

EUROPEAN SPALLATION SOURCE



Student projects in ML at ESS

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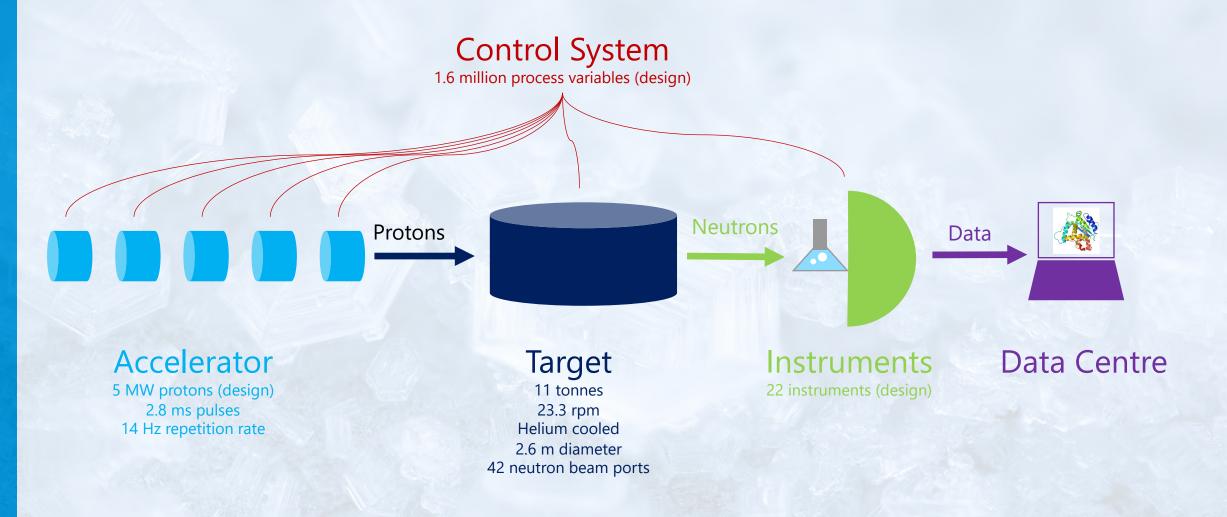






The ESS Machine





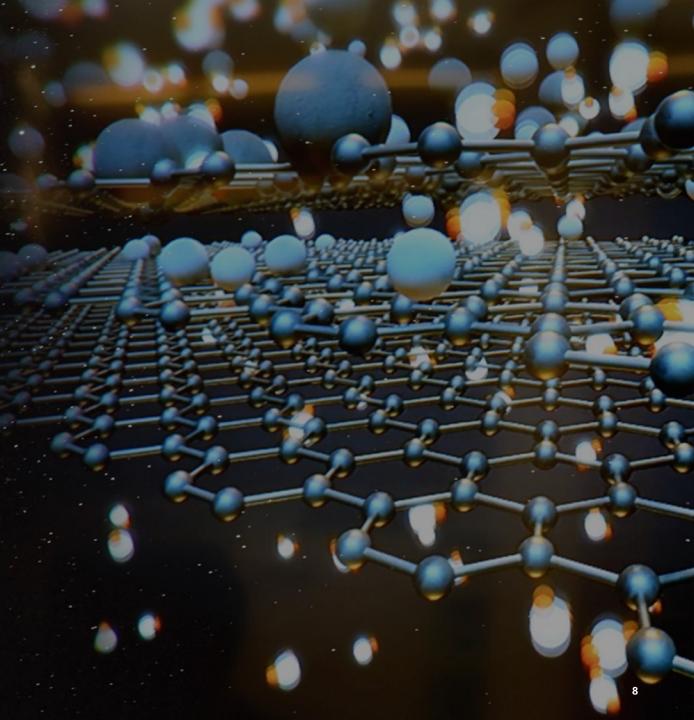


ESS is a user facility.

Scientists from all over the world will be welcomed to ESS with their specimens to do experiments.

Expectations:

- 800 experiments per year
- 3 000 guest scientists per year



Challenges



- Accelerator based facilities are some of the worlds most complex systems
- ESS is a user facility with a 95% availability goal
 - High availability requirements on equipment
 - The control system plays a key role for the availability of the facility



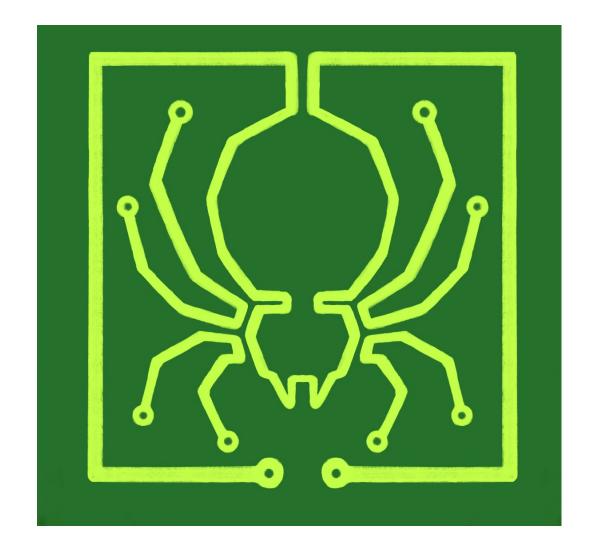
Control System Machine Learning Project

ess

2019 - 2023

Explore if machine learning can be used to:

- Increase facility availability.
- Increase efficiency of operation
- Enhance process understanding
- Lower operational and maintenance costs
- Decrease commissioning time



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Student Project: Tuning the DTL

ess

Developing an ML-based model for RF tuning of DTL machine at ESS

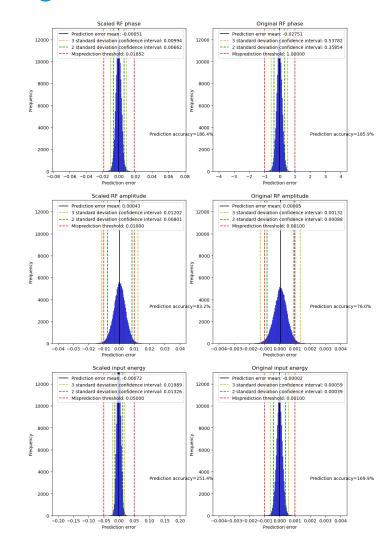
Institute: Automatic Controls LU

Course: Master's Program in Machine

Learning, Systems and Control

ESS Supervisor: Natalia Milas (accelerator)





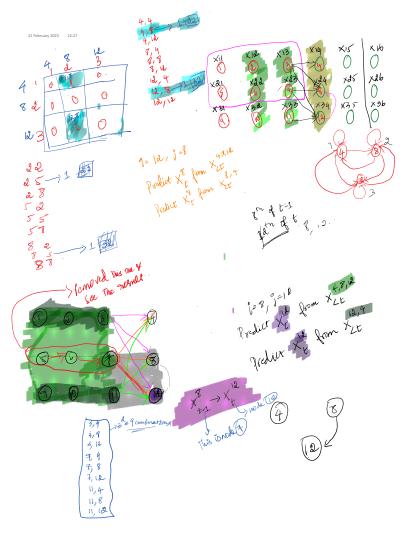
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Student project: Alarms

Causal event processes and alarm analysis at ESS

- Department: Automatic controls, Lund University.
- Degree: MsC in Machine Learning,
 Systems and Control





New Section 1 Page

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Student Project: Alarm Cascades



https://drops.dagstuhl.de/opus/volltexte/2023/19098/

Common Alarm Problems

- Many alarms are unnecessary
- Some alarms are missing
- Many alarms have badly tuned parameters
- Some alarms has a higher priority than others.
- Many alarms are only relevant in certain operational states
- A fault often leads to several consequences

Analyzing Complex Systems with Cascades Using Continuous-Time Bayesian Networks

Alexsandro Bregon & Department of Informatics, Systems and Communication, University of Milano-Bicocca, Italy Karin Rathsman ⊠∰ 0 European Spallation Source ERIC, Lund, Sweden

Marco Scutari ⊠ 😭 👵

Department of Automatic Control, Lund University, Sweden

ADSTRUCT

Interacting systems of events may exhibit cascading behavior where events tend to be temporally twice the standard of the standard o Interacting systems of events may exhibit cascaring benavior where events tend to be temporary clustered. While the cascades themselves may be obvious from the data, it is important to understand conditions of the cascades themselves may be obvious from the data, it is important to understand to the data of the cascades themselves may be obvious from the data, it is important to understand the data of the cascades themselves may be obvious from the data, it is important to understand the data of the cascades themselves may be obvious from the data, it is important to understand the data of the data citatered. While the cascades themselves may be obvious from the data, it is important to understand which states of the system trigger them. For this purpose, we propose a modeling framework based which states of the Doubles and Aller es of the system trigger them. For this purpose, we propose a modeling transevork observa-ous-time Bayesian networks (CTBNs) to analyze cascading behavior in complex systems. on continuous-time Bayesian networks (CTBNs) to analyze cascading behavior in complex systems.

This framework allows us to describe how events propagate through the system and to identify I has trainerwork allows us to describe now events propagate through the system and to mens likely sently states, that is, system states that may lead to imminent cascading behavior. Morror of the state of the sta likely sentry states, that is, system states that may lead to imminent cascading behavior. Moreover, CTBNs have a simple graphical representation and provide interpretable outputs, both of which are constant when commendation with Associate accounts. We also describe account when the constant when t important when communicating with nomain experts. We also develop new methods for knowledge extraction from CTBNs and we apply the proposed methodology to a data set of alarms in a large

2012 ACM Subject Classification Mathematics of computing → Markov processes; Mathematics of

Keywords and phrases event model, continuous-time Bayesian network, alarm network, graphical Digital Object Identifier 10.4230/LIPIcs.TIME.2023.8

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Many real-world phenomena can be modeled as interacting sequences of events of different Many real-world phenomena can be modeled as interacting sequences of events of different types. This includes social networks where user activity influences the activity of other types. Instructed social networks where user activity induseries are activity to other users [11]. In healthcare, patient history may be modeled as a sequence of events [46]. In the contrast of the contrast and the contrast and the contrast are contrast are contrast and the contrast are contrast and contrast are contrast and contrast are contrast are contrast and users [11]. In healthcare, patient instory may be modeled as a sequence of events [40]. In this paper, we focus on an industrial application in which the events are alarm signals of a sequence of the contract of the contra this paper, we rocus on an industrial application in which the events are alarm signals of a complex engineered system. As an illustration, consider Figure 1. Three different alarms of a part of the control of the co complex engineered system. As an injustration, consider Figure 1. Inree different alarms

(A, B, and C) monitor a process each within an industrial system. These processes may, for (A, D, and U) monitor a process each within an infiniterial system. These processes may, for instance, represent measured temperatures or pressures. An alarm transitions to on when its assauce, represent measured temperatures or pressures. An anim transitions to on when its the process it monitors leaves a prespecified range of values and transitions to off when the

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Student project: Anomaly detection

https://gupea.ub.gu.se/handle/2077/78206



Title: A Software Process Workflow for Smart Anomaly Detection Systems

Degree: BSc Software Engineering and

Management

ESS Supervisor: Target division and ICS

University: Chalmers and Göteborg University



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Next Project

Find a system owner with a problem to solve and data.

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- Coupler motors in the super conducting cavities?
- Vibrations target wheel?
- Camera control sampling environment?



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