Integration of Reinforcement Learning and Discrete Event Simulation Using the Concept of Experimental Frame

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Outline

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- Basics
 - Structure of Simulation Based Experiments (SBE)
 - Concept of Experimental Frame (EF)
 - Reinforcement Learning (RL)
- SBE with integrated RL using EF
- Case study with MATLAB/SimEvents
- Conclusions

Introduction

Observation

Simulation models are often (tricky) implemented to fit RL needs

→ complicated model structures and limited reusability of comps & meths

Objectives

(M&S conform model & experiment design)

Clear separation between:

Model Under Study (MUS) and

Context of use (experiment)

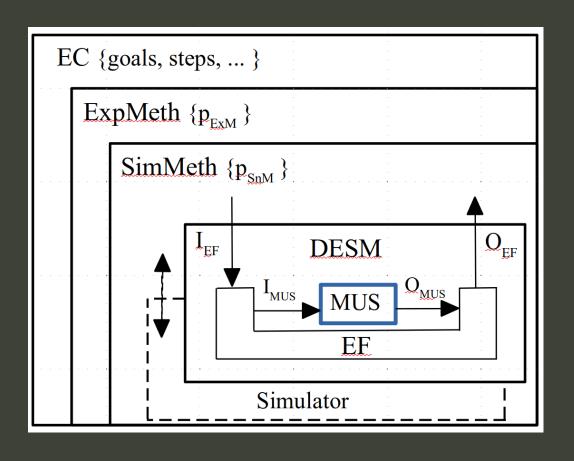
to support:

Independent development and

General reusability of MUS and experiment methods

Basics

Structure of Simulation Based Experiments (SBE)



EC Experiment Control

ExpMeth Experiment Method

SimMeth Simulation Method

Simulator (MATLAB/SimEvents)

DESM Discrete Event

Simulation Model

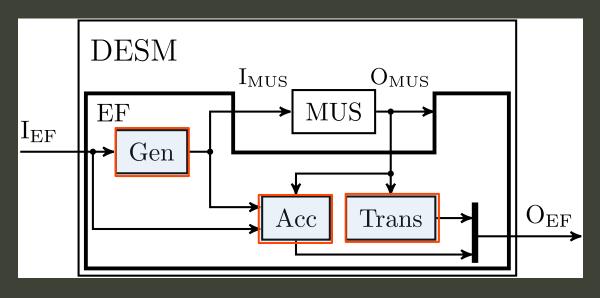
EF Experimental Frame

MUS Model Under Study

The MUS is part of an experiment, involving multiple levels of methods.

DESM structure using Experimental Frame (EF)

(EF introd. by B.P. Zeigler)



- DESM is divided into MUS & EF
- **EF** specifies the conditions under which a **MUS** is experimented with

Formal definition:

$$EF = \langle T, \Omega_{I}, I_{MUS}, O_{MUS}, C, \Omega_{C}, SU, I_{EF}, O_{EF} \rangle$$

T may differ from MUS

Generator

comp. Ω_{I} for I_{MUS} and EF other comps

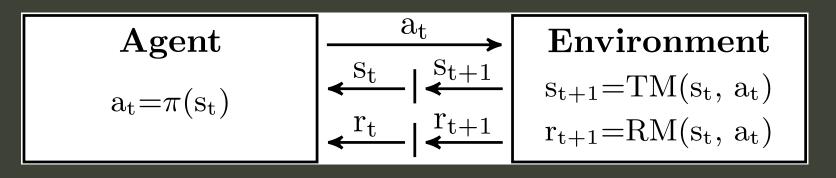
Transducer

comp. values of interest and SU based on O_{MUS}

Acceptor

checks compliance of $\Omega_{\rm C}$ based on C \subset ${\rm O_{MUS}}$

Reinforcement Learning (RL)



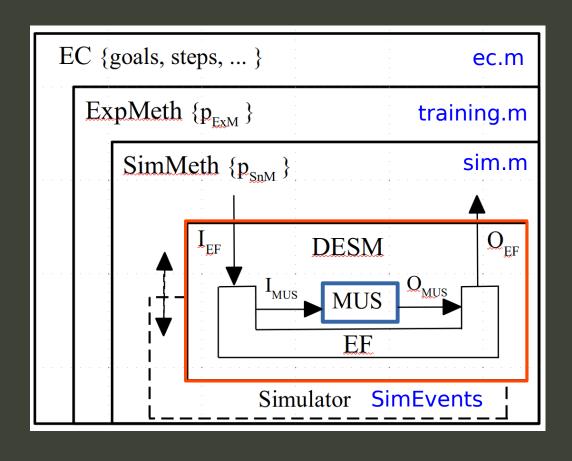
- t order of tupels (a, s,)
- a_t action (aeA)
- s_t state (seS)
- r_t reward (reR)
- TM transition model
- RM reward model
- π policy

- Agent observes state s_t of environment
- Agent chooses an action a_t according to its policy $\pi(s_t)$
- Environment executes its TM and RM and responds with (st+1 rt+1)
- Agent improves (learns) policy $\pi(s_t)$ to maximize the cumulative reward
 - Various learning approaches (Q, DQN, ...)
 - Training is done by repetition of episodes starting with environment in s₀ to s_{final} | s_{abort}

SBE with integrated RL using EF

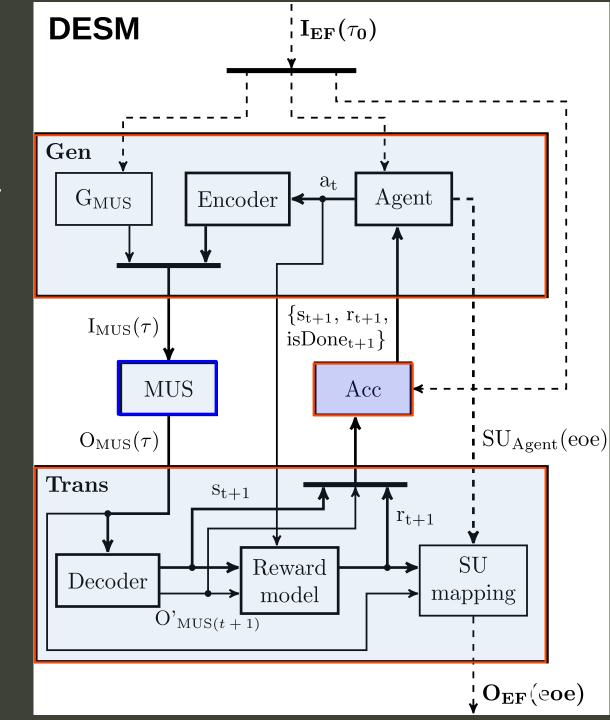
Structure of a SBE with integrated RL

(e.g. with MATLAB/SimEvents)

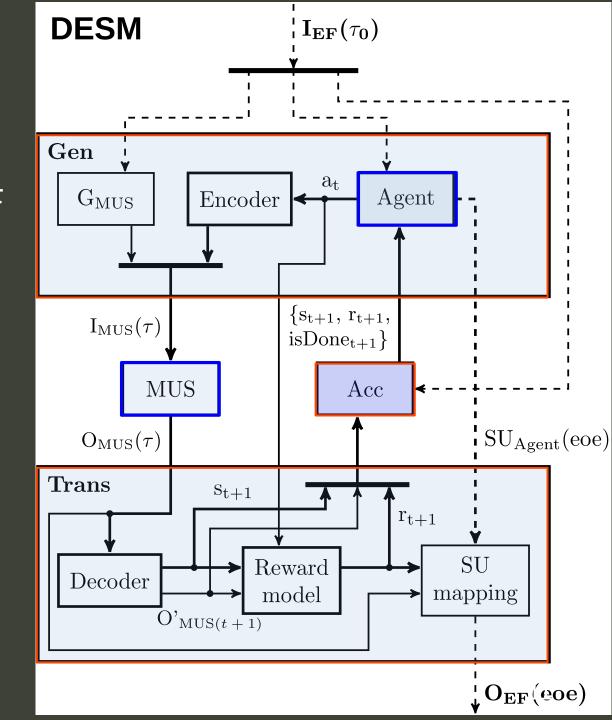


- **EC** sets training-, sim-, and DESM parameters
- **ExpMeth** is the **training** alg. and ctrls computation of episodes
- SimMeth ctrls sim run (1 episode)
- Simulator executes sim run
- **DESM** implements
 - MUS (as part of RL Env)EF (Agent & RL specific Env.)

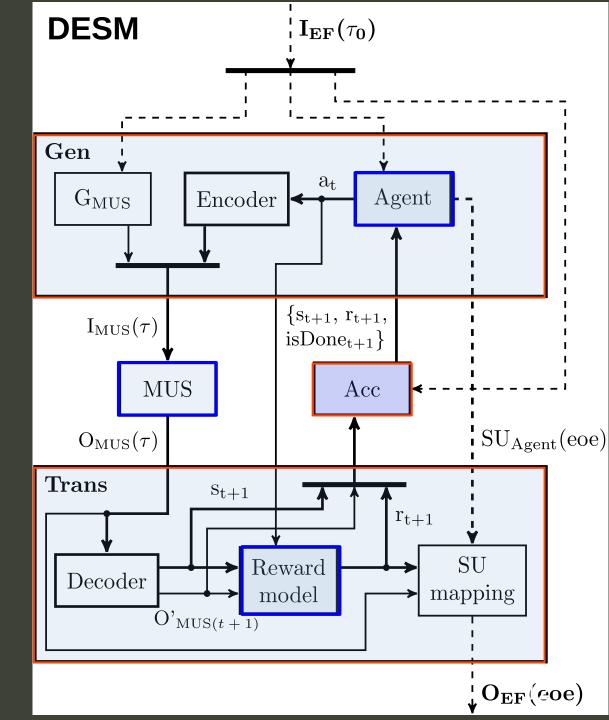
- MUS: discr event system with contin time τ
- **EF** comps are time-triggered or event-driven by MUS outputs → **sequent. order t** of RL



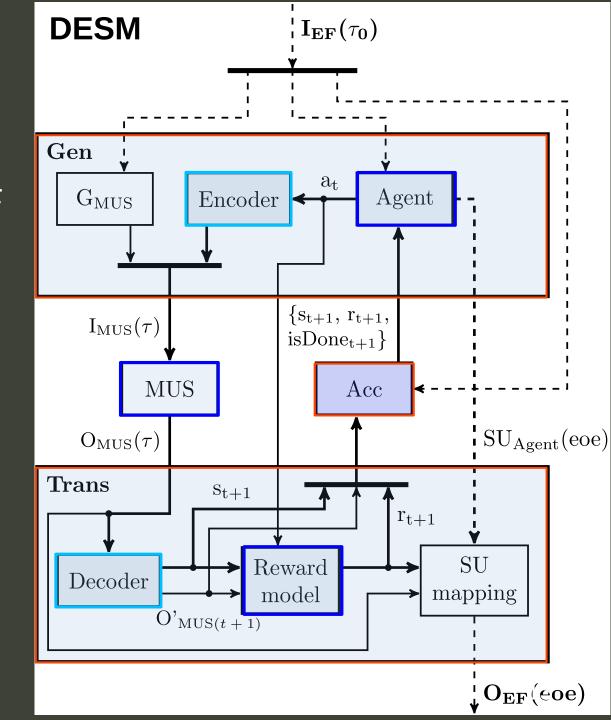
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- Agent is a Generator a_t=Agent(s_t, r_t, isDone)



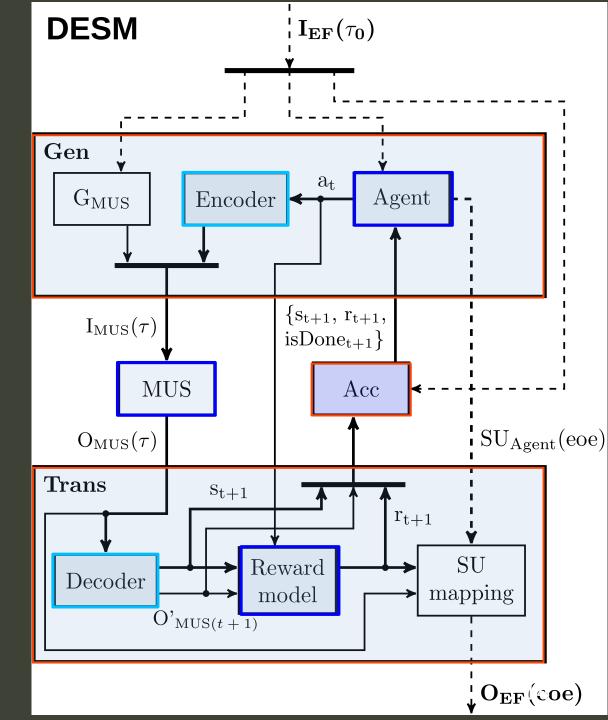
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- Reward Model (RM) is a Transducer comp
 → not part of MUS, r_{t+1}=Reward(s_{t+1}O'_{MUS})



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- Reward Model (RM) is a Transducer comp \rightarrow not part of MUS, $r_{t+1} = \text{Reward}(s_{t+1}, O'_{\text{MUS}})$
- Encoder & Decoder transform the differing state/action representation of MUS & RL
 I_{MUS}(τ)=Encoder(a_t), [s_{t+1},O'_{MUS}]=Decoder(O_{MUS}(τ))
 MUS + Decoder are the TM in sense of RL

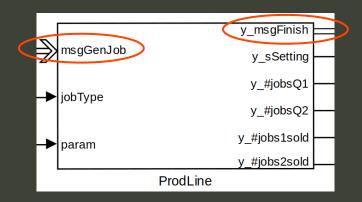


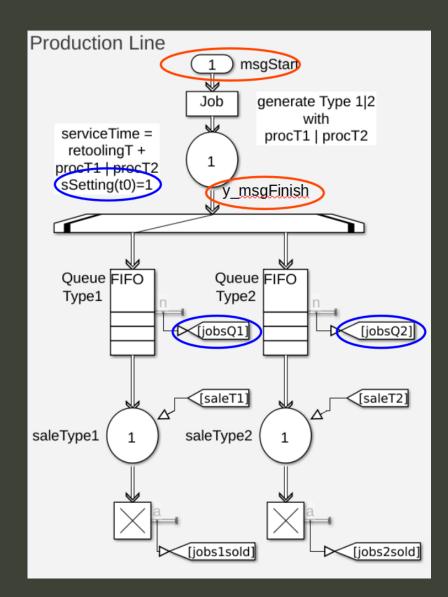
- MUS: discr event system with contin time τ
- **EF** comps are time-triggered or event-driven by MUS outputs → **sequent. order t** of RL
- Agent is a Generator a_r=Agent(s_r, r_r, isDone)
- Reward Model (RM) is a Transducer comp \rightarrow not part of MUS, $r_{t+1} = \text{Reward}(s_{t+1}, O'_{\text{MUS}})$
- **Encoder** & **Decoder** transform the differing state/action representation of MUS & RL $I_{MUS}(\tau) = \frac{Encoder}{a_t}, [s_{t+1}, O'_{MUS}] = \frac{Decoder}{O_{MUS}(\tau)}$ MUS + Decoder are the TM in sense of RL
- Acceptor checks run conditions and sets isDone=0|1 for terminating RL episode



Case study with MATLAB/SimEvents

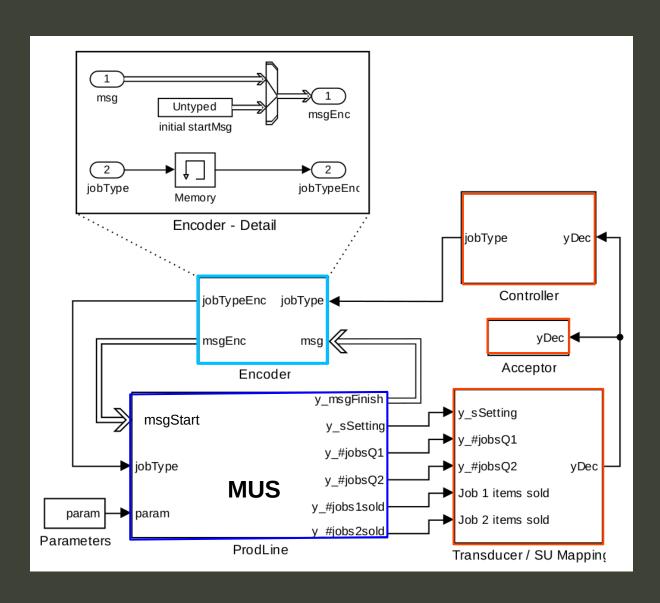
The MUS: simple ProductionLine





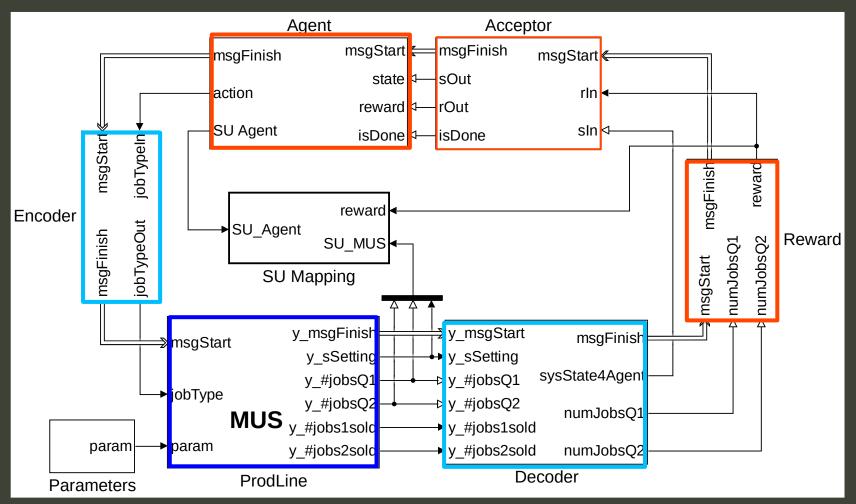
- Generation of different jobTypes is triggered by input event msgStart
- Service time of 1st server depends on inputs jobType and param
- Changing jobTypes require retooling time
- Jobs are routed to type-specific downstream queues/servers with different service time → output event y_msgFinish
- Goal: find best control strategy for injecting jobs to balance content of downstream queues

Structure of MUS and EF using a heuristic ctrl



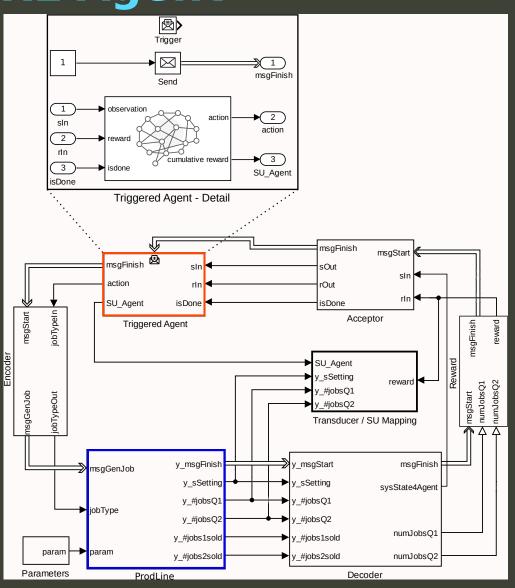
- MUS ProdLine
- **EF Generator Controller** computes next jobType based on Transducer output yDec
- EF Generator Encoder provides MUS conform inputs (msgStart, jobType)
- **EF Transducer** transforms MUS outputs for Controller (yDec with queue diff., ...) and computes SU
- **EF Acceptor** checks queue diff. and time condition $\tau < \tau_{final}$ to exit sim run

Structure of MUS and EF using a Q-Agent



- Same MUS Prodline
- EF is triggered by MUS output events
- EF Generator Q-Agent computes action values a.
- EF Generator Encoder transforms at to MUS inputs (msgStart, jobType)
- EF Transducer Decoder transf MUS outputs to RL conform values s_{t+1}
- EF Transducer Reward computes r_{t+1}
- EF Acceptor checks all values and sets isDone

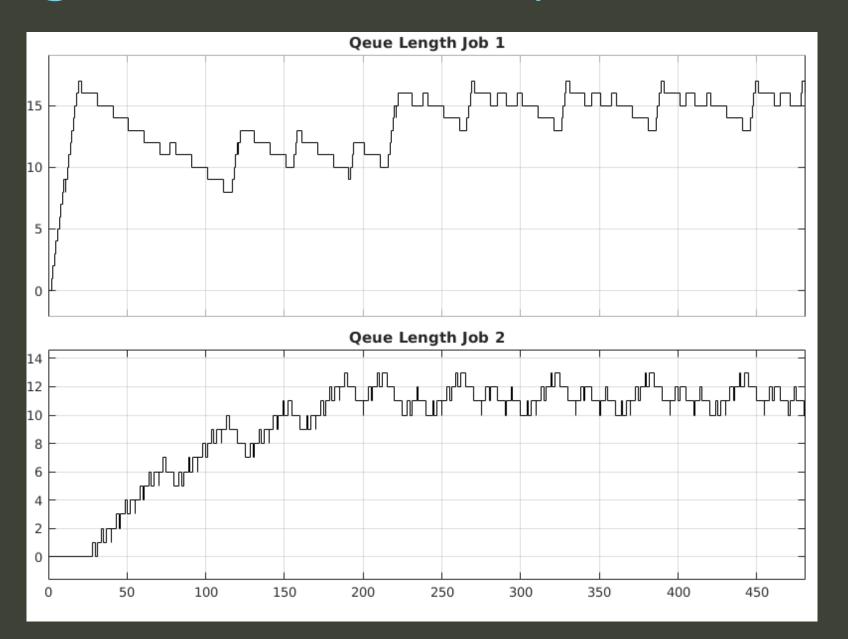
Structure of MUS and EF using MathWorks' RL Agent



- Same MUS Prodline
- Nearly the same EF
 - Q-Agent is replaced by MathWorks' RL Agent
 - BUT RL Agent isn't designed for event-driven simulations

 → using Trigerred Subsystem as a workaround
- RL tbx provides an ExpMeth train and a specific SimMeth sim (different from regular sim method)

Training Result after 5000 episodes



Conclusions

- Structure of SBE and concept of EF provide a clear methodological approach for integrating Discrete Event Simulation (DES) and RL
- The MUS and the experiment methods can be developed independently and reused in different contexts
- Case study depicted the reusability of a MUS in three different experiments

Backyard Slides

Operation of Decoder in the EF (for the Example with Q-Agent)

 when MUS output event y_msgFinish(τ), then

Transducer. Decoder

transforms MUS outputs y_sSetting(τ), y_#jobsQ1(τ), y_#jobsQ1(τ)

to the **single RL state s**_{t+1} **sysState4Agent**

computes other values of interest

activates Transducer.Reward via event

```
\begin{aligned} qlQ1 &= max(y_{numJobsQ1}, qlength_{max}) \\ qlQ2 &= max(y_{numJobsQ2}, qlength_{max}) \\ s_{t+1} &= (sSetting-1) \cdot (qlength_{max} + 1)^2 + qlQ1 \cdot (qlength_{max} + 1) + qlQ2 + 1 \end{aligned}
```

Operation of Reward in the EF (for the Example with Q-Agent)

Transducer.Reward computes

r_{t+1} value based on the values of interest numJobsQ1_{t+1} numJobsQ1_{t+1} instead of RL next state s_{t+1}

activates Acceptor via event

$$r_{t+1} = \begin{vmatrix} 100 & | & qlQ \ 1 \ge 10 \land qlQ \ 2 \ge 10 \\ qlQ \ 2^2 & | & qlQ \ 1 \ge 10 \land qlQ \ 2 < 10 \\ qlQ \ 1^2 & | & qlQ \ 1 < 10 \land qlQ \ 2 \ge 10 \\ & \frac{qlQ \ 2^2 \cdot qlQ \ 1^2}{100} & | & else \end{vmatrix}$$

Operation of Acceptor in the EF (for the Example with Q-Agent)

Acceptor monitors condition

```
T < T
```

and sets **isDone= 0|1** to go on or exit episode by **Agent**

s_{t+1},**r**_{t+1} are passed to the **Agent**

activates Agent via event

ACCEPTOR EXTENSION USING VALUES OF INTEREST if $(qlQ1-qlQ2)^2 \ge diff_{max}$, then isDone=1, else isDone=0