Cyber Risk Assessment of Traditional and Automated Machine Learning in Autonomous Control Systems

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Background & Purpose

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Background

- Advanced reactor designs include semi-autonomous or fully autonomous control systems (ACS).
    - Reduces overhead operations and maintenance cost [1].
    - Allows for online monitoring and diagnostics.
    - Makes minute adjustments to controls without human intervention.
- Machine learning (ML) based digital twins (DTs) are a growing consideration for ACS implementations.
    - Globally, the energy sector's use of ML is expected to grow by 29.88% between 2022 and 2029– equivalent to $37.4 billion [2].

Purpose

- This presentation is meant to highlight methodology and thought process behind determining cyber-risks and attack threats.
- More specifically how you (as nuclear engineers and medical physicists) can design systems with cybersecurity in mind.
- A simplified cyber-risk risk assessment of traditional and automated ML (AutoML) for ACS is shown in this presentation.

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Motivation

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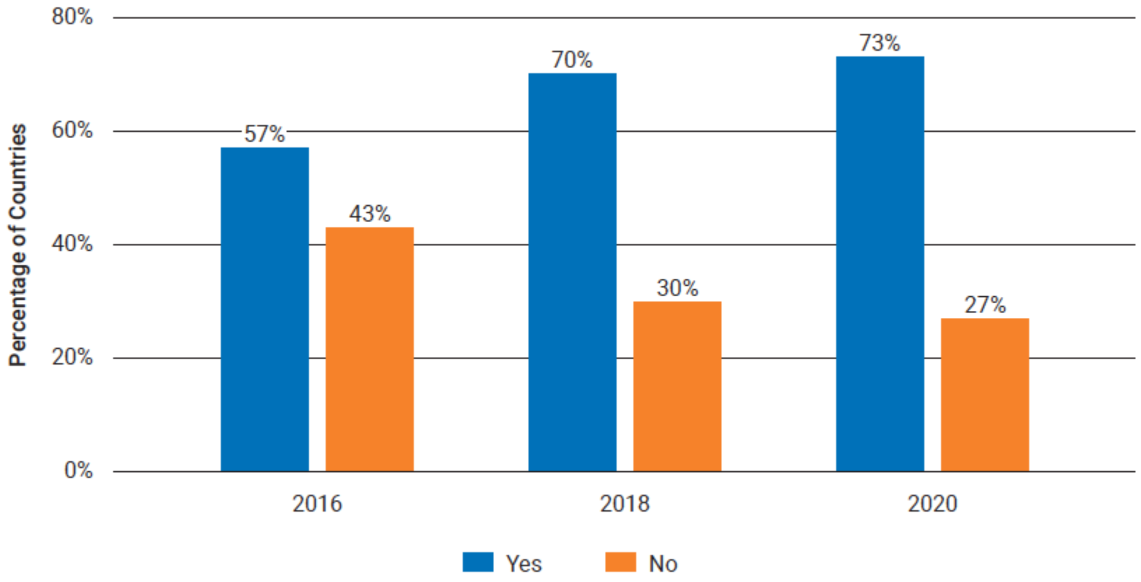
Percentage of Countries that Require Nuclear Facilities to Protect Against a Cyber Attack



[3]

- **Cybersecurity** should be at the forefront of ACS development to ensure safe and reliable operations.
- According to the **Nuclear Security Index (NTI)**, cybersecurity is becoming more important for protecting nuclear facilities [3].
- **10 CFR 73.54:** ensure that “digital computer and communication systems and networks are adequately protected against cyber attacks, up to and including the design basis threat as described in § 73.1” [4].
- Previous work **by Idaho National Laboratory (INL)** includes a cyber-risk assessment framework for ACS [5].

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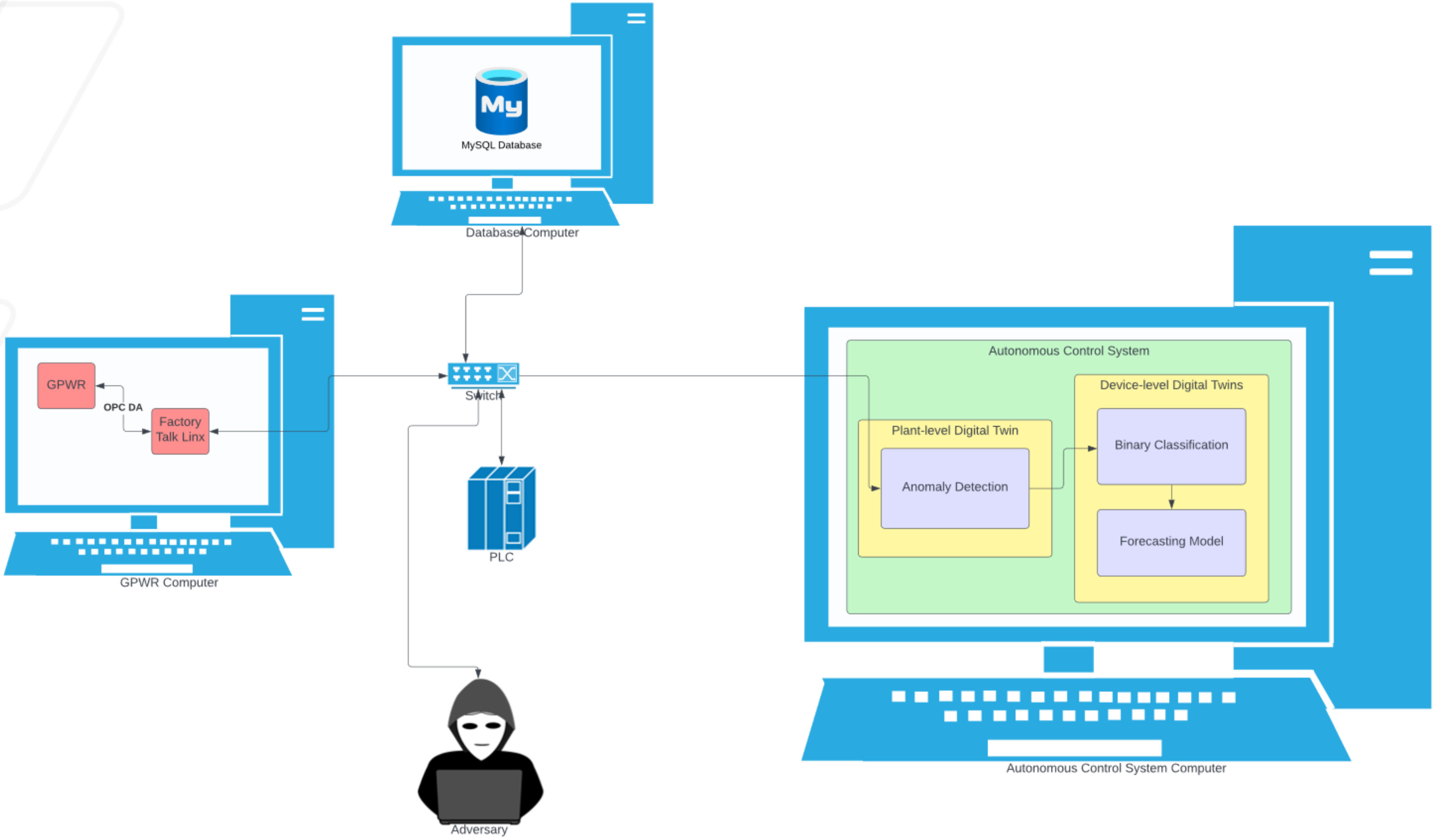
Cyber-Physical Testbed Development



- **Cyber-Physical Testbed** includes the Generic Pressurized Water Reactor (GPWR) [6] and FactoryTalk Linx [7] to communicate to a programmable logic controller (PLC). The PLC communicates GPWR values to the ACS.
- **ACS** consists of a plant-level DTs to determine if the reactor is in an abnormal state and two device-level DTs to determine if the steam generator is undergoing a transient and forecasting steam generator flow rate.

In this scenario, the reactor is “air-gapped” from unsecured networks, meaning the adversary must have physical access to the system to launch attacks.

Data Collection and Storage

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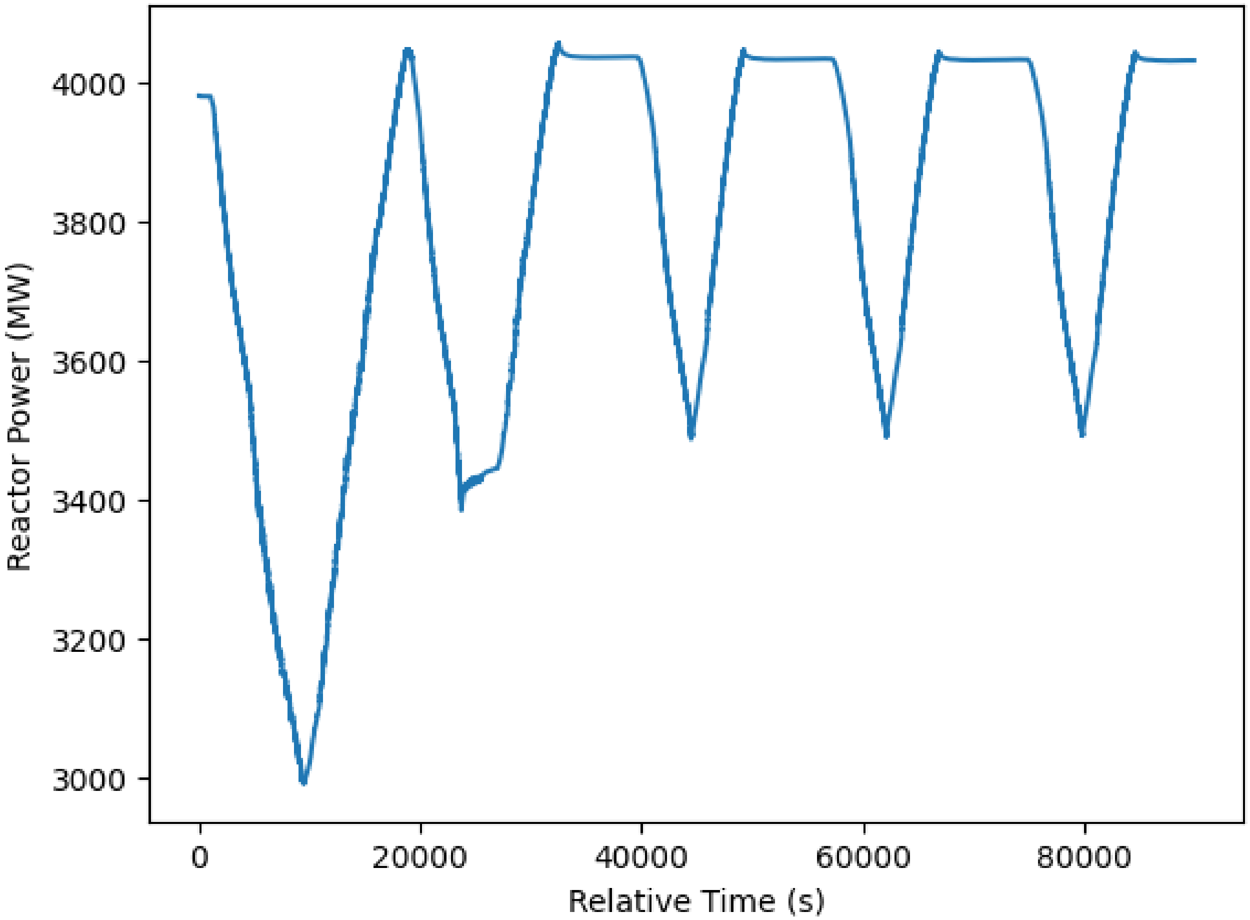
Transient and Steady State Reactor Power Training Scenario



- On **training**, the ACS queries a separate system **MySQL database** [8] to obtain the training dataset for each DT.
  - Training data was obtained assuming a beginning of life (BOL) scenario.
    - Power was ramping over 420 minutes shown in figure.
    - The MySQL database pulled 70 variables related to steam generator 1 and overall plant-health ever 50 ms.
    - Training data was split into 70% training 30% validation.
- **Real-time data** is ingested by a **Pylogix** [9] call on the ACS following training to convert PLC CIP packets into usable dataframes.
  - Real-time data was 100% power BOL conditions to determine cyber-attack effects.

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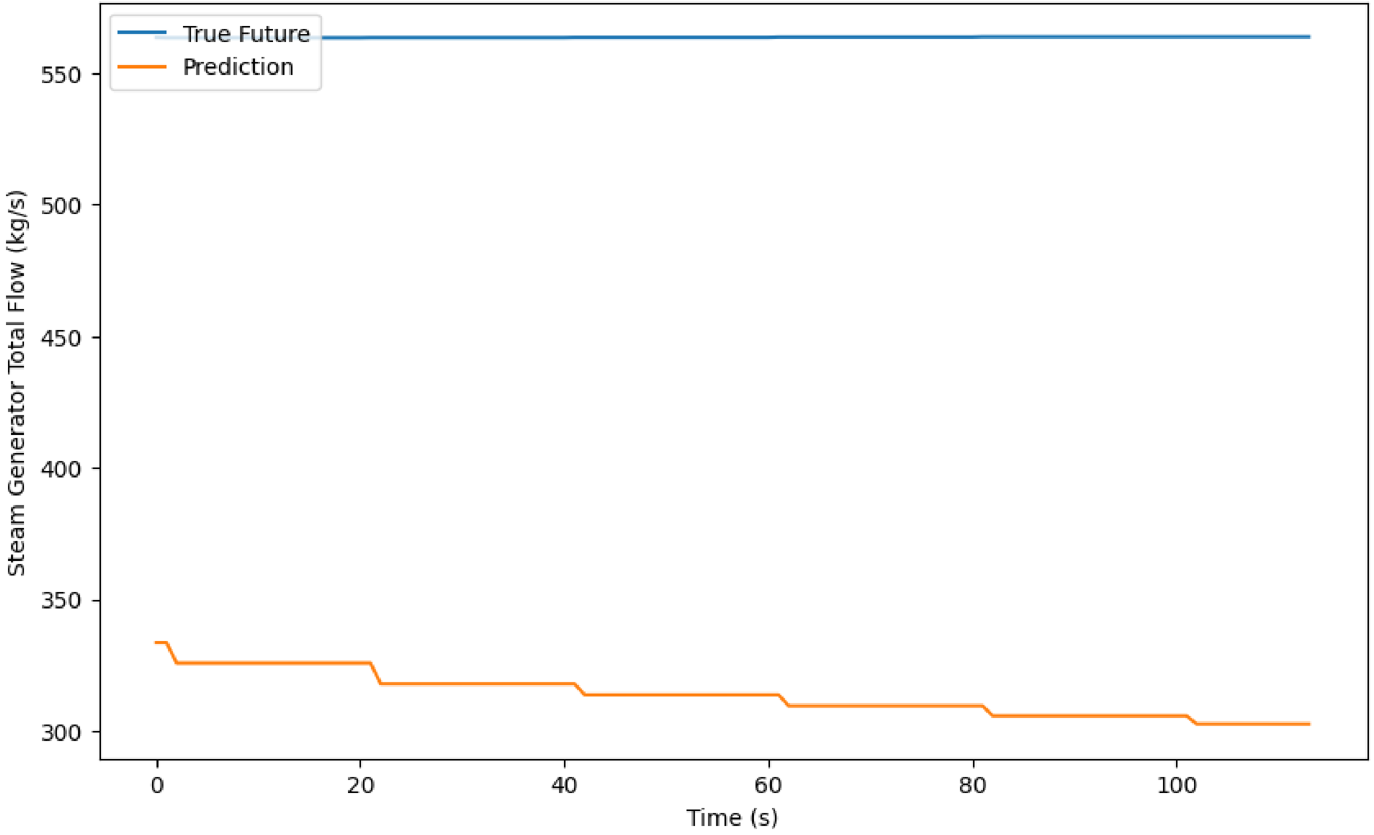
Unified Kill Chain

[10]

False Data Injections Attack Process

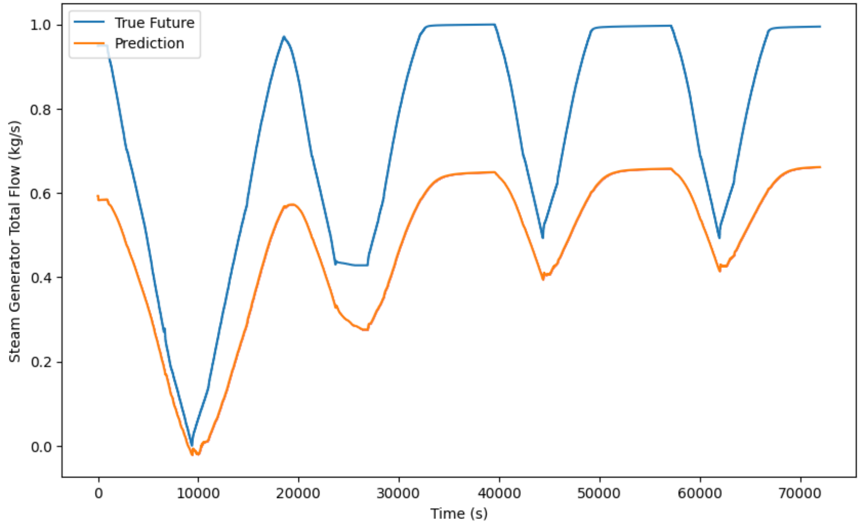
Traditional ML forecasted steam generator 1 flow after false data injection on real-time data



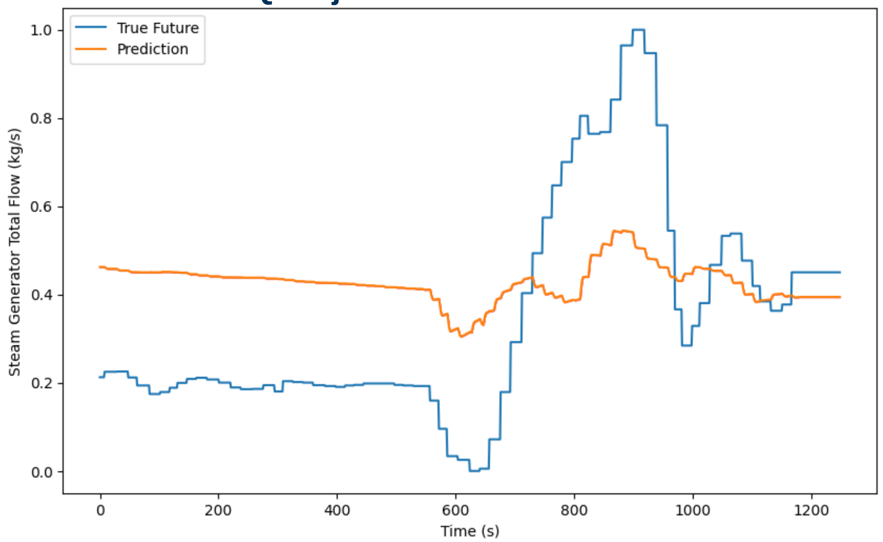
- PLCs use **Common Industrial Protocol (CIP)** [11] to communicate.
- **Initial Foothold:** Use Wireshark [12] while connected to internal network to filter out User Diagram Protocol (UDP) calls
    - Determine the PLC, GPWR, and ACS as well as PLC manufacturer.
- **Network Propagation:** Conduct a man-in-the-middle (MITM) attack using Ettercap [13] to address resolution protocol (ARP) poison the PLC and ACS.
- **Action on Objectives:** Collect and decrypt CIP packets to determine highly correlated GPWR tag values by looking up CIP tables.
    - Inject modified CIP packets using Scapy [14].
        - Steam generator 1 control valve positioning was reduced from nominal 50% open to 30% open.

SQL Injection Process

AutoML forecasted steam generator 1 flow after SQL injection on training data



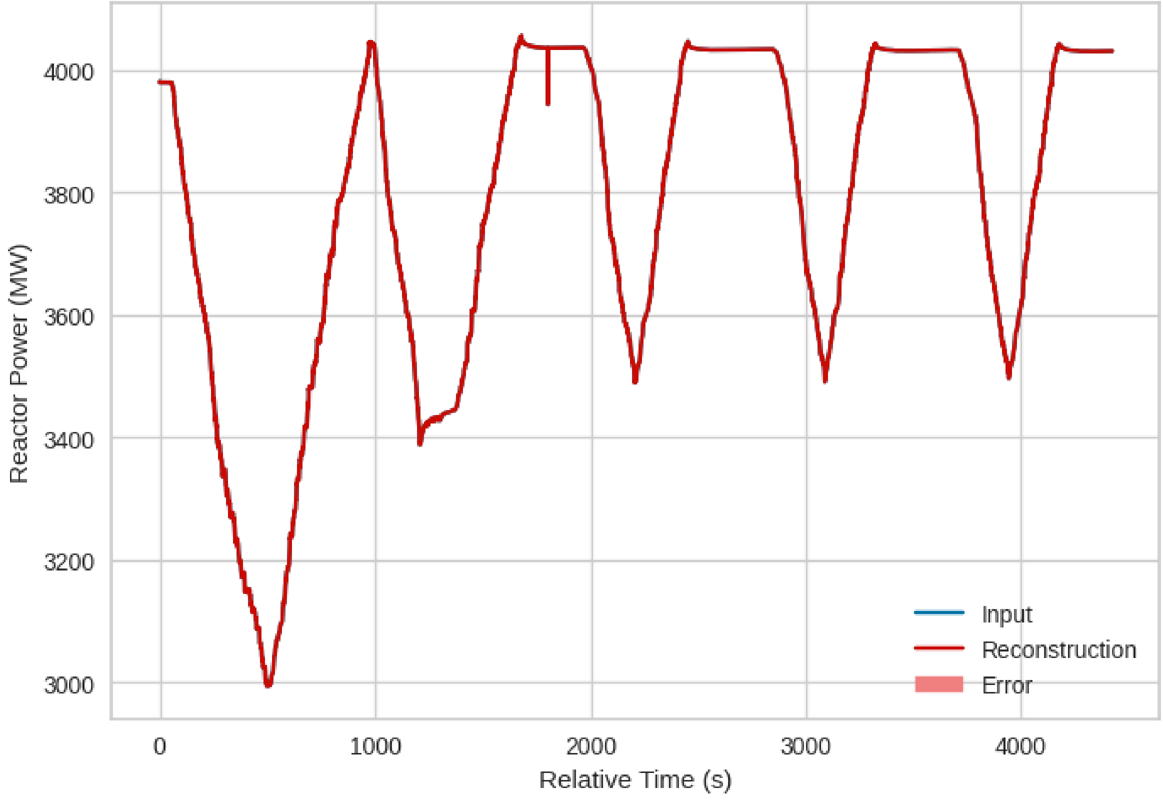
AutoML forecasted steam generator 1 flow after SQL injection on real-time data



- **Initial Foothold:** Use Wireshark to determine MySQL server by scanning for port 3306.
- **Network Propagation:** Use Metasploit [15] for a brute force dictionary attack to guess user password and login.
  - Otherwise, kill the server using a denial of service (DoS) attack using Hping3 [16], starting the server again using --skip-grant-tables to bypass authentication.
- **Action on Objectives:** Monitor SQL logs to determine what the autonomous control system is trained on.
  - Select and modify the highest correlated tags using SQL commands.
    - Steam generator 1 feedwater in was changed to allow be consistently the maximum flow rate.

Adversarial Hyperparameter/Weight Tuning

AutoML Reactor Power Training Reconstruction after Adversarial Hyperparameter Tuning



- Model **hyperparameters and weights** are typically saved periodically during the training process and can be accessed through the **Secure Shell protocol (SSH)** or **MySQL queries**.
- **Initial Foothold:** Use Wireshark to scan for port 22 for SSH or port 3306 for MySQL to determine the ACS.
- **Network Propagation:** Use Metasploit for a brute force dictionary attack on SSH or MySQL.
  - Otherwise, generate and send malicious code to user to add Secure Socket Layer (SSL) public keys for SSH or MySQL.
  - If choosing MySQL, a user defined function (UDF) will have to be created (if not preexisting) and executed to allow for Bash commands in MySQL.
- **Action on Objectives:** Decrypt files using the Python Joblib [17] library and modify the hyperparameters/weights.
  - Hyperparameters/weights were tuned to make 50% of the training dataset appear anomalous as opposed to the normal 1.7%.

Qualitative Cyber-Risk Assessment

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Traditional ML Cyber-Risk Matrix

Likelihood \ Impact	Low Impact	Medium Impact	High Impact
Low Likelihood	Hyperparameter Tuning via Malware	SQL Injections via authentication bypass	Hyperparameter /Weight Tuning via preexisting UDF
Medium Likelihood	-	Weight Tuning via Malware	-
High Likelihood	-	SQL Injections via Brute force Login	False Data Injections via CIP injections

AutoML Cyber-Risk Matrix

Likelihood \ Impact	Low Impact	Medium Impact	High Impact
Low Likelihood	Hyperparameter /Weight Tuning via preexisting UDF	Hyperparameter Tuning via Malware	SQL Injections via authentication bypass
Medium Likelihood	-	Weight Tuning via Malware	-
High Likelihood	False Data Injections via CIP injections	-	SQL Injections via Brute force Login

- Likelihood is qualified by complexity and amount of insider knowledge to complete the attack.
- Impact is qualified by the change in the model’s accuracy metrics following the attack.
- As shown, the likelihood of each of the attacks across both matrices stays the same, but the impact changes.

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Risk Mitigation Strategies

- Mitigation strategies to reduce “red zone” risk
- Protecting ML models against SQL injections via brute force login:
  - Disable legacy authentication (password authentication) [18].
  - Set a maximum number of tries and sessions before being locked out of MySQL.
  - Set up a MySQL monitoring system to monitor for unauthorized or abnormal changes to training data.
- Protecting ML models against false data injections via CIP injections:
  - Implement a deep packet inspection (DPI) system and firewall for ethernet connections [19].
  - Use built in security functionality to encrypt CIP packets [20].

Summary & Future Work

Summary

- AutoML and traditional ML models are inherently tied for cyber-risk when examined in terms of likelihood and impact of false data injection, SQL injection, and adversarial hyperparameter/weight tuning.
- Traditional ML is more impacted by false data injections whereas AutoML is more impacted by SQL injections.
- To mitigate the risk of cyber attacks, strategies were presented for ACS system designers to implement during the development phase.

Future Work

- Develop more attack scenarios to fully encapsulate cyber-risk of traditional and AutoML.
- Determine if cyber-risk is different across different AutoML packages.
- Develop higher fidelity testbed to simulate more reactor subsystems and analyze the impact of cyber attacks on coupled devices.
- Implement and test the effects of proposed risk mitigation techniques.

Acknowledgements

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References

[1] R. T. Wood, B. R. Upadhyaya and D. C. Floyd, "An Autonomous Control Framework for Advanced Reactors," Nuclear Engineering and Technology, vol. 49, no. 5, pp. 869-904, 2017.

[2] Maximize Market Research, "AI in Energy Market: AI is accelerating innovation in the energy sector as it continues to change the way of organizations and industries operate," December 2022. [Online]. Available: https://www.maximizemarketresearch.com/market-report/ai-in-energy-market/166396/#details. [Accessed 27 February 2023].

[3] Strengthen Cybersecurity at Nuclear Facilities - NTI Nuclear Security Index. (2020, July 22). NTI Nuclear Security Index. https://www.ntiindex.org/recommendation/recommendation-4-2/

[4] § 73.54 Protection of digital computer and communication systems and networks. (n.d.). NRC Web. https://www.nrc.gov/reading-rm/doc-collections/cfr/part073/part073-0054.html

[5] C. Spirito, P. Lamb, S. Aghara, C. Duffley, J. Strandburg, J. Coble and F. Zhang, "Cyber Threat Assessment for Autonomous and Remote Operations for Advanced Reactors," Idaho National Laboratory, Idaho Falls, 2021

[6] Western Services Corportation, "3KEYMASTER™ Generic Pressurized Water Reactor," Western Services Corportation.

[7] Rockwell Automation, "FactoryTalk Linx," Rockwell Automation, [Online]. Available: https://www.rockwellautomation.com/en-us/products/software/factorytalk/operationsuite/communications/linx.html. [Accessed 19 February 2023].

[8] Oracle, "MySQL," Oracle, 2023. [Online]. Available: https://www.mysql.com/. [Accessed 19 February 2023].

[9] D. Roeder, "Pylogix," GitHub, 2023. [Online]. Available: https://github.com/dmroeder/pylogix. [Accessed 19 February 2023].

[10] Pols, P. (n.d.). Unified Kill Chain: Raising Resilience Against Cyber Attacks. https://www.unifiedkillchain.com/

[11] Common Industrial Protocol (CIPTM) | ODVA Technologies. (n.d.). ODVA. https://www.odva.org/technology-standards/key-technologies/common-industrial-protocol-cip/

[12] Orebaugh, A., Ramirez, G., Beale, J., & Wright, J. D. (2007). Wireshark & Ethereal Network Protocol Analyzer Toolkit. https://ci.nii.ac.jp/ncid/BB01482189

[13] A. Ornaghi and M. Valleri, "Ettercap," [Online]. Available: https://www.ettercap-project.org/about.html. [Accessed 19 February 2023].

[14] S, R. R., Rohith, R., Moharir, M., & Shobha, G. (2018). SCAPY- A powerful interactive packet manipulation program. https://doi.org/10.1109/icnews.2018.8903954

[15] Maynor, D., & Wilhelm, T. (2007). Metasploit Toolkit for Penetration Testing, Exploit Development, and Vulnerability Research. In Elsevier eBooks. https://doi.org/10.1016/b978-1-59749-074-0.x5000-4

[16] Liang, L., Zheng, K., Sheng, Q., & Huang, X. (2016). A Denial of Service Attack Method for an IoT System. https://doi.org/10.1109/itme.2016.0087

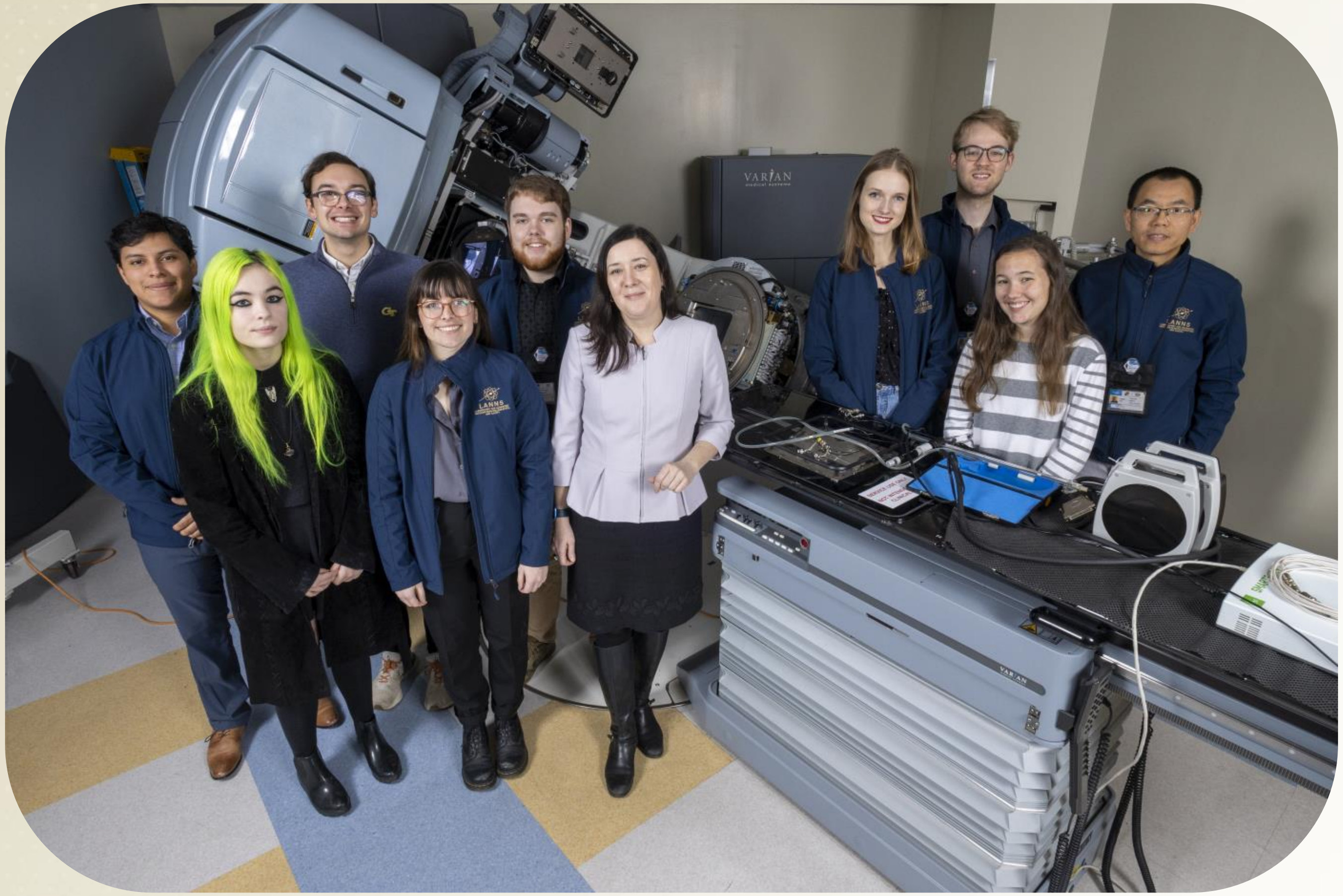
[17] PyCaret Team, "PyCaret Documentation," GitHub, 2023. [Online]. Available: https://github.com/pycaret/pycaret. [Accessed 19 February 2023].

[18] Microsoft, "Securing SQL Server," Microsoft, 17 February 2023. [Online]. Available: https://learn.microsoft.com/en-us/sql/relational-databases/security/securing-sql-server?view=sql-server-ver16. [Accessed 19 February 2023].

[19] Massachusetts Institute of Technology Review Insights, "Best practices for bolstering machine learning security," Massachusetts Institute of Technology, 14 November 2022. [Online]. Available: https://www.technologyreview.com/2022/11/14/1062881/best-practices-for-bolstering-machine-learning-security/. [Accessed 19 February 2023].

[20] Rockwell Automation, "ControlLogix 5580 and GuardLogix 5580 Controllers," Rockwell Automation, 2023. [Online]. Available: https://www.rockwellautomation.com/en-us/support/documentation/technical/programmable-controllers/controllogix-and-guardlogix-control-systems.html. [Accessed 19 February 2023].

Thank you



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