EUROPEAN
SPALLATION
SOURCE

Causal event processes and alarm analysis at ESS

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PRESENTED BY KARIN RATHSMAN

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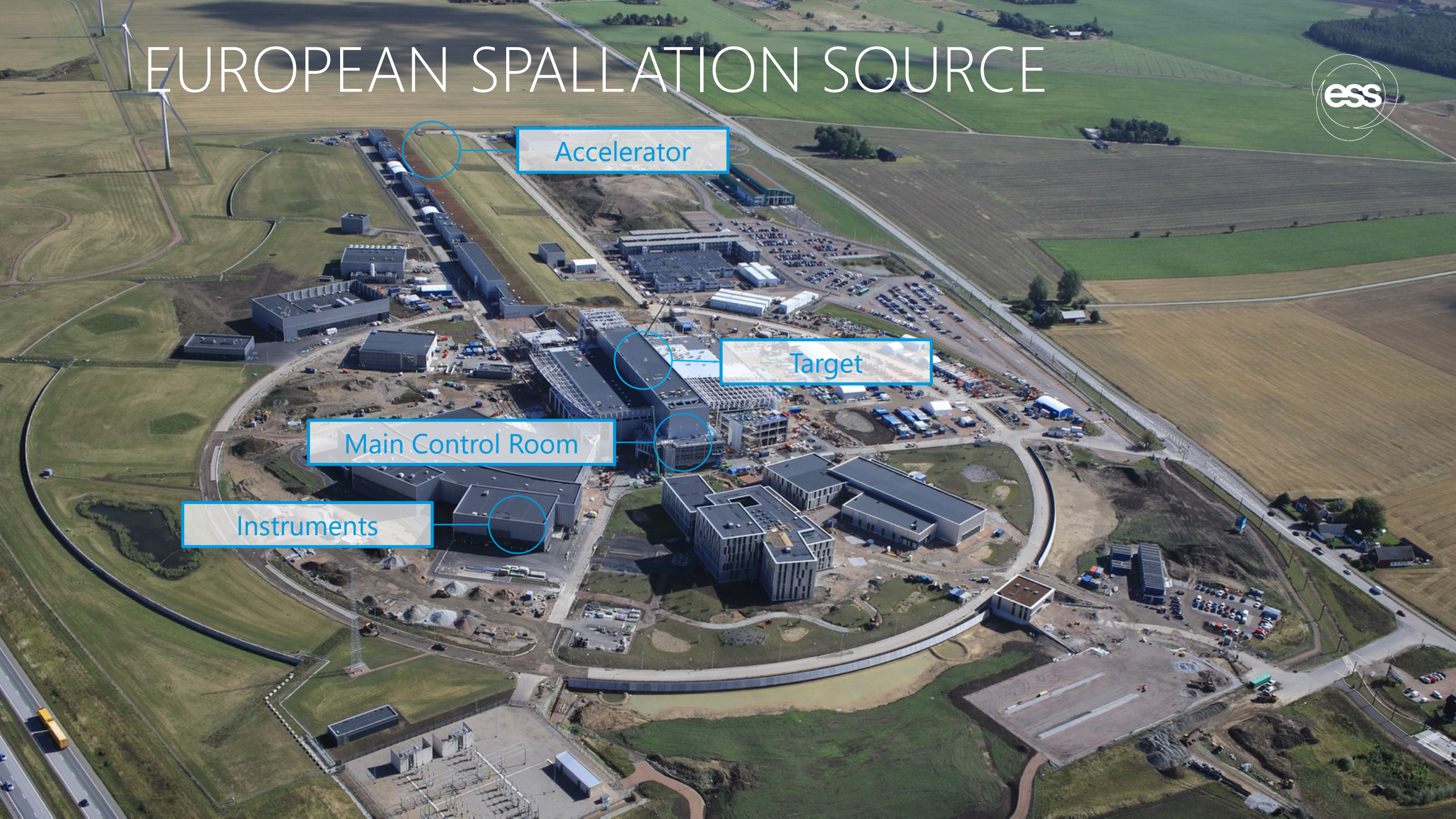
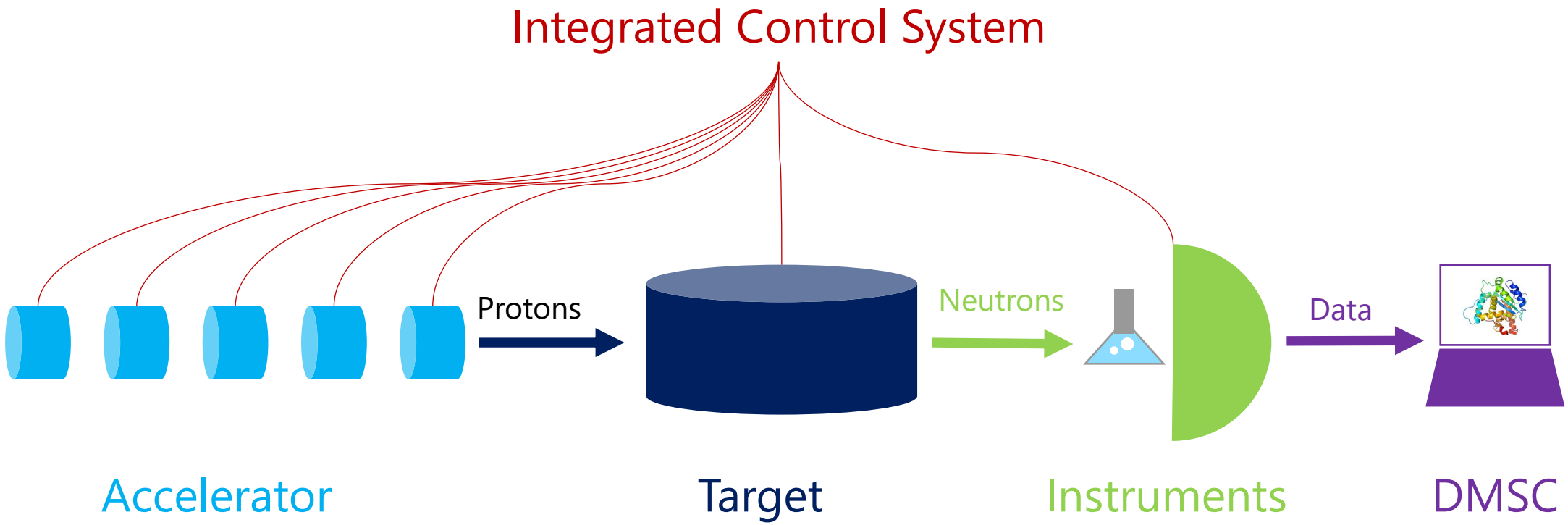


The ESS Machine

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Challenges

What could possibly go wrong?

- Accelerator – based facilities are some of the worlds most complex systems
  - Large variety of systems, both advanced and non-advanced.
  - Thousands of devices and millions of control signals.
- 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

Explore if machine learning can be applied to the control system in order to

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

Alarm Handling

Common alarm problems

- Many alarms are unnecessary
  - System owners tend to define alarm that are relevant to them, but are not necessary relevant for operators.
- Some alarms are missing
  - Missing sensors or forgotten
- Many alarms have badly tuned parameters
  - Correct limits not known during the design.
- Some alarms has a higher priority than others.
  - Need a faster response or has a higher criticality.
- Many alarms are only relevant in certain operational states
  - Appears as irrelevant alarms in other situations.
- A fault often leads to several consequences
  - Causes alarm cascades.

Methods for alarm data analysis

Table 1
Approaches to alarm data analysis.

		Alarm rationalization		Online operator support				Root cause analysis
		Alarm similarity analysis	AF similarity analysis	AF template extraction	Online AF classification	Alarm prediction	Dynamic alarm suppression	Alarm-based RCA
Time series analysis	ACT binary series	[13,14,6]						[15]
	Binary series	[13,16,17]			[4]			[5]
	Multi-valued series							[18]
	Continuous-valued series	[19,14]						
Sequence mining	Set		[20,7]	[9]	[9]		[21]	
	Sequence		[20,7,22]	[8]	[8]	[10,23]		
	Time-stamped sequence	[24]	[3,25,26]	[27]	[28]			
	RTN time-stamped sequence				[29]		[11]	

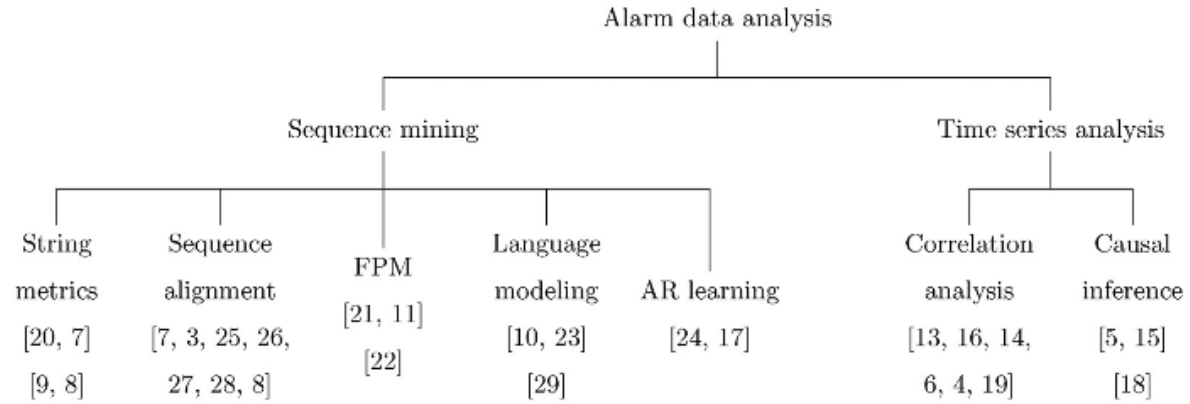
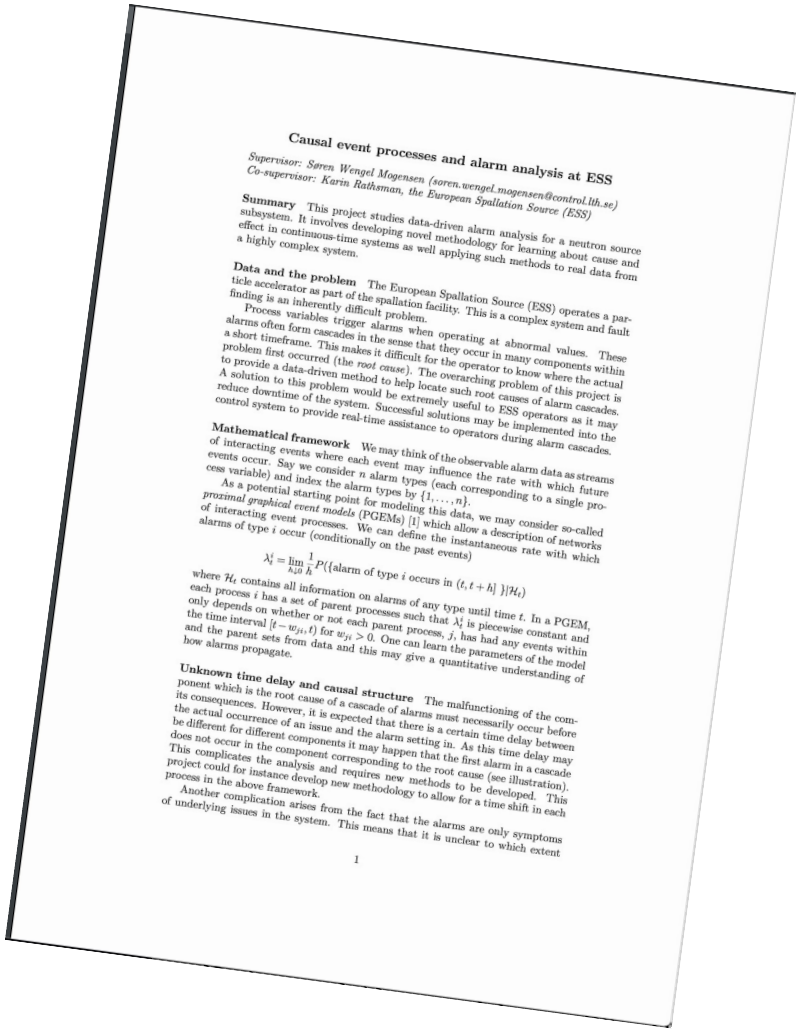


Fig. 1. Family tree of methods for alarm data analysis.

Proposal

Causal event processes and alarm analysis at ESS



Causal event processes and alarm analysis at ESS

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Co-supervisor: Karin Rathsman, the European Spallation Source (ESS)

Summary This project studies data-driven alarm analysis for a neutron source subsystem. It involves developing novel methodology for learning about cause and effect in continuous-time systems as well applying such methods to real data from a highly complex system.

Data and the problem The European Spallation Source (ESS) operates a particle accelerator as part of the spallation facility. This is a complex system and fault finding is an inherently difficult problem.

Process variables trigger alarms when operating at abnormal values. These alarms often form cascades in the sense that they occur in many components within a short timeframe. This makes it difficult for the operator to know where the actual problem first occurred (the *root cause*). The overarching problem of this project is to provide a data-driven method to help locate such root causes of alarm cascades. A solution to this problem would be extremely useful to ESS operators as it may reduce downtime of the system. Successful solutions may be implemented into the control system to provide real-time assistance to operators during alarm cascades.

Mathematical framework We may think of the observable alarm data as streams of interacting events where each event may influence the rate with which future events occur. Say we consider n alarm types (each corresponding to a single process variable) and index the alarm types by $\{1, \dots, n\}$.

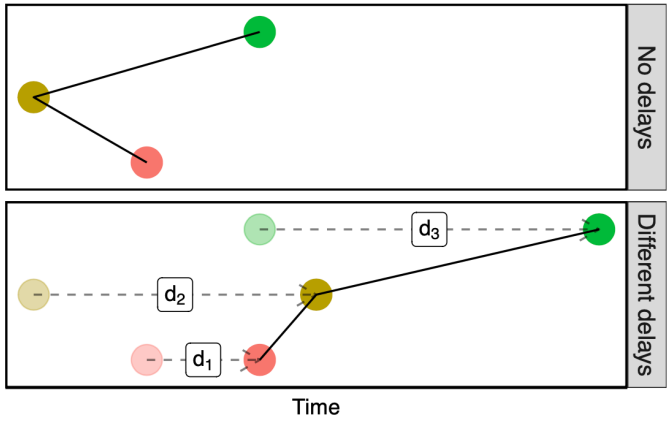
As a potential starting point for modeling this data, we may consider so-called *proximal graphical event models* (PGEMs) [1] which allow a description of networks of interacting event processes. We can define the instantaneous rate with which alarms of type i occur (conditionally on the past events)

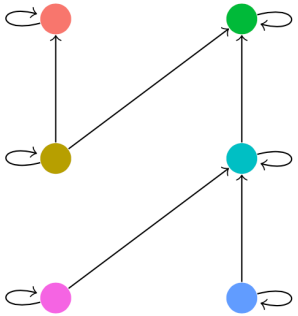
$$\lambda_t^i = \lim_{h \downarrow 0} \frac{1}{h} P(\{\text{alarm of type } i \text{ occurs in } (t, t+h]\} | \mathcal{H}_t)$$

where $\mathcal{H}_t$ contains all information on alarms of any type until time t. In a PGEM, each process i has a set of parent processes such that λ_t^i is piecewise constant and only depends on whether or not each parent process, j, has had any events within the time interval $[t - w_{ji}, t)$ for $w_{ji} > 0$. One can learn the parameters of the model and the parent sets from data and this may give a quantitative understanding of how alarms propagate.

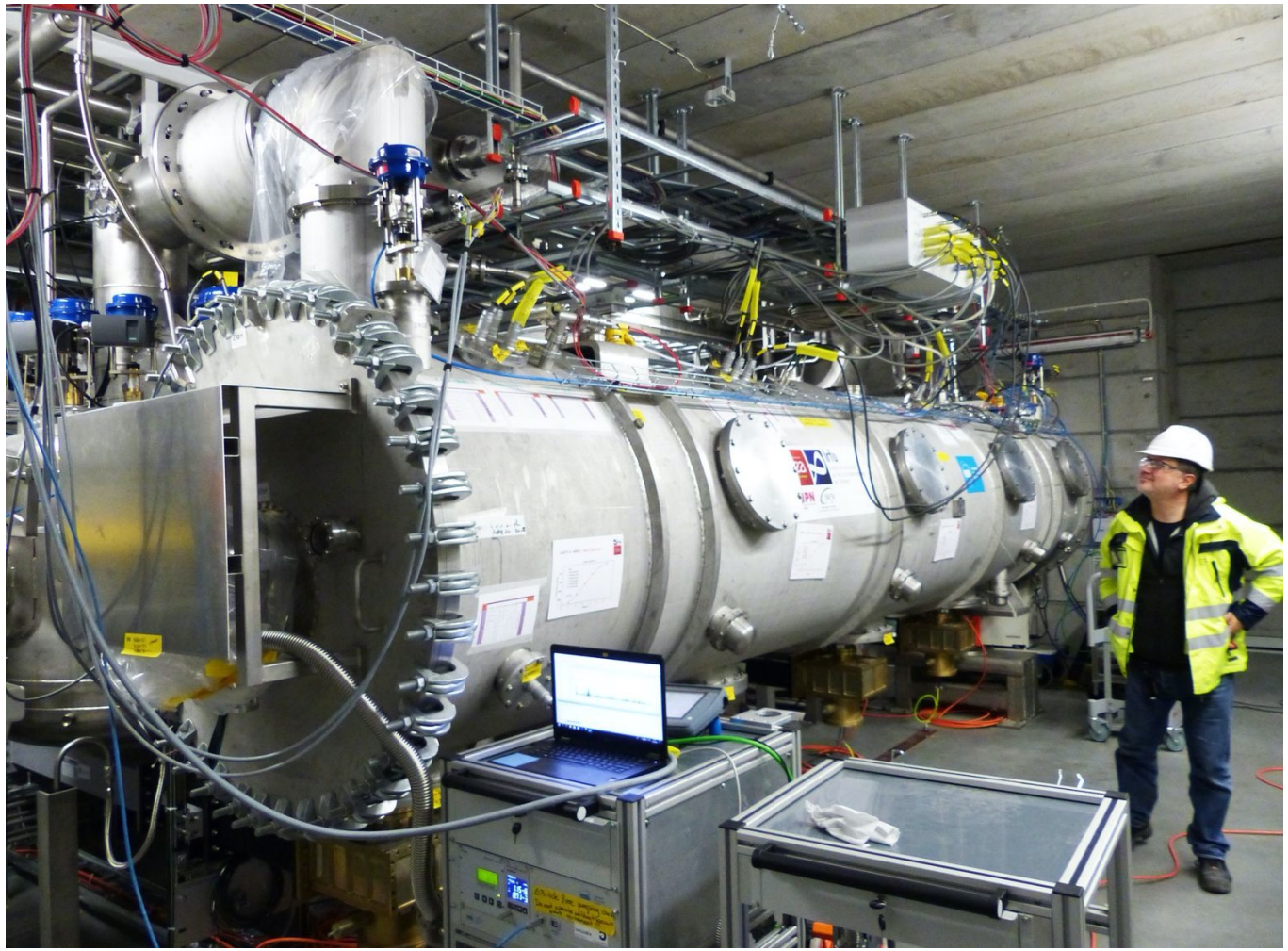
Unknown time delay and causal structure The malfunctioning of the component which is the root cause of a cascade of alarms must necessarily occur before its consequences. However, it is expected that there is a certain time delay between the actual occurrence of an issue and the alarm setting in. As this time delay may be different for different components it may happen that the first alarm in a cascade does not occur in the component corresponding to the root cause (see illustration). This complicates the analysis and requires new methods to be developed. This project could for instance develop new methodology to allow for a time shift in each process in the above framework.

Another complication arises from the fact that the alarms are only symptoms of underlying issues in the system. This means that it is unclear to which extent

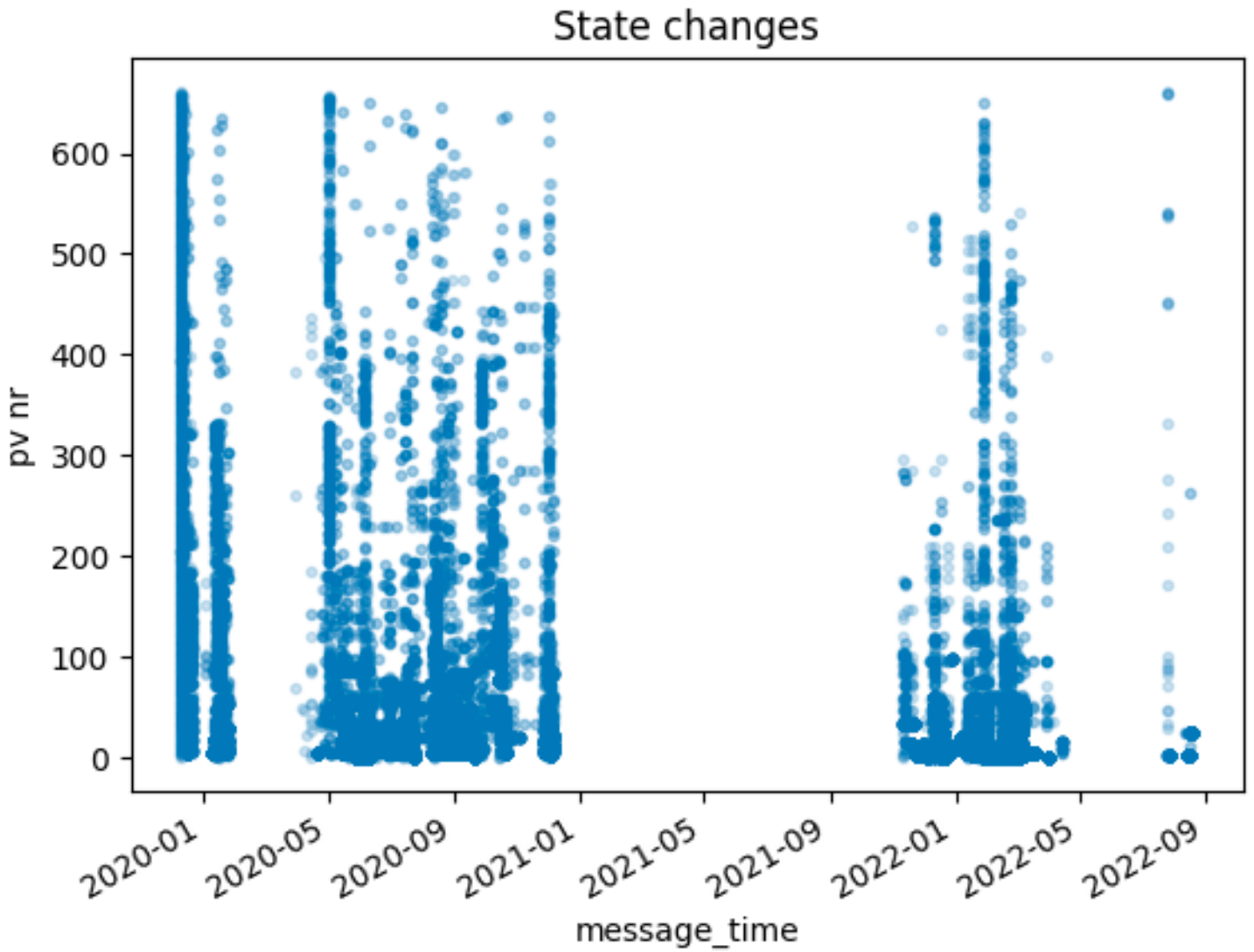




Cryogenics system



Alarm Cascades



Thank You!

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