COST TU1402: Quantifying the Value of Structural Health Monitoring

Contribution to the 1st Workshop, 04.-05.05.2015, DTU, Denmark

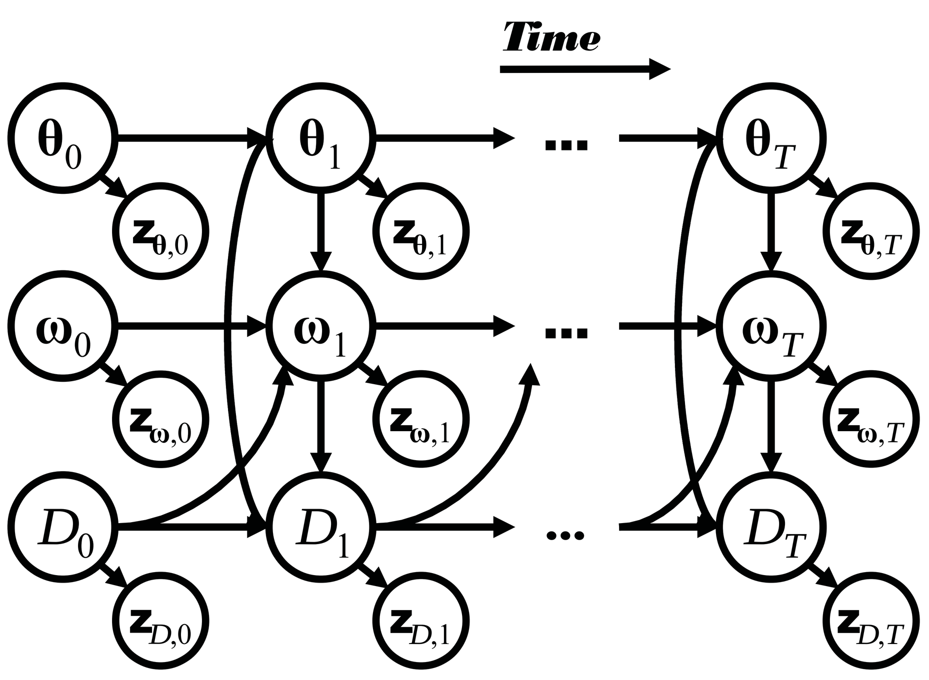
Modeling Structural System Deterioration using Bayesian Networks (BNs)

Jesus Luque *and* Prof. Daniel Straub

Engineering Risk Analysis Group, TU München

BNs can efficiently model single component deterioration

BNs have become popular in engineering risk analysis due to their intuitive nature and their ability to handle many dependent random variables. The graphical structure of the BN is formed by nodes and directed links. The nodes represent random variables or deterministic parameters, and the links the dependence among nodes. BNs allow quantifying the impact of inspections and monitoring on the reliability of the structure, and so facilitate maintenance decisions and the planning of future inspections. In the past, Bayesian analysis has mainly been performed at the component level, e.g. Figure 1 shows a BN deterioration model where the probability of failure of a single structural component is updated using inspection and monitoring outcomes [1].



θ: *Time invariant Parameters*

ω: *Time-variant parameters*

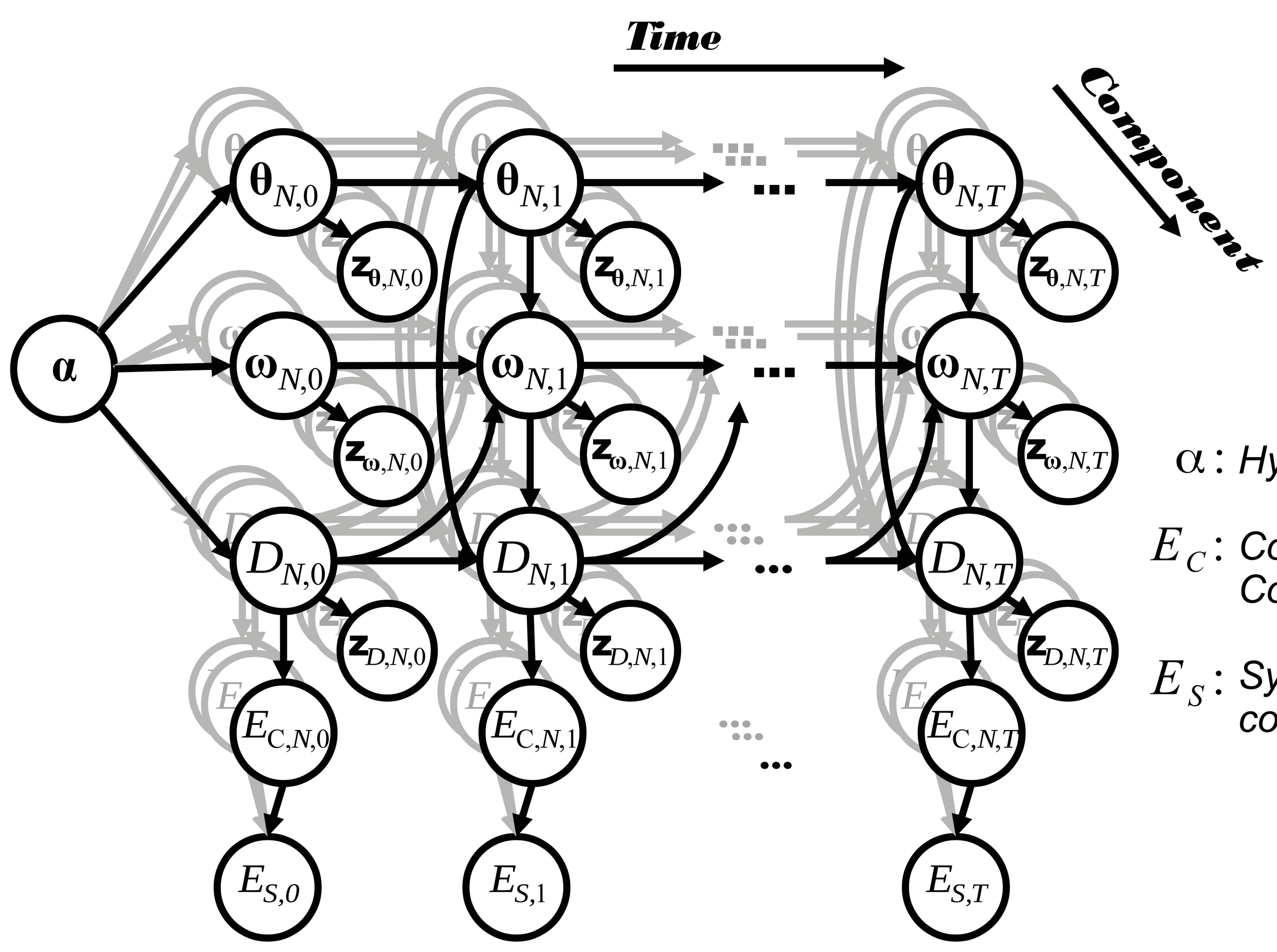
D: Deterioration model

Z: *Observations (inspections/monitoring systems)*

Fig 1. Generic BN of the deterioration model at the component level. The sub-index indicates the time step.

The structural system is modeled through a hierarchical Bayesian network

Only a few publications consider the updating of the reliability at the structural system level. We have extended a BN model from the component to the system level and provided an efficient algorithm that assesses the reliability of a deteriorating system when partial observations of its condition are available. The deterioration factors of the system components are interrelated using a hierarchical structure and a set of hyperparameters **α**, which model the correlation structure among components (Figure 2). The algorithm for performing Bayesian updating at the system level is based on the forward-backward algorithm for exact inference and operates recursively among components and time steps [2].



α: *Hyperparameters*

E_C: *Component Condition*

E_S: *System condition*

Fig 2. Generic BN of the deterioration model at the system level. The sub-indices indicate the component number and time step.

Given the observations, the system reliability is updated accurately and faster

Comparison with the standard Markov Chain Monte Carlo (MCMC) algorithm shows good agreement in different case studies, e.g. the Daniels system (Figures 3 and 4), and Zayas frame (Figures 5 and 6). Computation times are orders of magnitude lower than MCMC and are independent of the magnitude of the probability of failure and of the number of inspection and monitoring results.

Daniels System

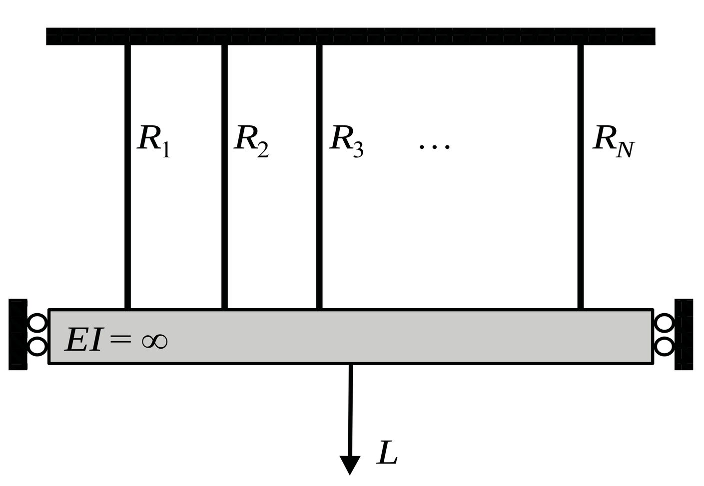


Fig 3. Daniels system with independent and identically distributed capacities R_1,…,R_N and external load L.

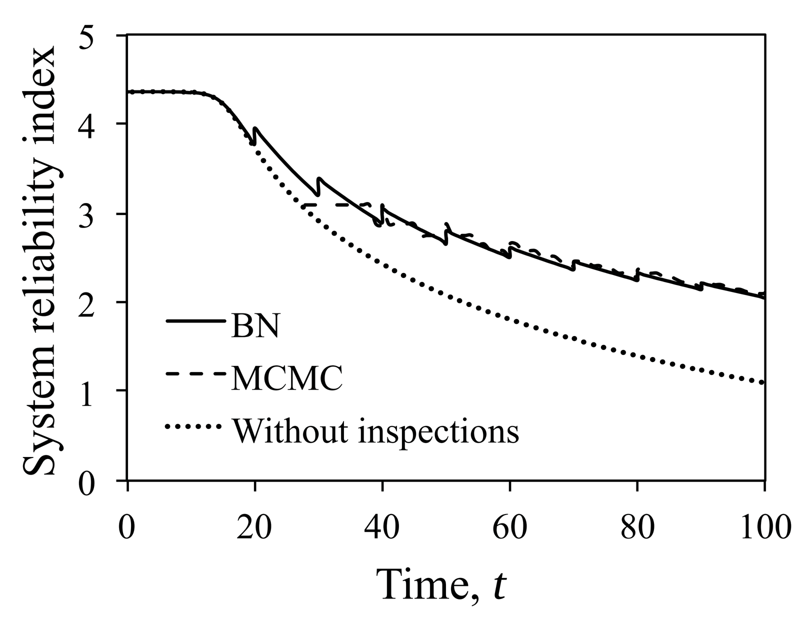


Fig 4. Reliability index of the Daniels system with 10 components after no detection of a crack in all inspection times (every 10 years) using exact inference (BN) and Markov Chain Monte Carlo. Results are also compared to the reliability without inspections.

Zayas Frame

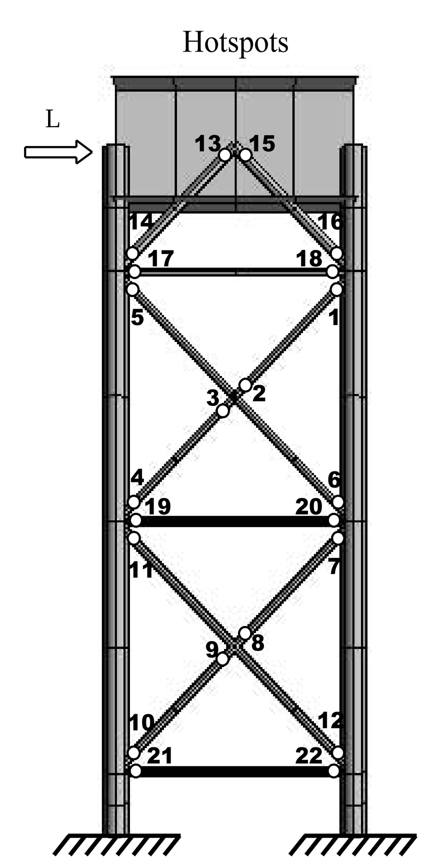


Fig 5. Zayas steel frame structure subject to fatigue deterioration with 22 hotspots (white circles) and external load L.

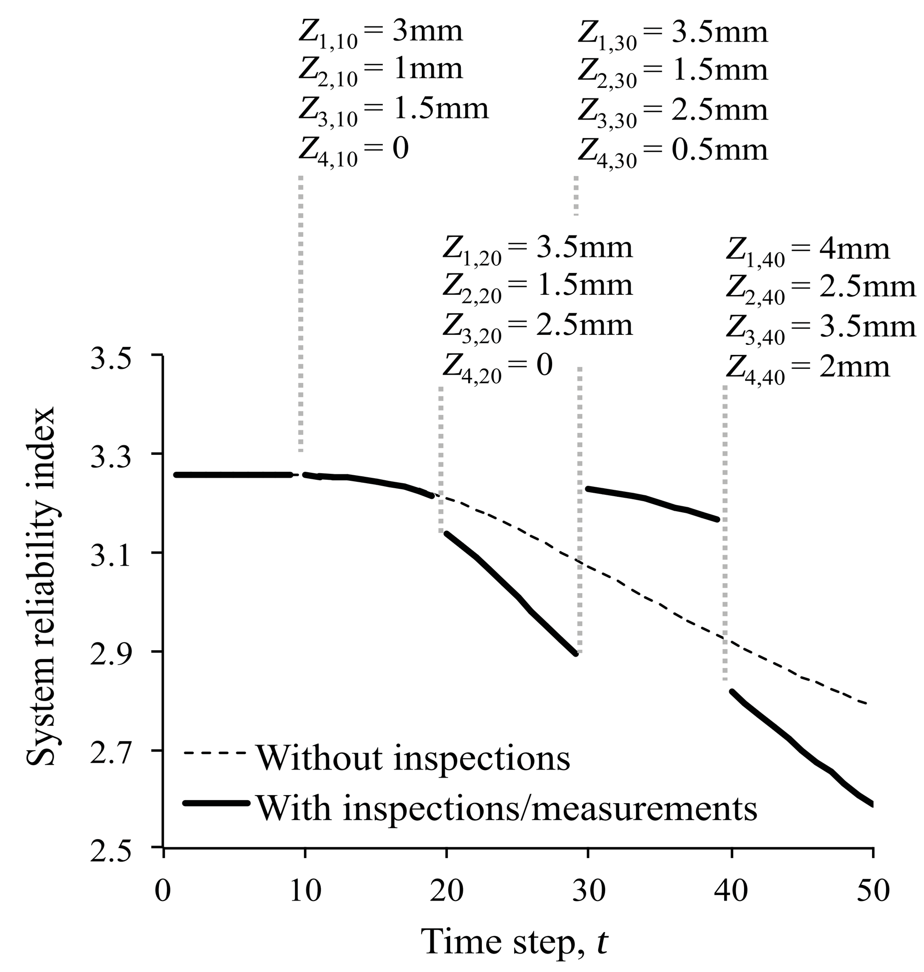


Fig 6. Reliability index of the system for the conditional case (i.e. with inspection) with observations from hotspots 1 to 4 at time steps 10, 20, 30 and 40. A measurement of 0 represents a no-detection case.

References

[1] Straub, D., (2009). Stochastic modeling of deterioration processes through dynamic Bayesian networks. Journal of Engineering Mechanics, Trans. ASCE, 135(10), pp. 1089-1099.

[2] Luque, J., Straub, D., (2015). Probabilistic modeling of system deterioration with inspection and monitoring data using Bayesian networks. Proc. 12th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP12, Vancouver, Canada.