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Bayesian identification of parameters for modelling chloride ingress into reinforced concrete

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1. Introduction

Corrosion in reinforced concrete(RC) structures :

- Shorten the lifetime of RC structures
- Generate important damages after 10 or 20 years (Rosquoët et al. 2006; Bonnet et al. 2009)

→ Inspection to determine concentration level of chloride is important to:

- Minimizing the risks and consequences of corrosion initiation
- Ensuring optimal levels of serviceability and safety

Comprehensive parameter identification from limited inspection data → important for optimizing maintenance costs and improving lifetime assessment

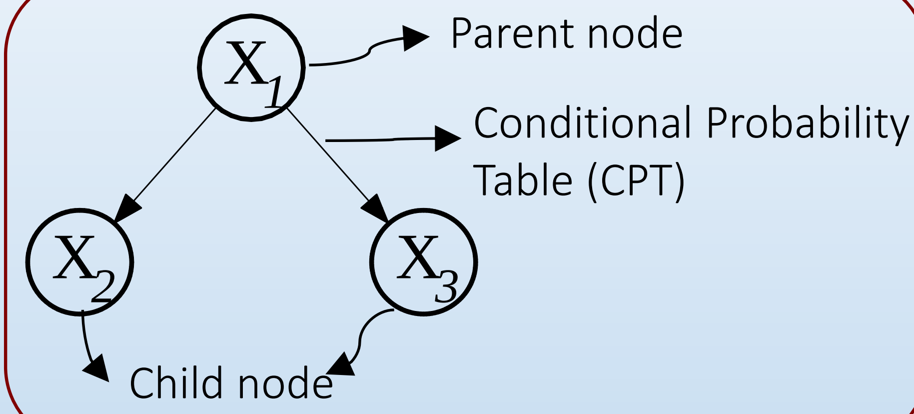
Bayesian network →
- Updating probabilities (Richard et al. 2012)
- Parameter identification (Bastidas-Arteaga et al. 2012)
- Improving BN configuration for identification

OUTLINE

1. Introduction
2. Bayesian identification and its application to chloride ingress
3. Influence of BN configuration on identification
   3.1 General aspects for comparison of BN configurations
   3.2 Identification using one point in depth of inspection
   3.3 Identification using full depth of inspection
4. Assessment of the probability of corrosion initiation
5. Conclusions and perspectives

2. Bayesian identification and its application to chloride ingress

Bayesian network (BN)



Chloride ingress model

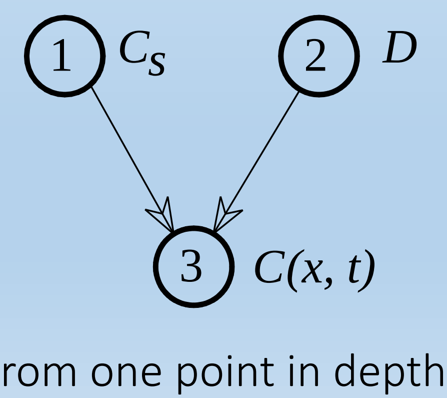
[Tuutti 1982]

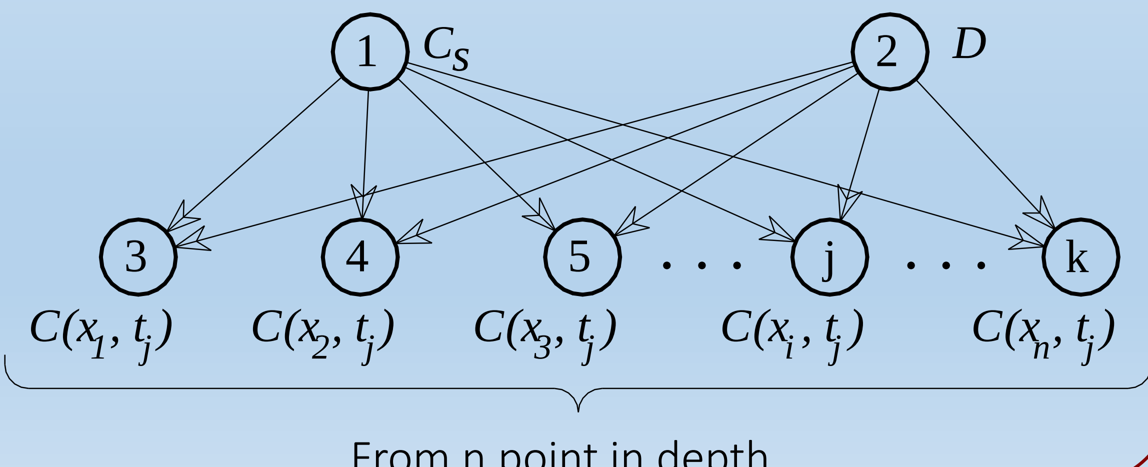
$$C(x,t) = C_s\left[1 - erf\left(\frac{x}{2\sqrt{Dt}}\right)\right]$$

With:

- Cs: chloride surface concentration (kg/m^3)
- D: effective chloride diffusion coefficient (m^2/s)

The BN apply to chloride ingress





2. Bayesian identification and its application to chloride ingress

Assuming that Cs and D are independent: $p(D,C_s) = p(D).p(C_s)$, the probability $p(C(x,t))$ can be calculated as follow (Nguyen. 2007):

$$p(C(x,t)) = \sum_{D,C_s} p(C(x,t) \mid D,C_s)\, p(D,C_s)$$

Introducing some evidences from chloride profiles collected, $p(C(x,t) \mid o)$, the posterior distribution can be computed by applying Bayes' theorem:

$$p(D \mid o) = p(D \mid C(x,t))\, p(C(x,t) \mid o) \quad \text{with} \quad p(D \mid C(x,t)) = \frac{p(C(x,t) \mid D)\, p(D)}{p(C(x,t))}$$

$$p(C_s \mid o) = p(C_s \mid C(x,t))\, p(C(x,t) \mid o) \quad \text{with} \quad p(C_s \mid C(x,t)) = \frac{p(C(x,t) \mid C_s)\, p(C_s)}{p(C(x,t))}$$

All the determination of these conditional probabilities are carried out by the Bayesian Network Toolbox (BNT) (K.P. Murphy) on the Matlab® Software

Discretization of parameters

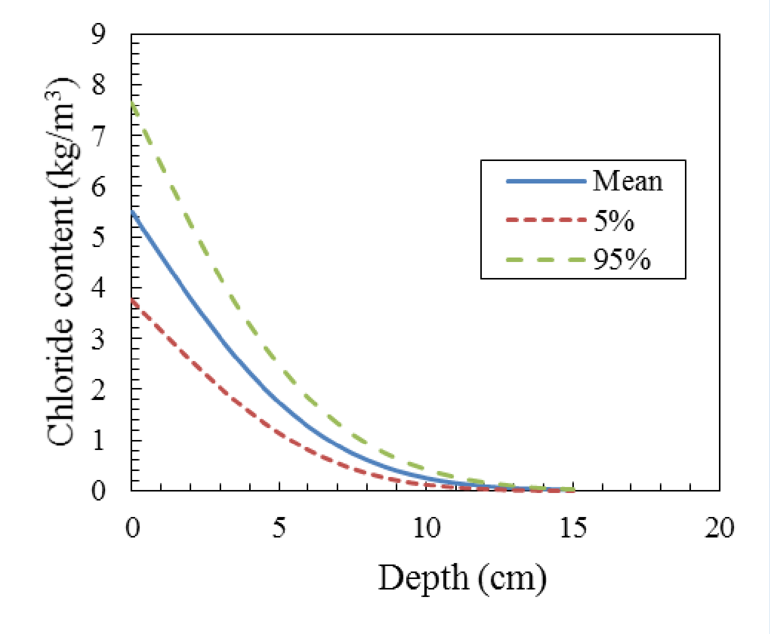
Parameters	Number of intervals	Priori distribution	Range
C_s (kg/m^3)	16	Uniform	(1; 17)
D (m^2/s)	20	Uniform	(2e-12 ; 8e-12)
C(x,t) (kg/m^3)	-	-	(0 ; 17)

Theoretical values for generating numerical evidences (Vu & Stewart 2000)

Parameters	Distribution	Mean	Standard deviation
C_s	Lognormal	5.5 (kg/m^2)	1.2(kg/m^2)
D	Lognormal	4e-12 (m^2/s)	5E-13(m^2/s)

MCS

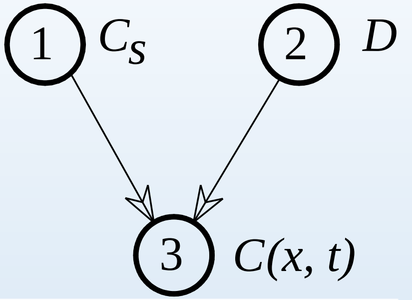
10000 profiles at t_{ins} =10 years



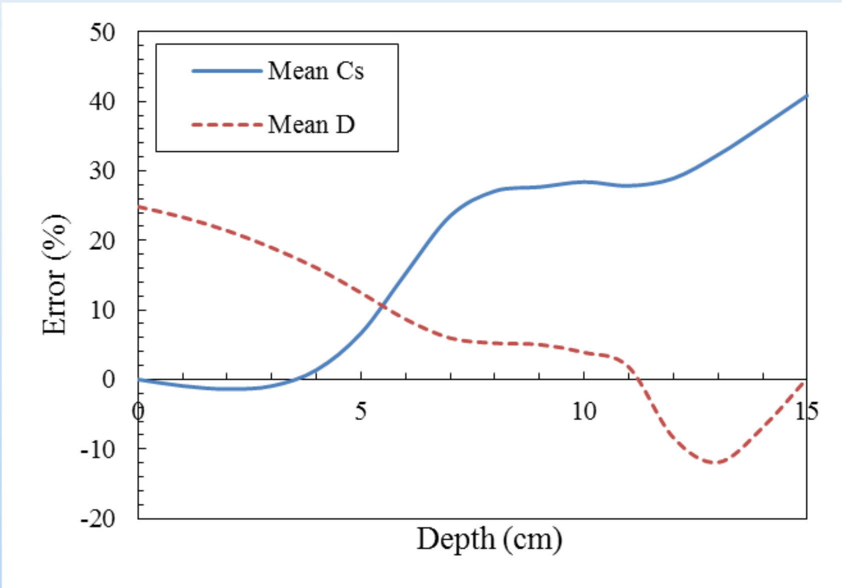
Evaluating configurations

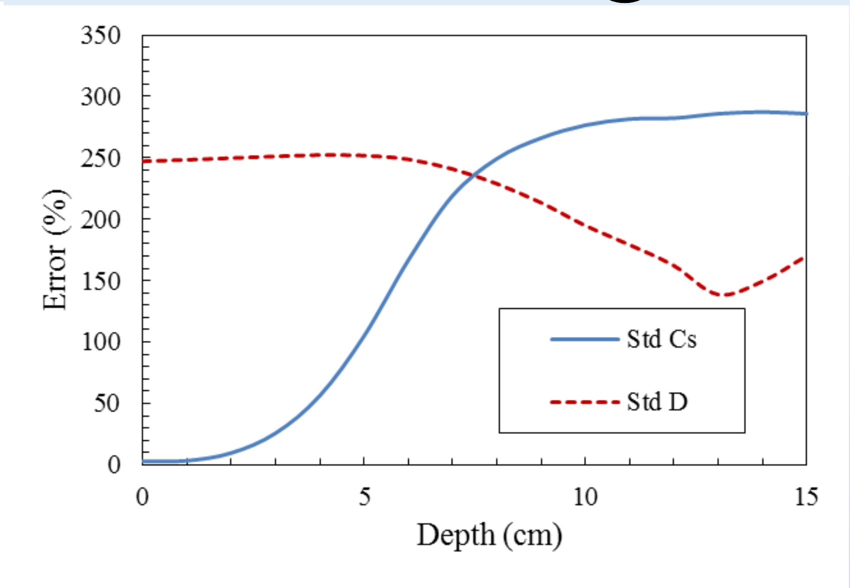
$$Error(y) = \frac{y_{identified} - y_{theory}}{y_{theory}}.100\%$$

y : represents for the mean or the standard deviation of parameters



- Inspection time t_{ins} = 10 years
- The BN consists of three nodes: Cs, D and C(x,t)



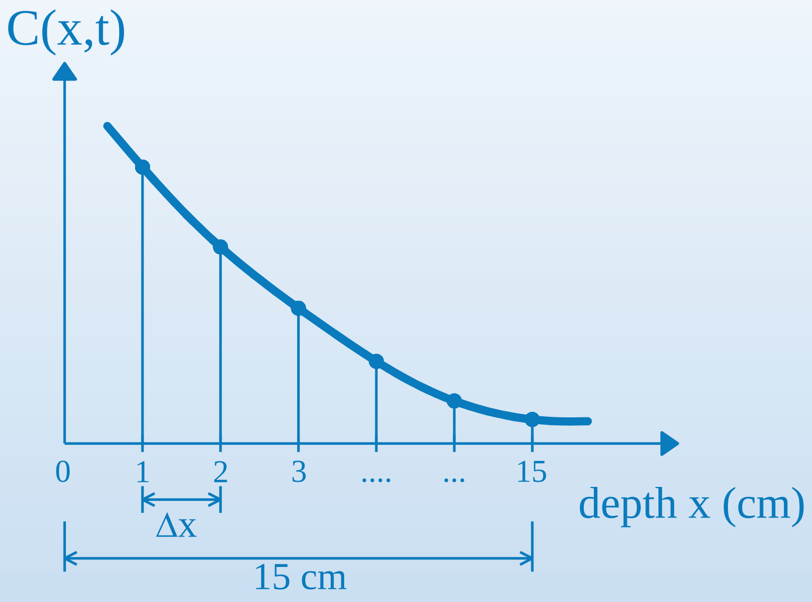


Results:

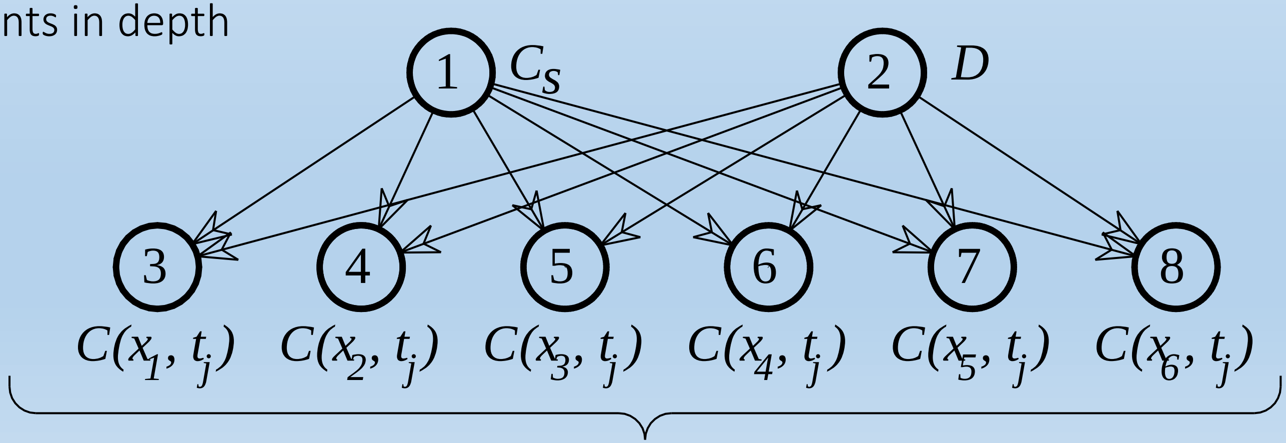
- The chloride concentration at the surface is most valuable in the identification of Cs.
- The chloride content at deeper parts reduces the error on the identification of D.
- However, using evidence from one point in depth could not give a good estimation for D.

Discretization the inspection depth

Case	Δx (cm)	Discretization	Number of points in depth
1	3	0:3:15	6
2	2	0:2:15	8
3	1	0:1:15	16
4	0.5	0:0.5:15	31
5	0.3	0:0.3:15	51
6	0.2	0:0.2:15	76

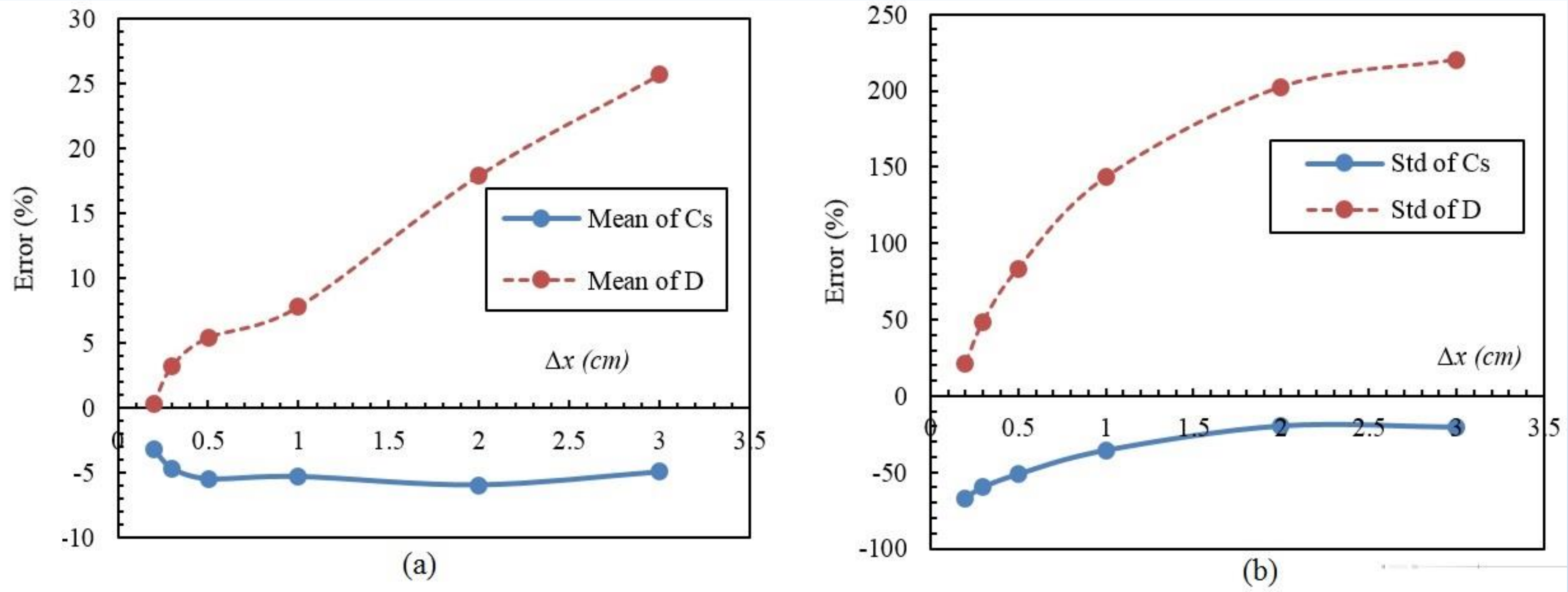


- Inspection time t_{ins} = 10 years
- The BN consists of : Cs, D and n child nodes C(x,t) corresponding to number of points in depth



Δx= 3cm (6 points in depth)

Errors in identification using full depth of inspection



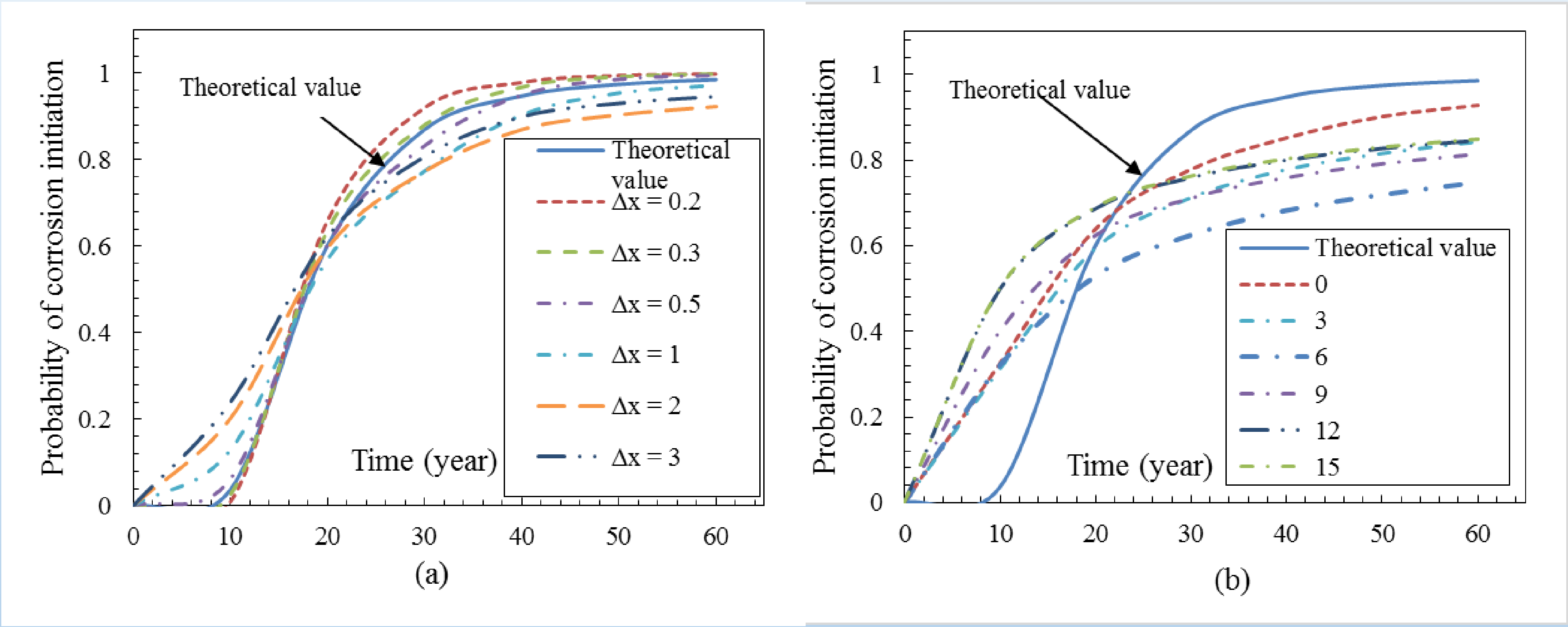
Results:

- Using several measurements could not improve the identification of Cs.
- Discretizing the inspection depth into small intervals could give a better estimation for D.

Probability of corrosion initiation with sufficient data:

a. From full inspection depth

b. From single point inspection depth

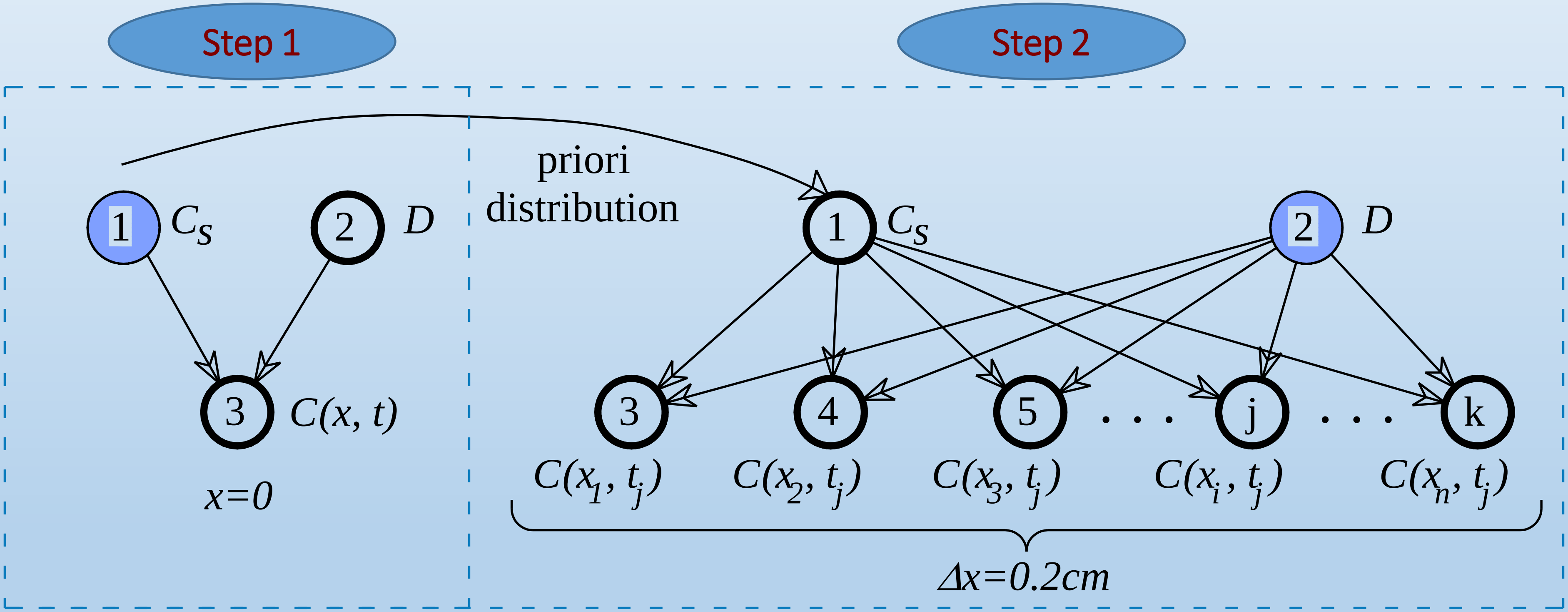


Results:

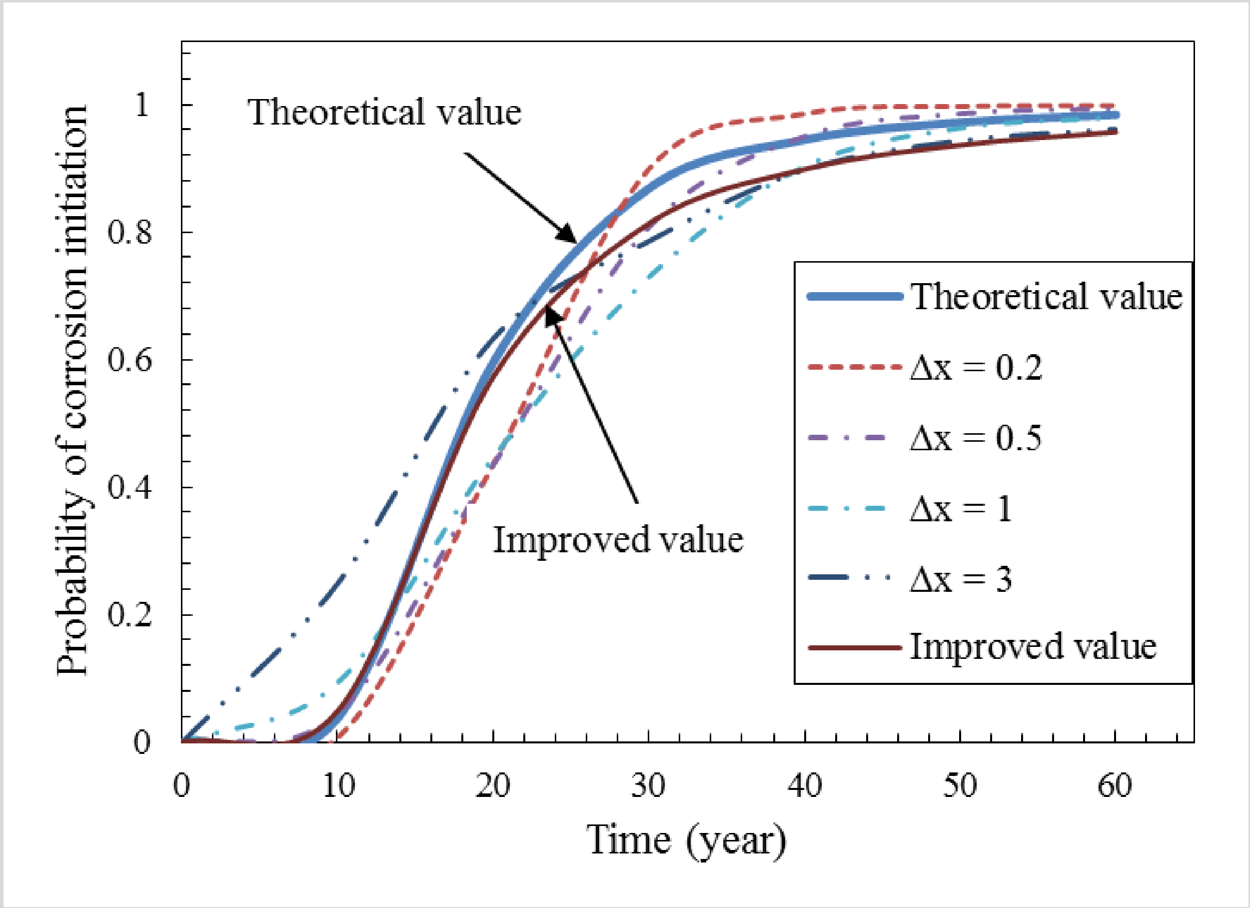
- Δx is small → the prediction results are more close to the target.
- Using data from one depth point → the predictions are unsatisfied

Improving the prediction of probability of corrosion initiation with limited data:

- 15 chloride profiles
- Improving:



5. Assessment the probability of corrosion initiation



Results:

- With limited data, improved value is more close to the target

Conclusions:

- Bayesian networks could provide a probabilistic model for identification random parameters from inspection data
- Each parameter corresponding to a configuration providing the best estimation:

  + For Cs: using evidences from $x \approx 0$

  + For D: using evidences from small Δx

- With limited data, an improved procedure could give a prediction closing to the target.

Perspectives:

- Dealing with different inspection times
- Application to real data
- Extension to other chloride ingress models
- Consideration of measurement errors.

THANK YOU FOR YOUR ATTENTION