Defense Systems Information Analysis Center

University of Dayton Research Institute

Emerging Applications of Machine Learning (ML) and Predictive Analytics in Naval Energy Autonomy

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This presentation is primarily based on the following article and other relevant papers mentioned in the slides:
Z. Jiang, S. C. Miller, and D. Dunn. "Emerging Applications of Machine Learning and Predictive Analytics in Naval Energy Autonomy," *DSIAC Journal*, 2023.

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Outline of Presentation

- Background and challenges
- Driving force for U.S. Navy to use ML and predictive analytics in energy systems
- Features of an ML analytics solution
- Control system based on ML and model predictive control, for autonomous energy systems
- Applications of ML methods for naval energy systems
- Anticipated benefits and recommendations for future development
- Summary

Background

- U.S. Navy facilities consume considerable energy.
- Programs to reduce energy costs at these facilities related to distributed/renewable generation, energy storage, or energy efficiency technologies.
- Traditionally, controls and optimization of energy systems at installations are addressed at the component levels:
  - Generator controllers, battery controllers, etc.
- Sensors in distributed power plants and load centers to collect and visualize the big data for hundreds or even thousands of parameters and variables.

Figure Credit: NAVFAC EXWC

How could we use these large data sets to help improve energy utilization efficiency and reduce energy costs?

Challenges in Operations

- Microgrids can provide improved resilience, but challenges still exist in autonomous operations.
  - Real-time, system-wide energy optimization.
  - Load profiles, renewable energy availability, fuel/electricity prices, etc.
- Multiple generators can operate at their full or partial capacities, leading to varying fuel efficiency points.

Figure Credit: NAVFAC EXWC

- Load shedding is expected to be based upon a dynamic priority level, which depends on the operation data, scenarios, or user preference.
- Enhanced situational awareness about generator fuel efficiency, load patterns, and other components is essential to higher efficiency of the entire microgrid.
- Traditional control solutions do not capture or address all these factors effectively.

Driving Force

- Modeling energy flow processes, understanding the options and impact of potential energy-saving technologies, and even automating energy saving processes are very important.
- Proposed ML solution by the UDRI team combines the benefits of data-driven Bayesian neural networks (NNs) with a physics-guided learning framework where probabilistic weights are considered for learnable parameters.
- To enhance the predictive analytics and control system for microgrid operation in a contract with NAVFAC EXWC.
- To improve the energy forecasting accuracy, reduce energy costs across the Navy shore establishment, reduce redundant equipment and U.S. Department of the Navy new equipment orders, etc.

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Challenges & Innovation in Physical System Modeling

- Physics-based modeling provides high fidelity but faces challenges.
  - System dynamics not known at time of design.
  - Model parameters vary with mission profiles.
- ML methods can analyze data and extract useful insight, but uncertainty not fully captured.
  - Operation data available from various sensors.
  - ML algorithms and computing resources available to accelerate the learning process.
- Bayesian learning to concisely capture the uncertainty based on probability.
  - Bayesian inference derives posterior distributions from prior distributions.
  - Based on new observations (i.e., evidence).
- While physical or NN models generate point-to-point predictions, Bayesian inference captures probability distributions of parameters across wider operational ranges.

Physical-Digital-Probabilistic Triplet Framework for System Dynamics Modeling and Learning

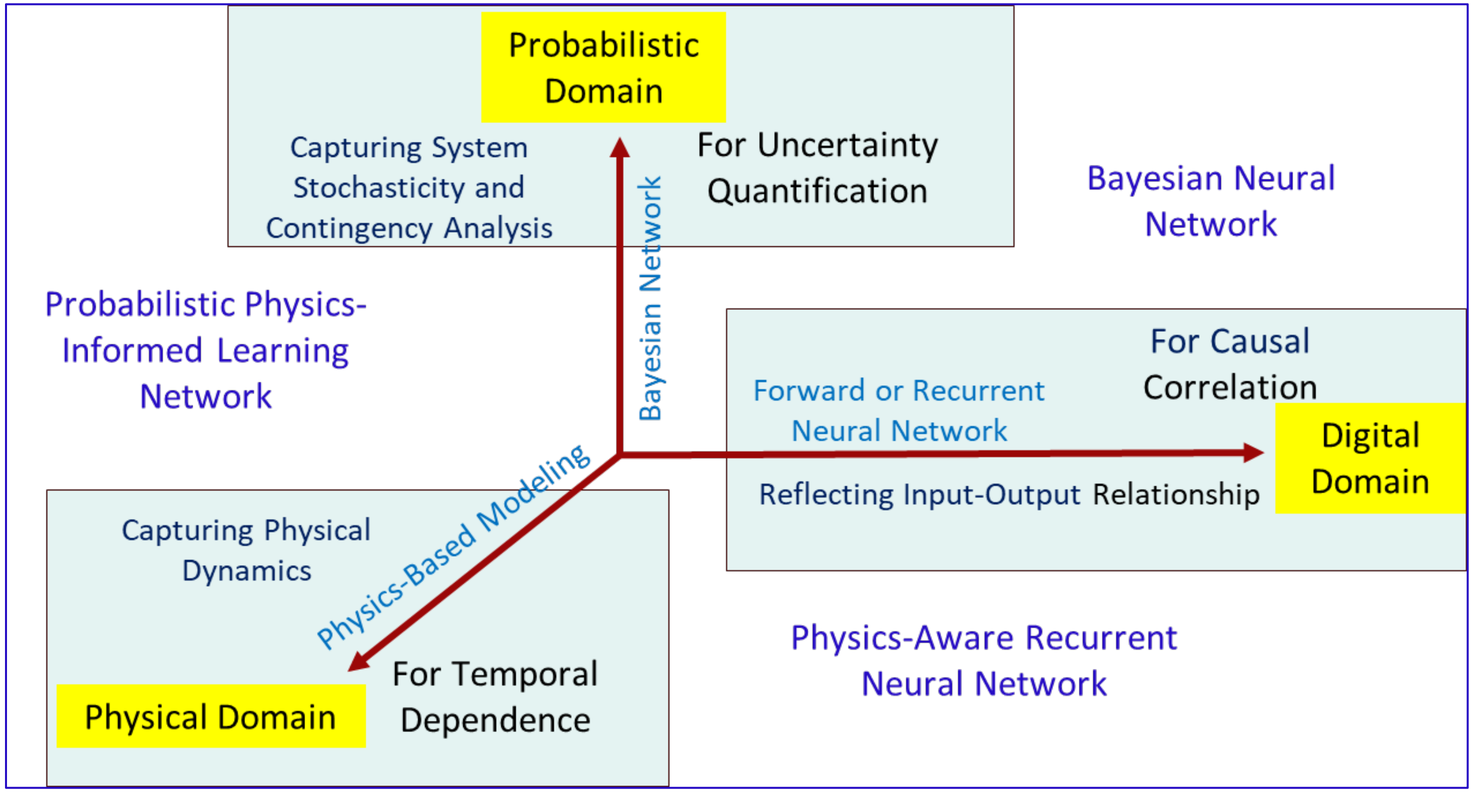


Figure Credit: UDRI

Physical-Digital-Probabilistic Triplet Concept

Realization Options

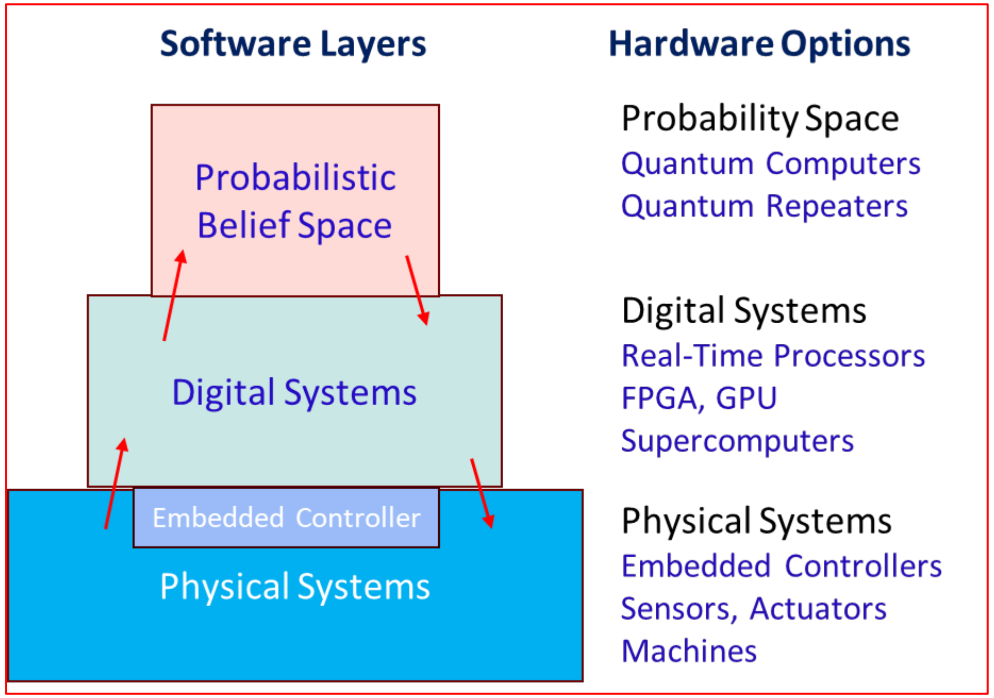
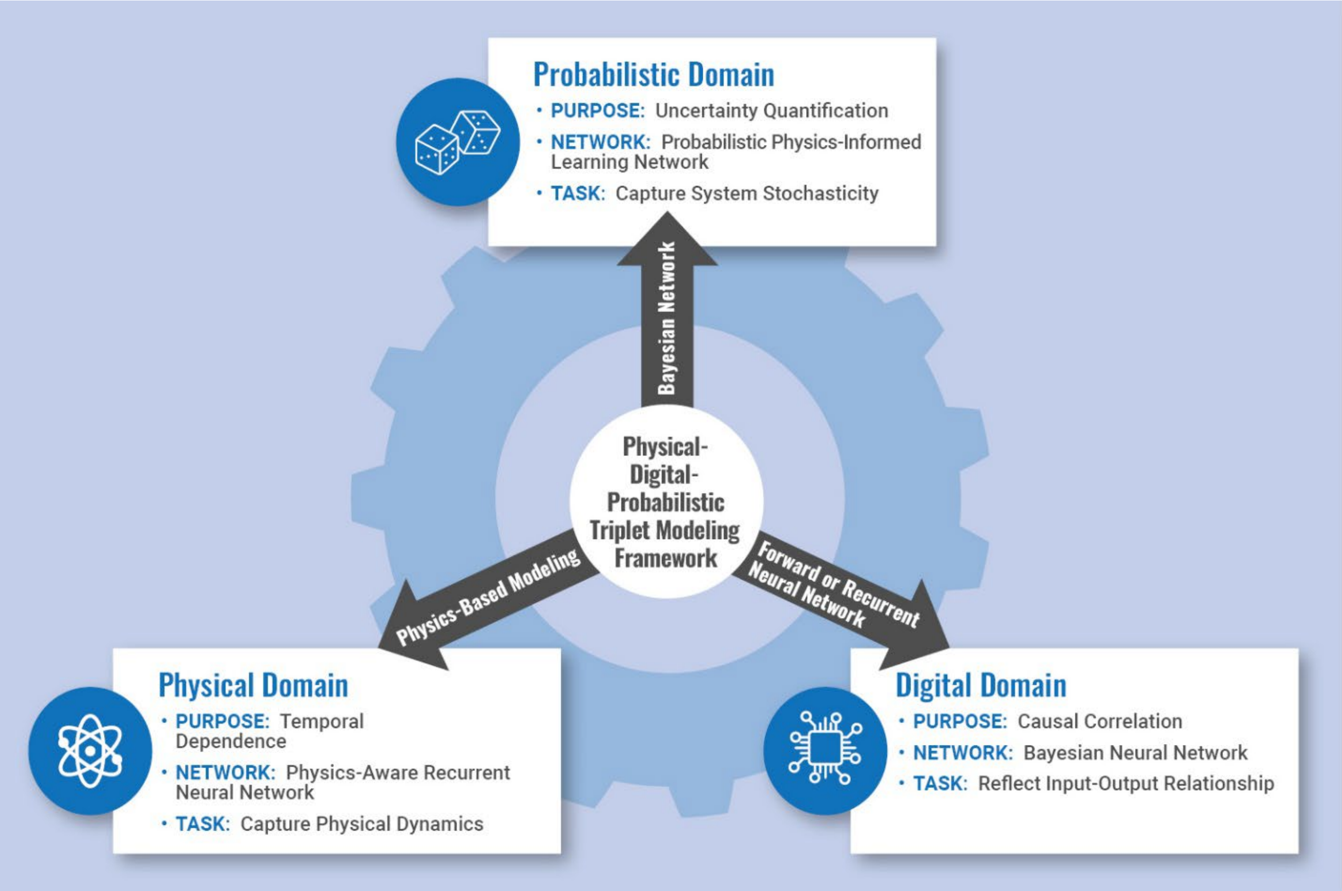


Figure Credit: UDRI

Features of an ML Analytics Solution

- **Physics-based models** to represent known knowledge, integrated into design of an NN to improve model accuracy.
- **NN learning capability** to learn patterns/features and general trends from operational data and predict potential behaviors given a new set of input data.
- **Bayesian inference** to capture uncertainty and probability distribution of variables and factors.



Z. Jiang, S. C. Miller, and D. Dunn. "Emerging Applications of Machine Learning and Predictive Analytics in Naval Energy Autonomy," *DSIAC Journal*, 2023.

Hybrid Learning/Physics-Based Modeling Approach

Physical Model
Known Knowledge

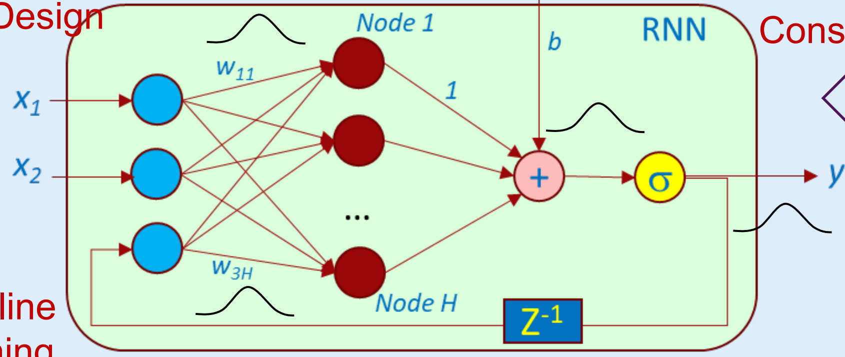
ML Model
Bayesian NN

Common Information Model
Ontology CIM

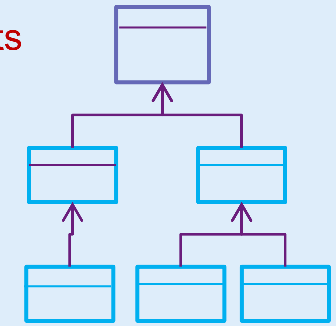
A. Prior knowledge about model equations, known at time of design.

1. Physics-Informed Network Design

$$\begin{cases} \dot{x} = f(x,u,t) \\ g(x,u,t) = 0 \\ h(x,u,t) \leq 0 \end{cases}$$



Rules / Constraints



Traditional Symbolic Representation

B. Knowledge about system structure, parameters, constraints.

2. Online Learning

C. System dynamics and uncertainty learned from real-time operation data.

$pdf(\theta)$

3. Learned Parameters and Distributions

4. Multi-Model Fusion Considering Operational Constraints

5. Converted Back in a Format Understandable to Humans

Sampling distribution at time instant *k*

Sample *j*
$$\begin{cases} X(k+1) = A_k X(k) + B_k U(k) \\ Y(k+1) = C_k X(k+1) + D_k U(k+1) \end{cases}$$

6. Hybrid Symbolic/Vector-Based Knowledge Representation

D. New knowledge learned from data.

Combines known physical knowledge at time of design and learning capability of data-driven methods during runtime.

Z. Jiang and J. Saurine. "Data-Driven, Physics-Guided Learning of Dynamic System Models," AIAA Science & Technology Forum, January 2023.
Z. Jiang and K. Beigh. "Bayesian Learning of Dynamic Physical System Uncertainty," AIAA Aviation Symposium, June 2022.
Z. Jiang and K. Beigh. "Data-Driven Modeling of Dynamic Systems Based on Online Learning," AIAA Propulsion & Energy Forum, August 2021.

Long Short-Term Memory (LSTM) NN

- LSTM NNs are a subclass of recurrent NNs.
- These networks have additional stored states resulting from the past output, and the state storage can be internally controlled subject to the network status itself.
- Such controlled states can be regarded as gated memory blocks in NNs, and they serve as LSTM's key components in controlling information flow.
  - Forget Gate – determines which data should be forgotten or removed from the cell state.
  - Input Gate – determines which data from the current input and previous output will be fed into the cell state as new information.
  - Output Gate – determines which data from the updated cell state will be used as output.

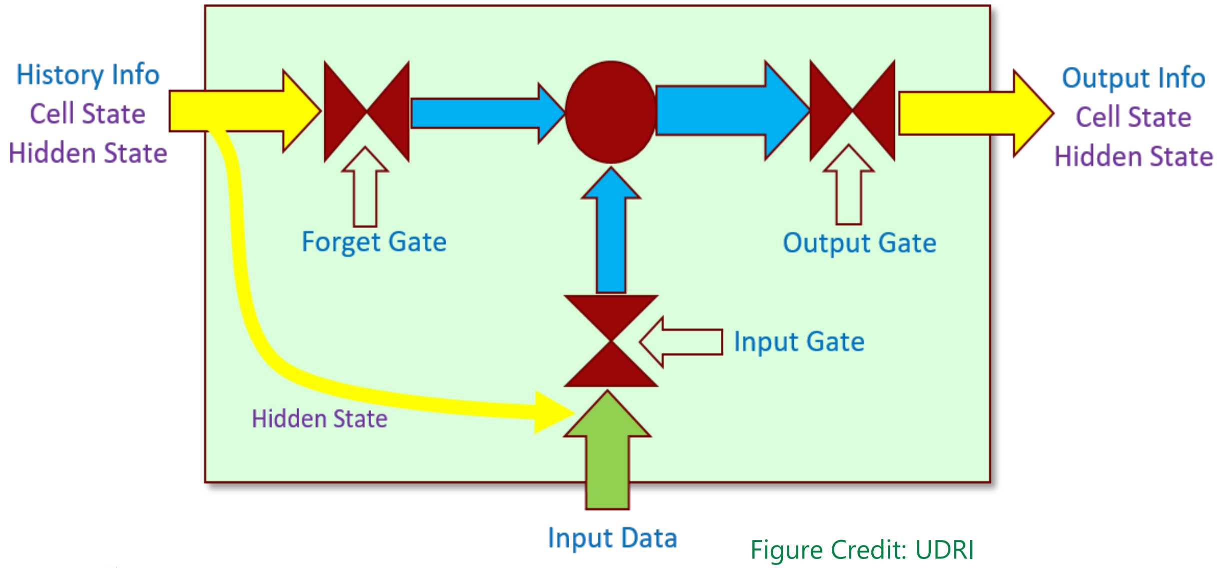


Figure Credit: UDRI

LSTM Cell Structure – Remembering History Information

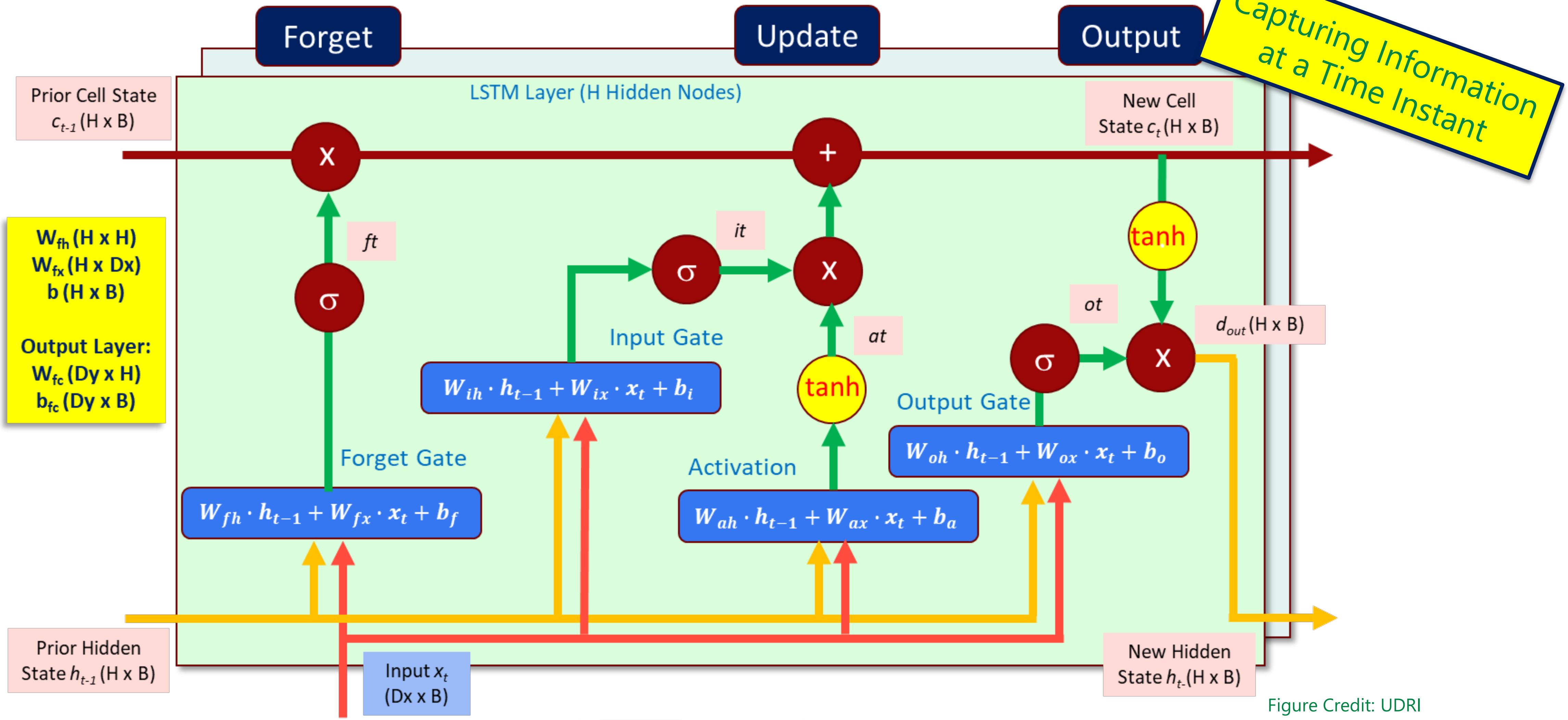


Figure Credit: UDRI

LSTM Network – Modeling Time Sequences

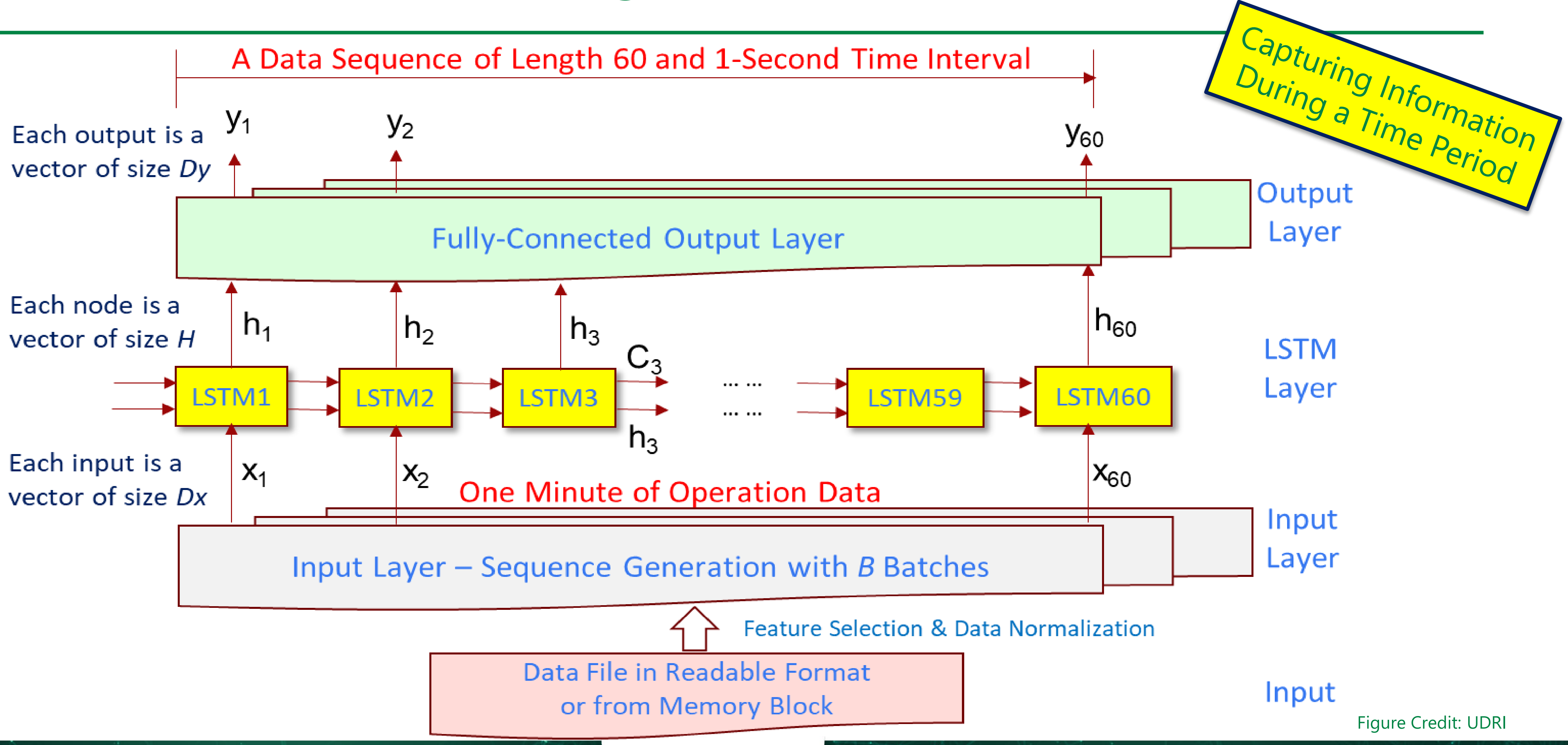
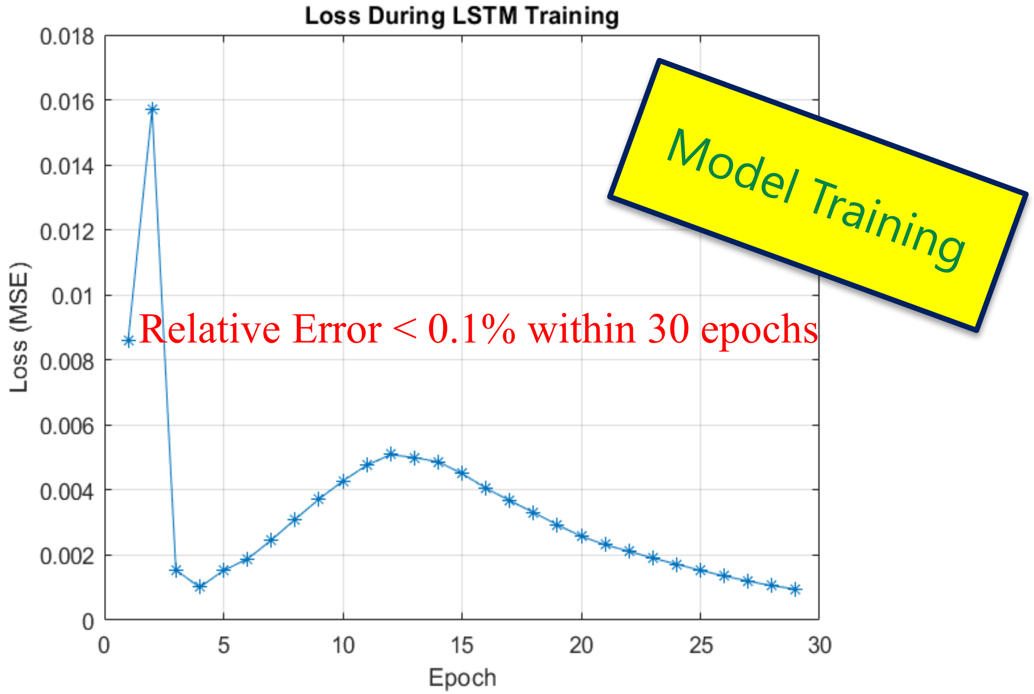


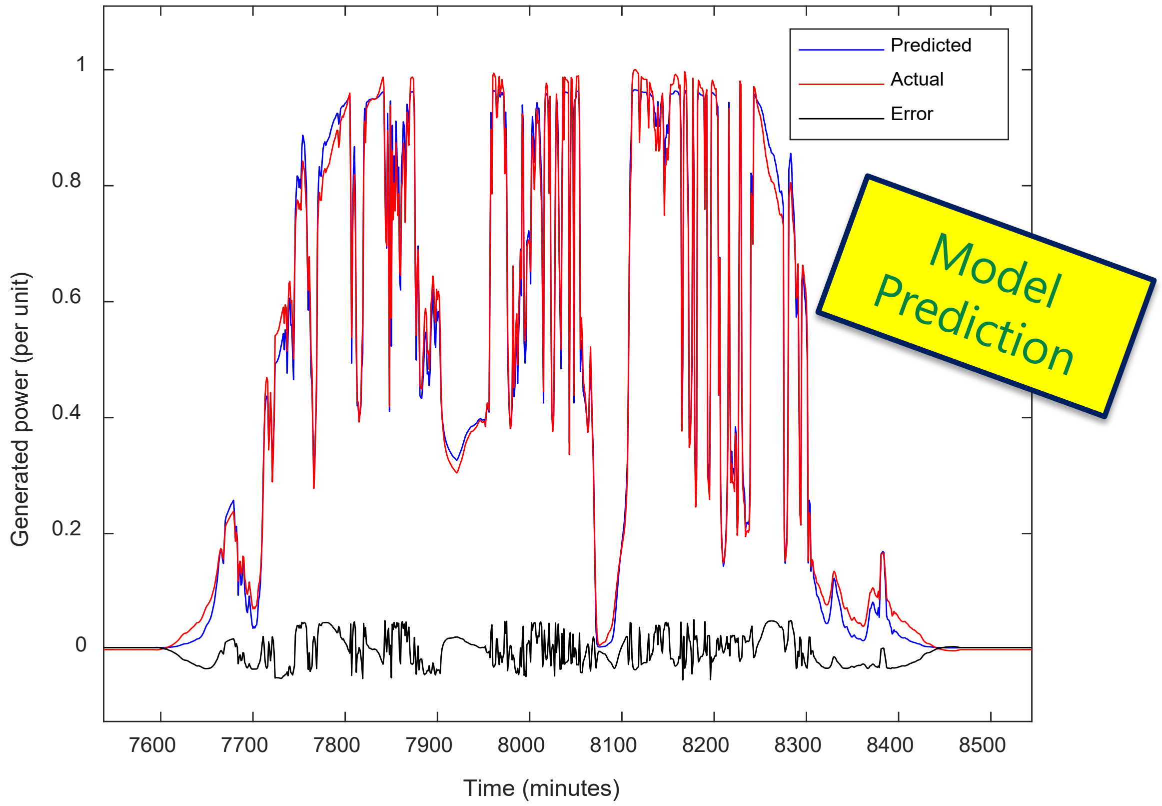
Figure Credit: UDRI

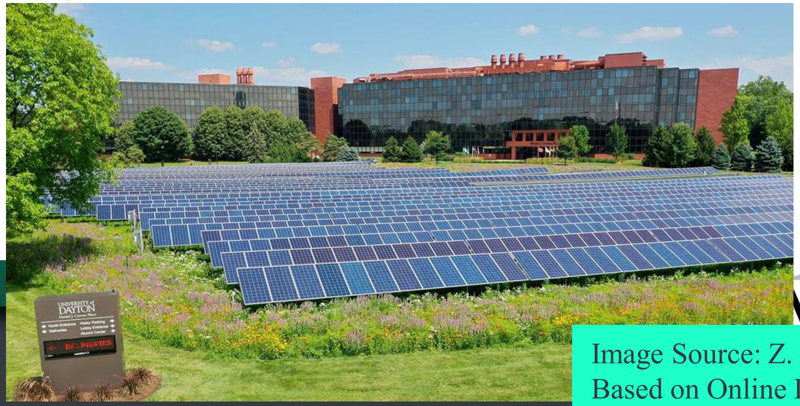
LSTM Neural Network Prediction Model in Operation

Loss function (training error) in each epoch



Predicted and actual power production on August 6, 2019





Solar power installation on UDRI campus

Image Source: Z. Jiang and K. Beigh. "Data-Driven Modeling of Dynamic Systems Based on Online Learning," AIAA Propulsion & Energy Forum, August 2021.

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Control Solution Based on ML and Model Predictive Control

AI-Driven Predictive Control

- Model predictive control
- ML at runtime

Value Proposition

- Increased efficiency
- Improved resiliency
- Enhanced stability
- Reduced costs

Advantages

- System-level coordination
- Situational awareness
- Operational constraints
- Optimization

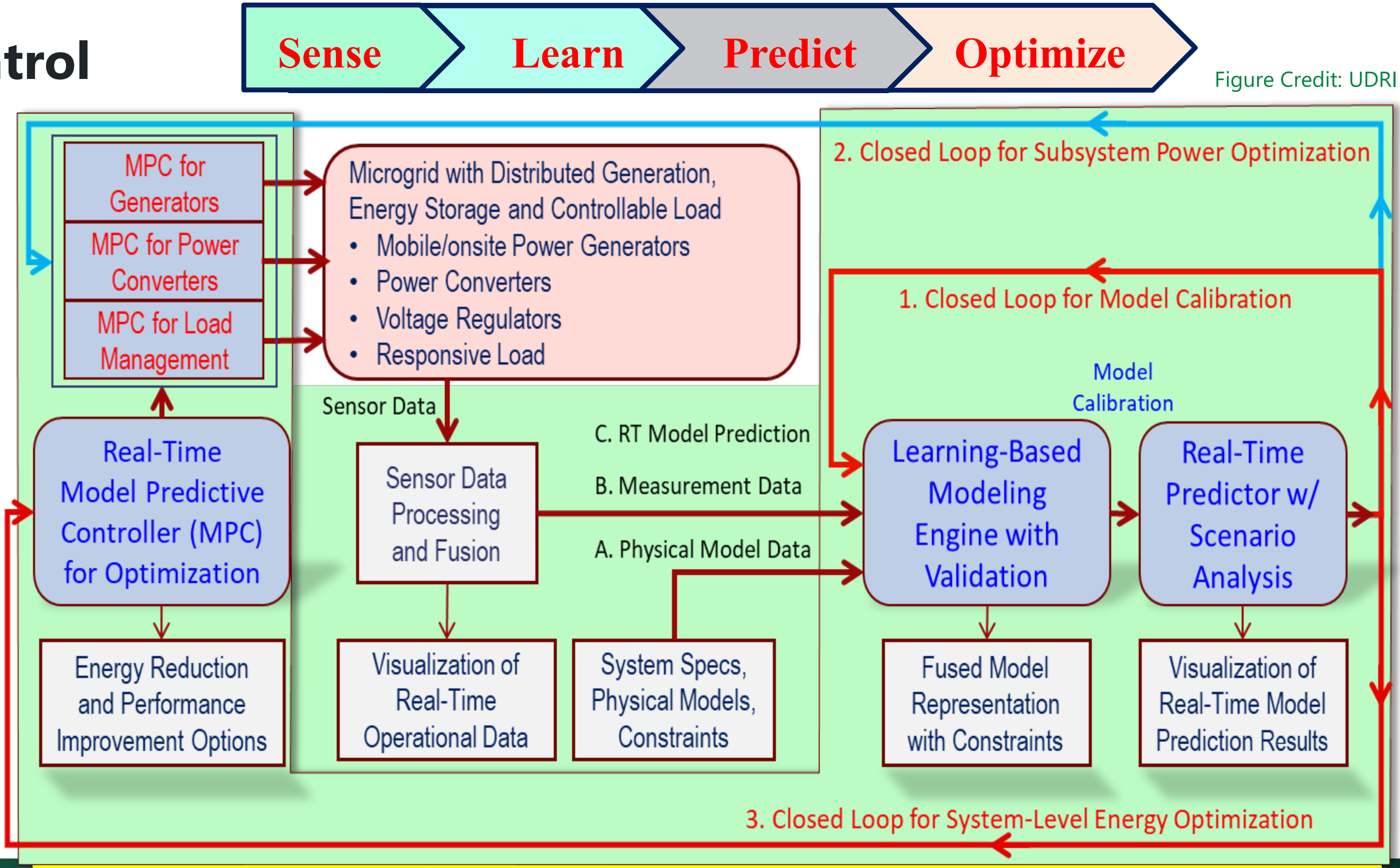

Figure Credit: UDRI

Physics-based artificial intelligence (AI) system that mimics how human intelligence works

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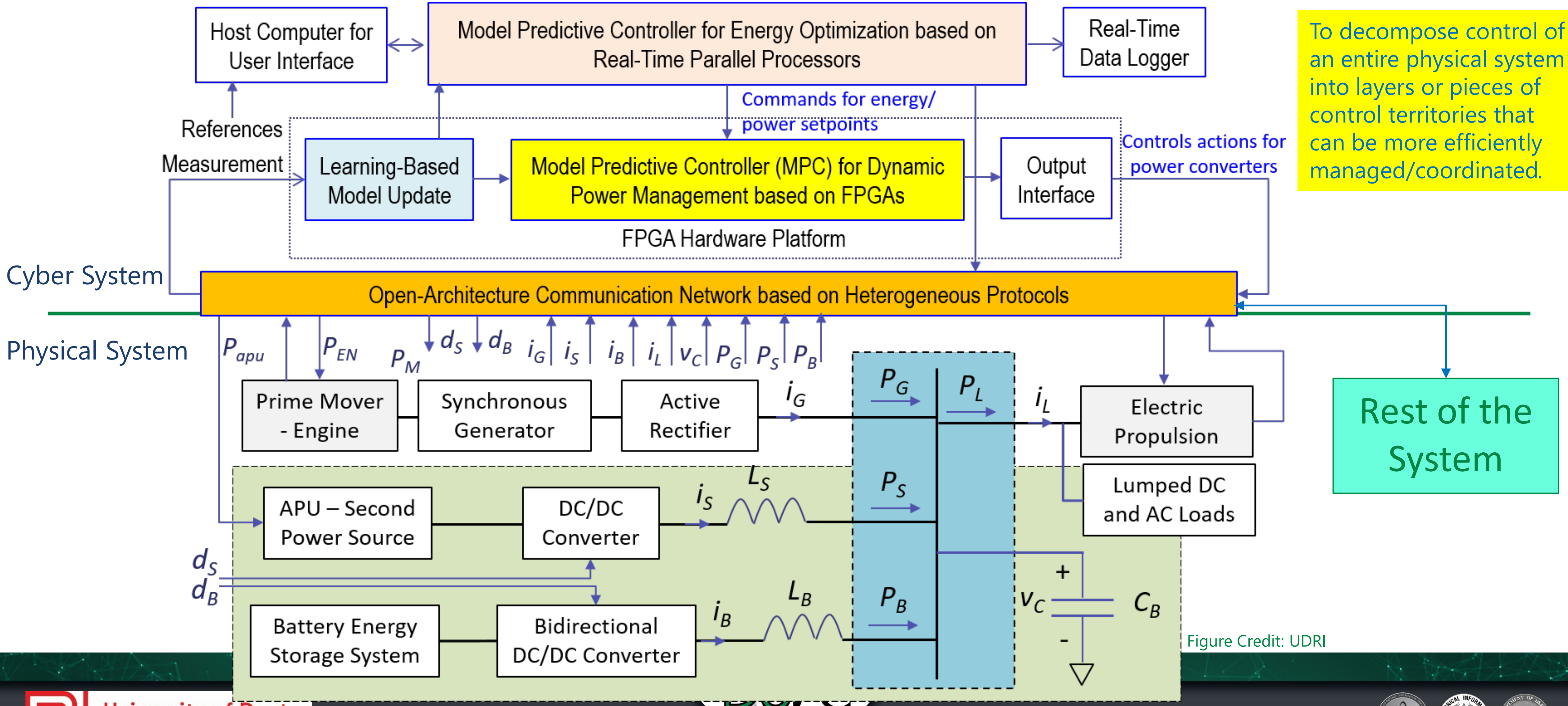
Multilayer Model Predictive Control (MPC) Framework



To decompose control of an entire physical system into layers or pieces of control territories that can be more efficiently managed/coordinated.

Figure Credit: UDRI

Formulation of MPC Scheme (1)

Model Equation $f(X,U)=0, Y=l(X,U)$

$$g(X,U)=\begin{bmatrix} u-u_{max} \\ u_{min}-u \\ x-x_{max} \\ x_{min}-x \end{bmatrix} \leq 0 \qquad (1)$$

Discretization
$$\begin{cases} X(k+1)=A_k X(k)+B_k U(k) \\ Y(k+1)=C_k X(k+1)+D_k U(k) \end{cases} \qquad (2)$$

Objective $\text{Min } \sum_{k=1}^{N_P} C_k(X,U)$ e.g., $C_k(X,U)=k_Y\left(Y_k-Y_{ref}\right)^2+k_U\left(U_k-U_{ref}\right)^2$ (3)

Constraints
$$\begin{cases} h_k(X,U)=A_k X(k)+B_k U(k)-X(k+1)=0 \\ g_k(X,U)+z_k=0 \qquad \text{k} = 1 \text{ to } N_P \end{cases} \qquad (4)$$

Lagrangian
$$\mathcal{L}\,(U,X,\lambda,z,\mu)=\sum_{k=1}^{N_P} C_k(X,U)+ \sum_{k=1}^{N_C} \lambda_{c,k}^T\left(g_{c,k}(U(k))+z_{c,k}\right)+\sum_{k=1}^{N_P} \lambda_{x,k}^T\left(g_{x,k}(U(k))+z_{x,k}\right)+\mu\cdot\left(\sum_{k=1}^{N_C} ln\left(z_{c,k}\right)+\sum_{k=1}^{N_P} ln\left(z_{x,k}\right)\right) \qquad (5)$$

Formulation of MPC Scheme (2)

Define $\theta = \begin{bmatrix} u \\ \lambda \\ z \end{bmatrix}$. The goal is to find the best vector θ so that the Lagrangian is minimum.

According to the first-order optimality conditions, i.e., Karush–Kuhn–Tucker (KKT) condition,

$$\min \mathcal{L}\,(U, X, \lambda, z, \mu) \quad \Rightarrow \quad \frac{\partial L\,(u,x,\lambda,z,\mu)}{\partial \theta} = 0$$

Nonlinear function of θ

By Newton's method, to find θ,

$$\theta^{\,n+1} = \theta^{\,n} + \square \tag{6}$$

$$J \cdot \Delta\theta = J \begin{bmatrix} \Delta u \\ \Delta\lambda \\ \Delta z \end{bmatrix} = -\phi \quad \Rightarrow \quad \Delta\theta = -J^{-1}\phi \tag{7}$$

where $$\phi = \begin{bmatrix} \nabla_u \mathcal{L} \\ g(u) + z \\ \lambda Z \cdot Z - \mu z \end{bmatrix} \tag{8}$$

$$J = \begin{bmatrix} H_u \mathcal{L} & \nabla_u g(u) & 0 \\ \nabla_u{}^T g(u) & 0 & I \\ 0 & Z \cdot Z & \mu I \end{bmatrix} \tag{9}$$

Gradient Vector

Jacobian Matrix

Z. Jiang and A. Raziei. "Hierarchical Model Predictive Control for Real-Time Energy-Optimized Operation of Aerospace Systems," AIAA/IEEE EATS Symposium, August 2019.

Operation of Two-Layer MPC in an Example Power System

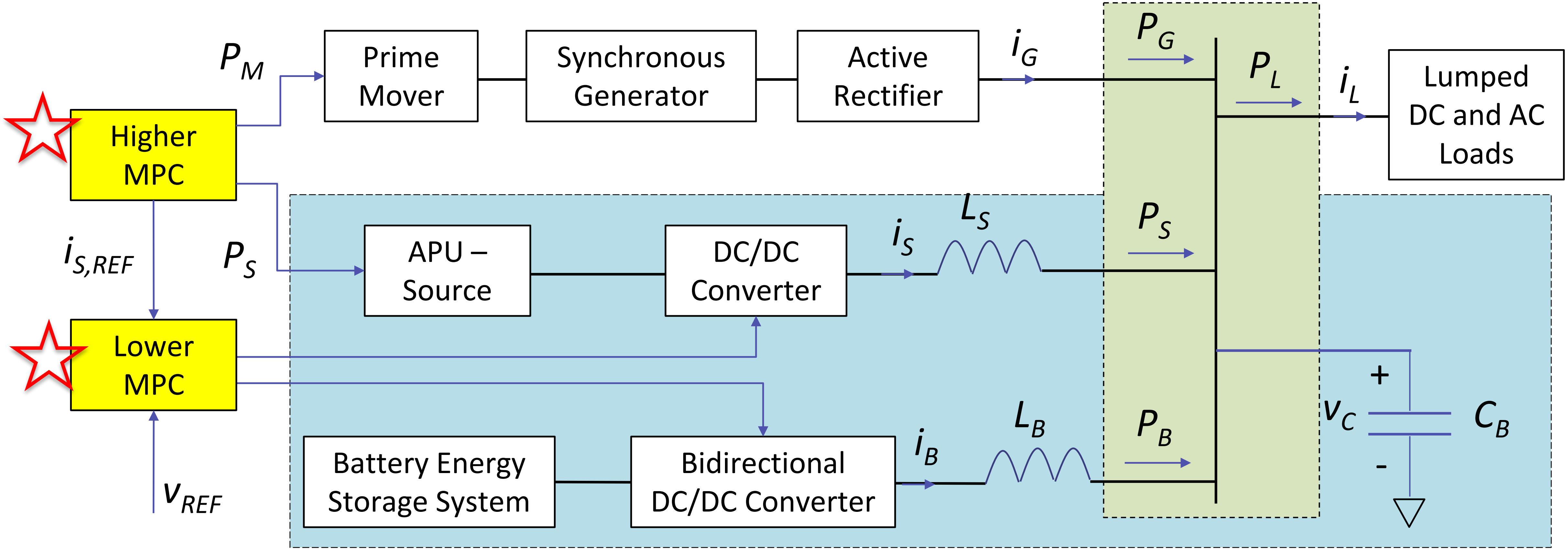


Figure Credit: UDRI

Hierarchical MPC decouples system-wide energy optimization (higher-level MPC) from fast power management (lower-level MPC) in a synergistical manner.

Higher-Level MPC

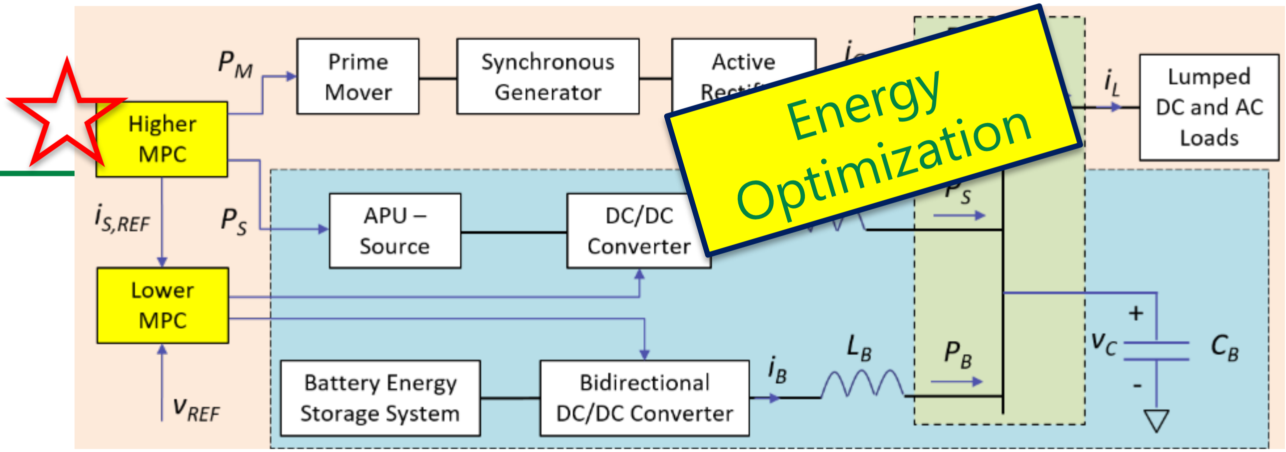


Figure Credit: UDRI

Model Equation

$$P_B(k) = P_L(k) - P_G(k) - P_S(k)$$

$$E_B(k) = E_0 - T_c \sum_{j=1}^{k} P_B(j)$$

$$\frac{dP_G}{dt} = \frac{1}{T_G}(P_M - P_G) \xrightarrow{\text{Discretization}} P_G(k) = c_1 P_M(k) + c_2 P_G(k-1)$$

Objective $min\ C = \sum_{n=1}^{N_p} \left[w_G (P_G(k) - P_e)^2 + w_B P_B(k)^2 + w_S P_S(k)^2 + w_E \left(E_B(k) - E_d(k)\right)^2 \right]$

Constraints

$$0 \le P_M(k) \le P_{M,max} \qquad 0 \le P_S(k) \le P_{S,max}$$ Control

$$-\Delta P_{M,m} \le \Delta P_M(k) \le \Delta P_{M,m} \quad -\Delta P_{S,m} \le \Delta P_S(k) \le \Delta P_{S,m}$$ Rate of change

$$E_{min} \le E_B(k) \le E_{max}$$ State

Lower-Level MPC

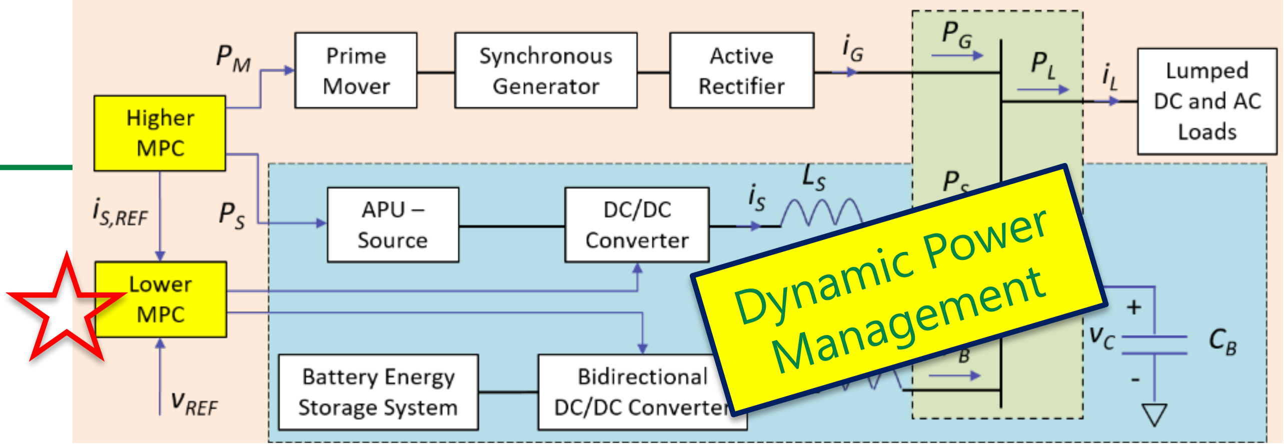


Figure Credit: UDRI

Model Equation

$$\begin{cases} \dfrac{di_S}{dt} = \dfrac{1}{L_{fc}}\left(d_S v_S - R_1 i_S - v_C\right) \\ \dfrac{di_B}{dt} = \dfrac{1}{L_B}\left(d_B v_B - R_2 i_B - v_C\right) \\ \dfrac{dv_C}{dt} = \dfrac{1}{C_B}\left(i_G + i_{fc} + i_B - i_L\right) \end{cases}$$

Discretization

$$\begin{bmatrix} i_S(k+1) \\ i_B(k+1) \\ v_B(k+1) \end{bmatrix} = A_k \begin{bmatrix} i_S(k) \\ i_B(k) \\ v_B(k) \end{bmatrix} + B_k \begin{bmatrix} d_S(k) \\ d_B(k) \end{bmatrix}$$

Objective

$$\min C = \Sigma_{k=1}^{Np}\left(w_i\left(i_S(k) - i_{S,REF}(k)\right)^2 + w_v\left(v_B(k) - v_{REF}(k)\right)^2\right)$$

Constraints

$$\begin{cases} 0 \leq d_S(k) \leq 1 \qquad 0 \leq d_B(k) \leq 1 & \text{Control} \\ -D \leq \Delta d_S(k) \leq D \qquad -\mathrm{D} \leq \Delta d_B(k) \leq \mathrm{D} & \text{Rate of change} \\ i_{B,min} \leq i_B(k) \leq i_{B,max} & \text{State} \end{cases}$$

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Capabilities Developed

Modeling, Simulation, and Optimization Capabilities

- Data-driven, ML-based modeling ability for energy systems
  - With varying temporal, probabilistic, and categorical characteristics
- Real-time prediction capability considering dynamics, uncertainty, and causal relationships
- Real-time operation optimization functionality
- Real-time hardware-in-the-loop (HIL) simulation
  - With hybrid physics/learning-based models

Functionalities in Power Systems

- Learn/validate a compact representation of complex components from offline operational data
- Update/calibrate the model with online operational data
- Learn uncertainty in model parameters/dynamics and consider contingencies in prediction
- Accelerate the real-time simulation and HIL testing with compact learning-based models

Applications of ML and Predictive Analytics in Naval Energy Autonomy

- Utility Planning – Predictive Analytics
  - Renewable energy production prediction
  - Load profile forecasting
  - Energy efficiency prediction
- Facility Management
  - Energy management for buildings or vehicles
  - Digital twin for test facilities
  - Predictive maintenance
- Microgrid Applications
  - Military microgrids
  - Microgrid test bed
- Shipboard Power Systems
- Naval Aviation Operational Energy

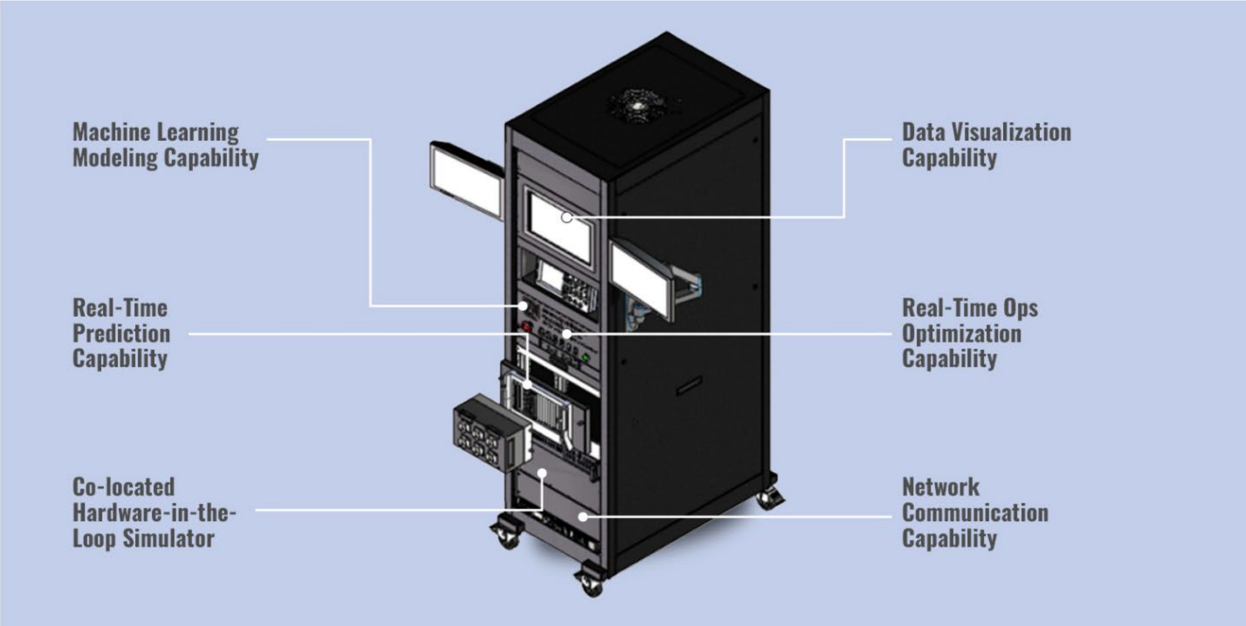


Figure Cerdit: Z. Jiang, S. C. Miller, and D. Dunn, Adapted From a Concept Design Art Image Codesigned by Advint LLC

To Next 3 Slides

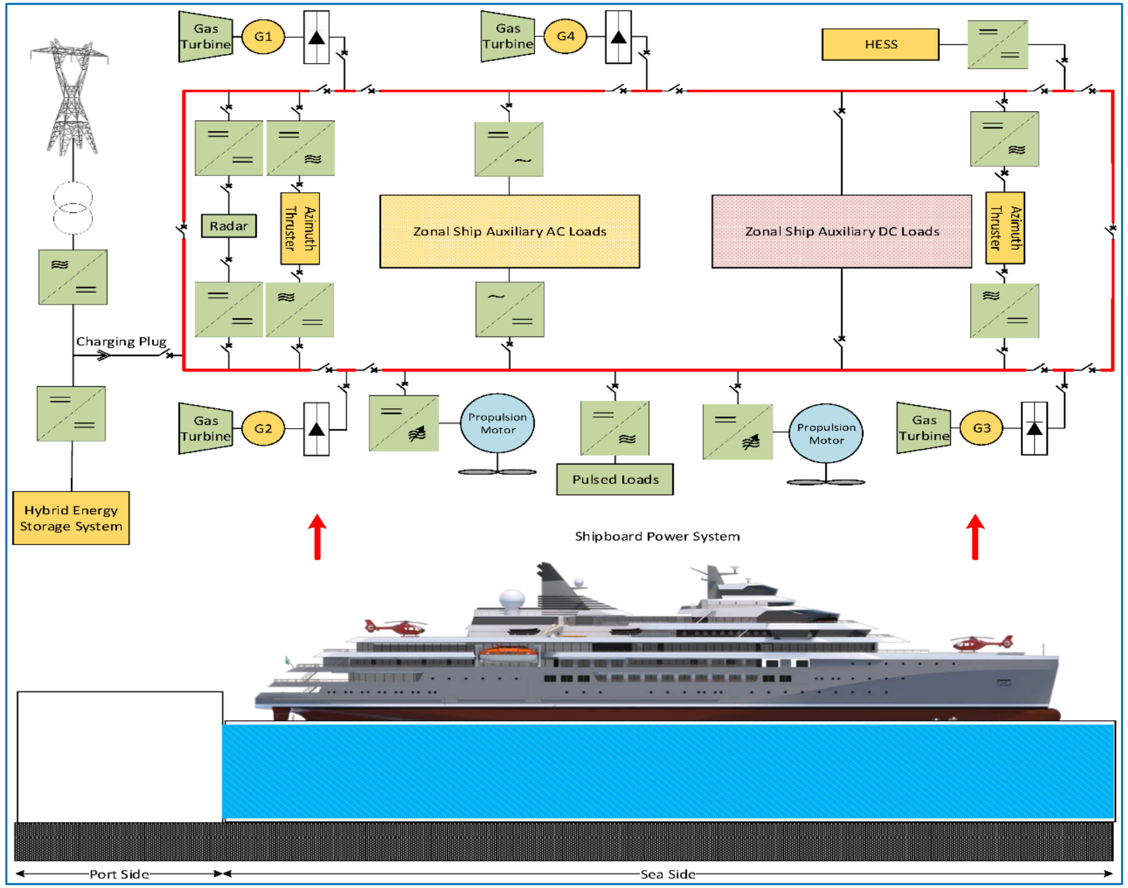
Microgrid Applications

- Data-Driven, ML-Based Modeling
- Real-time Prediction Capability
  - Renewable production
  - Load profiles and demand prediction
  - Utility price
- Real-time Operation Optimization
  - Generation costs
  - Power delivery losses
  - Energy reserve and stability
- Real-Time HIL Simulation
  - Power availability
  - Resilience
  - Power quality
  - Protection

Figure Credit: NAVFAC EXWC

Shipboard Power Systems

- Widely applicable to shipboard power systems, especially electrified warships, due to versatile energy flows and flexible control opportunities.
- Involving complex components, such as prime movers, generators, energy storage, distribution circuits, and sophisticated loads (directed energy, high-power radar), with operational constraints.
- Optimized operation of propulsion/power systems reduces system weight/size and improves fuel consumption and operation costs of military systems where power is used.
- AI-driven digital engineering methods and tools can reduce development, acquisition, sustainment, or total ownership costs of fielded systems.

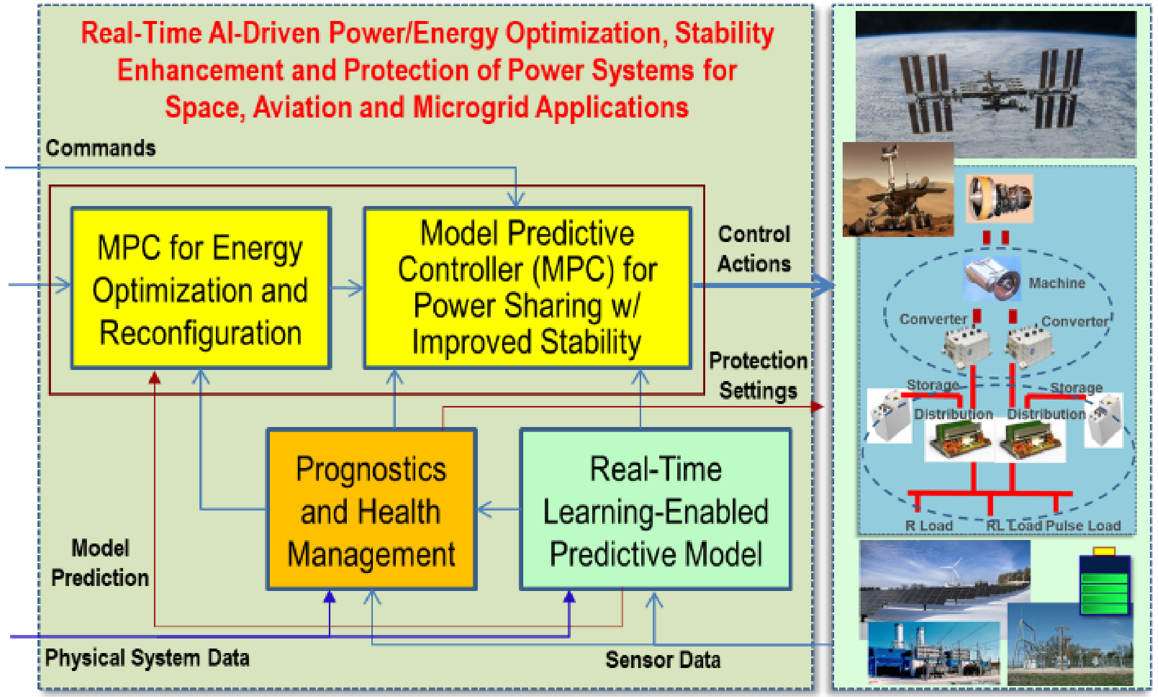


https://www.mdpi.com/1996-1073/11/12/3492

M. U. Mutarraf, Y. Terriche, K. A. K. Niazi, J. C. Vasquez, and J. M. Guerrero. "Energy Storage Systems for Shipboard Microgrids—A Review," *Energies* **2018**, *11*, 3492, https://doi.org/10.3390/en11123492

Naval Aviation Operational Energy

- Naval Aviation Operational Energy systems also benefit from ML and model predictive control:
  - Safety, weight, size, maneuverability, and agility are high-priority features.
- Desired advantages include:
  - Predictive optimization in real-time.
  - Proactive actions prior to operational changes.
  - Meeting economic, operational, or safety constraints.
- Total operation costs considerably reduced by:
  - Maintaining optimal dynamic energy reserve.
  - Decreasing energy losses.
  - Optimizing mission profiles.
  - Benefiting from automated operation.



Z. Jiang, H. Huang, and S. Hossain. "A High-Fidelity, Low-Latency, FPGA-Based, Real-Time Development Platform for Advanced Aircraft Power Systems," *AIAA/IEEE Electric Aircraft Technologies Symposium (EATS)*, July 2018.

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Anticipated Benefits

- Improve military capabilities due to enhanced power and energy performances enabled by AI technologies.
  - Captures energy system dynamics, degradation, and uncertainty into the model in a data-driven manner, which would be difficult to capture or otherwise unavailable.
  - Provides mechanisms for online continuous model learning/validation.
  - Enables fast (real-time) HIL simulation to gain insights into the system behaviors, greatly reducing the design and development time/cost of military energy systems.
  - Empowers an integrated control platform to proactively manage energy flows among subsystems to achieve better efficiency/performance and improve autonomy.
- Validation needed in realistic application systems may include energy savings, cost savings, and power quality and resilience improvements.

Recommendations for Future Development

- Demonstrate prototypes and validate their advantages.
  - Validate the effectiveness and accuracy of ML algorithms and models for forecasting generator fuel efficiency and load profiles based on operational data.
  - Conduct power HIL testing of a prototype AI-driven, predictive optimizer to evaluate the effectiveness of learning-based prediction and model-based predictive optimization functionalities in a realistic microgrid.
  - Perform field demonstration at a U.S. Department of Defense (DoD) installation site and validate the performance of the ML-driven predictive optimizer prototype so the technology can be transitioned to the field faster.
- For future development, ML can also be used in the test/evaluation stage.
  - Screen and down select test scenarios faster.
  - Automatically analyze test data to determine correlations in system parameters or conditions.
  - Generate candidates of best design options.
  - Diagnosis/prognosis and preventive maintenance.

Summary

- Emerging applications of AI and ML technologies in naval energy autonomy and digital transformation
- Potential impact on operational autonomy
- Benefits across the DoD's power and energy ecosystems
- Impact of AI and ML techniques will be multiplied when combined with other emerging digital technologies such as:
  - Sensor fusion through universal learning
  - Predictive analytics by deep-learning and data science methods
  - Computational cognitive science
  - Optimization techniques
  - Quantum computing

Questions and Discussions

Thank you for your attention!