Advanced Methods for Systems' Modeling and Simulation II:

Object-oriented modeling for the reliability analysis of infrastructure systems

Part I: Short Introduction to Object-oriented Modeling

- Stochastic simulation – basic Monte Carlo methods for reliability analysis
- Object-oriented modeling approach – framework
- How to build an object-oriented model

Part II: Application to Complex Engineering Systems:

Reliability analysis of large-scale electric power systems

- The IEEE Reliability Test System 1996 and its implementation
- Results

Part I: Short Introduction to Object-oriented Modeling

Stochastic simulation – basic Monte Carlo methods for reliability analysis (I)

Simulation:	an abstraction of a real system by a computer program in order to mimic and analyze its behavior

Monte Carlo technique:	stochastic simulation using algorithmically generated random numbers

A simple example for estimating the unavailability *Q* of a system :

Assume a system consisting of *N* components, where:

s_i: state of the *ith* component (boolean)
Q_i: failure probability of the *ith* component
R_i: random number for the *ith* component; R_i ~uniform[0,1]

then, assuming independent failures :

$$s_i \begin{cases} 0 & (success) \quad if \quad R_i > Q_i \\ 1 & (failed) \quad if \quad 0 \le R_i \le Q_i \end{cases}$$

Stochastic simulation – basic Monte Carlo methods for reliability analysis (II)

1. sample the states of all components („throw the dices“) to get the system state *s*:

$$s = \{s_1, \ldots, s_i, \ldots, s_N\}$$

2. Perform system analysis to judge whether *s* is a failure state or not:

$x_j = 0$ if the system is in the up state

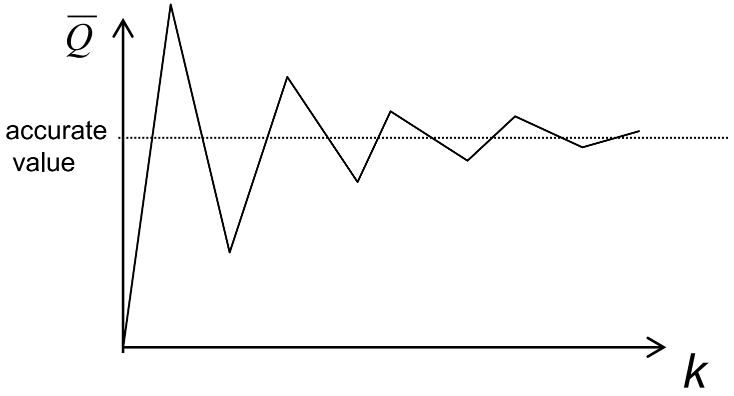
$x_j = 1$ if the system is in the down state

3. Performing *k* system state samples, the unbiased estimate of the system unavailability then is given by:

$$\boxed{\overline{Q} = \frac{1}{k}\sum_{j=1}^{k} x_j}$$

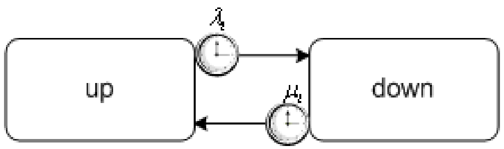
with variance:

$$V(\overline{Q}) = \frac{1}{k}V(x) = \frac{1}{k(k-1)}\sum_{j=1}^{k}(x_j - \overline{Q})^2$$



Stochastic simulation – sequential Monte-Carlo simulation

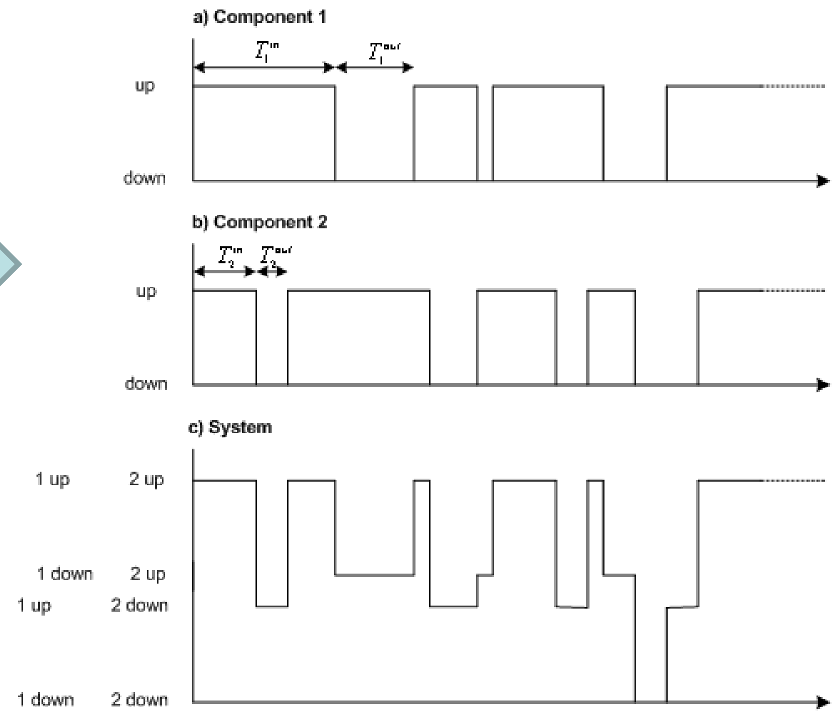
Component model



$$T_i^{in} = -\frac{1}{\lambda_i}\ln R_i^{in}$$

$$T_i^{out} = -\frac{1}{\mu_i}\ln R_i^{out}$$

Time sequence



Combining Monte Carlo Techniques with Object-oriented modeling

<u>Advantages for reliability analysis:</u>

- Monte Carlo simulation helps to overcome the problem of the **state space explosion**:

  Consider a system of *N=20* components with two states (e.g. up state and down state). A "state enumeration approach", such as a "complete" fault tree, or a markovian chain would have to consider $2^N = 2^{20} = 10^6$ system states!

- Object-oriented modeling helps to explicitly consider **time-dependent interactions** between the components and to integrate feedback loops, which is not possible in "static approaches" such as fault tree analysis.

<u>Disadvantages for reliability analysis:</u>

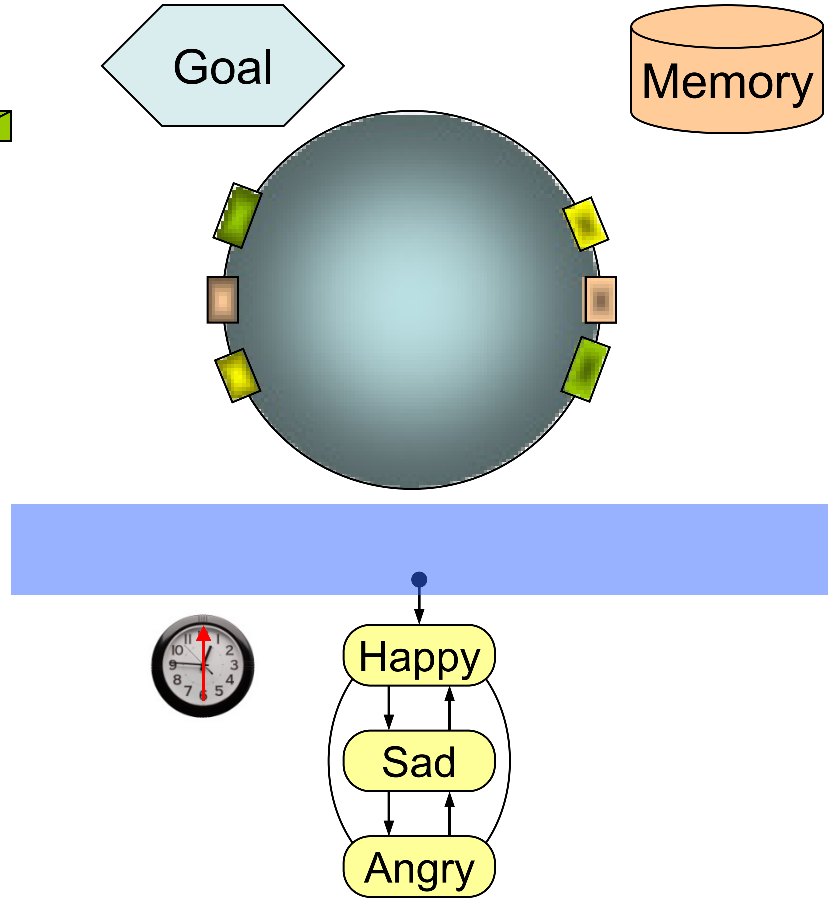
- The simulation primarily aims at calculating mean values. **Some critical scenarios might be missed.**
- Depending on the analyzed system, the **validation** of the simulated system behavior might be a **difficult task**, due to lack of operational experience regarding low-probability-high-impact scenarios.

Object-oriented modeling approach – framework

- Modeling the behaviour of the **components** (objects) and their interaction with the environment
- Stochastic simulation (Monte Carlo methods) of all components to investigate the **macro-behaviour** of the whole system
- In contrary to established methods for risk analysis (ETA, FTA) the observed scenarios and system states *s* are not predefined, but they emerge during the simulation (**emergence**)
- Frequency and consequence of events are determined "**experimentally**"

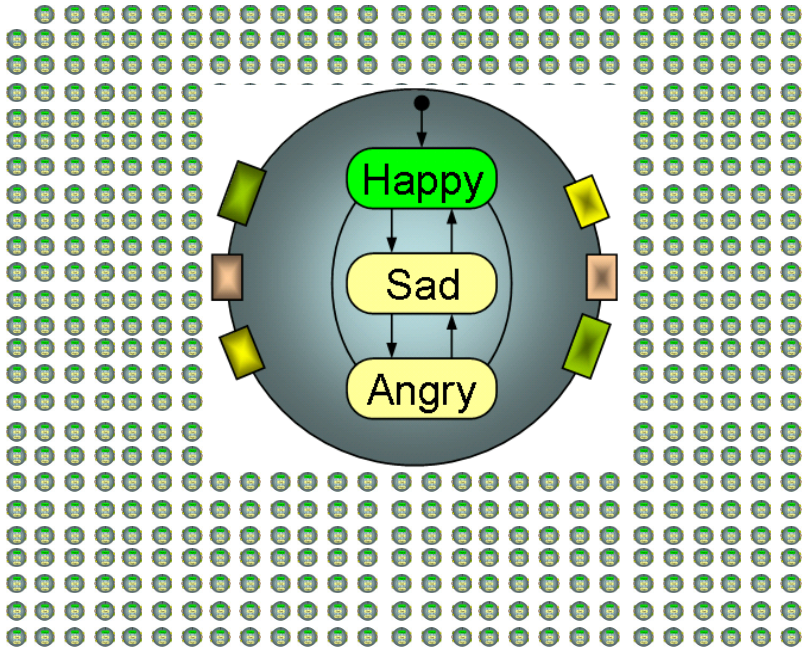
An object…

- **Has different states**
  (F̲inite S̲tate M̲achine, FSM)
- Is capable of interaction with its environment (e.g. other objects)
- has „receptors“ and „effectors“ for specific („messages“) and non-specific (environmental variables) signals
- Can act randomly
- May have a memory (learning)
- Can strive for a goal



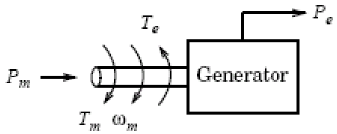
Simulation of N objects

- One single object does not tell us much about the behaviour of its macro-system
- Therefore every component of a system has to be modelled separately by an object
- By the computational simulation of all objects, the global system behaviour and the system states *s* emerge



What can be represented by objects?

- Humans (e.g. operators)
- Components (e.g. turbine)
- Machines (e.g. power station)
- Whole systems
  (e.g. energy systems)



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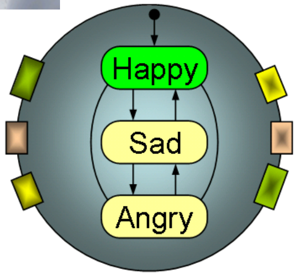

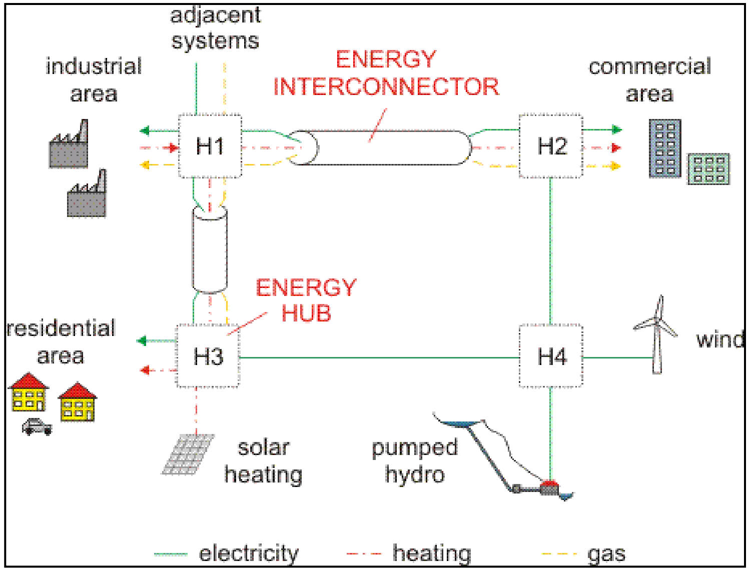

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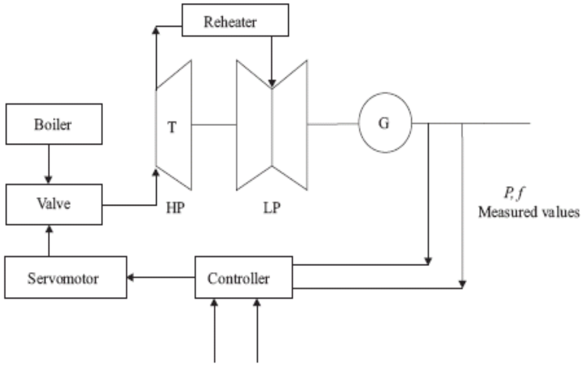

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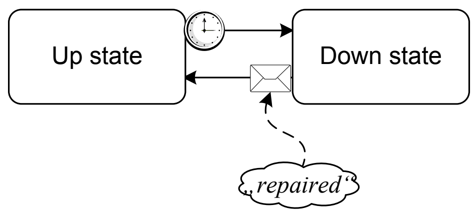
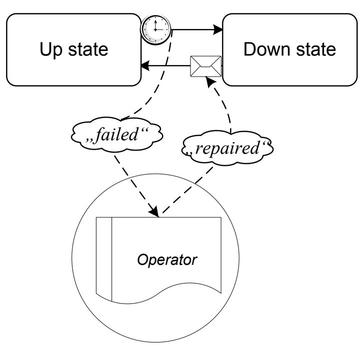
How to build a simplified object-oriented model for reliability analysis

1. Identify the components of the system
2. Determine the states of each component by making use of FSM, eg:

3. Determine the transitions between the states and their triggers (e.g. lapse of time or signal from outside)



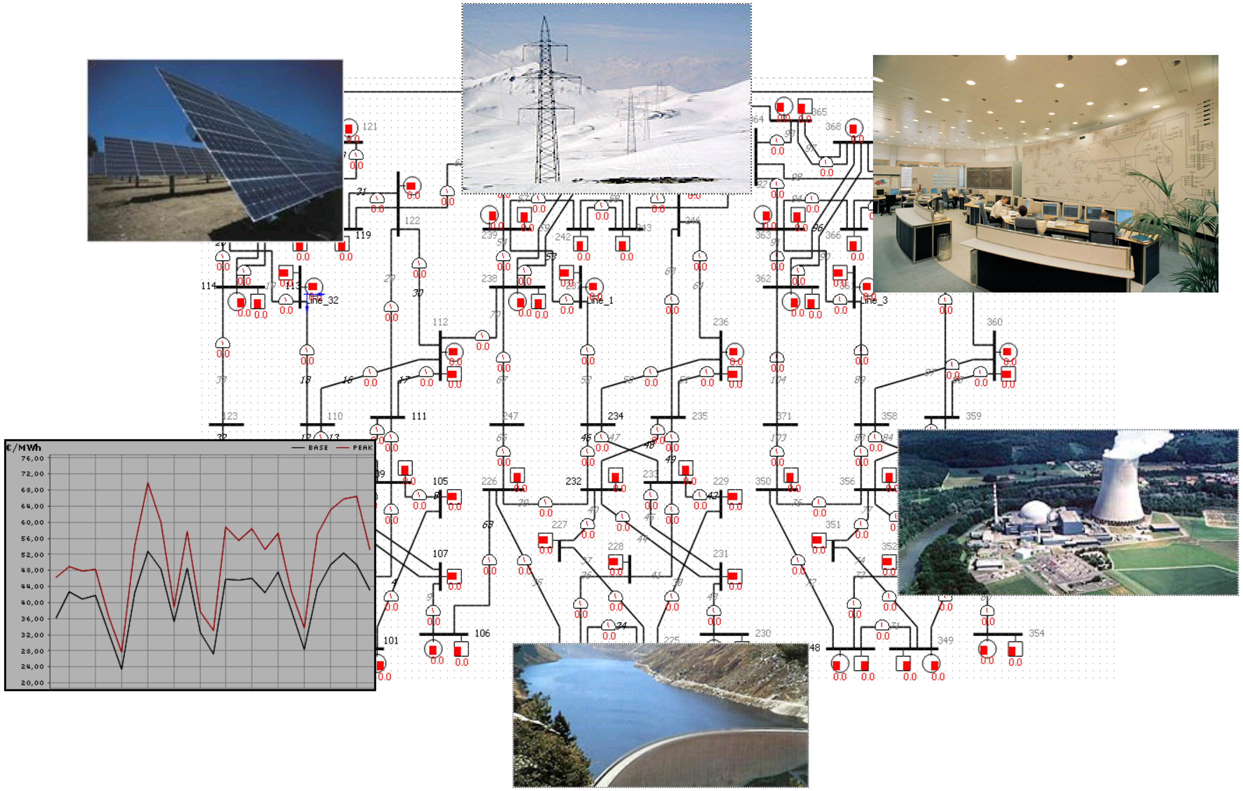
4. Establish the communication among the objects:



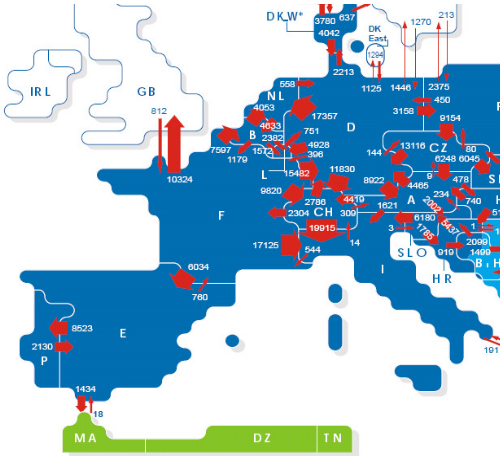
5. Simulate your model to generate the system states *s* and estimate $\overline{Q}$

Part II: Application to Complex Engineering Systems

Reliability Analysis of Electric Power Systems



Background and Motivation (I)



Source: UCTE 2006

Developments within the landscape of the European electric power system:

- ➢ *electricity market liberalization*
  - intricate, decentralized market structure with numerous competing players
  - extensive (international) trading without adequate technical upgrades
- ➢ *increasing amount of distributed generation and renewables*
  - less predictable power sources
  - variable load flow patterns
- ➢ *pervasive use of ICT*
  - more intelligent system operation
  - new risks due to interdependencies

⇨ **Unprecedented operational complexity**

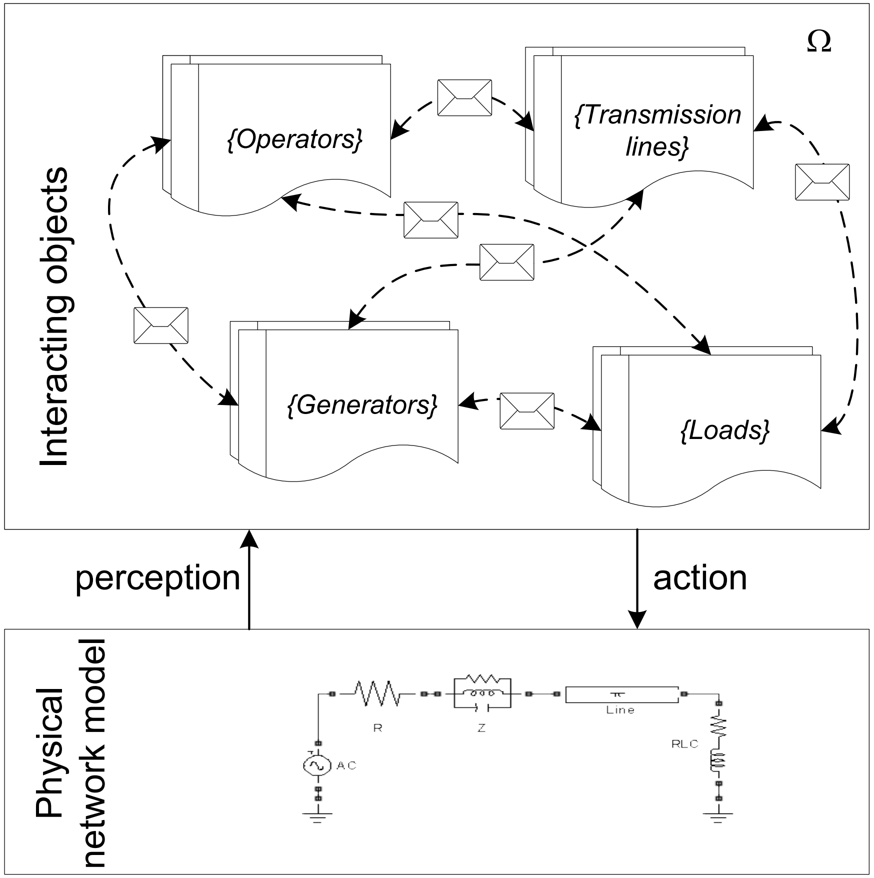
Background and Motivation (II)

However:

Reliability policies and assessment methodologies did not keep pace !

- *N-1 rule*
  - deterministic approach
  - predefined set of anticipated faults, focus on „worst-case“ contingencies
  - relevant failure states or the actual „worst-case scenario“ might be missed !!
- *Current probabilistic approaches*
  - limited to specific aspects (e.g. to a single component), or
  - oversimplified (e.g. cascading failures)

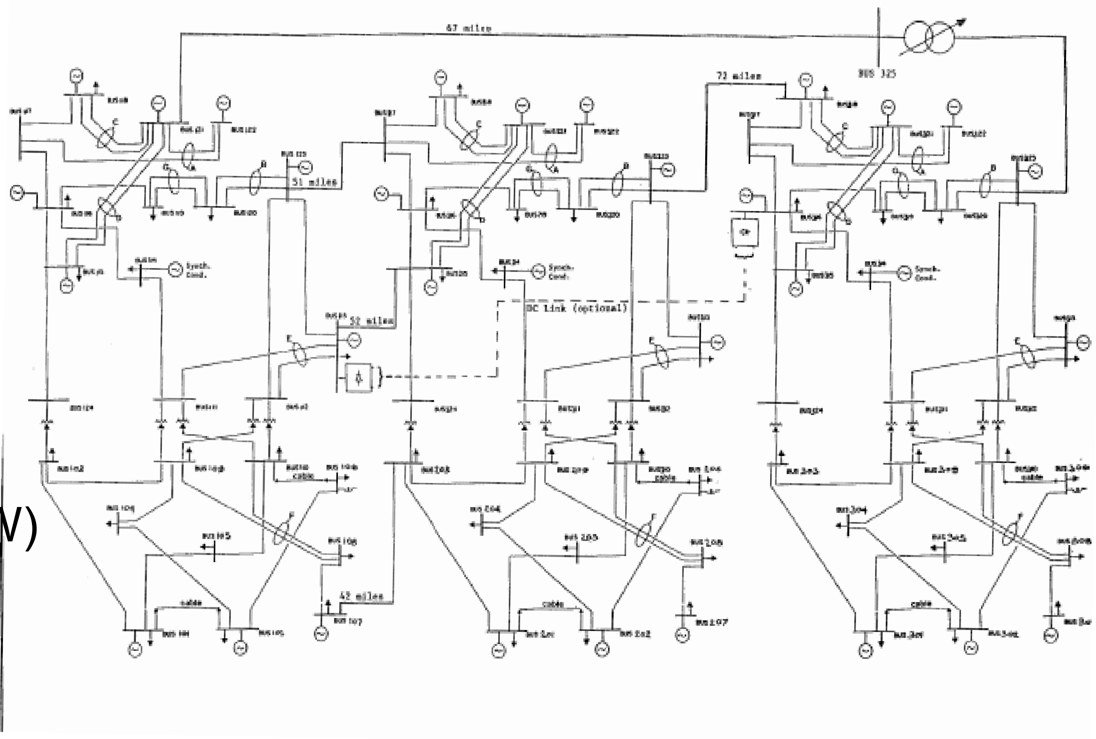
Modeling the Electric Power System – Two-layers approach:



The IEEE Reliability Test System 1996 (RTS `96)

➢ Basic system layout

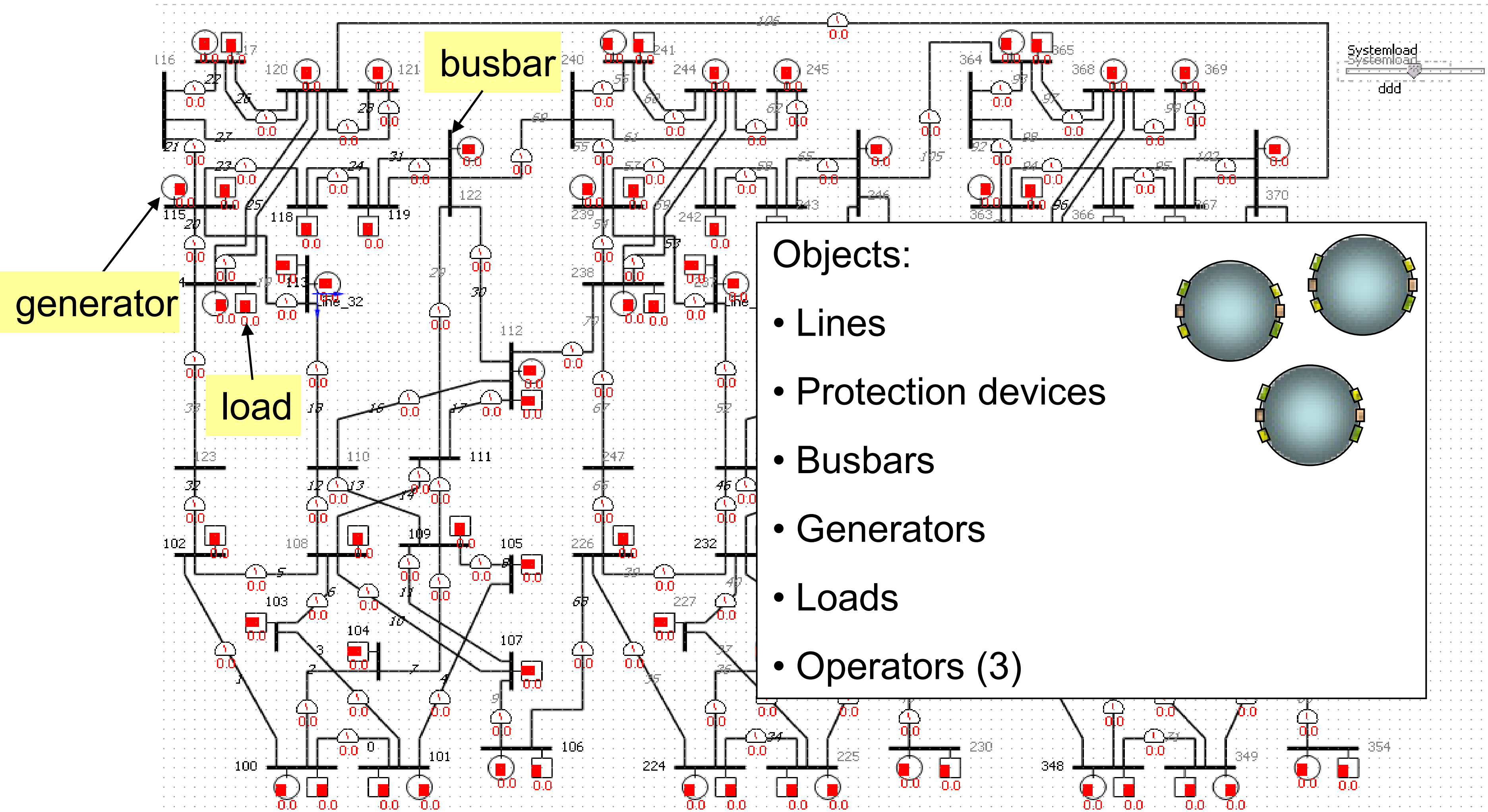
- 72 busbars
- 107 transmission lines
- 99 generators
- 51 loads
- Voltage levels: 230/138 kV
- Installed capacity: 10‘215 MW (CH: ~12‘000 MW)
- Peak load: 8‘550 MW (CH: 9‘650 MW)



➢ Available data

- physical component data: branch reactances, operational thresholds etc.
- load curves (hourly, daily, weekly)
- reliability data: component outage and repair rates, min. down times, etc.

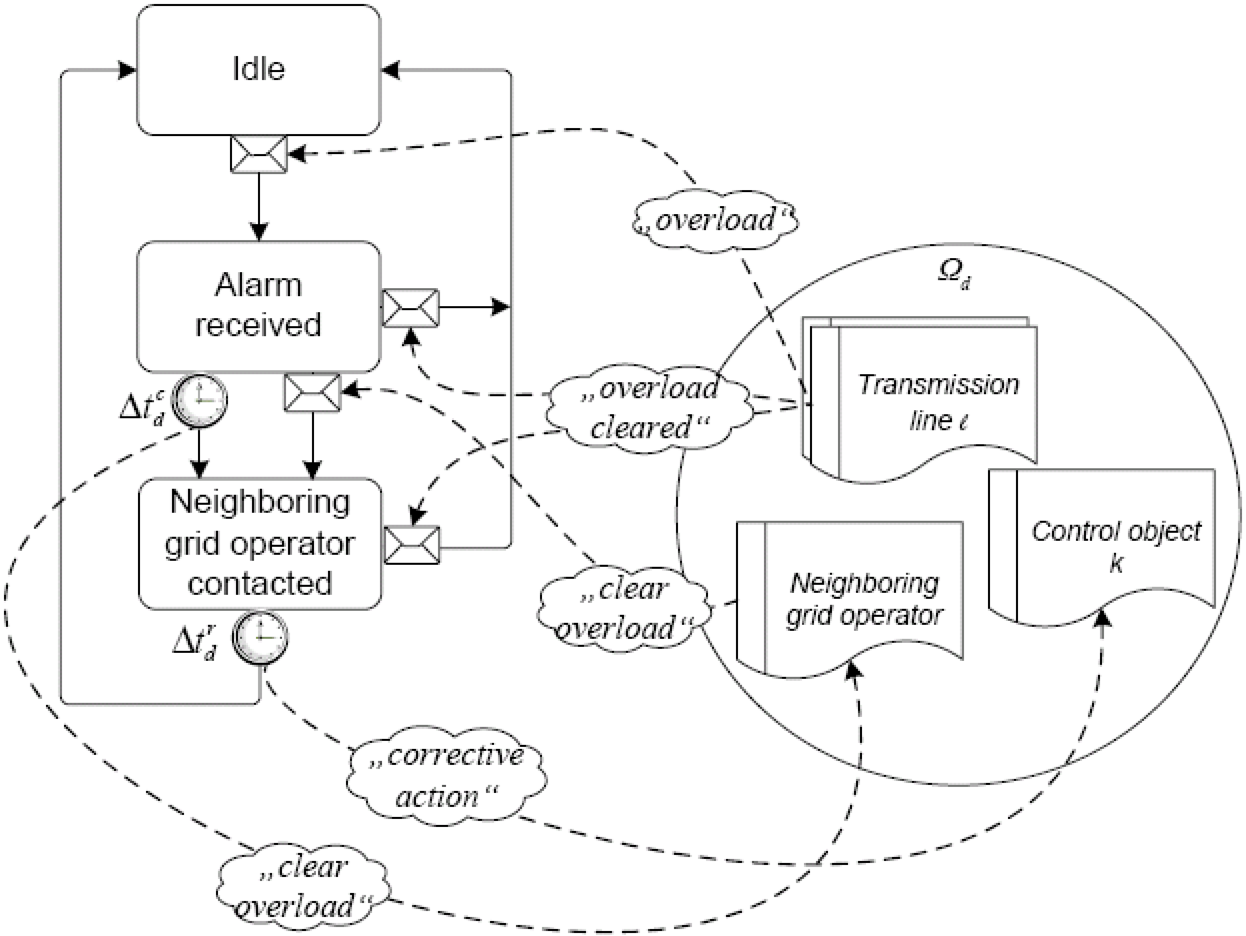
The RTS `96 - Implementation in AnyLogic



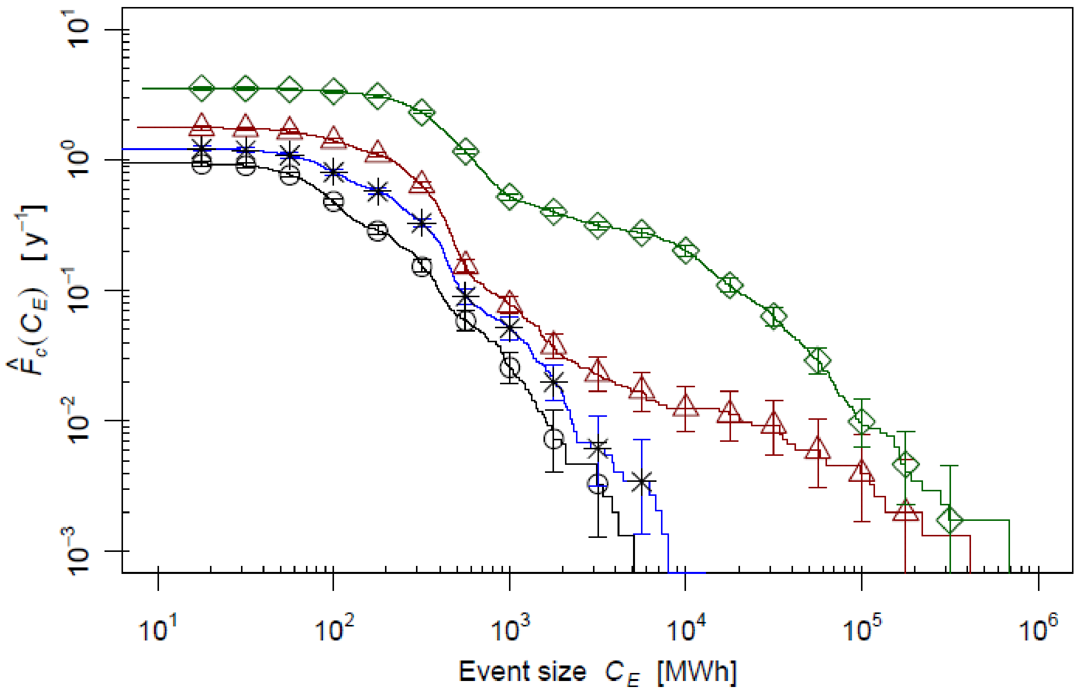
Objects:

- Lines
- Protection devices
- Busbars
- Generators
- Loads
- Operators (3)

Objects: The Operator as an Example

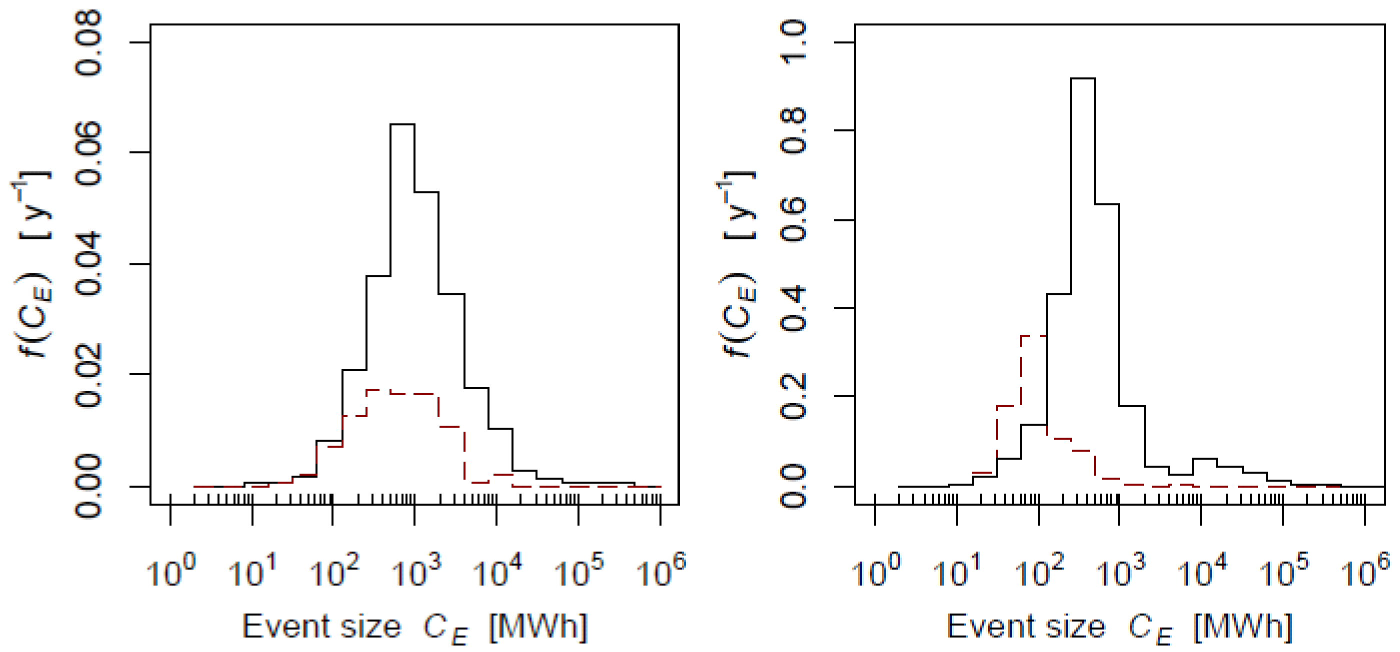


Results:
A) Expected Frequencies of Blackouts



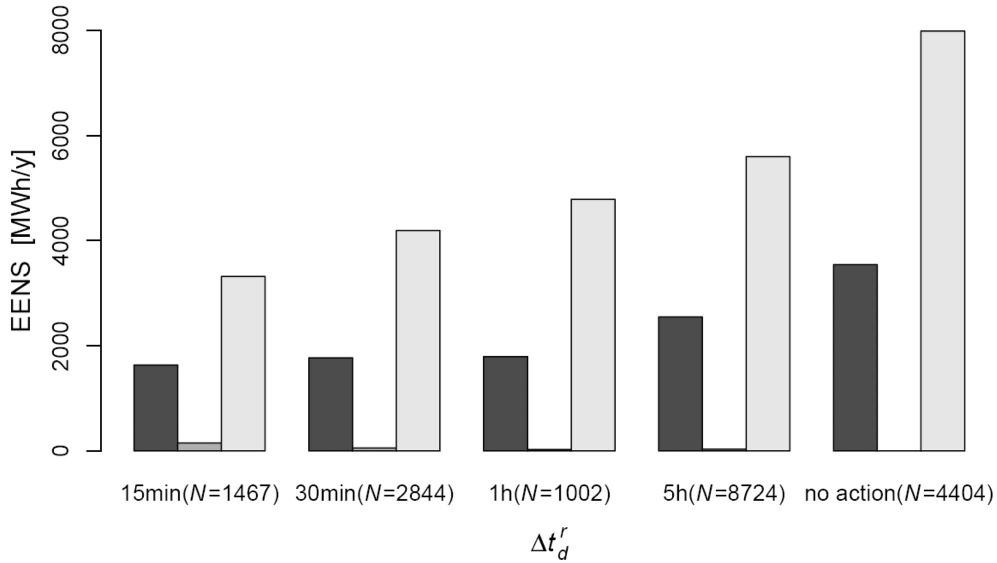
Complementary cumulative blackout frequencies for four different system loading levels L=1.0, 1.1, 1.2 and 1.37 (circles, stars, triangles and diamonds, respectively) without operator intervention. The error bars indicate the 90% confidence interval.

Results:
B) Blackout causes



Impact of increasing the system loading from L=1.0 (dashed line) to L=1.37 (continuous line) on the absolute frequencies of blackouts caused by generation inadequacy (left) and system splitting (right).

Results:
C) Influence of the operator response time on the system reliability



Influence of the operator response time on the EENS due to generation inadequacy (left, black bar), operator action (middle, dark-grey bar) and system splitting (right, light-grey bar) for L=1.37.

EENS: Expected Energy Not Supplied