

Deep Learning Enhanced Time-step Control in Pseudo Transient Analysis for Efficient Nonlinear DC Simulation

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**Accelerating
DC analysis
with deep
learning**

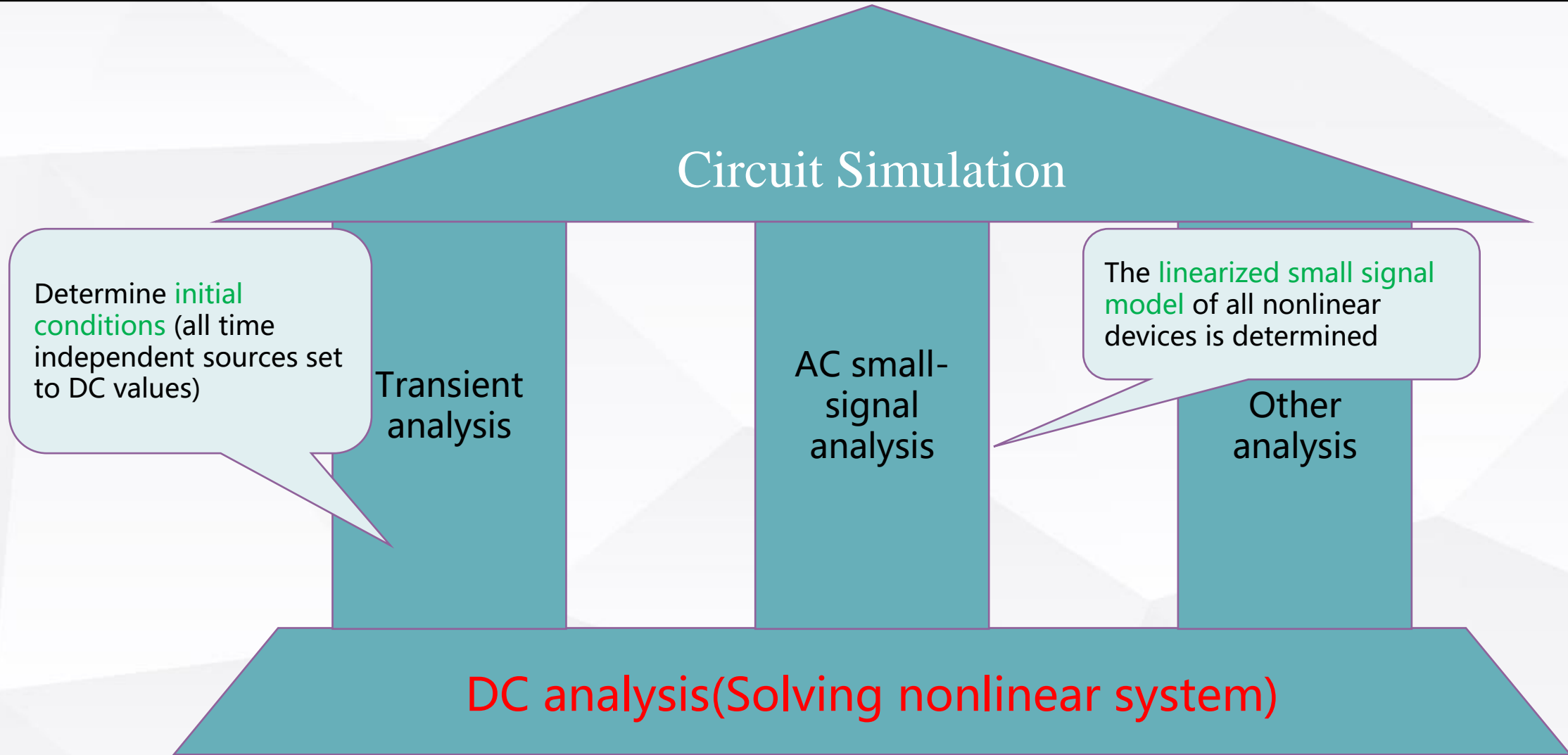
04

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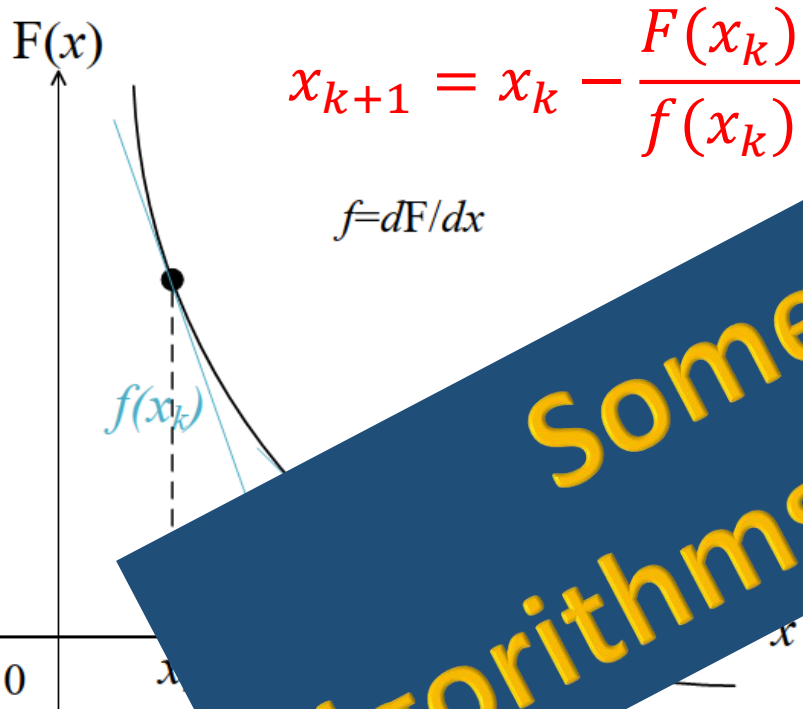
01 Background



Circuit simulation is a crucial step for **verifying** circuit design and Direct current (DC) analysis, which locates DC operating points, is the **first and fundamental** step in circuit simulation.

01 Background

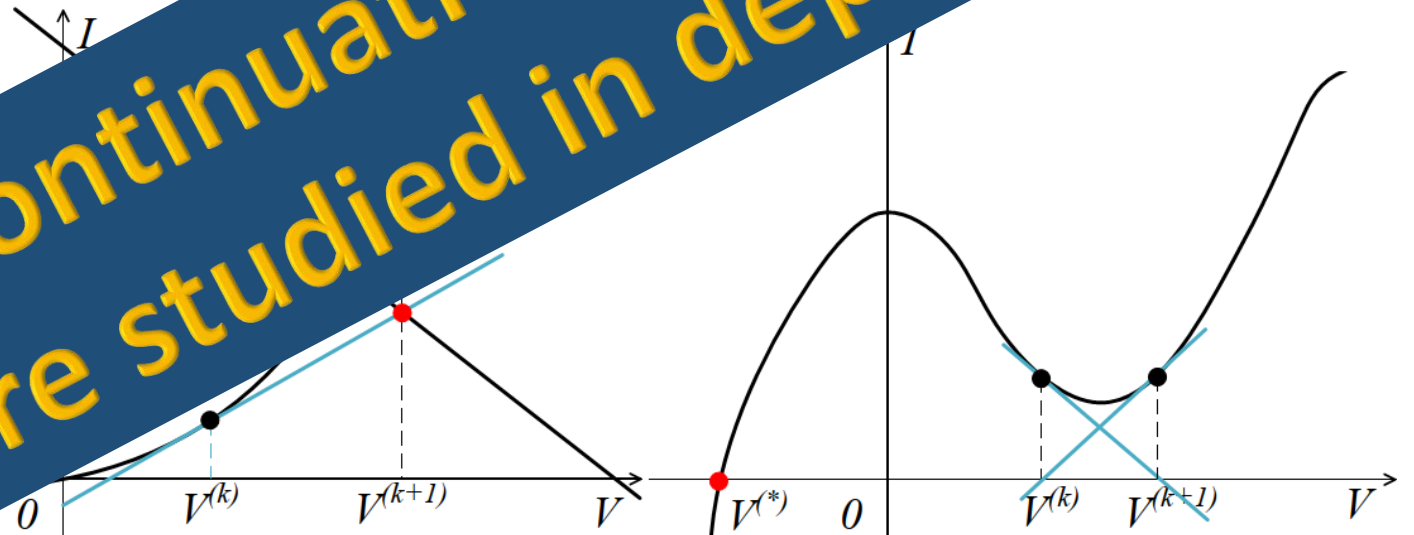
Newton-Raphson method: second-order convergence



$$x_{k+1} = x_k - \frac{F(x_k)}{f(x_k)}$$

$f = dF/dx$

Some continuation algorithms are studied in depth.

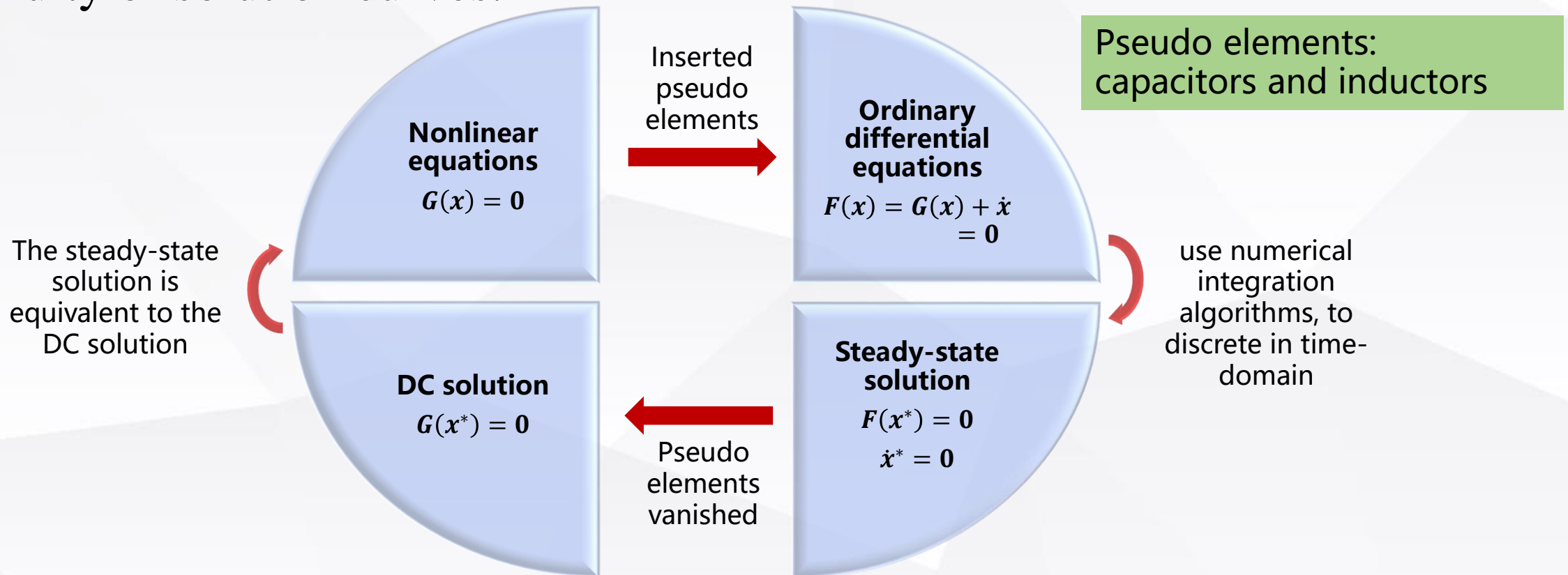


(a) Numerical overflow of the solution (b) Oscillation of the solution

However, its convergence is often limited by **the choice of initial value** (a)(b) and **the dominance of the main diagonal matrix**.

01 Background

PTA(Pseudo Transient Analysis) is the currently most **powerful** and **promising** continuation approach because of its ease of implementation and good continuity of solution curves.



01 Background

Ordinary differential equations:

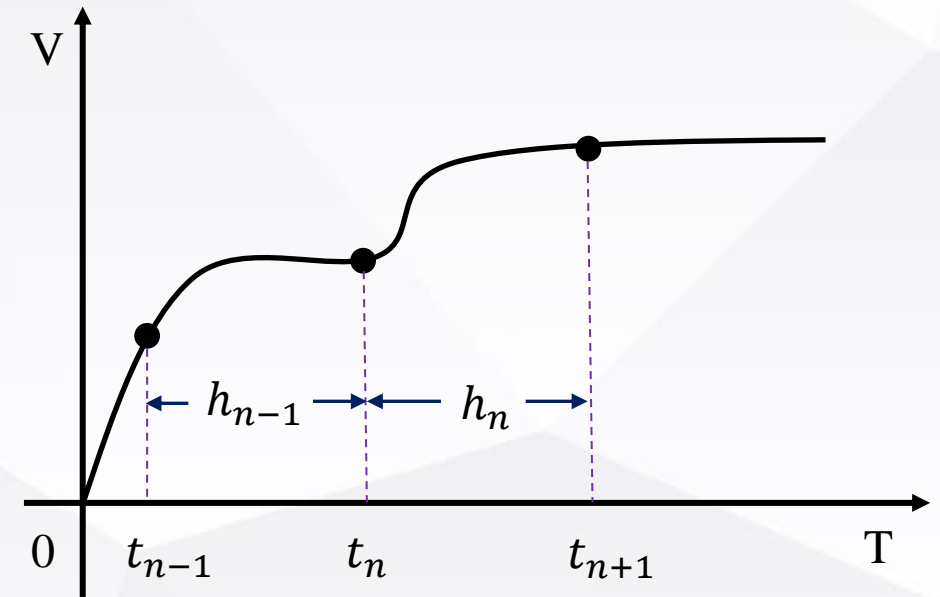
$$F(x) = G(x) + \dot{x} = 0$$

Use BE(Back Euler) to discretize above ODEs:

$$\dot{x} = \frac{dx}{dt} \Big|_{t=t_{n+1}} = \frac{x_{n+1} - x_n}{t_{n+1} - t_n} = \frac{x_{n+1} - x_n}{h_n}$$

The **time-step control method** determines the number of discrete nonlinear equations to be solved, which involves **time-consuming** and **resource-consuming** NR iterations.

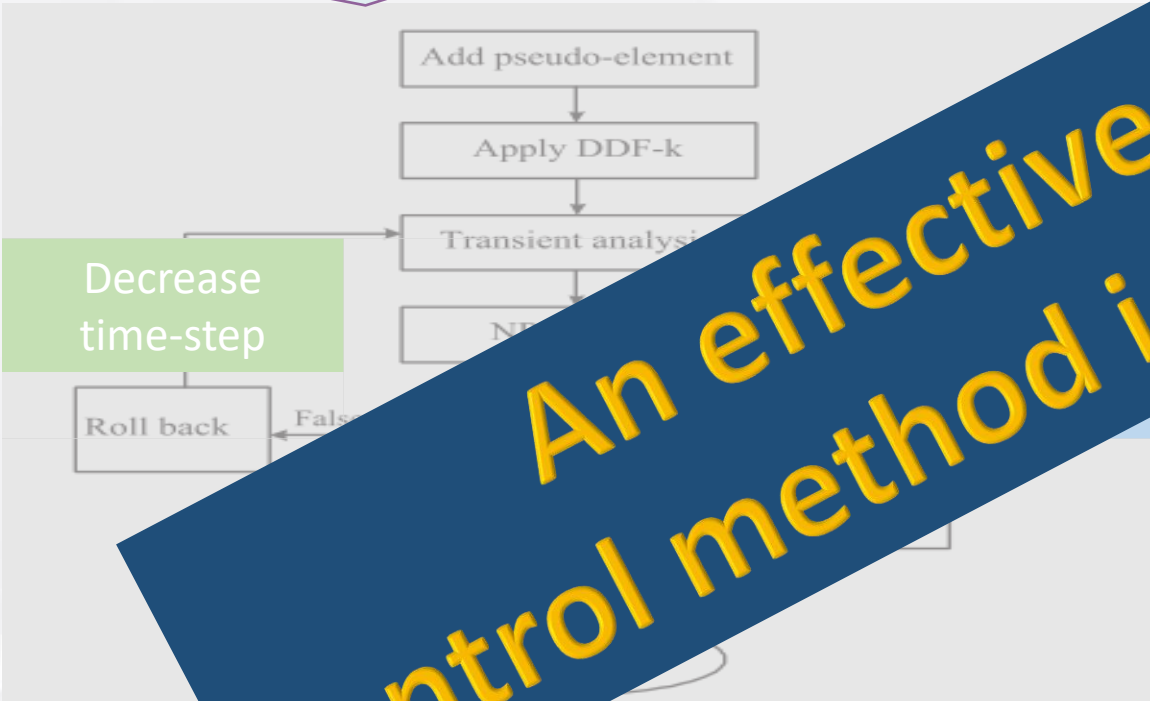
How to select h for each PTA step as the **time-step control method**



02 Motivation

The time-step control methods[3], [4] based on simple formulas have been proposed to accelerate PTA.

An effective time-step control method is highly desirable!



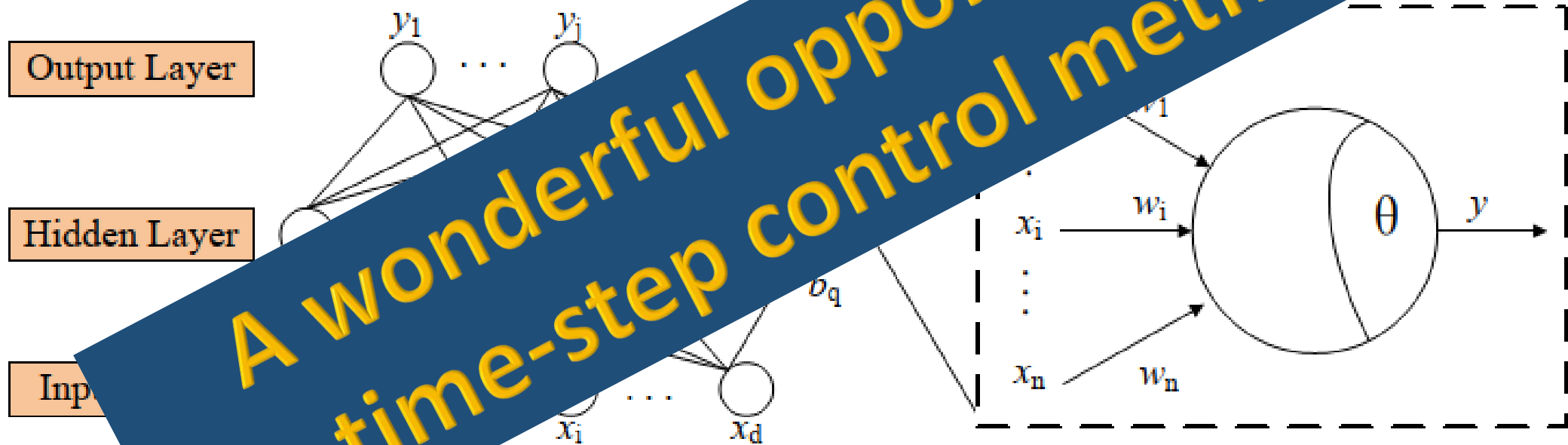
- control methods are **ineffective** under the following conditions:
- (1) Different circuits have different time step requirements;
 - (2) Different simulation stages of the same circuit have different time step requirements.

[3] Wu X, Jin Z, Niu L et al. An adaptive time-step control method using numerical integration algorithms with artificial damping for solving nonlinear DC circuits[J]. Nonlinear Theory and Its Applications, IEICE, 2014, 5(4): 511-516.

[4] Wu X, Jin Z, Niu L et al. An adaptive time-step control method in damped pseudo-transient analysis for solving nonlinear DC circuit equations[J]. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, 2017, 100(2): 619-628.

02 Motivation

With the rise of deep learning, many complex problems have been solved [5] [6].



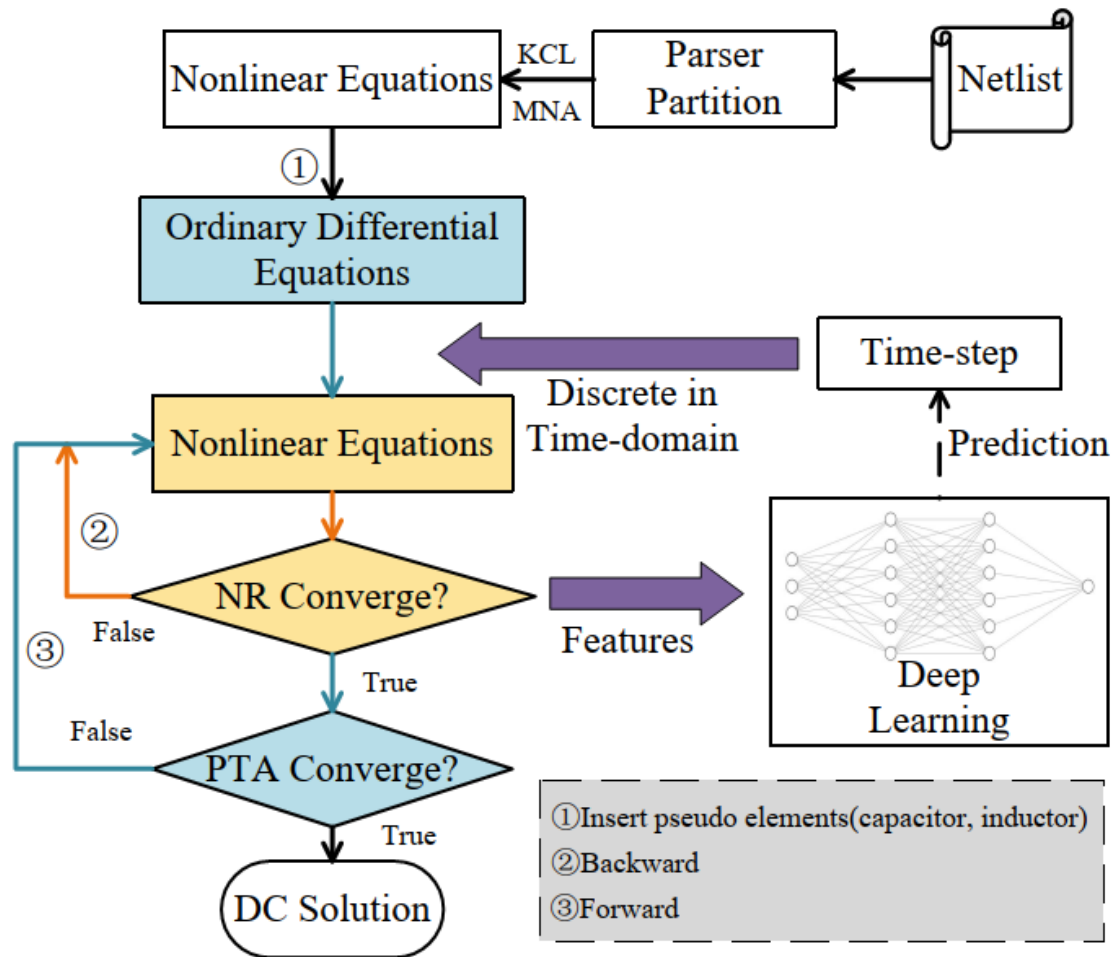
A wonderful opportunity for time-step control method.

Deep learning is a subset of machine learning that focuses on learning from data without the need for explicit programming of the internal rules and representation layers of sample data. Especially, it has good fitting ability for complex nonlinear relations such as computer vision, natural language processing, etc.

[5] D. A. Forsyth and J. Ponce, Computer vision: a modern approach. prentice hall professional technical reference, 2002.

[6] E. Cambria and B. White, "Jumping nlp curves: A review of natural language processing research," IEEE Computational intelligence magazine, vol. 9, no. 2, pp. 48–57, 20.

03 Accelerating DC analysis with deep learning



Challenge1:
There is no the dataset of the optimal time-step as label and also no precise definition for the optimal time-step in PTA

Challenge2:
Different types of circuits have different requirements for optimal time-step

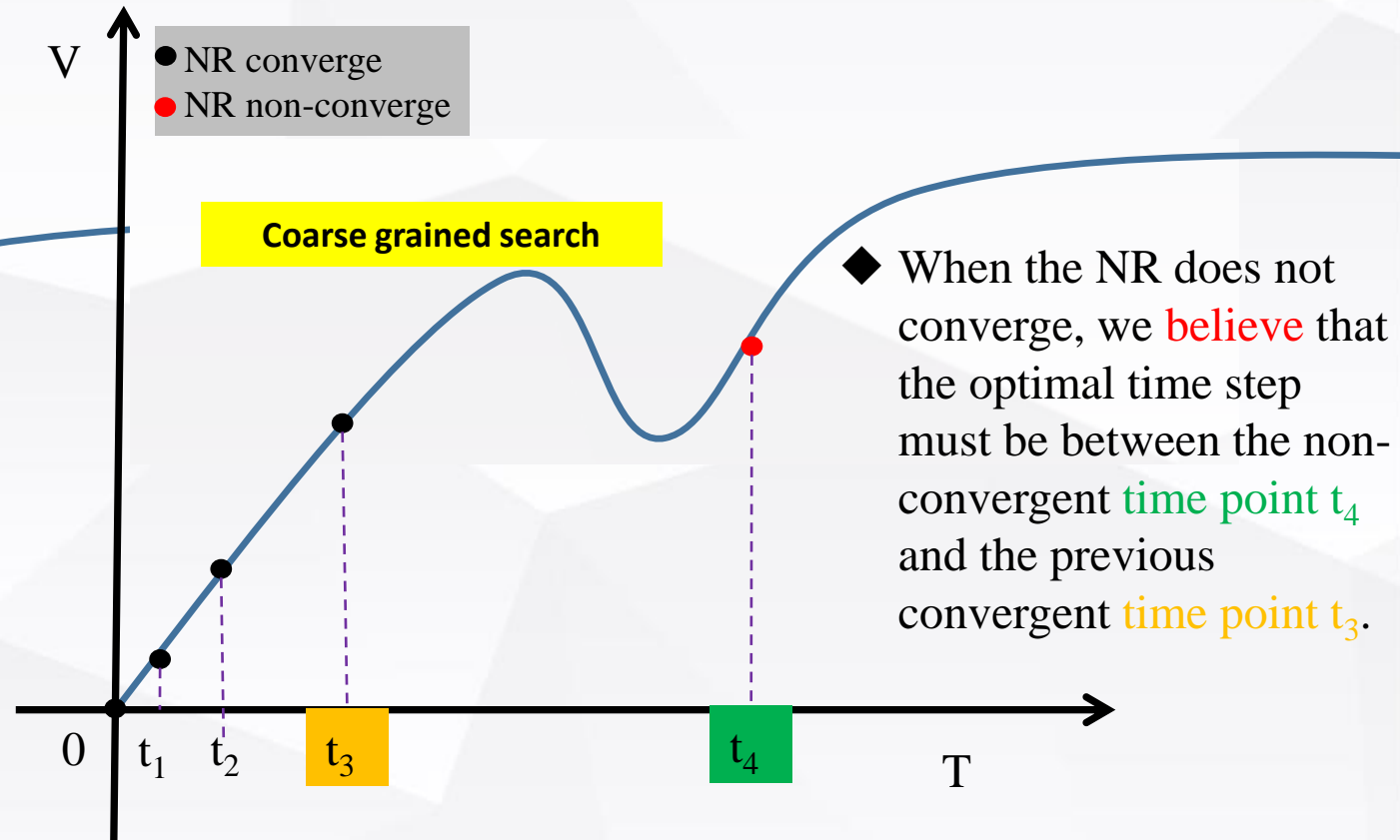
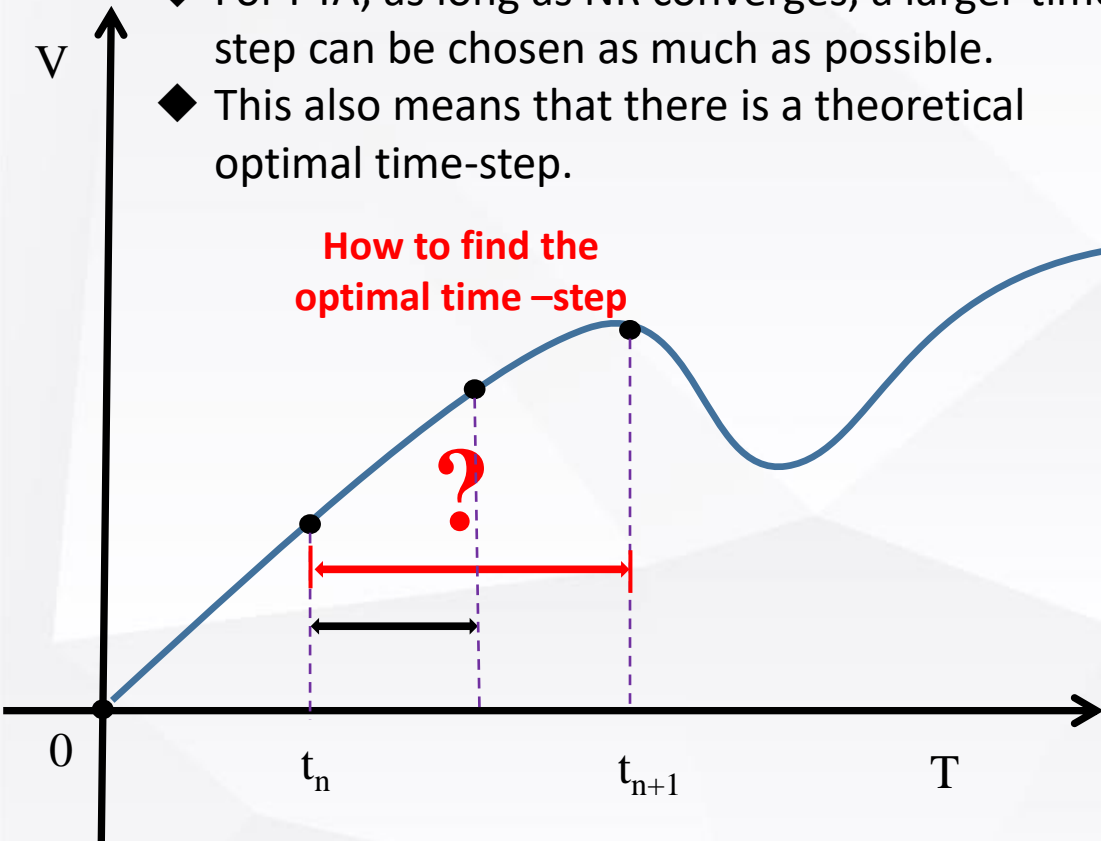
Challenge3:
The sequence over time of PTA time-step

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Challenge1: There is no the dataset of the optimal time-step as label and also no precise definition for the optimal time-step in PTA.

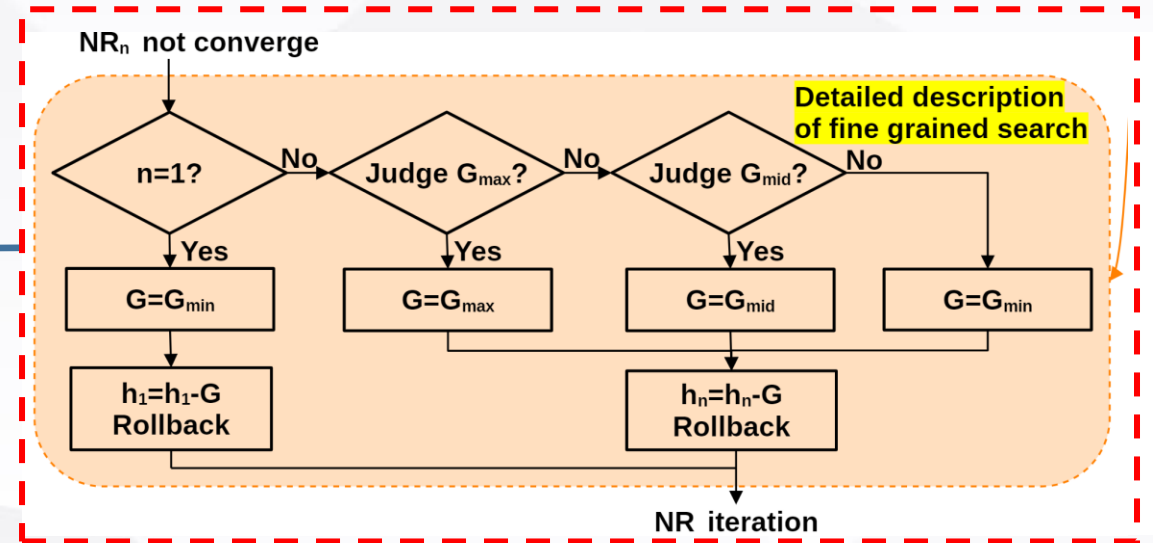
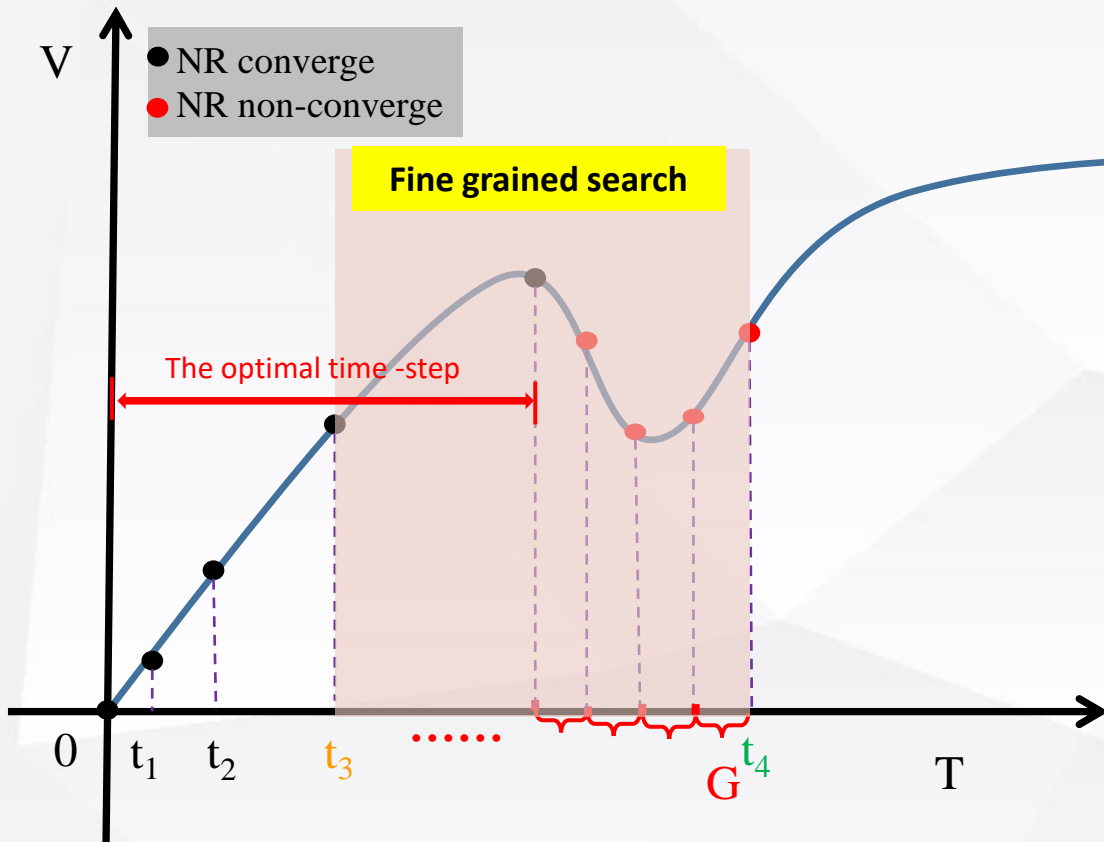
➤ Solve Challenge1: Coarse and Fine Grained Hybrid Sampling

- ◆ For PTA, as long as NR converges, a larger time-step can be chosen as much as possible.
- ◆ This also means that there is a theoretical optimal time-step.



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➤ Solve Challenge1: Coarse and Fine Grained Hybrid Sampling



- ◆ To ensure the efficiency of searching strategy, an **adaptive granularity** trick for a fine grained process is adopted, which can choose different granularities according to the order of magnitude of time step.

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Challenge2: Different types of circuits have different requirements for optimal time-step

➤ Solve Challenge2: Features selection

- ◆ While different circuit types require different time-step requirements, we select conventional **process variables** in circuit solving **but not circuit characteristics** as features. It can be utilized as to identify the distinct time-step necessities.
- ◆ Based on expert experience, we selected the following features from the perspective of solving ordinary differential equations.

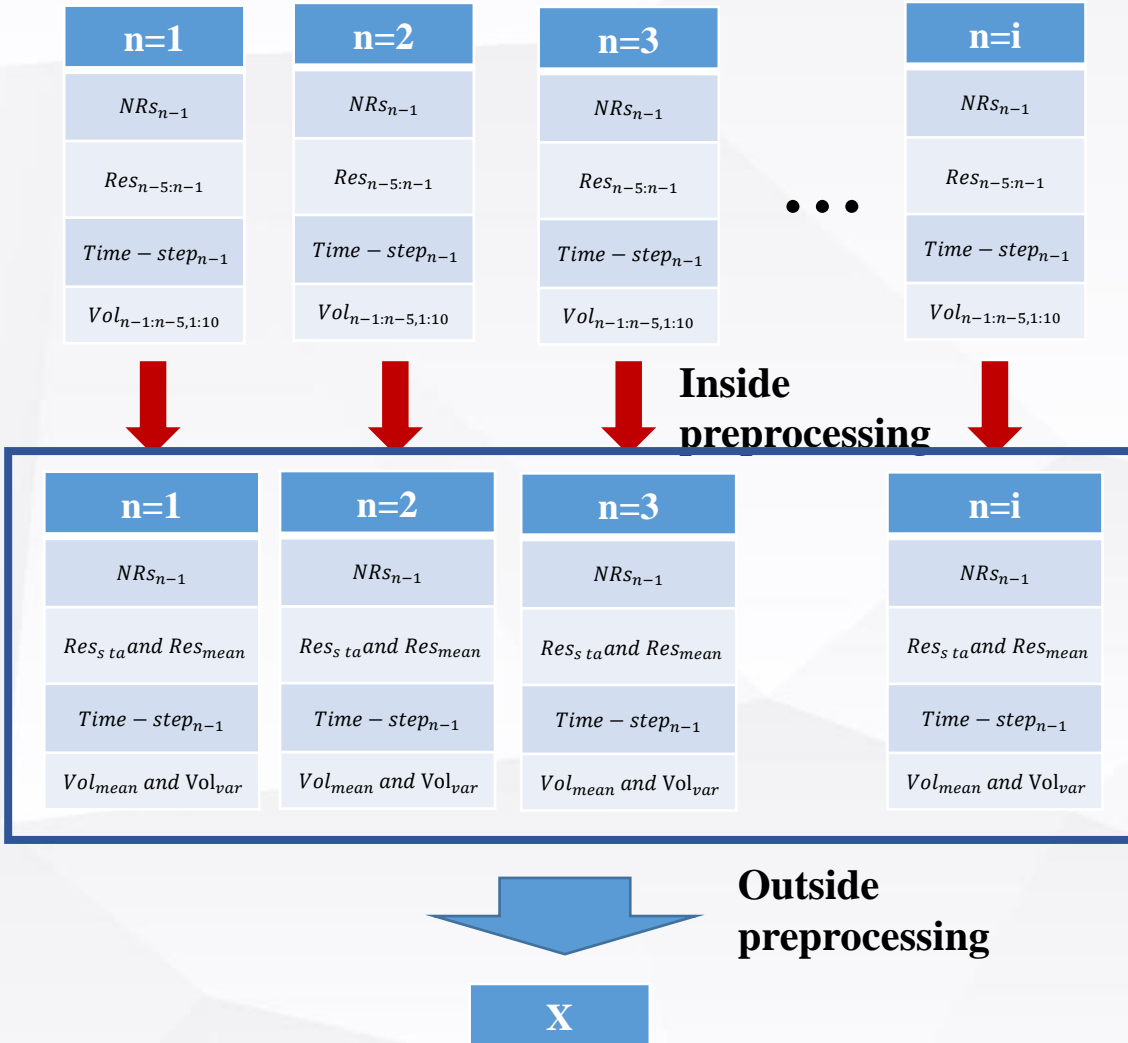
For the n PTA step:

Features	Brief Description	Data Type
NRs_{n-1}	Evaluate the difficulties of NR convergence at previous optimal time-step	Scalar
$Res_{n-5:n-1}$	Evaluate whether equation is close to final solution at five discrete time points respectively	Vector
$Time - step_{n-1}$	The previous optimal time-step	Scalar
$Vol_{n-1:n-5,1:10}$	The ten voltage solution curves in descending order of fluctuation	Matrix

The data types are **not all the same**, so special data processing methods are required.

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➤ Two-stage data preprocessing strategy



- ◆ **Inside data preprocessing strategy.** Describe the fluctuations of the voltage solution curve and residuals .

$$Res_{mean} = \bar{Res} = \frac{\sum_{i=1}^k Res_i}{k}$$

$$Res_{std} = \sqrt{Res^2} = \sqrt{\frac{\sum_{i=1}^k (Res_i - \bar{Res})^2}{k-1}}$$

$$Vol_{mean} = \bar{Vol} = \frac{\sum_{i=1}^k Vol_i}{k}$$

$$Vol_{var} = \frac{\sum_{i=1}^k (Vol_i - \bar{Vol})^2}{k-1}$$

- ◆ **Outside data preprocessing strategy.** Normalized each column of the training set.

$$x' = \frac{x - X_{min}}{X_{max} - X_{min}}$$

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Challenge3: The sequence over time of PTA time-step

➤ Solve Challenge3: Long Short Term Memory

The forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

The input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$C'_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

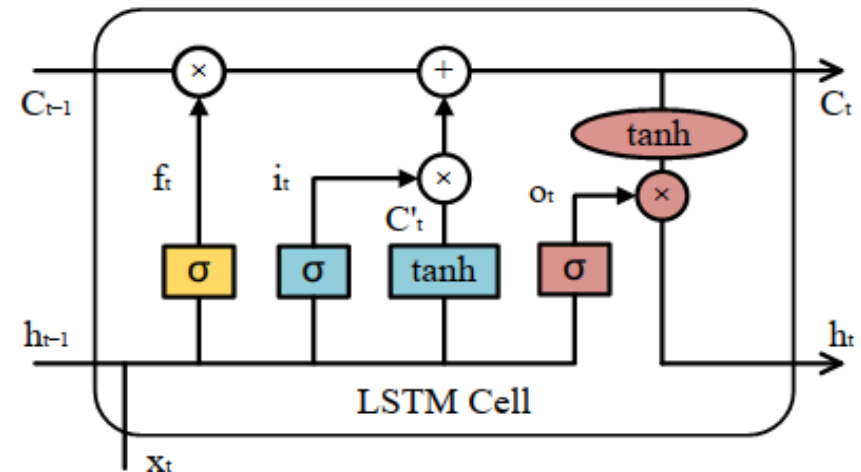
$$C_t = i_t \cdot C'_t$$

The output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

- ◆ Due to the timing nature of PTA time-step control, **LSTM** is employed to deal with timing information because it can deal with the **problem of gradient disappearance** in time-sequence information from back propagation.



04 Performance

➤ Environment Setup:

Software Environment:

- (1) Model of Deep Learning: Python and PyTorch
- (2) Simulator: WSPICE
- (3) Operation System: Windows11

Hardware Environment:

- (1) CPU: Intel (R) Core (TM) i7-8565U
- (2) Memory: 512G
- (3) Frequency: 1.80GHz

➤ Training Set: 745 samples from 5 circuits

04 Performance

➤ Simulation Efficiency:

Circuit characteristics and simulation efficiency for DPTA

Better generalization

circuit	nodes	eqn	bjt	mos2	mos3	c	r	v	number of NR iters			speedup	
									conventional	adaptive	ours	vs. conventional	vs. adaptive
nagle	26	54	23	0	0	1	11	5	2093	1948	672	3.11	2.90
ab_ac	25	28	0	31	0	22	1	3	3961	3947	265	14.95	14.89
ab_integ	28	32	0	31	0	24	3	4	4540	4406	402	11.29	10.96
ab_opamp	28	31	0	31	0	24	4	3	2417	2536	430	5.62	5.90
e1480	145	204	0	28	0	17	130	3	5553	5514	369	15.05	14.94
mosrect	6	10	0	4	0	0	2	2	838	826	84	9.98	9.83
schmitfast	5	19	0	6	0	0	0	2	5681	5691	176	32.28	32.34
slowlatch	12	37	0	0	14	0	1	5	9382	9353	264	35.54	35.43
fadd32	161	178	0	288	0	25	0	17	1968	1859	284	6.93	6.55
TADEGLOW6TR	18	18	0	3	0	0	18	1	145	102	70	2.07	1.46
THM5	26	26	9	0	0	0	0	1	5331	5324	127	41.98	41.92

- ◆ The proposed method outperforms conventional method [7] up to **41.98X** and adaptive method [8] up to **41.92X** in terms of NR iterations in damped pseudo-transient analysis(DPTA).

[7] Wu X, Jin Z, Niu D, et al. A PTA method using numerical integration algorithms with artificial damping for solving nonlinear DC circuits[J]. Nonlinear Theory and Its Applications, IEICE, 2014, 5(4): 512-522.

[8] Wu X, Jin Z, Niu D, et al. An adaptive time-step control method in damped pseudo-transient analysis for solving nonlinear DC circuit equations[J]. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, 2017, 100(2): 619-628.

04 Performance

➤ Simulation Convergence:

- ◆ This is a **particularly important improvement** for PTA.
- ◆ Nonconvergence issues is **extremely difficult** for simulator to deal with and the cause is often unable to be accurately located.

Improvement convergence for DPTA on some circuits

circuits	convergence		
	conventional	adaptive	ours
bjtff	N/A	N/A	479
schmitslow	N/A	N/A	468
toronto	N/A	N/A	364
add20	N/A	N/A	673
mem_plus	N/A	N/A	858
ram2k	N/A	N/A	526
voter	N/A	N/A	1261
jge	N/A	N/A	1342

Number of NR iters

05 Conclusion

- The optimal time-step is approximated by **coarse and fine grained hybrid sampling strategy**.
- The time-step control method enhanced by **LSTM** model and based on **feature selection** and **two-stage data preprocessing strategy** has better generalization and simulation efficiency.
- Experimental results demonstrate a fine speedup: up to **41.98X**.



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Thanks!