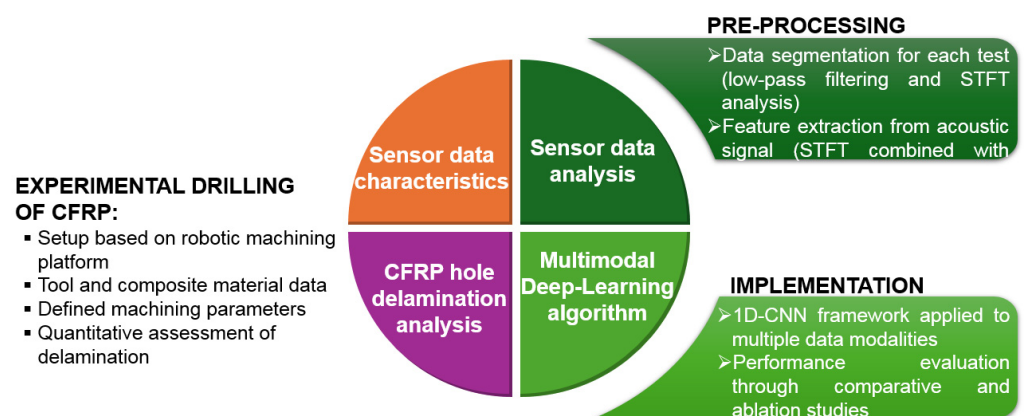


Figure 13. Workflow proposed by Choi et al. [98] for CFRP delamination prediction in robotic drilling, integrating sensor data acquisition, hole delamination analysis, pre-processing of multimodal signals, and implementation of a 1D CNN algorithm.

Probabilistic approaches have also been explored. Zhang and Xu [99] employed Gaussian process regression (GPR) to estimate the delamination factor in CFRP laminates, with drill diameter, feed rate, and spindle speed as inputs. GPR offered strong generalisation even with relatively small training datasets, while its probabilistic nature provided confidence intervals around predictions, making it particularly suitable for uncertainty-aware quality modelling. For hybrid stacks, adaptive modelling frameworks have been proposed. Yao et al. [100] developed an adaptive support vector regression (SVR) model enhanced by a modified arithmetic optimisation algorithm (AOA). The optimisation strategy dynamically tuned SVR hyperparameters through random disturbance operators, enabling the robust prediction of entry and exit delamination in CFRP/titanium drilling. The model achieved accuracies exceeding 96%, outperforming conventional ML baselines such as random forests and decision trees. Finally, Zhang et al. [101] analysed the drilling of CFRP laminates with prefabricated delamination, introducing the equivalent delamination factor

(F_{ed}) as a descriptor of exit damage. Quadratic nonlinear regression (QNR) was used to model axial force evolution, while SVR predicted F_{ed} from process parameters and defect geometry. The QNR achieved error below 13%, whereas the SVR reached a maximum error of 3.8%. The study demonstrates that combining regression and machine learning enables the accurate prediction of exit damage, supporting the repair-oriented drilling of pre-damaged laminates.

3.4.2. Predictive Modelling of Burr Formation (Metallic Alloys)

Burr formation remains one of the most critical defects in drilling metallic alloys, particularly at the exit and interfacial regions of thin sheets and stacks [10,102]. Predicting burr height is essential because excessive burrs not only increase post-processing costs to deburring but it also compromises the service life of the component as well as the assembly tolerances. To date, the most widespread approaches for burr prediction are still analytical models, which attempt to capture the physical mechanisms of burr generation based on cutting mechanics and plastic deformation [103–105]. Recent advances in predictive modelling have progressively shifted burr formation analysis in metallic drilling from purely correlations to intelligent data-driven approaches. Kim and Lee [106] investigated burr type classification in drilling of AA7075 using AE sensing, comparing a conventional back-propagation ANN with a CNN trained on AE spectrograms. Their study demonstrated that CNN-based feature extraction achieved higher accuracy (0.94) than ANN (0.86) and introduced a drilling burr control chart to map process parameters to burr categories for real-time supervision. Complementing this sensing-oriented approach, Mondal et al. [107] developed an adaptive neuro-fuzzy inference system trained on Taguchi-designed data for AA6061 drilling, which was coupled with a teaching-learning-based optimisation (TLBO) algorithm to minimise the burr height and thickness. The hybrid ANFIS-TLBO strategy identified optimal parameter settings that were experimentally validated, demonstrating its effectiveness for offline process planning. Karnik et al. [108] provided an earlier yet influential contribution by benchmarking the response surface methodology (RSM) against ANN models for burr height and thickness prediction during AISI 316L drilling. Their results showed that ANN models consistently achieved superior predictive accuracy and captured nonlinear interactions beyond the capability of quadratic RSM formulations. Extending this line, Mondal et al. [109] employed regression modelling integrated with a flower pollination algorithm (FPA) to optimise burr height in aluminium drilling, with an ANN used for cross-validation of predictions. The FPA regression framework efficiently converged towards minimum-burr conditions, confirming its suitability for data-limited contexts. Collectively, these studies illustrate the breadth of AI-based strategies, ranging from sensor-driven classification to hybrid optimisation, that now underpin burr prediction and suppression in metallic alloys. More recently, Prashanth and Hiremath [110] studied the dry micro-drilling of commercially pure titanium with Ti-Al-N-coated carbide tools, developing comparative prediction frameworks based on generalised regression neural networks (GRNNs), ANFISs, and multiple regression analysis (MRA). Their results indicated that GRNN and ANFIS models achieved significantly higher predictive accuracy (means errors <6%) than regression-based approaches (errors up to 12%), enabling a reliable estimation of burr height alongside thrust force and radial overcut.

3.4.3. Predictive Modelling of Other Hole Quality Indices

The growing interest in AI-driven surface integrity evaluation has recently been highlighted in a prospective study by Ghosh et al. [111], who reviewed a decade of advances in machine learning and deep learning methods for surface roughness prediction across precision manufacturing processes. Their work emphasised that intelligent models, espe-

cially when combined with multi-sensor data and edge computing, are pivotal for enabling zero-defect manufacturing strategies. Beyond burr formation and delamination, other indicators such as surface roughness, circularity, and dimensional accuracy are equally critical for assessing hole quality in drilling. Ranjan et al. [112] proposed a multimodal modelling strategy for micro-drilling, combining signals of force, torque, and vibration to train an ANFIS predictor. The approach aimed to anticipate surface roughness and roundness errors, showing that fusing heterogeneous sensor data improved the reliability of in-process quality prediction. Dedeakayoğulları et al. [113] focused on drilling SLM-produced Ti6Al4V parts, where microstructural variability complicates surface finish. They compared ANN and ANFIS models to forecast surface roughness (R_a) from process parameters, demonstrating that data-driven models can guide the selection of cutting conditions in additive-manufactured alloys. Tabacaru [114] carried out a comparative assessment of predictive frameworks, contrasting response surface methodology, ANN, and image-based descriptors for roughness estimation in drilling. His study highlighted that AI models provide more robust and transferable predictions than purely statistical formulations. In a broader perspective, Shilpa and Yendapalli [115] provided a comprehensive overview of surface roughness estimation techniques for drilled surfaces, highlighting the wide spectrum of approaches ranging from classical statistical tools (ANOVA, Taguchi design, regression models) to data-driven methods such as ANNs. Their analysis underlined how input variables including spindle speed, feed rate, drill diameter, and hole depth can be mapped to surface roughness indices (e.g., R_a , R_q , R_t), either through direct empirical models or through surrogate learning. Importantly, the review emphasised that, while contact methods remain widely used in laboratory investigations, indirect approaches such as image processing, X-ray computed tomography, or replica-based methods are increasingly employed in industrial contexts due to their non-destructive nature and compatibility with in-process monitoring. In this context, artificial intelligence-based models are recognised as particularly effective in capturing the nonlinear relationships between drilling parameters and surface finish, enabling the creation of predictive models that can be transferred to different materials and drilling configurations. Figure 14 summarises the input–model–output pipeline adopted in this review for predictive hole-quality modelling, from process/sensor data to AI-based estimators of delamination, burrs, and surface/dimensional indices.

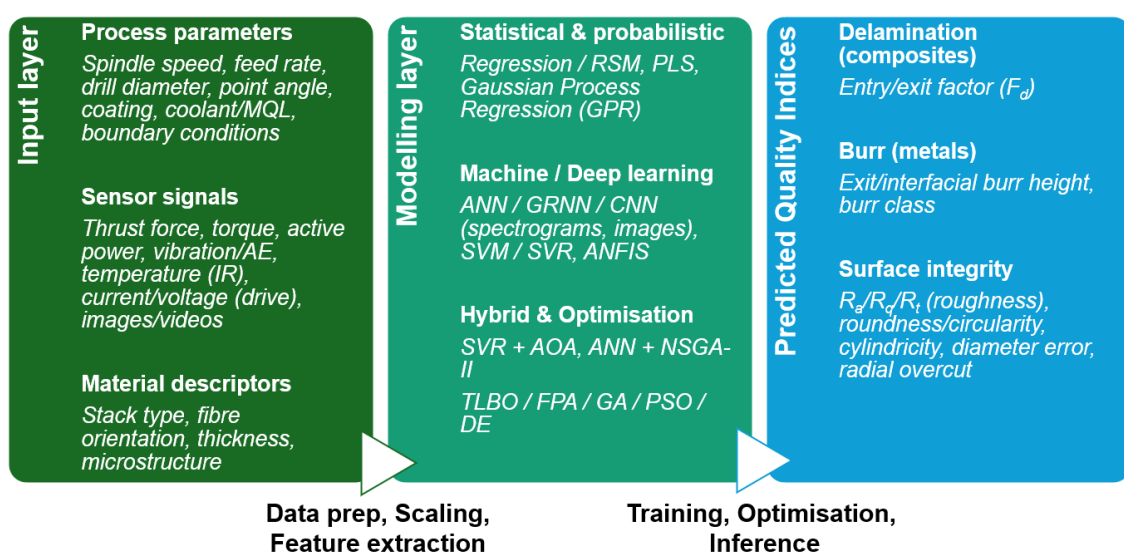


Figure 14. Conceptual map for predictive quality modelling in drilling: process/material descriptors and multi-sensor signals feed statistical/ML/optimisation methods to estimate quality indices.

4. Challenges and Research Gap

The progress in AI-based drilling optimisation is promising, but several substantial challenges and gaps remain that must be addressed so that these techniques become reliable and transferable in industrial settings. Two related issues emerge as central: data availability and quality, and model generalisability across materials, geometries, and tool conditions.

One problem is the scarcity of large, high-integrity datasets encompassing both sensor signals and validated quality outcomes. In many studies, datasets are collected under narrow experimental conditions (single workpiece type, fixed tool geometry, limited feed/speed range), often with small sample sizes. This limits model robustness and increases the risk of overfitting. For example, a recent work on CFRP drilling used virtual sample generation (VSG) to augment limited data and mitigate this issue [116]. Similarly, the review proposed by Zhong et al. [117] highlights that many published works do not include sufficient test or validation sets outside the training domain to assess real-world performance. Data quality adds further complications: heterogeneous sensor modalities, varying sampling rates, lack of calibration or synchronisation, measurement noise, and inconsistencies in the labelling of defect outcomes (e.g., what constitutes “delamination exit damage” or “burr height”) all degrade model performance. Under such conditions, even methods that perform well under lab conditions show poor transfer to production machines, where variability in material batches, tool wear, fixturing, and environmental temperature further amplify errors. Furthermore, under specification (i.e., the inability of a model to demonstrate that it has captured the true underlying causal structure rather than spurious correlations) is increasingly recognised as a threat to generalisability [118,119]. To move forward, several research directions are essential. First, the creation of curated, shareable multi-sensor datasets and harmonised feature extraction protocols is essential. Mohamed et al. [18] shows how heterogeneity in sensors, sampling, calibration, and feature extraction undermines comparability and generalisation; it explicitly calls out the need for consistent dimensionality-reduction/feature-selection guidelines and discusses practical pathways (e.g., tool-embedded nodes, wireless transmission, and normalisation to decouple process settings). Second, adopt transfer learning with multi-source domain adaptation to cope with distribution shifts across materials, tools, and fixtures. Wang et al. [120] demonstrated an integrated multi-source, dynamically adaptive framework that learns domain-invariant representations via attention mechanisms and sliced-Wasserstein alignment, improving cross-domain quality prediction on thin-walled parts. Third, physics-informed machine learning approaches offer a promising route to bridge data-driven methods and mechanistic models. Toth et al. [121] integrated the Taylor-type tool-life equation with Gaussian processes, showing that grey-box models outperform pure black-box or purely mechanistic baselines and are better suited to resource-efficient machining. Finally, explainable AI (XAI) methodologies are increasingly recognised as a necessary complement to predictive performance. Brusa et al. [122] showed how SHAP (Shapley additive explanations)-based attribution identifies the most influential features and stabilises diagnostic performance in rotating machinery; analogous SHAP-guided screening on drilling features (force harmonics, AE RMS, current transient, IR peaks) can prune spurious predictors and enforce physics-consistent behaviour.

5. Conclusions and Future Overlook

An analysis of the recent literature confirms that drilling, despite its apparent simplicity, remains one of the most complex and critical operations in manufacturing, especially in the aerospace sector. The progressive integration of artificial intelligence has opened up unprecedented opportunities for tool condition monitoring, defect prediction, and adaptive control. Machine learning and deep learning models have demonstrated superior capa-

bilities compared to traditional mechanistic or empirical approaches, particularly when leveraging data from multimodal sensors. However, their full implementation in industrial environments is still hampered by issues of data availability, model generalisability, and robustness under varying boundary conditions.

Looking ahead, a promising direction for research is the integration of artificial intelligence-based monitoring and control with sustainable manufacturing goals. Drilling is inherently energy-intensive, and its large-scale adoption in aircraft assembly implies significant cumulative consumption. As discussed in Section 3, recent studies suggest that AI-based models combined with spindle power or current monitoring are a powerful means of prediction hole quality. These can be extended beyond quality prediction to provide real-time indicators of energy efficiency. Integrating energy awareness into optimisation models, through multi-objective formulations that balance quality, productivity, and environmental impact, represents a practical approach to reducing resource consumption while maintaining aerospace standards. A second trajectory concerns the industrial scalability of AI-enhanced drilling. Modern robotic and CNC systems already provide native access to machine signals, while end-effectors increasingly integrate force, torque, vibration, and acoustic sensors into compact multifunctional platforms. These technological developments reduce the need for bulky external systems, enabling the seamless implementation of adaptive monitoring and control strategies in real assembly lines. Edge computing and digital shadow architecture further accelerate this transition, ensuring low-latency execution and creating a bridge to the comprehensive digital twins of the drilling process. Finally, several future research perspectives emerge. The systematic creation of shared, high-quality datasets is necessary to strengthen cross-domain generalisation and to benchmark algorithms under realistic operating variability. Physics-informed learning represents another promising direction, combining the interpretability and extrapolation capability of mechanistic models with the flexibility of data-driven approaches. Moreover, explainable AI techniques should be more widely adopted, not only to increase model trustworthiness but also to align predictions with a physical understanding of wear, damage, and defect mechanisms.

Another crucial consideration concerns the drilling of thin-walled structures, which are increasingly common in aerospace assembly. Unlike bulk or rigid components, thin configurations introduce complex dynamic phenomena such as local bending, interlayer gap formation, and system instability. These effects strongly alter thrust force evolution, chip evacuation, and defect formation mechanism (e.g., burr morphology and loss of roundness). Consequently, it is not sufficient to apply AI models trained on conventional drilling datasets to these conditions, since they would fail to capture the additional sources of variability. Instead, reliable implementation requires a prior understanding of the underlying physical mechanisms through dedicated experimental and modelling studies, which then inform the design of tailored features, sensor strategies, and learning architecture. Only by integrating AI with informed knowledge of thin-structure dynamics can predictive models achieve robustness and industrial relevance in next-generation drilling applications.

Beyond the scientific advances discussed, the integration of artificial intelligence in drilling holds distinct and irreplaceable advantages that justify its continuous development. Unlike conventional control systems, smart drilling architectures are capable of self-learning and self-adaptation, allowing them to respond autonomously to process variability, tool wear, and material transitions without manual intervention. This capability is particularly valuable in aerospace manufacturing, where consistency, traceability, and zero-defect production are essential. Moreover, by combining real-time analytics with energy and resource-aware optimisation, smart drilling contributes to the sustainability and digitalisation goals of Industry 5.0. These features make AI integration not merely an

improvement, but an inevitable evolution towards more resilient, efficient, and sustainable manufacturing systems.

In conclusion, while artificial intelligence is rapidly transforming drilling into an intelligent, adaptive, and potentially sustainable process, its industrial application will depend on the ability to combine predictive performance with the scalability of results to real structural configurations and interpretability. Achieving this integration is not only a research challenge, but also a strategic necessity for the future of aerospace manufacturing.

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Abbreviations

The following abbreviations are used in this manuscript:

1D CNN	One-dimensional convolutional neural network
ACO	Ant colony optimisation
AE	Acoustic emission
AI	Artificial intelligence
ANNs	Artificial neural networks
ANFISs	Adaptive neuro fuzzy inference systems
AOA	Arithmetic optimisation algorithm
APSO	Adaptive particle swarm optimisation
Bi-GRU	Bidirectional gated recurrent unit
Bi-LSTM	Bidirectional long short-term memory
BI	Bayesian interference
BLSTMN	Bidirectional long short-term memory network
CG	Conjugate gradient
CID	Control internal data
CNN	Convolutional neural network
CNN-LSTM	Convolutional neural networks—long short-term memory
CNC	Computer numerical control
DIC	Digital image correlation
DLC	Diamond-like carbon
DE	Differential evolution
ETs	Extra trees
F_d	Delamination factor
F_{ed}	Equivalent delamination factor
FFT	Fast Fourier transform
FPA	Flower pollination algorithm
F_z	Thrust force
GA	Genetic algorithms
GBMs	Gradient boosting machines
GBR	Gradient boosting regressor
GPR	Gaussian process regression
GRNNs	Generalised regression neural networks
HMI	Human–machine interface
HSS	High-speed steel
LEPs	Local exponential patterns
LFVAD	Low-frequency vibration-assisted drilling

LM	Levenberg–Marquardt
LS-SVM	Least squares support vector machine
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MEMS	Micro-electromechanical systems
ML	Machine learning
MLP	Multi-layer perception
MQL	Minimum quantity lubrication
MRA	Multiple regression analysis
MRR	Material removal rate
MSE	Mean squared error
M_z	Cutting torque
NSGA-II	Non-dominated sorting genetic algorithm
PCA	Principal component analysis
PLS	Partial least squares
PSO	Particle swarm optimisation
QNR	Quadratic nonlinear regression
R_a	Average arithmetic roughness
RAD	Rotary assisted drilling
RANSAC	Random sample consensus
RF	Random forest
RMS	Root mean square
RMSE	Root mean square error
RNNs	Recurrent neural networks
R_q	Root mean square roughness
RSM	Response surface methodology
R_t	Total height of the roughness profile
SHAP	Shapley additive explanations
SSA	Singular spectrum analysis
STFT	Short-time Fourier transform
SVR	Support vector regression
SVM	Support vector machine
TCM	Tool condition monitoring
TLBO	Teaching–learning-based optimisation
UAD	Ultrasonic assisted drilling
VSG	Virtual sample generation
WPT	Wavelet packet transform
XAI	Explainable artificial intelligence

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