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Artificial Intelligence: Key Consideration and Effective Implementation Strategies

Industrial AI is the intersection of rules-based decision making, machine learning, and human insight.

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INTRODUCTION

Industrial Artificial Intelligence (IAI) brings advanced technology to the manufacturing floor, blending machine learning, decision-making rules, and human insight to solve complex problems and improve operations. But what exactly is IAI, and how can it benefit smaller manufacturers?

IAI is a smart assistant for your factory, but it must have human support to work. It has the capability to learn from your factory ecosystem of information — similar to how your phone can predict the next word you'll type or how streaming services suggest movies based on what you like. But for manufacturing, IAI can aid in identifying problems in machines, assist in predicting maintenance needs, or even help optimize material choices for the best product outcomes. Whether it's detecting issues at an auto part maker or selecting the right mix for concrete production, IAI can make your processes smarter, faster and more reliable.

This white paper will guide you through how to integrate IAI into your operations and unlock its potential. As we progress through this paper, we will focus on practical steps, answering some of the most common questions that small to medium-sized manufacturers (SMMs) have about IAI:

- **Do we need IAI for our shop?**
- **How do we know it's working?**
- **Is the investment in IAI worth the price, complexity, and risk?**

One of the goals of IAI is to take on repetitive, time-consuming tasks to free up humans to focus on more productive projects. By using IAI, manufacturers can boost productivity, improve product quality, and save on costs. To help you get started, let's break down the key elements of an IAI system and provide insights into how to assess its effectiveness for your specific needs.

What will follow is a best practice recommendation document compiled and directed by NIST's world class experts on practical IAI use and development, Dr. M.E. Sharp, the Industrial AI Management and Metrology team, and information contained in NIST's Artificial Intelligence Risk Management Framework (opens PDF).

Key Elements of an IAI System

Before diving into an IAI solution, it's important to understand the potential return on investment (ROI). How will this technology actually benefit your operations? Start by asking yourself a few essential questions about the system or asset you are targeting for IAI inclusion:

- What's the problem you're trying to solve, or the goal you're aiming for? Why do you need IAI to address this?
- What data or information is required? If a human were to do this task, what would they need?
- Who is the expert and end user of the system now? It's important to know the goals and behaviors of your system, and how will those who are running it be affected by inclusion of IAI?
- What results should you expect? If there was a true optimal for this system or task, how would you know it was there? This can help monitor any IAI additions and quantify their impacts.

An IAI model can often seem like a black box because it can be hard to understand how it arrives at its conclusions. Nonetheless — you can still evaluate its effectiveness and more importantly, its impact on your system, by exploring these aspects:

What goes into the box?

- What are the characteristics of the training data?
- What preprocessing has been/needs to be done?
- What are the parameters needed to train the model?

What is inside the box?

- What are the model assumptions?
- What type of inputs is the model looking for?
- How does the model train?
- What types of relationships is the model capturing/recreating?

What comes out of the box?

- What are the model's limitations? What is the range of inputs where it performs accurately?
- What units are being reported?
- What scenarios can cause the model to fail?

By addressing these questions, you will ensure that your IAI system delivers real value and integrates seamlessly with your manufacturing operations.

CHAPTER 1
Understanding IAI Benefits and Options

In recent years, IAI has become a forefront issue in manufacturing, often referred to as smart manufacturing or part of Industry 4.0. These terms represent the increasing use of AI to address manufacturing challenges — problems that were once thought impossible to automate or improve through traditional methods.

When considering the integration of IAI into your manufacturing processes, it's important to align these tools with your business's specific goals. While IAI can help solve a variety of problems, its true value comes when it targets specific challenges and provides clear, actionable benefits. For SMMs, IAI can make your operations more efficient, reduce waste, and improve quality — all while helping you stay competitive in an increasingly digital manufacturing environment.

Key Benefits of IAI for Small and Medium-Sized Manufacturers

IAI can transform your operations in several key areas:

1. **Reducing downtime**

   Predictive maintenance powered by IAI can help you anticipate when a machine is likely to fail before it happens. By analyzing performance data (such as temperature, vibration, or pressure readings), IAI identifies patterns that signal impending or progressing issues. This enables you to schedule maintenance proactively, which will save you from costly, unexpected breakdowns that halt production.

2. **Minimizing scrap**

   Real-time monitoring of product quality using IAI tools can detect issues early in the production

process. By flagging defects or inconsistencies — such as size discrepancies or surface imperfections — before they leave the production line, you can significantly reduce waste and improve the consistency of your products. This leads to higher customer satisfaction and fewer losses.

3. **Improving cycle time and efficiency**

   IAI models can help optimize production speeds by analyzing data from various stages of the manufacturing process. This allows you to fine-tune operations, improving cycle times, reducing bottlenecks, and ultimately increasing output. Over time, these efficiency gains will help you stay competitive, especially in industries with tight margins.

4. **Reducing human errors**

   One of the often-overlooked benefits of IAI is its positive impact on your workforce. By automating repetitive or physically demanding tasks, IAI can reduce human error and employee fatigue. This can lead to a safer, more productive workplace — key concerns for small and medium-sized manufacturers trying to keep skilled workers.

Choosing the Right IAI Tool for Your Needs

When exploring IAI tools, it's important to focus on how they meet your specific business needs. Here are some key factors to consider:

- **Can it solve your problem?** Make sure the IAI tool addresses and has formerly been validated on a sufficiently similar, well-defined challenge in your production process. Whether it's predictive maintenance, quality control, or supply chain optimization, the solution should be tailored to your needs.
- **How will you measure success?** Identify performance metrics that matter to your business, such as reduced downtime, lower scrap rates, or faster production cycles. This helps you evaluate the effectiveness of the tool.

- **Your team's capacity:** Ensure that your team has the bandwidth and the skills to implement and manage the IAI solution. In some cases, IAI tools may require specialized knowledge or training, so it's important to assess whether your team can effectively integrate and use the tool. Remember no tool (digital, physical, or otherwise) can run forever without maintenance. If your team does not have the onboard skills to monitor and maintain your IAI after deployment, seek out solutions that offer subscription based or service-based upkeep.

Two Main Categories of IAI: Rules-Based and Machine Learning

IAI tools can be broadly categorized into rules-based systems and machine learning models. Each approach has its strengths, and in many cases, they are used in tandem to address specific tasks. Understanding these options will help you select the right tool for your manufacturing challenges.

Rules-based models are easier to implement but have more limitations

Rules-based IAI operates strictly on predefined rules and requirements. These IAI tools are generally easier for humans to understand because they rely on equations, directives, or sets of if-then-type logic that tell the machine what to do. For example, in quality control, a rules-based system might flag products that deviate from set parameters (such as size or color).

Example:

- **If** a product is scratched more than 2mm, **then** flag it for inspection.
- **If** a part is outside of the acceptable color range, **then** discard it.

Advantages for SMMs:

- **Simplicity:** These systems are generally easier to implement and require less expertise to manage.
- **Stability:** Once set up, rules-based systems are stable and predictable.

However, rules-based tools have limitations — they only handle well-defined, narrow scope tasks where the behaviors and limitations are known. If something unexpected occurs in your production process, these systems might fail to adapt, resulting in errors.

Best for tasks like:

- Quality control of parts with defined criteria
- Monitoring equipment with simple operational thresholds

Machine learning models are more versatile but need lots of data

Machine learning (ML) is what most people think of when they hear the term AI. Machine learning algorithms are the class of AI that learn and adapt from the inputs they receive from the environment. A user does not always need to directly interact with the supporting algorithm to influence the behavior of the IAI system. Instead, the information it receives teaches the algorithm output based on some reward scheme that adheres to the user's defined requirements.

Example:

- **Predictive maintenance:** ML can analyze sensor data (e.g., temperature, vibration, pressure) to predict when a machine is likely to fail, allowing you to perform maintenance before a breakdown occurs.

Advantages for SMMs:

- **Versatility:** ML is adaptable and can handle complex situations with many variables, such as detecting subtle patterns in machinery behavior.
- **Scalability:** These systems can be trained to handle a wide variety of data types and can learn over time, improving their predictions as they receive more data.

However, machine learning requires a lot of data and computational power. You'll need to ensure you have enough relevant data for the system to learn effectively and resources to train staff on how to use the capability. Additionally, while machine learning tools are powerful, they can also be more complex to implement and maintain.

Best for tasks like:

- Predicting when equipment will need repairs in complex or connected systems.
- Optimizing production processes in complex or interconnected systems.

Finding the Right Fit for Your Manufacturing Facility

For SMMs, the key to successfully adopting IAI is understanding your business's unique needs.

- **Start small, but invest fully:** Begin with a focused problem (e.g., reducing downtime or improving quality control) and explore tools that address that specific issue. Commit to solving the problem with reasonable expectations and resources. A large portion of buyers remorse in IAI comes from over or under committing during the initial instantiation. Don't invest more that you are willing, but also don't expect a huge success from a bare bones trial.
- **Ensure data readiness:** Whether using a rules-based or machine learning model, ensure you have the necessary data and communications network to support your chosen solution. This may involve installing additional sensors or gathering historical data to aid in the initial training.
- **Build on success:** IAI is a trust-based tool that needs buy in not just from management, but also supervisors, line workers, and end users. Showcase wins and gains as you progress your IAI infrastructure to ensure all stakeholders have positive and reasonable expectations of how IAI will impact them.

By aligning IAI tools with your business goals, you can achieve measurable improvements in efficiency, quality, and safety, all while maintaining the flexibility and agility that small and medium-sized manufacturers need to thrive.

10 Common Pitfalls in Developing IAI Models

Developing IAI models comes with its own set of challenges. Many promising applications stumble due to a lack of rigorous assessment and alignment with core principles. To help you navigate this complex landscape, we've identified 10 common pitfalls that can undermine your IAI project:

1. **Sure, but why?:** Creating an IAI system that is technically correct but functionally useless or unnecessarily complex will waste resources.
2. **False equivalencies**: Too often models are qualified on systems or environments that are not suitably comparable. A model that can detect a micro fracture in a motor bearing is likely not the best choice to evaluate hull damage on the side of a shipping vessel. Data flow, volume, availability, source, and underlying algorithmic choices all impact the usefulness and scope of an IAI application. Just because it seems like a similar task does not make it a similar use case.
3. **Inappropriate training sets:** Be sure you are using the best possible and most relevant information to teach the model.
4. **Inadequate training sets:** Also, be sure the data sets are broad and complete enough to account for appropriate variances.
5. **Wrong question setup:** Be sure your model is learning to solve the right problem. How you frame the question directly impacts the results you'll get.
6. **Premature training termination:** Be sure to give the model enough time for learning. Early training termination can happen for many reasons — always check why the algorithm stopped learning during its initial training. If you buy a pre-trained algorithm, this also applies to the adaption phase or any follow-on training.
7. **Violation of model assumptions:** Every model has assumptions; be sure you are not violating them. If you don't know your assumptions, keep asking.
8. **Finding false correlations:** Watch out for false correlations — relationships that appear meaningful but are coincidental or caused by something unrelated to your task.
9. **Overfitting data:** A model can be so focused on the specific details and nuances of the training data that it fails to generalize and make accurate predictions on new, unseen data. It essentially memorizes the noise instead of learning the underlying patterns.
10. **Misleading performance metrics:** No single number can tell a complete story. An overall metric might look good when viewed alone, but it could hide significant deficits or misleading indicators of other aspects of system impact.

CHAPTER 2
Data, Assumptions, and Internal Processes for IAI

Building a robust and effective IAI model hinges on the data it learns from, and the assumptions and problem-solving shortcuts baked into its design. The quality, relevance, and source of the data are paramount as they directly influence the model's performance. A successful model requires appropriate, unbiased, and varied datasets that accurately reflect the real-world scenarios the IAI will encounter. Recognizing when data is inadequate or biased in a specific way is crucial, as flawed data will inevitably lead to flawed outcomes.

The Role of Data in IAI Success

The data used to train and operate your IAI system is the cornerstone of its effectiveness. Here's why it matters:

- **Quality over quantity:** It's important to understand that having more data doesn't automatically make the model better. What matters most is that the data accurately represents your manufacturing environment and the problem you're trying to solve. For example, if you're using IAI for predictive maintenance, the data should include data from your equipment over time, reflecting a variety of operational conditions (e.g., normal wear, occasional overuse, seasonal fluctuations).
- **Relevance and representation:** The data needs to be relevant to your use case. If you're using IAI to optimize production schedules, your data should cover factors such as machine uptime, downtime, production speed, and shift patterns. Data that doesn't reflect real-world operational conditions — like abnormal machine behaviors or sudden changes in market demand — will result in less reliable predictions.
- **Data sources:** Ensure that your IAI system can support content intake from all critical data sources. This might involve integrating data from machines, sensors, operators, or external systems like

inventory management or ERP software. In some cases, this may require integrating additional sub-collection systems or intermediaries that were not designed to work together. This is why it is crucial to have trusted experts of both IAI and your system working together when investing in IAI. If critical data sources are overlooked, the model could miss important signals that influence the outcome, such as sudden shifts in machine efficiency or supply chain delays.

Avoiding Bias and Inadequate Data

Data isn't always perfect, and it's important to be aware of potential problems that can arise in your datasets:

- **Missing or incomplete data:** Gaps in data can undermine the performance of your IAI model. For instance, if some machines have missing sensor readings or if historical data for a key production process is incomplete, the model may lack the necessary context to make accurate predictions. Identifying these gaps early and filling them is crucial.
- **Bias in data:** If your data is not diverse enough, your model might develop unwanted biases. For example, if your data comes primarily from one type of machine or a specific time period, the model might perform well under those specific conditions but fail when the environment changes. You should ensure that the data training and testing reflects the full range of scenarios your production line might encounter.
- **Data imbalance:** In predictive maintenance, if you have far more non-failure data points than failure data points, the model might become biased toward predicting no failure, ignoring the rare but critical failures. In cases such as this, it is often better to reframe the IAI to detect non-normal behavior to ensure usability. Balancing data inputs and framing the responses to best utilize the data you have is key to improving the model's ability to recognize less common but impactful events.

Overfitting: A Critical Challenge for Manufacturers

One of the most common risks to the unwary when developing an IAI model is overfitting — this occurs when the model learns the training data too specifically and loses the ability to generalize well. Often, this means the

model becomes too tailored to the particular conditions of your training dataset and struggles to generalize to new, unseen data. For example, a model trained on data from one machine might perform poorly when applied to a different machine.

Think of it like memorizing answers for a specific test. The model might perform well on the data it was trained on, but it won't handle new conditions effectively. To avoid overfitting, use these strategies:

- **Use diverse and representative data:** Ensure that the data used to train the model includes a variety of operational scenarios and conditions.
- **Regularly validate the model:** Test the model on new or previously unseen data to assess its ability to generalize. Be sure you have some external qualification of the expected output from this data being ingested by the model to compare and validate against the model output.
- **Simplify when possible:** A model with fewer parameters, and/or more general rules is often more effective than one that tries to capture every minor detail of the training data. Never make a model more complicated than needed. The best model for any job is the simplest that can still meet the requirements. Everything beyond that has the potential to add unnecessary complexity and risk.

Make Sure the Available Data Is Adequate for the Use Case

Use a data adequacy check to ensure available data is sufficient for your use case. You can divide the data adequacy check into two parts:

1. **Is the IAI connected to all the pertinent sources of information?**
    - Is the IAI system pulling data from all necessary networked digital sources (e.g., sensors, machine data, production schedules, supply chain systems)?
    - Are there any necessary external sources that are missing, such as operator notes or maintenance records? Missing critical data can lead to inaccurate conclusions, so ensure the system integrates all available data. Analog, or non-connected digital sources can be difficult and not intuitive for when and how to incorporate them into a model. Nonetheless, if they contain critical information about your system, you will want to find a way to include it in your modeling if you want the best results.

2. **Is the full scope and range of the use case represented in the training data?**
    - Does your training data cover the expected majority of potential conditions the model will encounter, including rare but significant scenarios (e.g., equipment failure under unusual conditions)? You can't plan for everything, but if it is a known condition, even a rare one, it should be accounted for and tested against within the model.
    - Does the data reflect all system configurations, machine types, shifts, and other variables in your operation? For example, if your factory runs two shifts but you only have data from one, the model might not perform well during the second shift.

The Importance of Continuous Monitoring and Feedback

IAI tools can be dynamic, allowing them to improve and evolve as they ingest new data. However, they can also stop learning or begin to perform poorly if standard conditions change too quickly or if the data they receive is incomplete. In some undesirable scenarios, dynamic IAI may even learn "bad" behaviors from the system and begin to rate them as normal. To keep your IAI system operating at its best, it's important to set up ongoing processes for monitoring, testing, and improvement. Key processes for continuous improvement:

- **Periodic Evaluations:** Real world systems and sensors will naturally change, evolve, and degrade over time. Establishing persistent, regular triggers for evaluations can help not only identifying or preventing lowered performance of your IAI, but also help to quantify the persistent value being gained from the IAI. Such periodic triggers could be calendar based, usage based, notable changes in system performance, and/or significant or novel changes to the system itself. Examples of significant changes could include actions like replacing old equipment, upgrading a system configuration, or substantial maintenance performed on a related system.
    - **Baseline Model Testing:** Maintain baseline and/or static models to help measure the performance of your IAI system as it evolves. Baseline IAI models are initial and/or updated models that have been fully evaluated and verified to provide a known level of performance and effectiveness for a use case. Freezing that model allows for later comparisons of new IAI systems or newer versions of systems that have adapted over time to verify that the current models are preforming as good or better than the old models on the new data. In some cases, it is appropriate to replace your reference baseline model periodically as well, but only after thorough and satisfactory evaluations have been performed.
    - **User Evaluations:** Set up mechanisms that allow operators and engineers to regularly provide feedback on IAI performance and usage. This can include performance reviews, alerts when the system makes poor predictions, or even automatic retraining when new data becomes available.
- **Proactive Testing:** Regularly test your IAI system in real-world conditions to see how it behaves across a variety of scenarios. For example, simulate different production line disruptions and replay old known disruptions (e.g., supply chain delays or machine breakdowns) to ensure the model can handle new unexpected events while still maintaining its ability to manage known ones.

For SMMs, successful IAI implementation is about more than just choosing the right tool. It's about understanding your data, continuously evaluating its quality and relevance, and establishing internal processes that allow your system to adapt and improve.

Basic Types of Data for an IAI Model

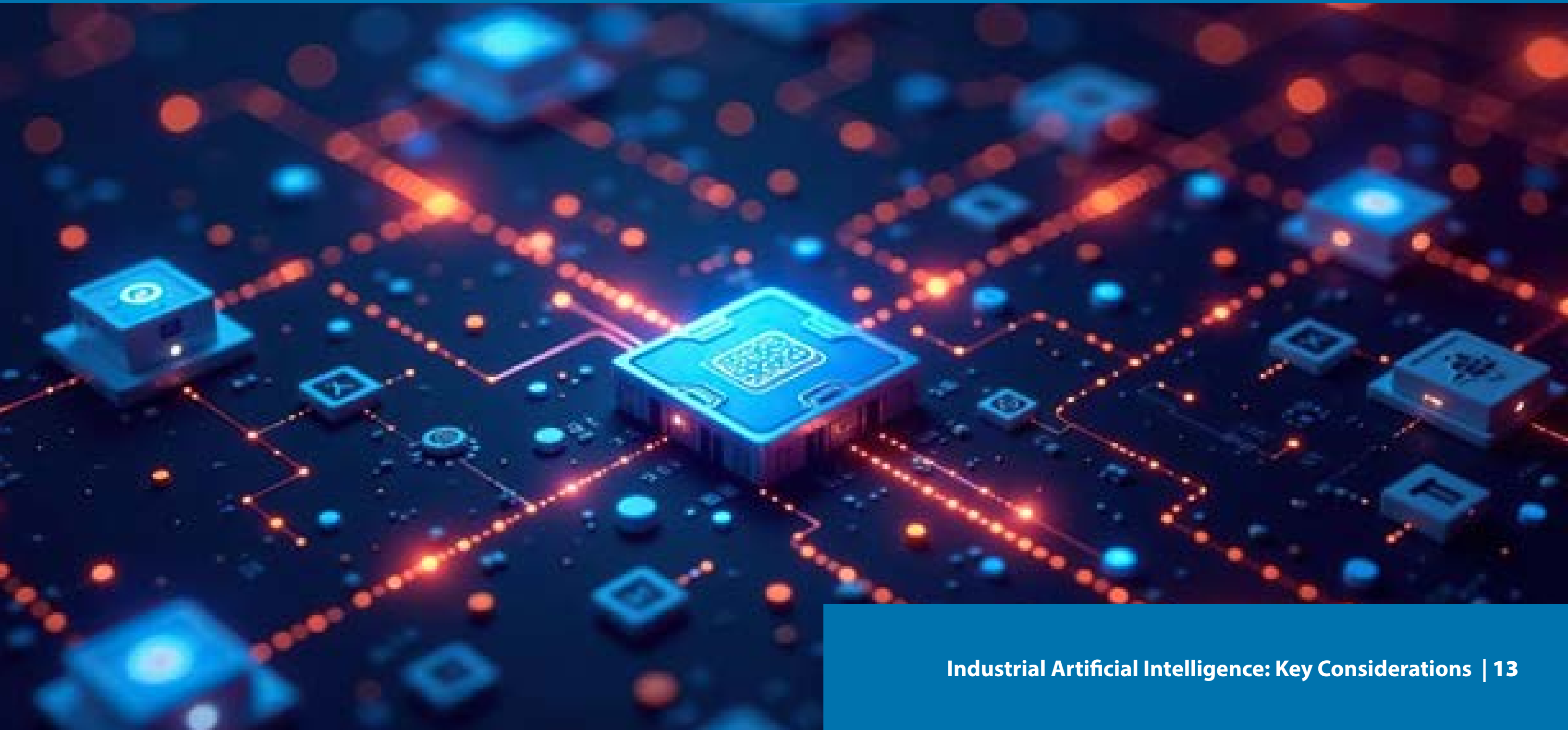
Different IAI models are designed for different tasks and to use different data types. If your goal is to predict equipment failure, you need an IAI model designed for predictive health evaluation, rather than designed for quality control. Even though machine health can be a factor in quality control, fundamentally these are two separate tasks that share a large overlap in needed data sources. Understanding the purpose of an IAI model is crucial in deciding whether it suits your application. Here are some of the many basic types of data that might be used in your IAI:

Time Series Versus Memoryless Information

- **Time series (time stamped or ordered) data:** This type of information is required when values or events progress predictably over time. Time scales for this may depend on your system, but a general principle is you need to be able to track at least a significant portion of the system's PF interval — the span of time between the earliest detectable sign of disruptions and system failure. The most common sources and uses of time series data are from monitoring physical systems or equipment for tasks like predictive maintenance and analyzing production line output.
- **Memoryless data:** These are the sources of information where sequencing of information is inapplicable, unneeded, or unavailable. In physical systems this may be a series of indications of the current state, status, or characteristics of a system. This may even include 'snapshots' of some time series data representative of an aspect of a system. In some cases, this is all that is needed for a task. Example use cases include forecasting upcoming conditions or to providing go/no go status before a duty cycle of operation. Many IAI models can accurately make long- or short-term predictions using memoryless information alone or in conjunction with sequence (time-series) data.

Discrete Versus Continuous

- **Discrete data:** This data can only take on specific, distinct values, such as a number of defective parts in a batch or the number of times a machine starts and stops in a day.
- **Continuous data:** This data can take on any fractional or decimated value within a given range, such as the temperature of a furnace or pressure in a pipeline.



Discontinuous Information

Discontinuities in data typically come in two forms that each need to be accounted for in different ways. These are most commonly artifacts within the data that are related more to the collection of the data than the source being represented by that data.

- **Sequence discontinuities:** These are typically gaps or significant variations in the space between individual samples. This makes the data appear 'jumpy' in a time series evaluation and needs to be treated with special care to best utilize both the short and long term scale information available within the data. Often periodic measurements, or intermittent processes will produce this type of discontinuity in data.
- **Response discontinuities:** These are areas of irregularity in the value being measured resulting from a significant drop in the resolution or precision of the response. This type of discontinuity may make the data seem discrete, or 'jumpy' given certain conditions and should be accounted for in IAI selection and evaluation with models that either ignore or can account for such jumps. Rapid system changes (expected or otherwise), or sensor calibration or capability issues are typical sources of these discontinuities**.**

Analytic Data Modeling Versus Nonparametric

- **Analytic modeling (equation or rule-based):** This modeling method assumes the data follows some understandable and representable human rules, such as a decision tree or a mathematical formula. This information can be time series or memoryless, but has the important quality of being formulaically predictable. When explainability is a priority, this type of data modeling can be much easier to work with and can create simplified and much more easily maintained models, but will often require more up front effort to ensure all the right rules have been set in place.
- **Nonparametric modeling:** This data model does not assume a specific mathematical form for the information and relationships, so it is more flexible and can capture complex patterns that don't follow a simple equation. The tradeoff is often found in the explainability and ongoing upkeep of the model. Nonparametric or black box models offer an up-front simplicity and applicability, while also demanding much more rigor and efforts to monitor them beyond their initial deployment. Most neural network based or commonly thought of machine learning algorithms use some version of this modeling approach to data.

CHAPTER 3
Key Considerations for IAI

When implementing an IAI model in your manufacturing facility, it's essential to evaluate its effectiveness in a way that goes beyond simple accuracy metrics. The true value of IAI is how it impacts the broader system and integrates seamlessly into your operational environment.

An IAI solution doesn't necessarily need to be perfect — it just needs to strike a balance between expected performance, usability and accuracy. It should be effective and easy to maintain, while also being able to scale with your business. This is where domain expertise plays a critical role. Collaborations during the initial deployment and development with end users who have a deep understanding of your specific manufacturing processes, equipment, challenges, and the nuances of your industry helps you set realistic expectations and reasonable levels of trust of your IAI model. This knowledge will help you:

- Set realistic parameters during model design.
- Understand potential physical limits and operational constraints.
- Identify common simplifications that are suitable for your specific needs.
- Develop output that corresponds to and is intuitive to a user's expectations about the system.

Simplifying complex problems into smaller, manageable tasks can also improve the effectiveness of IAI models. Using multiple IAI systems to handle individual components of a larger process can make it easier to train, test, and maintain the models. However, this modular approach may introduce new challenges, such as ensuring smooth integration between the different models. It is best to speak with both IAI and system experts together when making these and other modeling decisions.

Practical Steps to Validate and Maximize the Potential of IAI

Implementing IAI in your manufacturing operations can significantly improve efficiency, but it's essential to ensure that the models are reliable, trustworthy and trusted as well as aligned with your business goals. Consider these practical steps to validate and unlock the full potential of your IAI system:

- **Extensive testing:** Conduct comprehensive testing across various conditions and scenarios. This will help you understand where the model performs well and where it has limitations. Testing should simulate both typical and rare event situations to identify potential gaps in its capabilities. When possible, run "impossible" scenarios, both good and bad, to help create expected bounds of behavior and output from the model as warning signs and guideposts.
- **Continuous monitoring:** Some IAI systems support implementation of continuous monitoring to track the model's performance over time. When available, this can provide real-time performance tracking against some static or periodically updated baseline that allows you to detect deviations from expected behavior quickly, so you can take prompt corrective actions before problems escalate.
- **Scenario analysis:** Regularly run scenario analyses to simulate different operating conditions and assess how the model reacts. This proactive approach helps you anticipate challenges and ensure that the IAI system remains effective in dynamic and unpredictable environments.
- **Feedback loops:** Establish feedback loops to incorporate real-world data and experiences back into the model. A continuous improvement process allows your IAI system to adapt to changing conditions, refine its performance, and extend its verified capabilities.

Align IAI With Your Production and Business Goals

To evaluate IAI's effectiveness, measure its impact using key performance indicators (KPIs) that are directly aligned with your production and business goals. Don't just focus on basic metrics like accuracy and precision, as they may not provide a complete picture of the model's effectiveness and impact on your system. Instead, consider broader, system-level outcomes that matter most to your business.

For example:

- If the goal is to i**ncrease production rates**, focus on the actual increase in production volume and throughput.
- If you want to **reduce downtime**, assess how well the IAI predicts and prevents breakdowns or equipment failures. Compare metrics like mean time between failure or repair (MTBF, MTBR) of your system before, after and throughout the life of the IAI.

Additionally, estimating the best-case, worst-case, and most likely scenarios for your IAI model will help you understand its potential impact. When reviewing performance metrics, scrutinize how they were generated. Look for any biases in the data, such as imbalanced datasets or cherry-picked samples, which can lead to misleading results.

Finally, know the limitations of your IAI model. Understanding where the system excels and where it falters helps you implement necessary safeguards. No model is perfect, and identifying its boundaries ensures responsible deployment and avoids costly mistakes. Focus on verifying performance in frequent, likely, and high-risk scenarios to ensure reliable and safe operation.

It is important not to fall into the one-time fix misconception with IAI. Many tools and systems meant to improve operations become invisible as they do their job. In the overwhelming majority of cases, IAI is not a tool that can come in and do a one-time fix to your system and then be left alone. It needs constant care, oversight and maintenance to maintain its function. Regular tests provide clear indications and justifications for ongoing investments, budgetary or otherwise, into an IAI system, as well as indications when it's time to move on.

A Closer Look at False Alarm Rates: A Real-World Example

To better understand the challenges of evaluating IAI effectiveness, let's look at a real-world example. An IAI monitoring system was implemented in a manufacturing facility to detect machinery degradation early. The goal was to identify potential product flaws before they caused significant scrap, downtime, and maintenance costs. After a full day of production data was used to assess the model, the following metrics were provided:

- **Accuracy: 98%**
- **Precision: 90%**
- **Recall: 85%**
- **False Alarm Rate: 2%**

Despite these promising numbers, the IAI detection system failed when scaled. A deeper study revealed that although the detection system seemed to function properly, it was essentially giving the static indication of "good" which provided a statistically viable response that created those metrics. The system itself was already at such a high quality, less than 1% of the production line needed to be identified as "bad", thus the IAI seemed to be performing well. In reality, it was not functioning as advertised and it was actually causing additional unneeded line tests.

Never take a single set of representative values at face value without exploring the broader context that generated them. Let's explore some common potential issues with this example as a base:

- **Imbalanced data:** The system was trained on a dataset where noncompliance was rare (only 0.1% of the data). As a result, the model's high accuracy is primarily due to its ability to adequately mimic and respond to normal operations (99.9% of the data). This can lead to missed failures, as the model may not accurately identify the rare, critical failure events.
- **False alarms:** A 2% false alarm rate in a facility with thousands or hundreds of thousands of units processed daily, means that there could be dozens or even hundreds of false alarms each day. This can lead to alarm fatigue among maintenance staff, causing them to overlook genuine issues or ignore alarms entirely. Over time, this can undermine the system's effectiveness and make maintenance staff less responsive to real problems.
- **Contextual irrelevance:** The model's evaluation is based primarily on accuracy, but the key objective is to reduce unplanned downtime. In this case the additional false alarms increased unplanned downtime. But even if the IAI was behaving as intended, it may not be able to support downtime reduction if the IAI is not integrated with your maintenance scheduling system. Even accurate detections may not lead to timely action if there is no scheduled plan the IAI is able to inform. The system might flag issues, but if the necessary follow-up actions are not automated or clear, the benefits of detecting failures early could be lost.
- **Overfitting:** The model was trained and evaluated using data from a single day's worth of operations. This is far too limited of a training set. Many systems evolve over time or are impacted in some capacity by the yearly seasons. Taking any single slice of that may not reflect the full range of conditions and failures that can occur over time. Often models will be overfitted to a specific operational environment based on the training data set, causing it to struggle to identify patterns that differ only slightly from what was seen in the training data.
- **Impact on production:** High false alarm rates can cause unnecessary machine stoppages for inspection. This could result in more downtime from unnecessary checks than the model is saving by preventing actual failures. Over time, the cost of these interruptions could outweigh the benefits of the system's early failure detection.

IAI Is Not a One-Size-Fits-All Solution

The key is to remember that IAI isn't a one-size-fits-all solution. It works like a toolbox.

For example, a hammer can be used to build a house, but it can also be used to fix a chair. It's the same tool, but the way you use it depends on the job. Similarly, IAI can be used to solve many different manufacturing problems, but you need to choose the right tool for the job.

Here's how to get started:

1. **Understand the specific problem:** Are you trying to reduce defects? Improve efficiency? Predict machine failures? Knowing what you're trying to solve is key to picking the right IAI tool.
2. **Evaluate your facility's environment:** What data do you currently have? What systems and processes are already in place? IAI works best when it has access to the right information.
3. **Choose the right IAI tool:** Different IAI tools have different strengths and weaknesses. Make sure you understand what the tool can do, how it fits your needs, and how to adapt it to your facility.

Just as a skilled craftsperson knows which tool to use for a specific task, a successful manufacturer needs to understand how IAI can best solve their unique challenges. It's about finding the right fit among the technology, the problem, and the environment.

For example, if you want to improve quality control, IAI-powered computer vision might help detect defects in real-time. On the other hand, if you're trying to optimize production schedules, IAI could analyze historical data to predict future demand.

By understanding your specific needs and the available IAI tools, you can make informed decisions that will improve your manufacturing processes.

Is IAI the Right Solution For Your Business?

While IAI can be a game-changer, it's not always the best solution or tool for every problem. Consider the example of a manufacturer who is experiencing inconsistent quality in a specific part of their production process. They're considering implementing an IAI-powered vision system to identify defects in real time. Before investing in IAI, they could conduct a thorough root cause analysis using existing data and human expertise.

This might involve:

- **Analyzing production data:** Look for patterns in the data. Are certain production parameters — like machine settings or raw material quality — linked to defects?
- **Observing the process:** Have experienced operators review the process. Are there any obvious issues like machine miscalibration or operator fatigue?
- **Implementing simple process improvements:** Sometimes, a checklist, standardized procedures, or training might be all you need to solve the problem.
- **Compare the costs:** Weigh the costs of a simple fix versus implementing IAI, considering both the financial cost and time investment.

If simple process improvements don't solve the issue, or if the problem is too complex for traditional methods, then IAI could be worth considering. IAI is particularly useful for situations where human detection is too slow, or when a large amount of data needs to be analyzed quickly. But before implementing IAI, always evaluate if the simpler solution might be the right fit.

IAI Investment Considerations for Manufacturers

Implementing IAI into manufacturing requires careful consideration of direct costs, indirect costs including staffing needs, and other factors such as system integrations. MEP Centers have experts who can help you learn about IAI and implement a solution, including how to overcome perceived obstacles to IAI adoption, such as:

- **Costs:** Many IAI tools, especially those offered as a service (AIaaS), are subscription-based. The pricing might be based on usage (e.g., pay per API call). Some IAI tools are available as off-the-shelf software you can purchase, while others are custom-built solutions. IAI tools can range from a few thousand dollars for simple solutions to hundreds of thousands for complex, custom-built systems.
- **Staffing:** For basic applications, you might be able to integrate pre-built IAI tools with your existing systems with some training for your staff. If you're developing custom IAI solutions or dealing with highly specialized applications, you may need data scientists and/or machine learning engineers on staff (or hire a vendor specializing in IAI development and integration).

CHAPTER 4
The MEP National Network Is Here to Help

Every day, MEP experts around the country help manufacturers find the solutions they need. The MEP National Network™ has a proven track record and has helped U.S. manufacturers produce real impacts for more than 35 years.

The MEP National Network's ability to serve manufacturers depends on support from the entire manufacturing ecosystem. It works with local and federal government, workforce development organizations, educational institutions, economic development organizations, and federal labs, among others, to provide manufacturers with the resources and support that meet each firm's unique needs.

Connect With the MEP National Network

If you are interested in learning more about the MEP National Network, or how to work with NIST, please contact mfg@nist.gov. You can also visit our website for more resources and to connect with an MEP Center.

Contact an MEP Center

MEP National Network™

The MEP National Network advances U.S. manufacturing by helping small and medium-sized manufacturers grow, make operational improvements and reduce risk. At MEP Centers across the U.S. and Puerto Rico, over 1,400 manufacturing experts draw on deep industry experience to provide comprehensive, hands-on consulting and training solutions tailored to each manufacturer's unique challenges.

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