AccuraspravHub: Leveraging AI and Machine Learning to Define and Optimize Process Windows in Thermal Spray Operations

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Abstract—Consistent coating quality in thermal spray processes is challenging due to inherent complexity, operator-dependent controls, and evolving equipment conditions. While the use of advanced sensors for real-time process monitoring has grown, the effective integration of diverse data streams and the application of modern analytics remain limited. This paper presents the AccuraspravHub, a centralized data platform designed to harmonize booth parameters, in-situ plume measurements, maintenance schedules, and coating quality evaluations. By combining domain expertise with advanced analytics, including initial steps toward machine learning, the AccuraspravHub establishes robust datasets, identifies stable process windows, and provides proactive insights for process improvements. The approach is rooted in a realistic understanding of the complexities of thermal spray operations, emphasizing careful data construction, iterative refinement, and pragmatic adoption of informatics. Preliminary on-site trials with an aerospace industry partner have confirmed the platform's value in improving process consistency and establishing a reliable foundation upon which more sophisticated AI-driven process control can be developed over time.

Introduction

The thermal spray industry spans a wide range of processes and applications, relying on controlled melting, acceleration, and deposition of powdered materials onto substrates to produce coatings with critical functional properties [1]. Although longstanding methodologies and experienced operators have guided the optimization of parameters, the increasing complexity of modern applications, along with the need for enhanced consistency and reduced reliance on human intuition, is pushing the field toward more data-driven strategies [2, 3]. The demand for robust, quantitative insights arises from the intricate interplay between feedstock powder characteristics, booth parameters, and the thermal, kinetic, and geometric properties of the spray plume that directly influence coating quality.

Over the years, advanced sensors capable of providing real-time measurements of plume characteristics—such as particle temperature, velocity, and intensity distribution—have become more accessible. Tecnar's Accuraspray 4.0 sensor, for instance, has been widely adopted and recognized for its reliable monitoring capabilities. Even so, translating raw sensor data into actionable process adjustments remains a complex task. The path from measured plume properties to final coating microstructure is influenced by numerous intermediate variables, equipment maintenance states, and potential sources of variability. Traditional approaches typically rely on setting simple min-max tolerance windows for sensor readings. While this method offers a baseline of control, it lacks the sophistication needed to adapt to evolving conditions, multiple feedstock powders, and variations in equipment condition.

Recent interest in artificial intelligence, machine learning (ML), and broader informatics methods suggests that correlating coating properties with observed process conditions could be improved by systematic data integration and analysis. Nevertheless, applying these techniques to thermal spray is far from being straightforward. The diversity of process conditions, scarcity of well-structured datasets, and high costs associated with obtaining extensive experimental data limit the immediate and widespread use of ML-based approaches. The current research on applying ML to thermal spray process optimization demonstrate the complexity of building training datasets that genuinely reflect industrial realities [4-10].

In response, the AccuraspravHub is conceived as a platform that centralizes multi-source data, provides consistent data structures, and applies advanced analytics to identify stable process windows and emerging trends. Rather than claiming a turnkey ML solution, its approach is grounded in incremental progress. It begins with harmonizing data across sensors, booths, and laboratory results. It further proceeds to implement targeted analytics; and gradually moves toward ML integration once datasets are mature enough to support reliable modeling. This methodology acknowledges the complexities and economics of industrial environments and seeks to present a realistic path forward for the thermal spray community.

Experiments and Platform Description

The AccuraspravHub integrates diverse data sources within a single, coherent framework. Process parameters, including gas flows, power settings, and stand-off distances, are collected along with feedstock details such as powder composition, morphology, and particle size distribution. Simultaneously, the platform logs in-situ plume measurements from the Accuraspray 4.0 sensor, capturing particle temperature distributions, velocity profiles, and plume geometry attributes like width and intensity gradients. Complementing these process- and sensor-related data, the AccuraspravHub also records coating microstructural properties measured offline, including porosity, hardness, oxide content, and thickness uniformity.

A schematic representation of the AccuraspravHub environment is illustrated in Figure 1. One or multiple thermal spray booths, each equipped with an Accuraspray 4.0 sensor, collect in-situ plume data—such as temperature, velocity, and plume width—in real time. Operators begin by selecting or loading an established recipe, which includes powder specifications, booth parameters, and power settings. During spraying, the Accuraspray 4.0 monitors the evolution of the plume characteristics and transmits data to the Hub. Upon completion of a coating run, representative test coupons undergo laboratory analysis to verify microstructural and mechanical properties such as hardness or porosity. These lab results feed back into the Hub to refine process windows, highlight potential equipment wear, and maintain consistent coating quality for future production.

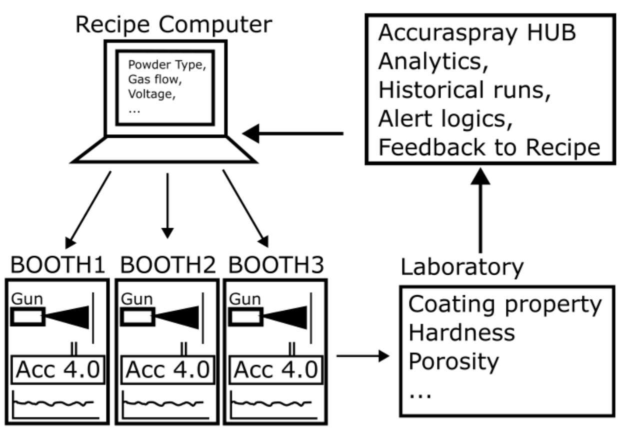

Fig. 1. Schematic representation of the AccuraspravHub environment in a multi-booth thermal spray production.

A key element of the approach lies in the collection and management of these datasets at an industrial partner's site, where a series of targeted runs were performed over the course of a year. The resulting data are currently used to illustrate the AccuraspravHub's functionalities and to refine its analytical capabilities.

The initial stage of this project focused on confirming the reliability of conventional methods. For instance, the well-established practice of defining min-max tolerance windows around particle temperature and velocity readings was maintained as a baseline. While these windows serve as first approximations for stable conditions, their limitations quickly become apparent when equipment ages, powder suppliers change, or the scale of production increases. By embedding these data within the AccuraspravHub, we can track how each of these tolerance windows evolves over time and across different scenarios, and we can begin to understand their suitability for new conditions. Thus, even before implementing ML, the platform provides a richer context, making it clearer how static thresholds might be modified or replaced by more nuanced, data-driven criteria.

Results: From Data Integration to Actionable Process Insights

During the trial period, the AccuraspravHub provided advanced analytics that moved beyond the simple verification of min-max conditions. By leveraging the integrated dataset, engineers were able to compare multiple runs over time and assess how stable the plume measurements remained within established tolerances. In cases where coating quality deteriorated, the AccuraspravHub allowed engineers to correlate this change with shifts in the recorded parameters. For example, slight drifts in particle velocity distributions, initially considered within the acceptable window, correlated with measured decreases in coating hardness. Although not a definitive proof of causation, such observations presented an opportunity to refine process windows and operator practices. The platform's insights helped highlight the cumulative effects of spray gun wear, subtle feeder instabilities, and changing powder lots, which individually might seem insignificant but collectively influence coating properties.

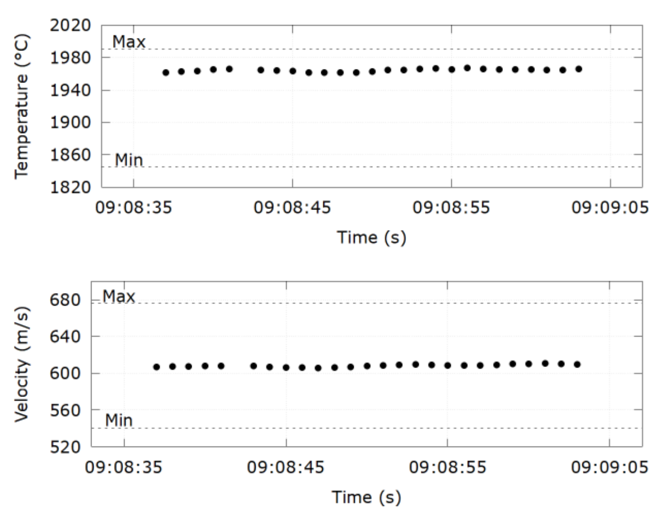

Figure 2. Particle temperature and velocity traces for three consecutive 30-second spray runs, plotted alongside pre-set min and max tolerance lines. All three runs remain within the prescribed process window, illustrating stable and repeatable conditions.

As an illustration, Figure 2 shows data from a typical run, measured over a 20-second spray period. The real-time traces of particle temperature and velocity are plotted alongside the pre-defined min and max tolerance lines. In this example, all the indicators have remained within the specified bounds, demonstrating stable spray conditions.

Figure 3 summarizes the temperature and velocity for several ranges runs. This condensed view highlights whether operating points are clustering within stable, predefined zones or gradually shifting out of range. Such side-by-side comparisons provide a clear indication of how consistent the process is from one run to the next, helping operators quickly verify that no immediate corrective action is needed. These proactive decisions could not have been made as confidently without a centralized data source that contextualized each run against historical baselines.

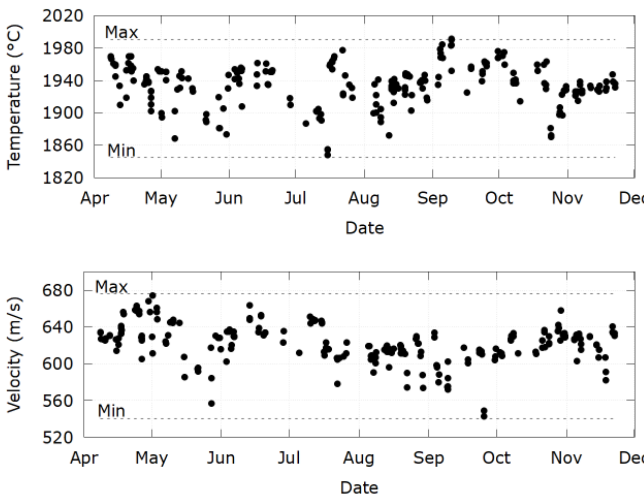

Figure 3. Temperature and velocity recorded over multiple runs. This summarized view rapidly reveals trends or deviations in plume characteristics, enabling proactive responses to maintain quality.

To further illustrate how in-situ plume characteristics relate to key mechanical properties, Figure 4 presents three charts that each plot temperature (left y-axis) and velocity (right y-axis) against a measured coating property on the x-axis. The top chart shows coating hardness, the middle chart shows tensile break bond, and the bottom chart shows Almen test deflection in inches. These properties were obtained from laboratory tests that, while essential for final qualification, can be time-consuming and costly. Vertical lines on each chart indicate minimum or maximum acceptable thresholds for the corresponding mechanical property. The results demonstrate that for this process setup, all data points lie above the minimum standards, suggesting that the plume temperature and velocity remained within an effective process window for depositing coatings that meet or exceed quality requirements.

By combining process data with laboratory results, operators gain both rapid feedback from real-time plume measurements and definitive confirmation from standardized mechanical tests. Although laboratory analyses often require additional resources and time, they serve as the gold standard for validating coating performance. The AccuraspravHub ensures that these data, once collected, are seamlessly integrated with run parameters and sensor readings, enabling a holistic assessment of how plume conditions influence final mechanical outcomes. This approach streamlines the qualification process, helping organizations balance the need for frequent, cost-effective monitoring with the rigorous certification demands of aerospace and other high-stakes industries.

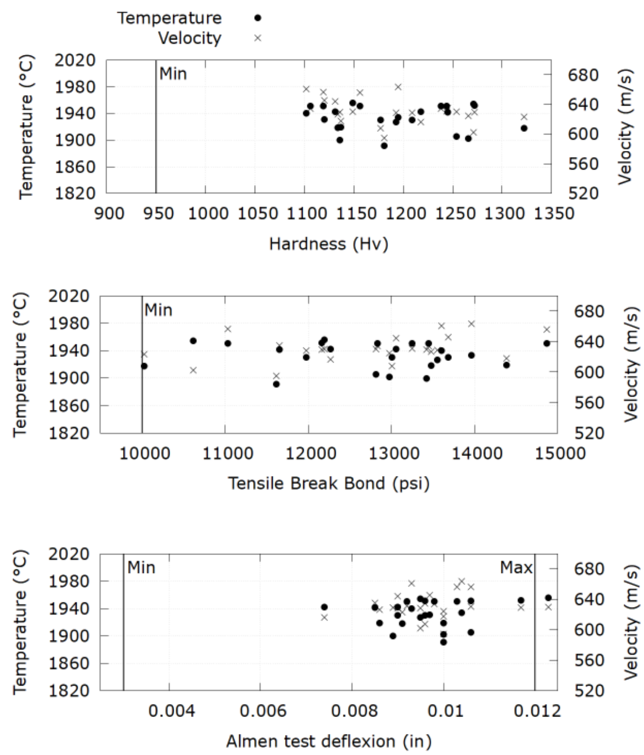

Figure 4. Three stacked charts illustrating the relationship between in-situ plume characteristics and key mechanical properties. Each chart plots temperature (left y-axis) and velocity (right y-axis) against a different coating property on the x-axis: hardness (top), tensile break bond (middle), and Almen test deflection (bottom). Vertical lines indicate required minimum or maximum thresholds for each property. All data points exceed the specified criteria, indicating that temperature and velocity remained within an effective process window for achieving acceptable coating performance.

During extended production campaigns, the AccuraspravHub monitors not only temperature and velocity but also the spatial consistency of the plume. As certain components of the spray gun begin to wear, the plume may shift from its original centerline, introducing what we refer to as “plume deviation.” Figure 5 provides a visual illustration, showing a photograph of the plume with the original reference position overlaid on the current plume shape. This comparison clarifies how the deviation is measured, as the plume gradually shifts from its nominal position. Figure 6 demonstrates how the mean plume deviation evolves over multiple runs, tracking the transition from acceptable to unacceptable conditions. When the deviation exceeds a predefined threshold, gun maintenance has proved to restore the plume profile. Observing this trend in near real time allows for proactive maintenance, preventing suboptimal coating outcomes by flagging the exact point at which wear-related drift becomes detrimental.

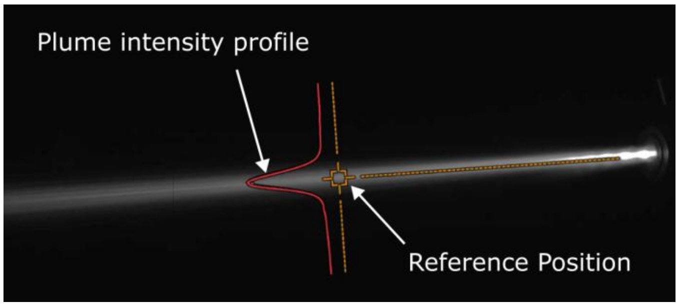

Figure 5. Photograph of the plume with an overlay indicating the nominal reference position and the current plume profile. The highlighted offset between the two profiles represents the plume deviation, which provides a clear visual measure of gun-related wear or misalignment.

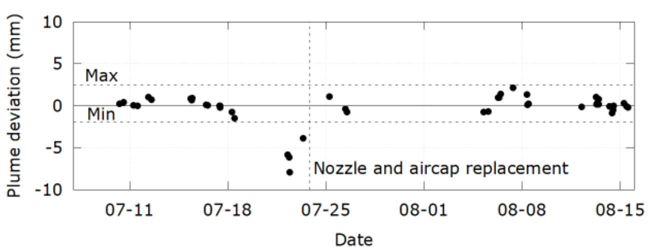

Figure 6. Evolution of the mean plume deviation over the course of multiple runs. The plume deviation remains near zero under normal conditions but increases as the gun wears, prompting replacement to return the spray geometry to its original configuration.

The AccuraspravHub is designed to function as a flexible and modular platform capable of supporting a range of thermal spray processes and sensor configurations. Although it is most straightforward to deploy in a booth equipped with an AccuraSpray 4.0 sensor—where temperature, velocity, and plume intensity data are readily available—the Hub's underlying data structure can accommodate alternative instrumentation. Whether the process is HVOF, atmospheric plasma spray, or another variant, and whether plume characteristics are measured by Tecnar's sensors or third-party devices, the goal remains the same: to centralize all relevant information in one location. This includes fundamental booth parameters, lab results, maintenance logs, and any in-situ plume measurements that offer insight into process stability. By allowing for multiple data formats and sources, the Hub avoids constraining users to a single process or sensor technology and instead provides a cohesive framework for collecting, correlating, and analyzing the critical data that underpin successful thermal spray operations.

The dataset, though still limited in size and scope relative to the ambitions of full-scale ML modeling, has demonstrated the immediate value of integrated data analytics. Plant managers and engineers found that having a single access point for all relevant information simplified the interpretation of process behavior. Over time, as these operators and decision-makers became familiar with the platform's capabilities, the trust in its outputs increased. This acceptance paves the way for the next steps, where more complex, automated methodologies may be introduced once the underlying data infrastructure is sufficiently robust.

Advancing Data Structuring and Preparing for Machine Learning

Building a dataset suitable for advanced machine learning involves more than simply aggregating data points. The complexity of thermal spray processes, involving multiple feedstock powders, evolving equipment states, and environmental fluctuations, demands meticulous data curation. The reliability of any future predictive model depends on the integrity and representativeness of the dataset used for training. As a result, the AccurasprayHub places strong emphasis on data quality, classification, and filtering before any ML algorithm is deployed.

One key challenge is the classification of runs and conditions into comparable sets. If data from a worn gun are mixed indiscriminately with data from a newly refurbished gun, or if powder feed inconsistencies are not recorded, then meaningful correlations can be obscured by confounding factors. The AccurasprayHub addresses this issue through a systematic approach to data tagging and filtering. Each run is annotated with contextual information, including equipment maintenance actions, changes in powder suppliers, and recorded environmental conditions. By making these context tags available, it becomes possible to isolate subsets of data that represent consistent scenarios, enabling more credible statistical and ML-based analyses.

Another fundamental task involves the rigorous detection and treatment of outliers. Sensor glitches, irregular powder feed events, or transient nozzle blockages can produce spurious data points that, if not flagged and addressed, might lead ML models astray. The AccurasprayHub incorporates methods for identifying and, where appropriate, discarding anomalous data. This cleansing process ensures that the core dataset better reflects the true operational envelope of the spray booth and prevents the model from "learning" patterns that do not exist.

As the datasets grow and become cleaner over time, the AccurasprayHub will gradually integrate ML-driven methods to further refine process windows and enable more predictive capabilities. Rather than rushing into complex algorithms, the focus remains on building confidence that the data itself is reliable. When the time comes to introduce ML for correlating spray characteristics with coating properties, the underlying dataset will be capable of supporting models that offer real industrial value. The result will be ML tools that not only produce accurate predictions under stable conditions but also remain robust as the spray booth evolves, as new powders are introduced, and as equipment undergoes natural wear.

This incremental approach is deliberate and pragmatic. Instead of proposing an all-encompassing ML solution with unrealistic expectations, the AccurasprayHub acknowledges the need to start with strong data fundamentals. It demonstrates to the thermal spray community that stepping stones exist between today's reliance on experience-based adjustments and tomorrow's predictive, autonomously adjusted process controls. By focusing on realistic data qualification tasks, this approach avoids the pitfalls of solutions that fail to gain traction when confronted with the messy realities of industrial production.

Discussion and Outlook

The AccurasprayHub represents a significant step toward more data-driven and less operator-dependent control of thermal spray processes. Its development considers the complexities and costs associated with generating high-quality industrial datasets. Rather than promising immediate breakthroughs in fully automated optimization, this approach acknowledges that progress will be incremental. The emphasis on building robust datasets, ensuring coherent data structuring, and gaining initial insights through visualization and trend analyses lays a solid foundation for introducing more advanced analytics.

As the platform matures, it will become feasible to integrate predictive maintenance models that anticipate when equipment conditions will drift out of the desired windows. Over longer time horizons, once a larger critical mass of validated data is available, more advanced ML techniques such as supervised learning or reinforcement learning can be employed to suggest dynamic adjustments to process parameters. These techniques could eventually enable stable deposition processes without continuous expert intervention. Moreover, the availability of a centralized data hub across multiple booths and production lines opens the possibility of harmonizing best practices and standardizing approaches at a larger scale, an outcome that could greatly benefit multi-facility operations.

The long-term vision is not merely the application of ML tools in a vacuum, but their integration into the everyday decision-making process within thermal spray facilities. This vision includes improving communication between operators and engineers, enhancing training efforts for new personnel, and ultimately offering decision-makers a clearer understanding of how their processes is performing. Over time, this increased transparency and control, will translate into better coating quality, improved equipment longevity, and more predictable production cycles.

Conclusion

Thermal spray processes demand an informed and nuanced approach to achieving consistent, high-quality coatings. Traditional methods, while effective to a point, rely heavily on operator experience and static tolerance settings that may not fully account for evolving process conditions, powder variabilities, or equipment wear. The AccurasprayHub addresses these limitations by providing a centralized platform for integrating, analyzing, and gradually refining the data that underpin the entire process chain.

This work emphasizes realism and practicality. It acknowledges that building a suitable dataset for advanced ML methodologies is challenging and time-consuming, that trust must be earned gradually, and that any complex analytics must rest on a stable foundation of reliable data. By focusing first on data structuring, classification, and consistency checks, the AccurasprayHub ensures that when ML algorithms are eventually introduced, they will deliver insights that are both meaningful and robust.

The incremental strategy presented here distinguishes our work from more speculative approaches. Instead of claiming an immediate revolution driven by AI, the AccurasprayHub marks the start of a journey toward data-informed decision-making, incremental improvements, and ultimately, more autonomous and predictive control of thermal spray operations. As a result, it sets the stage for a future in which thermal spray practitioners and ML experts can collaborate more effectively, blending domain expertise with computational intelligence, and steadily improving the quality and consistency of thermal spray coatings.

References

[1] Pawlowski, L. The Science and Engineering of Thermal Spray Coatings, 2nd Edition, Wiley, 2008.
[2] Fauchais, P., Heberlein, J. V. R., and Boulos, M. I. Thermal Spray Fundamentals, Springer, 2014.
[3] Matejicek, J., and Sampath, S. "In-Situ Diagnostics and Process Maps: An Approach to Reliable and Consistent Thermal Spray Coatings," Journal of Thermal Spray Technology, Vol. 12, 2003, pp. 90–102.
[4] Bishop, C. M. Pattern Recognition and Machine Learning, Springer, 2006.
[5] Benini, E. and Giacomello, M. "Data Mining and ML in Complex Industrial Processes: An Overview," International Journal of Production Research, Vol. 57, 2019, pp. 1–21.

[6] Wang, L., Fang, J. C., Zhao, Z. Y., and Zeng, H. P. "Application of backward propagation network for forecasting hardness and porosity of coatings by plasma spraying," Surface & Coatings Technology, Vol. 201, 2007, pp. 5085–5089.
[7] Guessasma, S., Montavon, G., Gougeon, P., and Coddet, C. "Designing expert system using neural computation in view of the control of plasma spray processes," Materials and Design, Vol. 24, 2003, pp. 497–502.
[8] Pakseresht, A. H., Ghasali, E., Nejati, M., Shirvanimoghaddam, K., Javadi, A. H., and Teimouri, R. "Development empirical-intelligent relationship between plasma spray parameters and coating performance of Yttria-Stabilized Zirconia," International Journal of Advanced Manufacturing Technology, Vol. 76, 2015, pp. 1031–1045.
[9] Guessasma, S., Montavon, G., and Coddet, C. "Modeling of the APS plasma spray process using artificial neural networks: basis, requirements and an example," Computational Materials Science, Vol. 29, 2004, pp. 315–333.
[10] Jean, M.-D., Lin, B.-T., and Chouw, J.-H. "Application of an Artificial Neural Network for Simulating Robust Plasma-Sprayed Zirconia Coatings," Journal of the American Ceramic Society, Vol. 91, 2008, pp. 1539–1547.

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