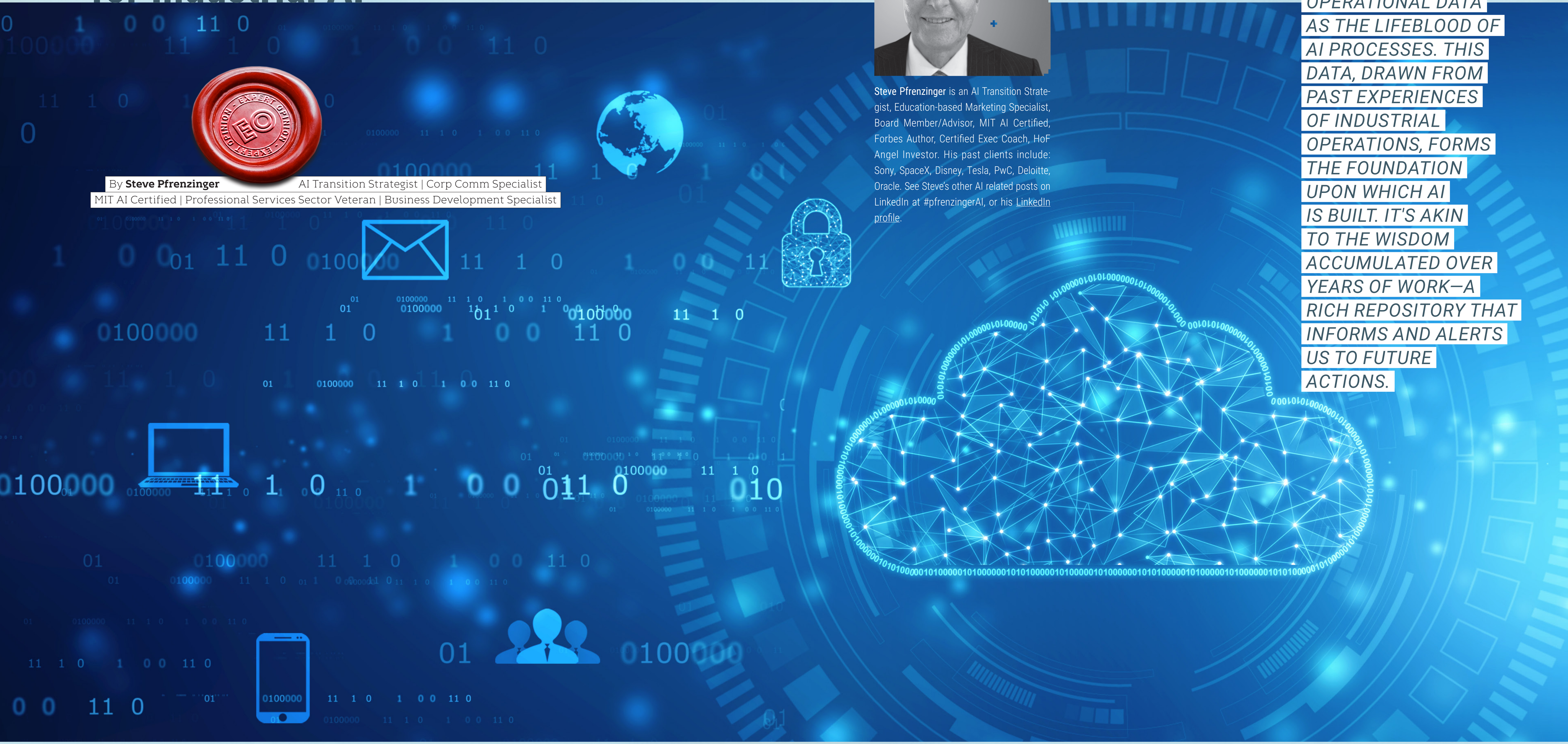
Smart Grid – Success Formula for Industrial AI



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IMAGINE THE VAST AMOUNT OF HISTORICAL OPERATIONAL DATA AS THE LIFEBLOOD OF AI PROCESSES. THIS DATA, DRAWN FROM PAST EXPERIENCES OF INDUSTRIAL OPERATIONS, FORMS THE FOUNDATION UPON WHICH AI IS BUILT. IT'S AKIN TO THE WISDOM ACCUMULATED OVER YEARS OF WORK—A RICH REPOSITORY THAT INFORMS AND ALERTS US TO FUTURE ACTIONS.

In today's fast-paced industrial landscape, including Smart Power Grids, the deployment of modern Artificial Intelligence (AI) systems is reshaping how the industry approaches efficiency, predictability, sustainability, and risk avoidance.

All involving major infrastructure and encompassing the monitoring and management of assets where catastrophic events can be massively expensive, disruptive, and dangerous.

To demystify the complex orchestration behind these modern systems, we can simplify the AI process into this easily digestible formula.

Data + IoT + ML = AI

...or **DIMA** for short. Let's delve into this formula, designed to empower non-AI-expert business leaders with the core knowledge to ask insightful questions and make informed decisions (a list of suggested questions is included at the end):

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1. Data: The Historical Backbone
Imagine the vast amount of historical operational data as the lifeblood of AI processes. This data, drawn from past experiences of industrial operations, forms the foundation upon which AI is built. It's akin to the wisdom accumulated over years of work—a rich repository that informs and alerts us to future actions.

And, in the power industry it appears significant amounts of data is being collected.

2. IoT: The Real-time Network
The Internet of Things (IoT) is a web of interconnected devices (e.g., sensors, data gathering machines, ...),

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each acting as a nerve ending in the vast expanse of an industrial body. These edge devices (e.g.. hydrogen, moister and temperature sensors) continually relay new operational data back to a central, cloud-based system—data captured in the throes of the industrial process, offering a real-time pulse on operations.

3. ML: The Training Regimen
Machine Learning (ML) is the rigorous training ground where AI learns to make sense of massive amounts of historical data. Like a massive datastore or a Large Language Model (LLM), ML algorithms digest past patterns to predict and optimize future outcomes. It's where data transforms into wisdom.

4. AI: The Intelligent Output
AI is the embodiment of a computer's ability to mimic human intelligence. It's the sophisticated offspring of the ML process above, operating on what's called a "neural network" (human-mind-like) structure. AI takes the baton from ML, running with the insights gleaned to steer industrial operations towards greater, more intelligent, and predictable heights.

Now, let's consider how this formula aids non-AI-experts in the industrial sector, particularly in evaluating a potential Smart Grid project. By breaking down the DIMA components, stakeholders can ask pivotal questions to ascertain the viability, affordability, and potential success of a major industrial AI implementation:

1. **Data Quality:** Do we possess historical data of sufficient quantity and quality to train the AI model in the machine learning (ML) process?
2. **Business Justification:** Is there a compelling business need for this project, and can the costs be justified? Do we have any build or buy options to consider?
3. *** Real-time Data Acquisition:** Are our systems capable of capturing new data as it emerges from the multitude of sensor-laden edge devices?
4. **Data Labeling:** Can we ensure historical data can be accurately labeled (identified) for effective use in ML training specific to our domain?
5. **** AI's Role:** What positions (roles) do we envision for AI in our cloud dashboards, comparing real-time data with historical data—assistant, peer, or manager?
6. **AI Autonomy:** Should our AI be empowered to autonomously respond to alerts, or will human oversight be necessary?
7. **AI in the Real World:** Will our AI be confined to computers, or will it take physical actions in response to alerts (e.g., using robots, drones, turn dials, flip switches, etc.)?
8. **Extending Asset Life:** Can we expect to extend the asset life of our major equipment to better meet our sustainability goals? Can you estimate by how much?
9. **Project Risk Assessment:** Considering the high stakes, how do we mitigate the risk that up to half of major DIMA projects may not meet expectations?
10. **AI's Internal Decision Making:** Warning! Today's AI systems repeatedly generate different outputs (answers) for the same inputs (questions) via what are called "non-deterministic" processes. Does AI's unpredictability and lack of transparency (i.e., its sources) in decision making create issues for our systems that require precision and repeatability?

Note:
In such cases (above), a hybrid approach that combines the repeatability and transparency of rule-based systems with the adaptability and variability of AI might be most effective.

By empowering key business leaders (managers, engineers, and utility professionals) with the standardized DIMA framework, all can foster a deeper understanding and cultivate a proactive culture of inquiry. This simple, yet strategic approach ensures that when it comes to integrating AI into large-scale industrial systems, every decision is data-driven, every key possibility is considered, and every investment is made with eyes wide open to the future.

** End-to-end IoT ecosystems are a DIMA requirement and available from numerous well-known providers, connecting remote edge devices (data gathering sensors) to cellular gateways to cloud databases to AI predictive analysis and appropriate action. Familiar providers here are CISCO Systems, GE Digital, Samsara, Sensata and Montage Connect.*

*** Beyond human talent, AI development needs tools, libraries, and platforms to speed development and deployment. Familiar platform providers are MS Azure and Amazon's AWS. PyTorch and TensorFlow are two of the most popular open-source libraries for machine learning and artificial intelligence projects.*