





Equipment Anomaly Detection Using an Auto-Encoder Neural Network







1 | January 21, 2020 | Proprietary | © 2019 Curtiss-Wright

"IT'S TOUGH TO MAKE PREDICTIONS – ESPECIALLY ABOUT THE FUTURE."

-- Yogi Berra or Neils Bohr, depending whether you prefer physics or baseball

... what we want is a machine that can learn from experience.

-- Alan Turing, 1947



The Challenge

- Aging equipment and workforce
 - Average age of nuclear plant in the US is 37 years old
 - Nine Mile Point started producing power 12/14/69
- Reduced workforce
- Competition and environmental regulations
- Need for increased efficiency and reliability

A study by Boeing found that 85% of all equipment failed at random no matter how much preventive maintenance measures were applied to equipment.*

ARC Advisory Group reports 82% of failures cannot be avoided with traditional equipment monitoring.*

*https://www.processingmagazine.com/maintenance-safety/article/15587836/why-times-up-on-preventive-maintenance

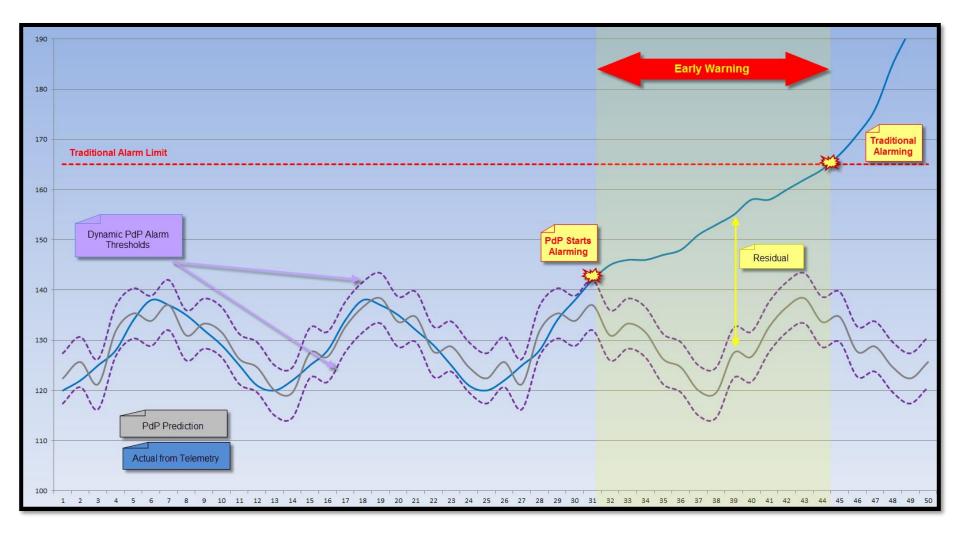
Equipment Anomaly Detection

"The identification of rare items, events or observations which raise suspicions by differing significantly from the majority of the data." -- Wikipedia

Equipment anomaly detection uses existing data signals available through plant data historians, or other monitoring systems for early detection of abnormal operating conditions.

Equipment failures represent the potential for plant deratings or shutdowns and a significant cost for field maintenance.

Anomaly Detection vs Traditional Alarming





Our History

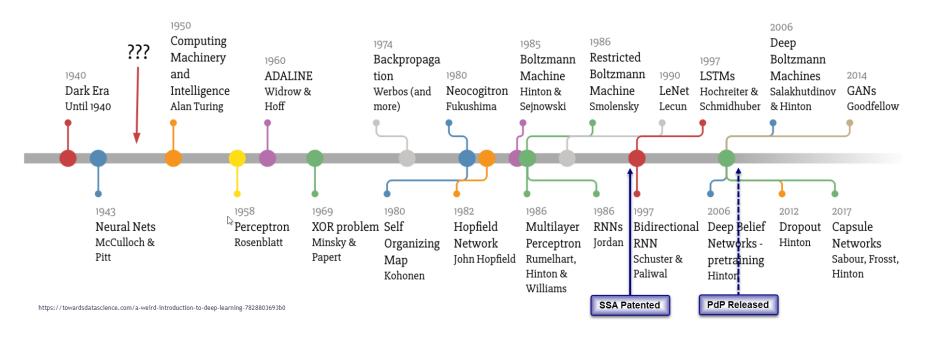
Pattern-Recognition Soft For Plant Surveillance	1988
United States Patent [19] Mott [54] METHOD OF SYSTEM STATE ANALYSIS [75] Inventor: Jack E. Mott, Idaho Falls, Id. [73] Assignee: E I International, Inc., Idaho Falls, Id. [21] Appl. No.: 240,262 [22] Filed: Sep. 6, 1988 [51] Int. Cl. ³	[11] Patent Number: 4,937,763 [45] Date of Patent: Jun. 26, 1990 Primary Examiner—Parshotam S. Lall Assistant Examiner—Michael Zanelli Attorney, Agent, or Firm—Hopkins, French, Crockett, Springer & Hoopes [57] ABSTRACT A process for monitoring a system by comparing learned observations acquired when the system is running in an acceptable state with current observations acquired at periodic intervals thereafter to determine if the process is currently running in an acceptable state. The process enables an operator to determine whether or not a system parameter measurement indicated as outside preset prediction limits is in fact an invalid signal resulting from faulty instrumentation. The process also enables an operator to identify signals which are
	Surveillance at TMI 1 Usin ecognition Techniques

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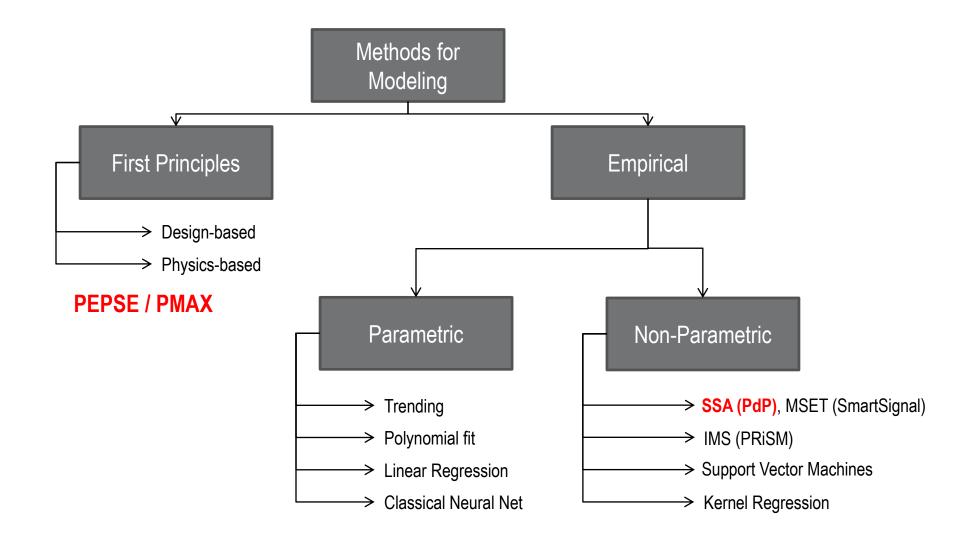
Waiting for Processing Power to Catch Up



PdP's underlying algorithm required maturing of computing architecture to provide the speed to make training and real time processing commercially viable. Also required migration of analog to digital and associated historians

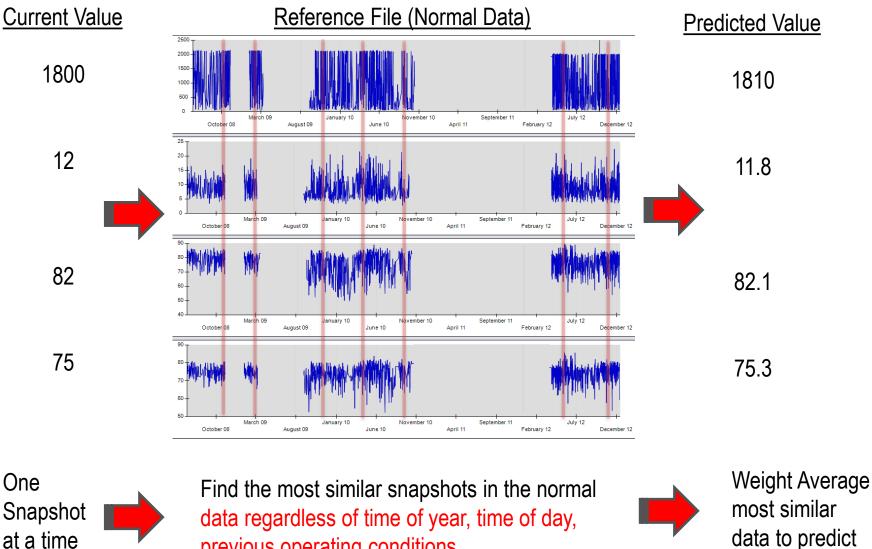


Predictive Analytic Methods





PdP (Similarity Based Model)

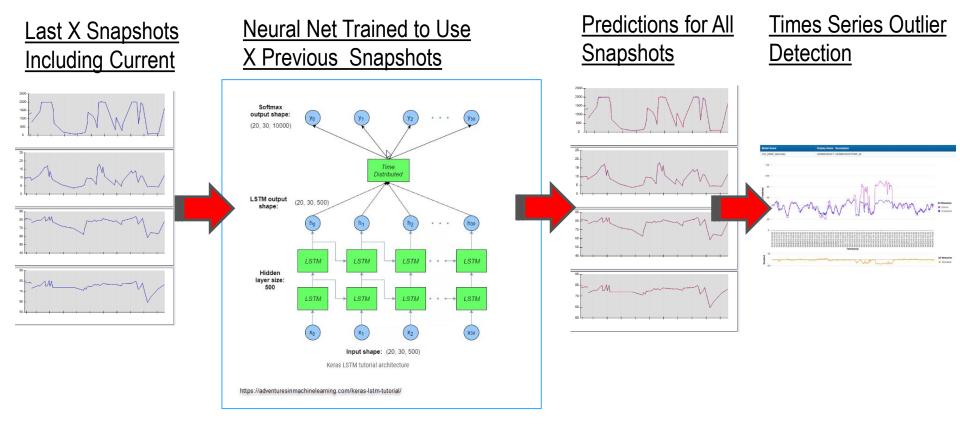


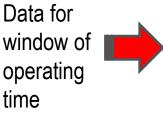
previous operating conditions

most similar data to predict



LSTM Neural Net plus time series outlier detection

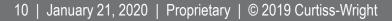




Neural Net Trained on normal windows of contiguous time series data representing normal operation including transients like ramping, start up and shutdown



Predictions reflect behavior leading up to current time



The Technical Challenge

- Requires marriage of equipment/process SMEs and technical SMEs (data scientist)
- Requires a high technical competency to implement and maintain
- Requires processing power beyond computing horsepower





The Data Challenge

- Lack of volume
- Lack of good data for training
- Normal vs. Failure
- Seasonality
- Start-ups and shut-downs
- Changing environmental conditions

Innovation as a Service

INNOVATION COOPERATIVE

LEAN CONSULTING ENGAGEMENT

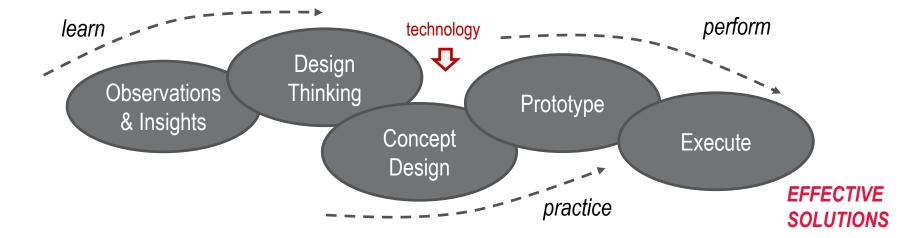


Customer discovery, outcomes

Identification of improvement opportunities

Collaborate focused on problem solving & solutions

STRUCTURED PROCESS





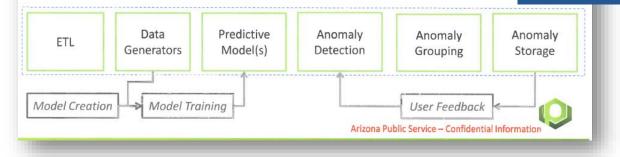
APS Equipment Anomaly Detection (EAD)

- Uses open-source packages
- Built as a platform rather than a solution
- Team has full access to plant data
- Semi-supervised Learning
- Efficient use of SMEs

System Framework

Flexible, General, Scalable, Expandable

- Each step is performed independent module
- Groups of sensors are associated with set of steps (pipelines), run independently and in parallel



Light Water Reactor Sustainability

INL/EXT-17-42918 Revision 0

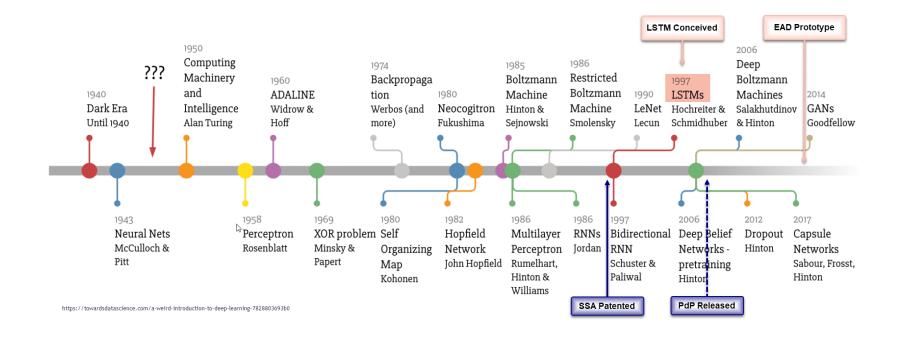
Program

Seamless Digital Environment – Data Analytics Use Case Study





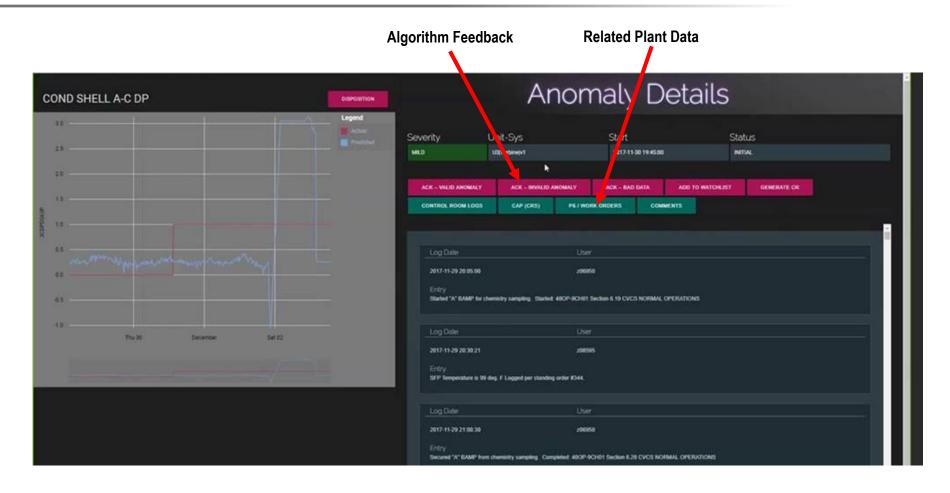
Waiting for Processing Power to Catch Up



EAD's underlying neural net algorithms also required maturing of computing architecture to provide the speed to make training and real time processing commercially viable.



APS Equipment Anomaly Detection User Interface



Graphical display of anomaly data, plus real-time connection to plant systems for control room logs, condition reports and work orders



The APS EAD Toolkit

Open Source

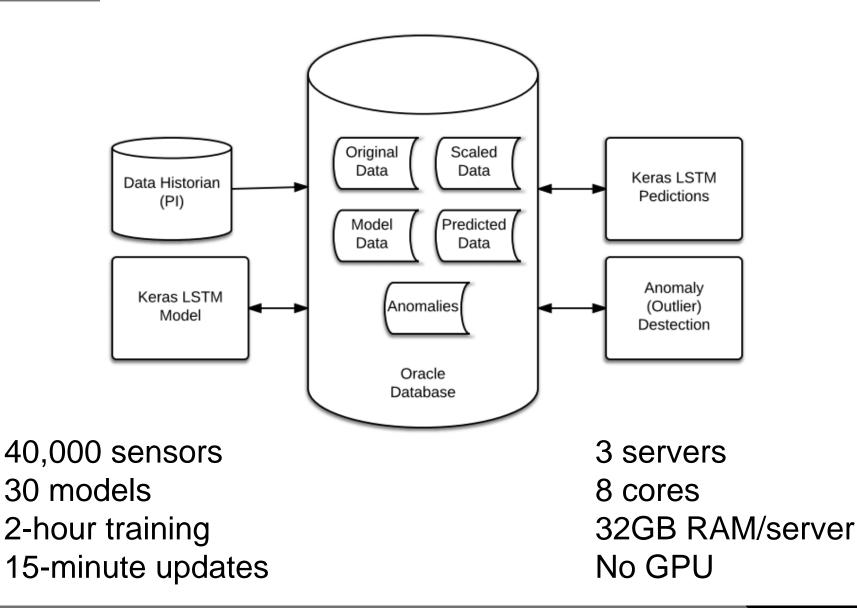
- R Programming
- Keras LSTM Autoencoder
- TSOutliers outlier detection

Commercial Products

- Oracle Database
- Domino Labs Containers
- NextAxiom Hyperservices
- PI Data Historian

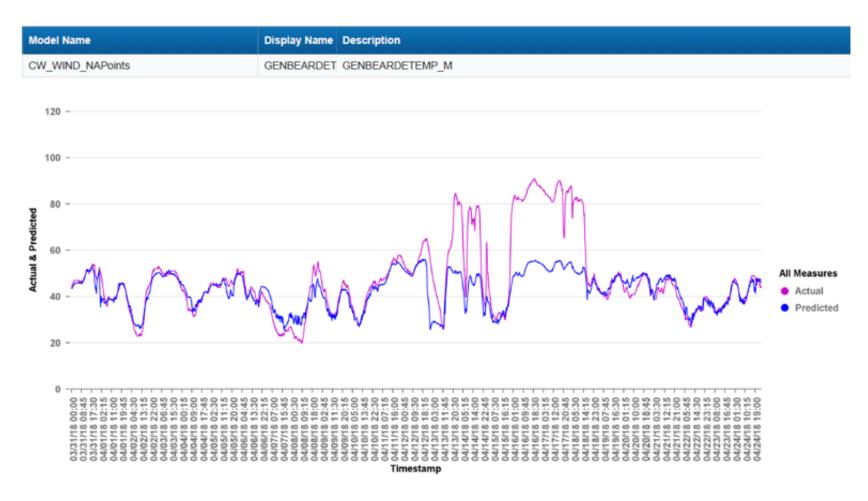


The APS EAD Architecture





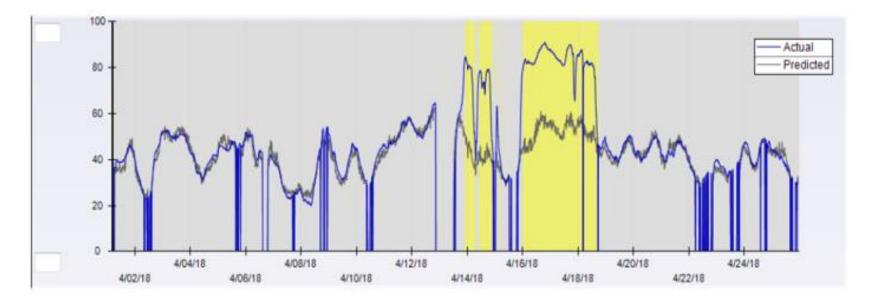
The Autoencoder Analysis



Autoencoder Analysis



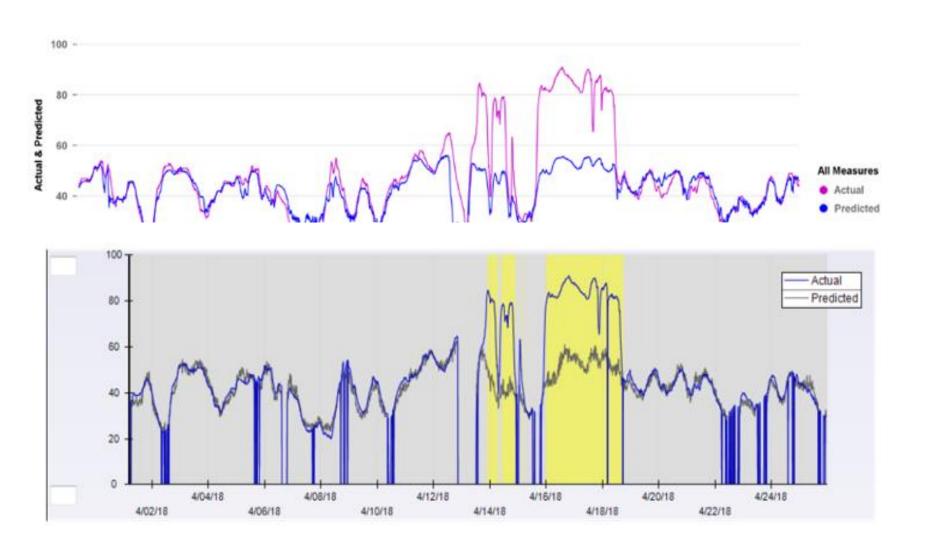
The System State Analysis



PdP System State Analysis



The Comparison





EAD Process Flow

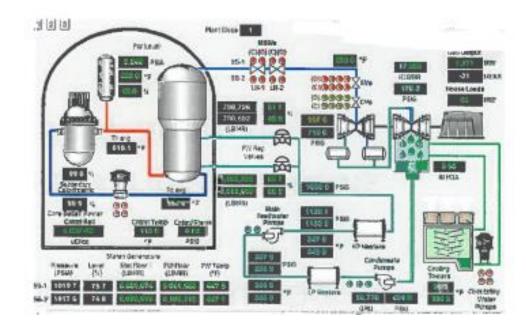


Anomalies are then presented to the user, and the user can provide feedback to adjust sensitivity of algorithm



Limitations in Existing EAD Prototype

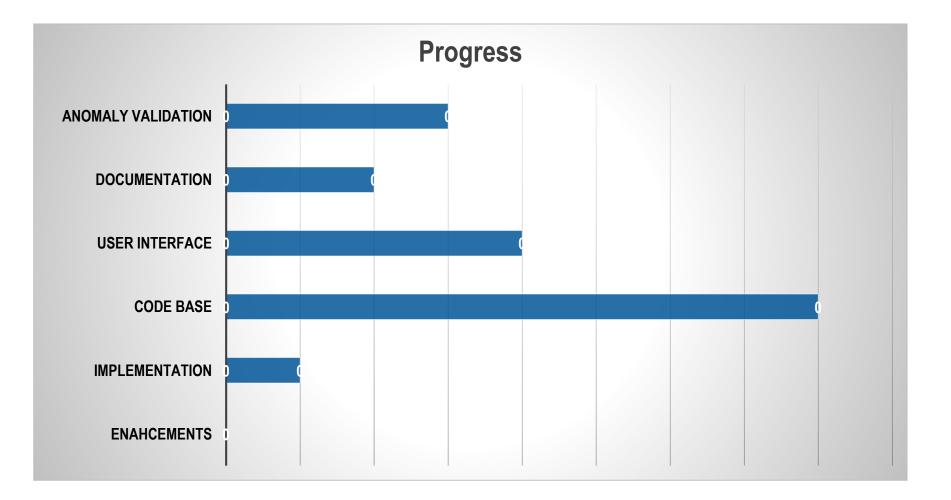
- "Kitchen Sink" Approach
- Lack of Investigative Tools
- No User Modeling
- No Sensor Controls



Generalize				
Client-Specific Tools	Document Software	Enhance		
Client-Specific Interfaces 3 rd Party Licenses	Description Algorithm Logic User Guide	Add User Interface Features Add Control Features	Implement Implementation Plan Support Model	



Current Commercialization State



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Potential Applications

- Start-Up/Shut-Down Models
- Hydro Plants
- Steam Plants
- Ultrasonic Data Analysis
- On-Board Diagnostics
- Wind Turbines
- Gas Turbines
- Switchyards

Our Present Work

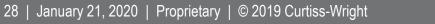
ASHBURN, Va. – December 3, 2019 – Curtiss-Wright's Defense Solutions division, today announced that, through its Reseller Agreement with <u>WOLF Advanced</u> <u>Technology</u>, it has expanded its family of open architecture <u>high performance</u> <u>embedded computing (HPEC)</u> processors designed for demanding ISR applications with the addition of three new NVIDIA Quadro Turing (TU104/6) GPU/inference enginebased OpenVPX[™] modules. Curtiss-Wright also announced the availability of a new AMD Radeon[™] (E9171) based XMC graphics engine card.

Designed to support compute-intensive ISR and EW systems, the fully rugged <u>VPX3-4925</u>, <u>VPX3-4935</u>, and <u>VPX6-4955</u> modules feature Tensor Cores (288, 384, and 768 respectively) that are ideal for accelerating tensor/matrix computation used for deep learning neural network training and inference used in deployed and artificial intelligence (AI) applications requiring TFLOPS of accelerated processing. These applications include high-performance radar, SIGINT, EO/IR, data fusion ingest, processing and display, and autonomous vehicles.

https://www.curtisswrightds.com/news/press-release/cw-announces-new-nvidia-quadro-turing-tu104106-gpgpu-processor-modules.html



Questions?







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