Graph Neural Networks for Power Systems Operation

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Deep Statistical Solvers & Power Systems Applications

- 2018 - 2022 : PhD student @ RTE R&D and Université Paris-Saclay

Graph Neural Networks for Tertiary Voltage Control

- 2022-2024 : Postdoc at Institut Montefiore in a project for RTE R&D

- Talk is about our latest work !
- But it does not include experimental results for now…
- *Topology-Aware Reinforcement Learning for Tertiary Voltage Control,* submitted to PSCC 2024 (power systems conference).
- Gives an idea of how GNNs can be applied for a real-life power systems problem.

- Collaboration between **RTE R&D** and **Institut Montefiore** (Liège Université).

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Background & Motivations

Background & Motivations

High Voltage Issues

- Increase in the frequency and intensity of high voltage events:
  - Can damage assets,
  - Caused by increase of renewables, new electricity uses, etc.
- Operators do not have time for that.

[1] P.Mandoulidis, V.Lampropoulos, C.Vournas, M.Karystianos, G.Christoforidis, A. Neris, and Y. Kabouris, “Controlling long-term overvoltages in lightly loaded transmission systems,” 2022.

Background & Motivations

Long Term Goal

- We want a decision support tool to assist operators.
  - Input : Operating condition x,
  - Output : Voltage setpoints y.
- The tool will not take control of the grid : it can only suggest an action (open-loop control).
- The tool cannot rely on expensive intermediate simulations.

Background & Motivations

Traditional Optimization

- Tertiary Voltage control can be cast as an Optimal Power Flow [2].
  - Mixed Integer Non Linear Problem.
  - Current resolution methods do not scale to real-life power systems.

[2] A. Castillo, “Essays on the ACOPF Problem: Formulations, Approximations, and Applications in the Electricity Markets »

Background & Motivations

Deep Learning

- Why not Deep Learning ?
  - Tremendous successes in various domains.
  - Solves complex problems that require a very high level of abstraction [3] [4] [5].

[3] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going Deeper with Convolutions,”
[4] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to Sequence Learning with Neural Networks,”
[5] D. Silver, A. Huang, C. Maddison, A. Guez, L. Sifre, G. Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Diele- man, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis, “Mastering the game of Go with deep neural networks and tree search,”

Initial Optimization problem

Initial Optimization Problem

Variables

- Let $x \in \mathscr{X}$ be an operating condition (i.e. a snapshot at certain instant).
  - Encompasses both its structure and its numerical features.

- Let $y \in \mathscr{Y}(x)$ be a tertiary voltage control decision.
  - Size depends on the number and nature of assets in x.

Initial Optimization Problem

Problem

- We look for a tertiary voltage control decision that minimizes a real-valued cost function c,

$$y^*(x) = \underset{y \in \mathcal{Y}(x)}{\arg\min}\ c(x, y).$$

- Tertiary voltage control includes both continuous and discrete variables.
- As a first step, we only consider generators voltage setpoints (continuous).

Initial Optimization Problem

Cost function

- As a proxy of what operators do, we consider

$$c(x, y) = c_J(x, y) + c_V(x, y) + c_I(x, y).$$

  - c_J penalizes power losses caused by Joule's effect.
  - c_v penalizes voltage violations.
  - c_I penalizes overflows.
- Computing c requires to run a black-box simulation.

Reinforcement Learning Problem

RL Problem

Distribution of Problem Instances

- We wish to solve the problem for a whole distribution p of operating conditions x.
- Given a certain x, we have to return a y in one step.
  - *Contextual Bandit*, typically addressed in Reinforcement Learning [6].

[6] R. S. Sutton and A. G. Barto, *Reinforcement learning: an introduction*.

RL Problem

Conversion to an RL Problem

We consider a probabilistic control policy Π_θ , such that

$$\theta^* = \arg\min_{\theta \in \Theta} \mathbb{E}_{\substack{x \sim p(\,\cdot\,) \\ y \sim \Pi_\theta(\,\cdot\,|x)}} \Big[c(x, y) \Big].$$

x can be viewed as a state, y as an action, and c as the opposite of a reward.

RL Problem

Policy Model

Control variables being continuous, we consider

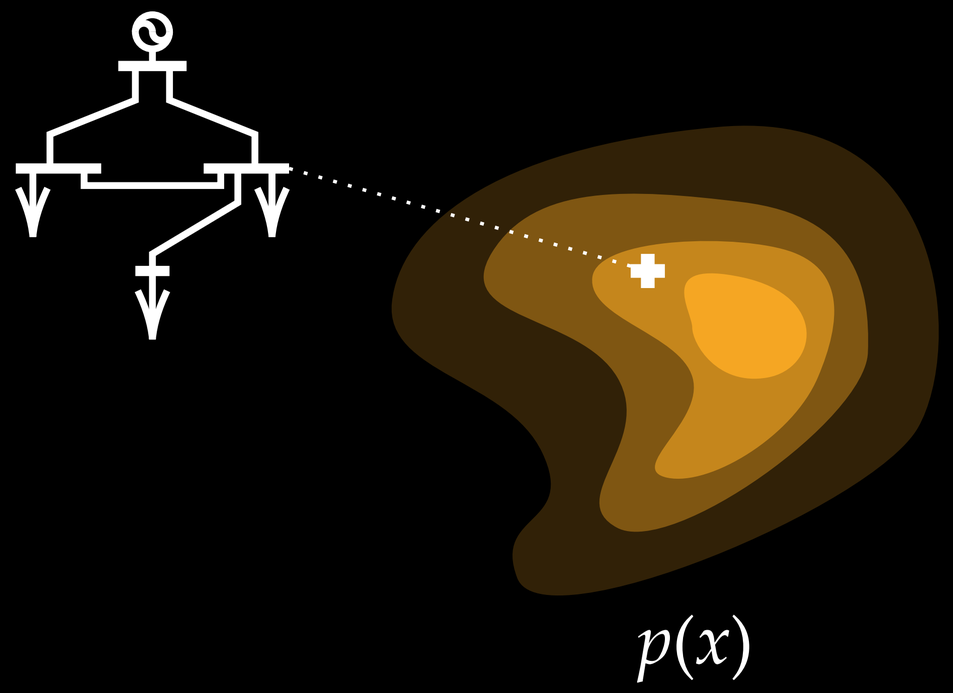
$$\Pi_\theta(\,\cdot\,|\,x) = \mathcal{N}(f_\theta(x), \sigma^2 \mathbb{1}),$$

where $\sigma > 0$ is fixed, $\mathbb{1}$ is the identity matrix, and f_θ is a neural network.

Hyper Heterogeneous Multi Graphs (H2MGs)

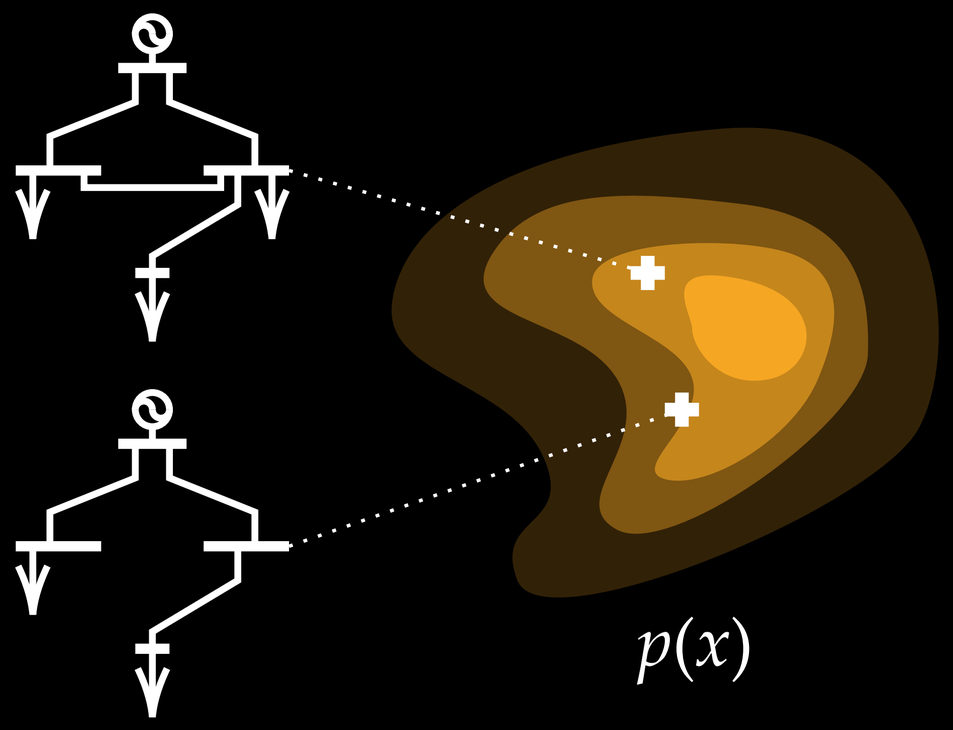
H2MGs

Operating Conditions Distribution



H2MGs

Operating Conditions Distribution



H2MGs

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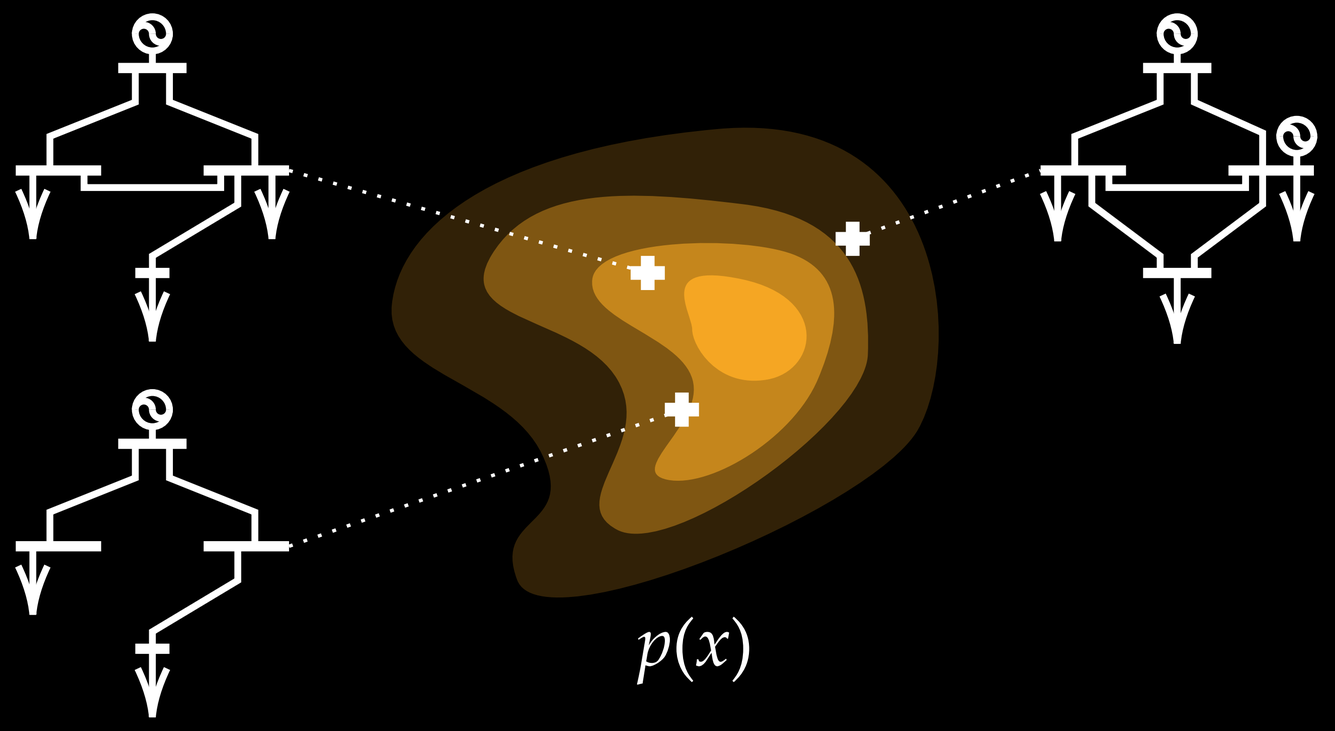
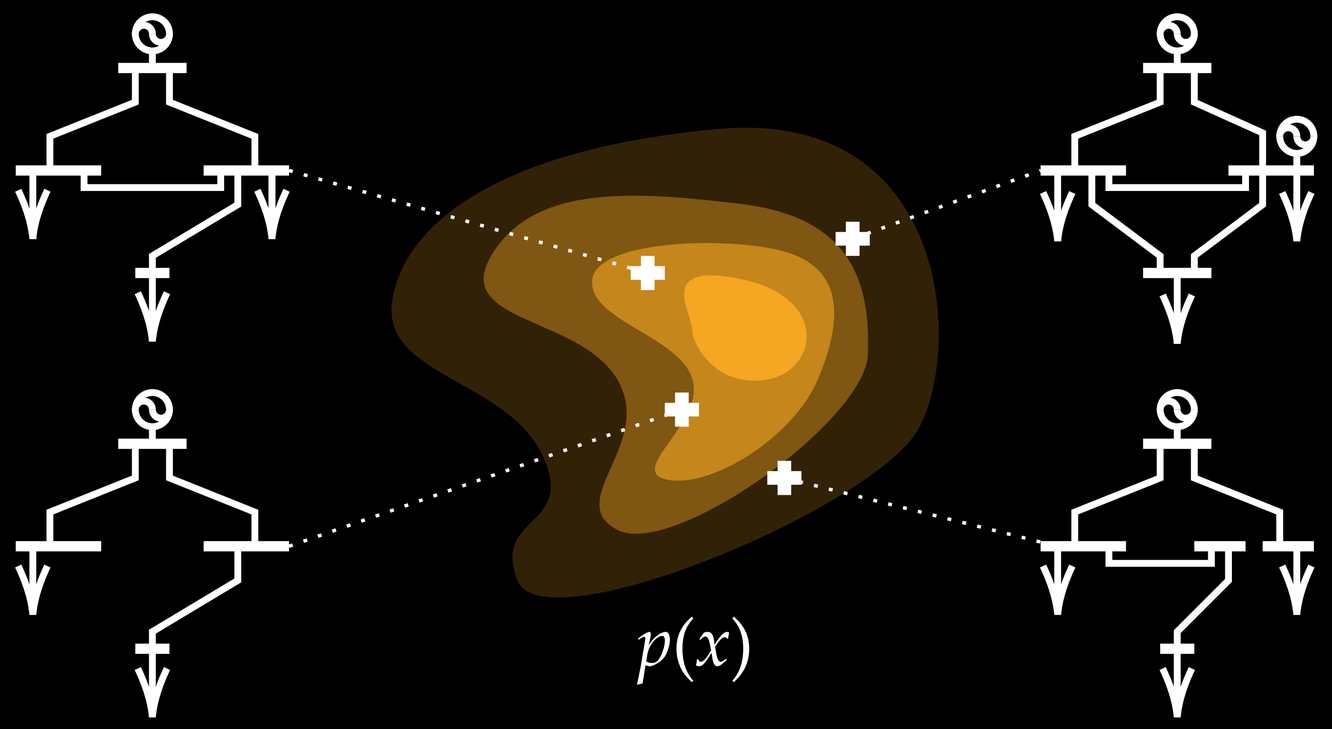


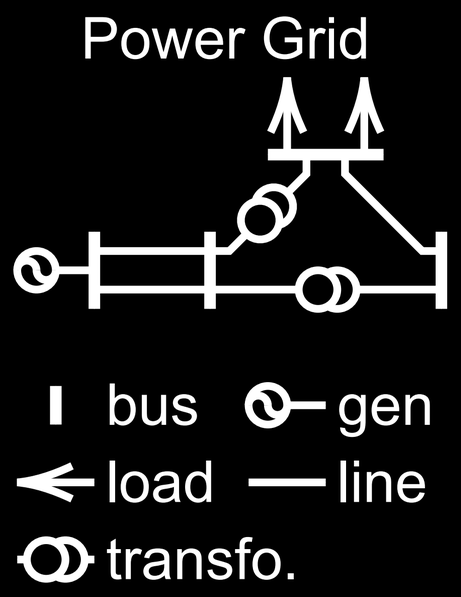
H2MGs

Operating Conditions Distribution



H2MGs

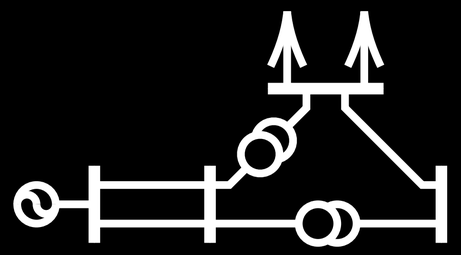
Data Representation



H2MGs

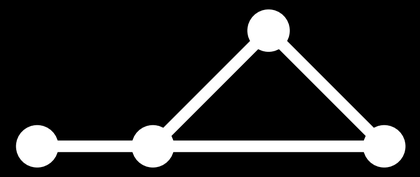
Data Representation

Power Grid



bus gen
load line
transfo.

Standard Graph

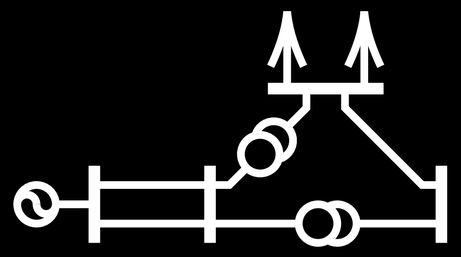


node
edge

H2MGs

Data Representation

Power Grid



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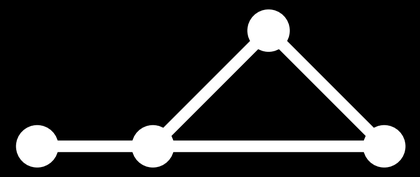
Standard Graph

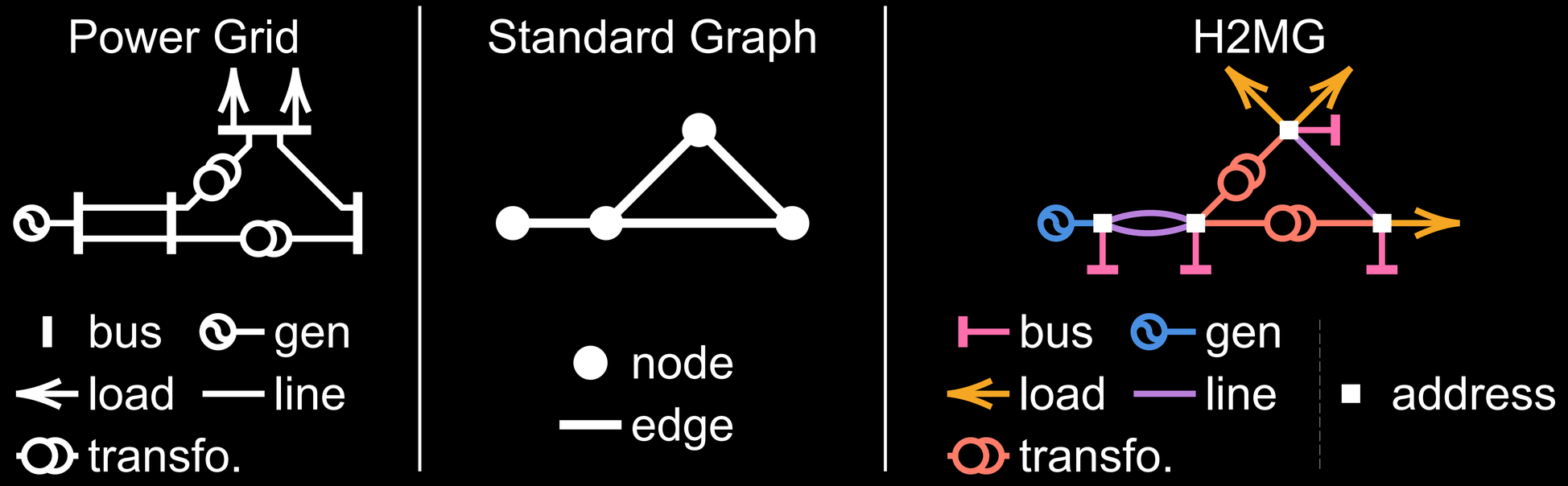


node
edge

Information loss !

H2MGs

Data Representation



H2MGs

Need for a Better Representation

- Actual power grids are :
  - Hyper graphs : Composed of hyper-edges of various orders,
  - Heterogeneous Graphs : Multiple classes of hyper-edges,
  - Multi Graphs : Multiple hyper-edges of the same class can be collocated.

B. Donon, “Deep statistical solvers & power systems applications,”

H2MGs

Graphical Structure

- Assets are referred to as *hyper-edges*.
- We denote by $\mathscr{C} = \{\text{bus, gen, load, line}, \dots\}$ the set of all classes of hyper-edges.
- For all class $c \in \mathscr{C}$, we denote by $\mathscr{E}_x^c$ the set of hyper-edges of class c.
  - Example : $\mathscr{E}_x^{line}$ is the set of transmission lines available in x.

B. Donon, “Deep statistical solvers & power systems applications,”

H2MGs

Graphical Structure

- Hyper-edges in x are interconnected through a set of *addresses* A_x.
- Addresses serve as interface between hyper-edges, and do not bear any numerical features.
- All hyper-edges of the same class c are connected to the same amount of addresses, through their ports $\mathcal{O}^c$.
  - A port $o \in \mathcal{O}^c : \mathcal{E}_x^c \to A_x$ is a mapping from an hyper-edge to an address.

B. Donon, “Deep statistical solvers & power systems applications,”

H2MGs

Graphical Structure

- Let $a \in A_x$ be an address.
- We define its neighborhood by :

$$N_x(a) = \{(c, e, o) \,|\, c \in \mathscr{C}, e \in \mathscr{E}_x^c, o \in \mathscr{O}^c, o(e) = a\}.$$

B. Donon, “Deep statistical solvers & power systems applications,”

H2MGs

Feature Vectors

- All hyper-edges of the same class bear feature vectors of the same size,

$$x = (x_e^c)_{c \in \mathscr{C}, e \in \mathscr{E}_x^c}.$$

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Neural Network Architecture

Neural Network Architecture

Overview

- Our policy Π_θ requires a trainable function f_θ to compute the mean of a Gaussian distribution.
- f_θ should take an operating condition x as input, and return a series of voltage setpoint values for each available generator.

B. Donon, “Deep statistical solvers & power systems applications,”

Neural Network Architecture

Encoding

At first, we encode feature vectors of all hyper-edges.

$$\forall c \in \mathscr{C}, \forall e \in \mathscr{E}_x^c, \qquad \tilde{x}_e^c = \Xi_\theta^c(x_e^c)$$

B. Donon, “Deep statistical solvers & power systems applications,”

Neural Network Architecture

Interaction

Then, we associate all addresses with latent coordinates $(h_a)_{a \in A_x}$, which we initialize at the origin.

$$\forall a \in A_x, \qquad h_a(\tau = 0) = [0,\ldots,0]$$

B. Donon, “Deep statistical solvers & power systems applications,”

Neural Network Architecture

Interaction

- Addresses then evolves in this latent space between $\tau = 0$ and 1 according to the following dynamical system (Neural Ordinary Differential Equation) :

$$\forall a \in A_x, \qquad \frac{dh_a}{d\tau} = \tanh\left(\sum_{(c,e,o)\in N_x(a)} \Phi_\theta^{c,o}(\tilde{x}_e^c, h_e(\tau), \tau) \right).$$

B. Donon, “Deep statistical solvers & power systems applications,”

Neural Network Architecture

Decoding

- Finally, we use the resulting latent state to produce a prediction for all hyper-edges that require one :

$$\forall c \in \mathscr{C}, \forall e \in \mathscr{E}_x^c, \qquad \mu_e^c = \Psi_\theta^c(\tilde{x}_e^c, h_e(1)).$$

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Neural Network Architecture

Overall System

- Here is the whole process,

$$\forall (c,e), \qquad \tilde{x}_e^c = \Xi_\theta^c(x_e^c),$$

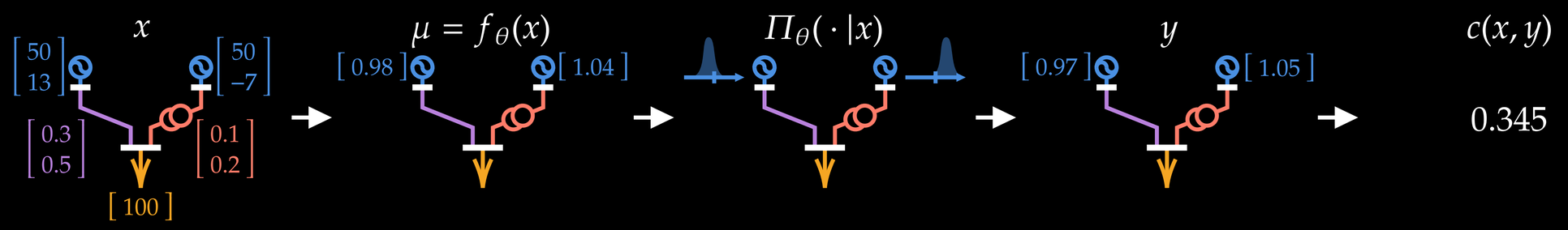
$$\forall a, \qquad h_a(0) = [0,\ldots,0],$$

$$\forall a, \qquad \frac{dh_a}{d\tau} = \tanh\left(\sum_{(c,e,o)\in N_x(a)} \Phi_\theta^{c,o}(\tilde{x}_e^c, h_e(\tau), \tau)\right)$$

$$\forall (c,e), \qquad \mu_e^c = \Psi_\theta^c(\tilde{x}_e^c, h_e(1))$$

Neural Network Architecture

Pipeline



Neural Network Architecture

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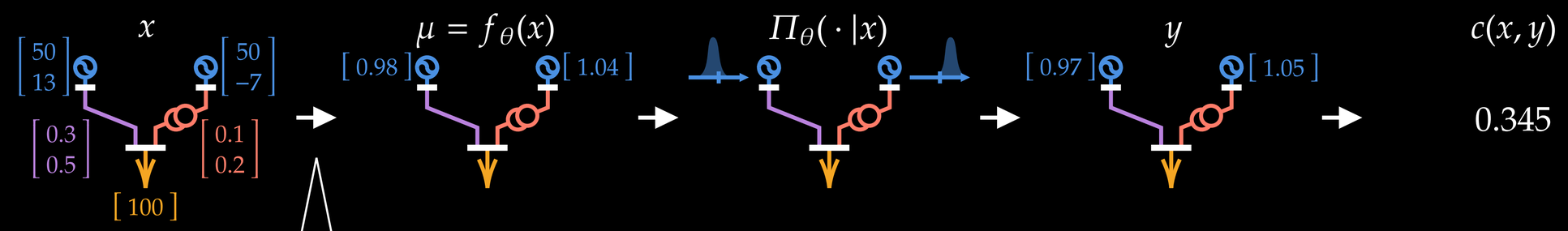
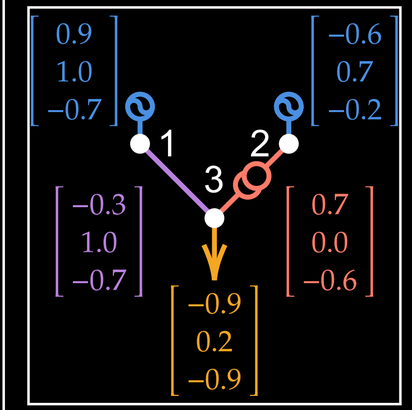


Encoding

$$\tilde{x}_e^c = \Xi_\theta^c\left(x_e^c\right)$$



Neural Network Architecture

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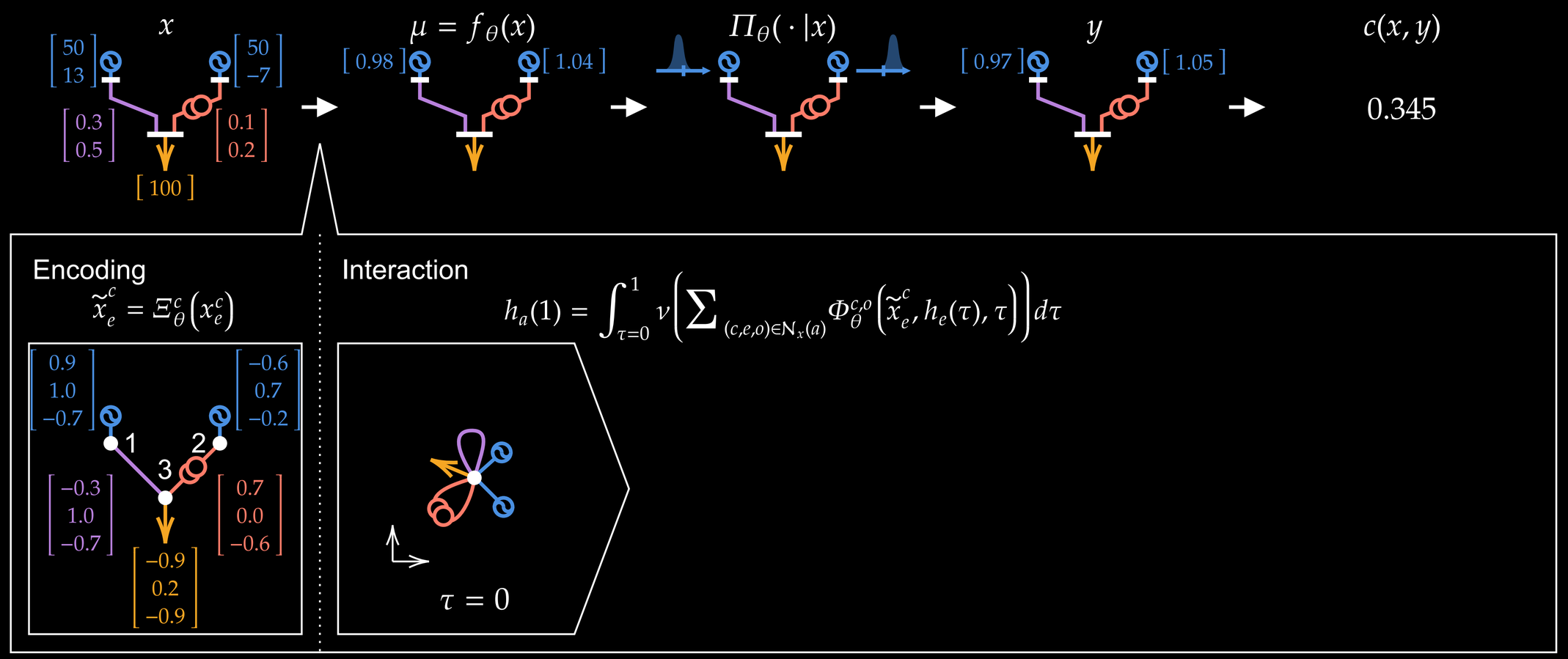

Neural Network Architecture

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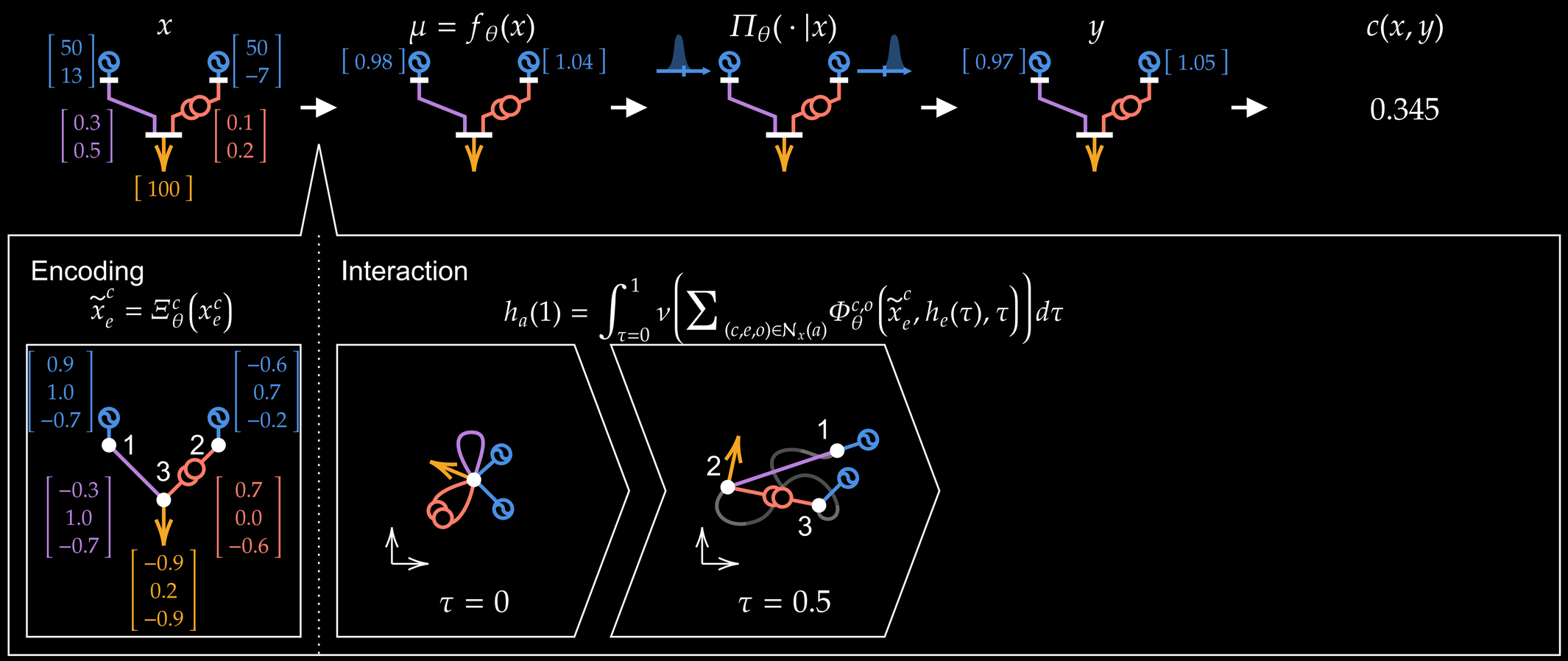
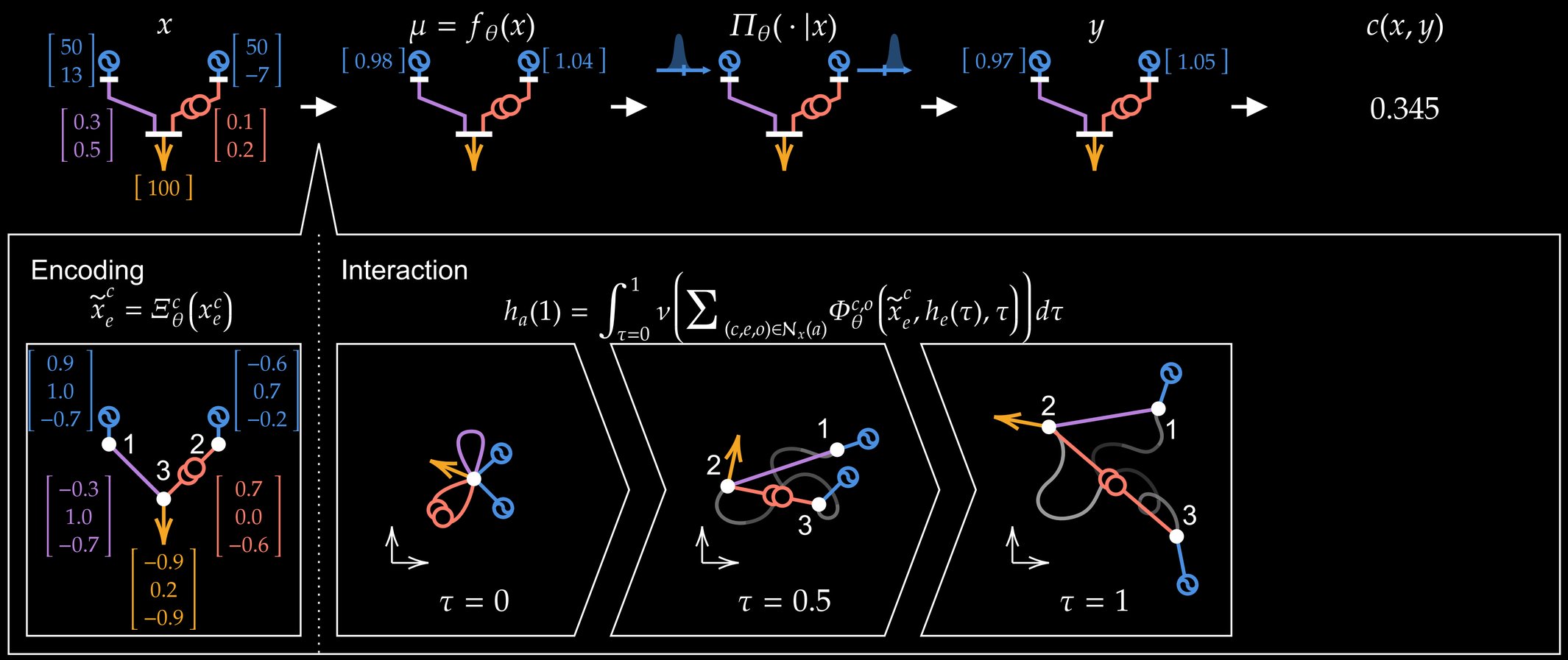


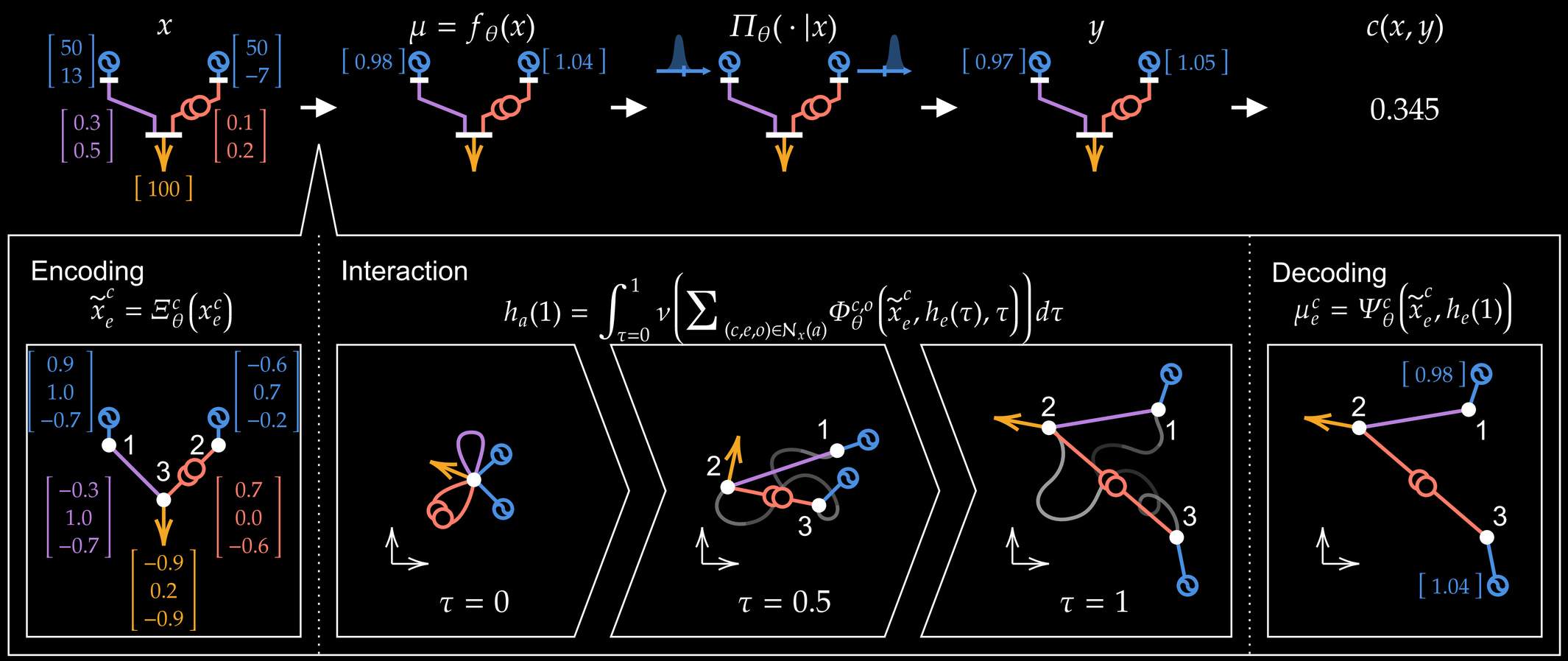
Neural Network Architecture

Pipeline



Neural Network Architecture

Pipeline



Policy Training

Policy Training

Algorithm

- Because of the absence of sequentiality, we have chosen a basic RL method called *REINFORCE*.

- For a certain x, we have

$$\nabla_\theta \mathbb{E}_{y\sim\Pi_\theta(\cdot|x)}\left[c(x,y)\right] = \mathbb{E}_{y\sim\Pi_\theta(\cdot|x)}\left[c(x,y)\,\nabla_\theta \log \Pi_\theta(y\,|\,x)\right].$$

- For a given x, we draw multiple actions $y \sim \Pi_\theta(\,\cdot\,|\,x)$ to obtain an empirical estimation of the right term.

Experiments

Experiments

Missing Data

- Artificial data for now.
- Results have not been published for now, but basically it works quite well !
- It works on datasets with varying number of generators, lines, transformers, etc.
  - Compatible with real-life data !

Future Work

Future Work

Main directions

- Improve sample efficiency of our training pipeline.
- Implement on real-life data.
- Consider discrete variables.
- Address other Power Systems issues.

Thank you !